

# Awareness and practice of using public generative AI solutions (such as ChatGPT) and social media among psychiatrists compared to other professionals: A pilot study

Ema Nicea Gruber<sup>1</sup>, Lucija Gruber Zlatec<sup>2</sup> & Sanja Martić Biočina<sup>3</sup>

<sup>1</sup> Ema Nicea Gruber, Forensic Unit R4, Department R, Mental Health Cen-tre Sct. Hans, Roskilde, Denmark

<sup>2</sup> Lucija Gruber Zlatec, BA, Master's student, Roskilde University, Roskilde, Denmark

<sup>3</sup> Sanja Martić Biočina, University Psychiatric Hospital Vrapče, Department of Social Psychiatry, Zagreb, Croatia

received: 13. 12. 2024;

revised: 2. 5. 2025;

accepted: 26. 5. 2025

## Summary

**Background:** The integration of generative artificial intelligence (AI) tools in healthcare has prompted growing interest and concern, especially among mental health professionals. This pilot cross-sectional study explored the awareness, use, and ethical considerations of public generative AI solutions and social media among psychiatrists ( $n = 27$ ) and professionals from other fields ( $n = 44$ ). An anonymous online questionnaire was administered between May and July 2024, collecting both quantitative and qualitative data. Nonparametric tests (Mann-Whitney U, Chi-square, Fisher's exact) were used due to the non-normal distribution and small sample size.

**Results:** Results revealed no significant difference in frequency of AI use between the groups. However, psychiatrists were more likely to report behavioral change based on AI-generated content ( $p = 0.025$ ) and felt more prepared to discuss AI with patients ( $p = 0.011$ ). Ethical concerns regarding AI-induced bias and discrimination were significantly more pronounced among psychiatrists ( $p = 0.049$ ). Both groups emphasized the need for institutional support, though psychiatrists more frequently mentioned GDPR compliance and evidence-based resources.

**Conclusions:** Despite limitations, including sample size and selection bias, this exploratory study highlights key differences in how professionals perceive and engage with generative AI. Findings support the need for targeted education and ethical guidelines in psychiatric practice regarding AI use.

**Keywords:** generative artificial intelligence, ChatGPT, psychiatry, ethics, social media, pilot study

\* \* \* \* \*

## INTRODUCTION

Artificial intelligence (AI) has made significant advancements across various industries, with healthcare being one of the fields most profoundly impacted (Zhang & Kamel Boulos, 2023). AI can be defined as a multi-disciplinary field that combines computer science and linguistics, aiming to create machines capable of performing tasks that typically require human intelligence (Sarker, 2022). Among the cutting-edge AI technologies, generative models, particularly OpenAI's Generative Pre-trained Transformer (GPT) models, such as ChatGPT, are seen as powerful tools with the potential to transform healthcare through their exceptional natural language processing (NLP) abilities (Zhang & Kamel Boulos, 2023). These language models can understand and generate human-like text, which makes them particularly suited for a variety of medical and healthcare applications (Zhang & Kamel Boulos, 2023).

Generative AI models, including public platforms like ChatGPT, have been recognized for their potential to induce paradigm shifts in healthcare education, research, and practice (Sallam, 2023; Tae Won, 2023). Previous studies highlight the following key benefits:

(1) improving scientific writing and promoting research equity; (2) enhancing healthcare research by aiding in dataset analysis, code generation, literature reviews, and facilitating experimental design and drug discovery; (3) supporting healthcare practice by streamlining workflows, saving costs, improving documentation, enhancing personalized medicine, and increasing health literacy; and (4) improving healthcare education by personalizing learning and emphasizing critical thinking and problem-based learning (Sallam, 2023). Recent studies also show that GPT-4's language model offers great potential in improving the accuracy and efficiency of medical research and clinical diagnostics (Lee et al., 2023).

Additionally, AI-based systems have demonstrated potential to improve psychiatric diagnosis (Cansel et al., 2023) and diagnose complex clinical cases (Eriksen et al., 2024). However, for AI to be responsibly integrated into psychiatry and healthcare, ethical frameworks and data protection measures are essential (Briganti, 2023). Despite its potential, AI chatbots must be used with caution due to their limitations (Arshad et al., 2023). Ethical concerns such as biases in training data and algorithmic transparency also need to be addressed to ensure responsible deployment in healthcare (Van Dis et al., 2023).

Nevertheless, concerns regarding ChatGPT and other AI models remain. These include ethical issues, copyright concerns, transparency and legal challenges, risks of bias, plagiarism, hallucinations, inaccuracies, cybersecurity vulnerabilities, and the spread of misinformation (Sallam, 2023). The “black-box” nature of AI models, including GPT models, raises significant concerns regarding the transparency and explainability of their outputs (Zhang & Kamel Boulos, 2023; Hassija et al., 2024). Studies examining interpretability methods, such as SHAP values and partial dependency plots, have highlighted the need for greater transparency in machine learning-based models, especially for predicting medical conditions like hypertension (Elshawi et al., 2019). Furthermore, the shift from statistical inference to machine learning in cardiovascular pharmacotherapy emphasizes the growing need for better understanding and interpretability of AI systems in critical healthcare contexts (Pavlov et al., 2024). Addressing data privacy, patient confidentiality, and algorithmic biases is crucial for ensuring the responsible use of AI technologies in healthcare (Zhang & Kamel Boulos, 2023). Furthermore, guaranteeing the accuracy and reliability of AI-driven decisions is essential, particularly in high-stakes medical contexts (Rosol et al., 2023).

### **Aims of the study**

To investigate awareness and practice of using public generative AI solutions and social media in psychiatrists compared to other professionals.

## **SUBJECTS AND METHODS**

### **Study Design and Participants**

This study was conducted using an anonymous online questionnaire between May 15th and July 15th, 2024. A total of 71 participants took part. The study was designed as a cross-sectional, exploratory survey intended to gather both quantitative and qualitative data.

### **Inclusion and Exclusion Criteria**

Inclusion criteria were: adults aged 18 or older, access to the internet and social media, sufficient understanding of the questionnaire language, informed consent to participate.

Exclusion criteria included: individuals under the age of 18, those who did not give informed consent.

No further demographic or professional quotas were used.

### **Recruitment and Sampling**

Participants were recruited using convenience sampling. A link to the questionnaire (in google forms) was distributed via various social media platforms, including Facebook, LinkedIn, and Twitter/X, as well as shared through personal and professional networks.

No targeted advertising or demographic filtering was applied.

This recruitment method introduces potential selection bias and limits the generalizability of the findings.

An online questionnaire was used to gather information from participants.

It included 48 questions, and the link to it was shared through various social media platforms.

Participation in the survey was anonymous and voluntary, and participants were informed that they have the right to skip or not answer any of the questions.

The questionnaire took approximately 15-20 minutes to complete.

Answers and personal data were kept completely confidential, following the General Data Protection Regulation (GDPR), and the research conclusions only provide aggregate information that does not identify individuals.

The study was led voluntarily and independent of external funding.

The full questionnaire is available as Appendix A.

Questions covered sociodemographic data, professional background, and subjective opinions. Binary (yes/no), ordinal (1–5 scale), and free-text responses were used.

Some questions required binary responses, such as ‘yes/no’ answers or categorical responses on a scale from 1 to 5, while other questions provided an opportunity for qualitative responses, allowing participants to write down their thoughts and opinions.

The qualitative responses were organized into categories.

### **Sample Size Considerations**

Given the exploratory nature of this study, the total sample size (n=71) was deemed acceptable for initial analysis, though relatively small for inferential comparisons. As the data did not meet assumptions of normality,

nonparametric statistical tests were employed to ensure robustness of the findings. However, we acknowledge that the limited sample size reduces the statistical power and increases the risk of both type I and type II errors. Therefore, the results should be interpreted with caution and regarded as preliminary, providing a basis for future research with larger and more representative samples.

Nonparametrics were used to analyze answers (Sheskin, 2004) because nonparametric methods do not require a normal distribution and can be used for ordinal or categorical data. They do not rely on specific distribution parameters. Nonparametric methods used: Mann-Whitney U test (nonparametric alternative to the t-test), Spearman's rank correlation coefficient (nonparametric alternative to Pearson's correlation) and Chi-square test (for analyzing categorical variables). Fisher's exact test was used for small samples (sample size cutoff 5).

**Mann-Whitney U test:** This test was used as a nonparametric alternative to the t-test because the data did not meet the assumption of normality. The Mann-Whitney U test is appropriate for comparing differences between two independent groups when the data are ordinal or when the assumption of normal distribution cannot be assumed. It is particularly useful for analyzing skewed distributions or data with outliers that may affect the results of parametric tests.

**Spearman's rank correlation coefficient:** This method was chosen as a nonparametric alternative to Pearson's correlation coefficient. While Pearson's correlation assumes that the relationship between variables is linear and that the data are interval or ratio scale, Spearman's rank correlation does not require these assumptions. Instead, it assesses the strength and direction of the monotonic relationship between two variables. This makes it suitable for ordinal data or when the relationship between variables is not linear.

**Chi-square test:** The Chi-square test was employed to analyze categorical variables. It assesses whether there is a significant association between two categorical variables. This test is appropriate for frequency data and does not require assumptions about the underlying distribution of the variables. It allows for the analysis of relationships between variables in contingency tables.

**Fisher's exact test:** This test was used when the sample size was small (with a cutoff of 5 per cell in the contingency table). Fisher's exact test is a nonparametric test that is especially useful for small sample sizes or when the expected frequencies in any of the cells of a contingency table are low. It provides a more accurate p-value when the Chi-square test's assumptions (expected cell frequencies) are not met, making it particularly suitable for small or sparse datasets.

## Use of ChatGPT

ChatGPT-4 was used with caution to support the following tasks: generating ideas, summarizing, paraphrasing, and checking grammar; assisting with data summarization and coding guidance (e.g., R, Python); providing feedback on text structure and clarity.

All decisions regarding data interpretation and manuscript preparation were made by the authors. ChatGPT was accessed via OpenAI's web interface (not API), between May 15 and July 15, and between September 20 and December 21, 2024.

The authors declare no financial interest or affiliation with OpenAI. ChatGPT is a Large Language AI model developed by OpenAI (OpenAI, 2024).

As it currently stands, ChatGPT does not qualify to be listed as an author in scientific articles unless the ICMJE/COPE guidelines are revised or amended (Sallem, 2023).

This analysis was performed using OpenAI's ChatGPT (GPT-4o) via the online chat interface. ChatGPT-4o was used during the periods from May 15 to July 15, 2024, and from September 20 to December 21, 2024.

Regarding model settings: Temperature and Top-p are parameters that control response variability. In the online ChatGPT version (which we are using), there's no option to manually adjust temperature and top-p—OpenAI sets these values internally. The default setting for temperature in the online ChatGPT interface is 1.0.

API version was not used.

The authors have no financial connection with the company OpenAI and do not make any commission if a reader chooses to start using Public Generative AI solutions.

## Ethics Statement

This research project and all related procedures were conducted in accordance with the ethical principles of the National Committee on Research Ethics, Copenhagen, Denmark, and fully complied with the General Data Protection Regulation (GDPR). Participation was voluntary and anonymous, and participants were informed of their right to withdraw at any point or skip any question without consequence.

According to Danish national guidelines, formal ethical approval is not required for studies that do not involve sensitive personal data, biological material, or interventions. Since this study collected only anonymous survey responses without identifiable or sensitive information, no formal application was submitted to a research ethics committee.

## RESULTS

A total of 71 participants took part in the study, which was conducted from May 15th 2024, to July 15th 2024, via social media and by sharing links to the questionnaire through social networks.

### Sociodemographic data:

Out of the total of 71, 27 participants were psychiatrists (38%) and 44 were other professions (62%). Out of 71 participants 22 (31%) were employed in Region Hovedstaden Psykiatri (Central Region in Denmark). Other professions included: computer scientist, IT manager, software engineer, occupational therapist, psychologist, students and teachers.

**Country of origin:** Psychiatrists from the study (in total 27): Denmark – 17 (62.96%), Croatia – 7 (25.93%), Serbia – 1 (3.70%), UK – 1 (3.70%). Other professions (in total 44): Denmark – 18 (40.91%), Croatia – 19 (43.18%), Sweden – 3 (6.82%), Ireland – 3 (6.82%), Slovenia – 1 (2.27%), United Kingdom – 1 (2.27%)

Age Distribution, Gender Distribution and Use of Public Generative AI among participants are shown in table 1.

The gender distribution in both groups: a predominance of women. Due to this imbalance, we did not perform a statistical analysis of responses by gender.

There is no statistically significant difference between the groups in the use of public generative AI solutions.

### Psychiatrists using public generative AI solutions:

Denmark (18 respondents): Yes: 50.00% (9 respondents), No: 50.00% (9 respondents); Croatia (6 respondents): Yes: 83.33% (5 respondents), No: 16.67% (1 respondent). Fisher's exact test for small samples (sample size cutoff 5): p-value is 0.341. In this small sample, there is no statistically significant difference in the use of public generative AI solutions between psychiatrists from Denmark and Croatia.

**Percentage of usage of public generative AI solutions among all respondents:** Only chatGPT 29,58%, Only Google Assistant 14,08%, Google Assistant and chatGPT 4,23%, none of the above 4,23%, only Siri 2,82%, Siri and chatGPT 11,27%, Siri and Google Assistant 1,41%

Out of the 71 participants, 14 (19.72%) use public generative AI solutions only in their private life, 24 (33.80%) use public generative AI solutions both in their

Table 1. Age Distribution, Gender Distribution and Use of Public Generative AI among participants

Category	Psychiatrists (n=27)	Other Professions (n=44)	All Participants (n=71)
<b>Age Distribution</b>			
<30 years	2 (7.69%)	10 (22.73%)	12 (16.90%)
30-39 years	4 (15.38%)	10 (22.73%)	14 (19.72%)
40-49 years	7(26.92%)	6 (13.64%)	13 (18.31%)
50-59 years	8 (30.77%)	15 (34.09%)	23 (32.39%)
>60 years	5 (19.23%)	3 (6.82%)	8 (11.27%)
Average Age (SD)	48.31 (11.10)	42.34 (14.33)	45.14 (12.93%)
<b>Gender Distribution</b>			
Women	21(77.78%)	29 (65.91%)	50 (70.42%)
Men	5 (18.52%)	13 (29.55%)	18 (25.35%)
Non-binary	1(3.70%)	1(2.27%)	2 (2.82%)
Gender Queer	0(0%)	1(2.27%)	1(1.41%)
<b>Use of Public Generative AI</b>			
Yes	15 (55.56%)	28 (63.64%)	43(60.56%)
No	12 (44.44%)	16 (36.36%)	28(39.44%)
Chi-Squared Statistic (p-value)	0.472 (0.492)		

private and professional life, 7 (9,86%) use public generative AI solutions only in their professional life, and 36.62% did not answer the question.

Out of 15 psychiatrists that use public generative AI solutions, 5 (37,5%) only use them in private life and 10 (62,5%) in private and professional life. Chi-Square Statistic: 7.064, p-value: 0.070.

There is no statistically significant difference in the distribution of responses between the two groups at the 5% significance level.

Testing for gender differences resulted in the chi-square statistic of 2.431 and the p-value of 0.656, indicating no significant difference in AI usage based on gender was found within either group.

Responses to the question “What are you using generative AI for ”were mostly in categories: writing and editing text, research and education, professional assistance and entertainment and relaxation.

Among other professionals, 29.55% (13 respondents) reported using AI a few times a week for a short period, while among psychiatrists, that percentage was at 33.33% (9 respondents).

Those having reported using AI once a month category included 25.00% (11 respondents) of other professionals and 18.52% (5 respondents) of psychiatrists.

Regarding daily use of AI for a short period, 11.36% (5 respondents) of other professionals responded affir-

matively, while among psychiatrists, that percentage is 14.81% (4 respondents).

Using AI a few times a week for longer periods accounts for 4.55% (2 respondents) of other professionals and 7.41% (2 respondents) of psychiatrists. The respondents using AI rarely included 2.27% (1 respondent) of other professionals, while none of the psychiatrists selected this response.

Additionally, 2.27% (1 respondent) of other professionals use AI as needed, not on a regular basis, while none of the psychiatrists gave this response. Using AI less than once a month included 4.55% (2 respondents) of other professionals, while no psychiatrists chose this option.

Finally, 20.45% (9 respondents) of other professionals and 25.93% (7 psychiatrists) responded that they never use AI solutions.

The result of the chi-square test for independence was 3.47, with a p-value of 0.84, indicating that there are no statistically significant differences in the responses between the groups of psychiatrists and other professionals regarding the frequency of AI solution usage.

Comparison of positive responses from psychiatrists and other professions with p-value differences between groups ( $p < 0.05$  to be statistically significant) to questions with yes-no answers are shown in figure 1. Statistically significant differences between the groups were not found in the responses to the questions presented in Figure 1.

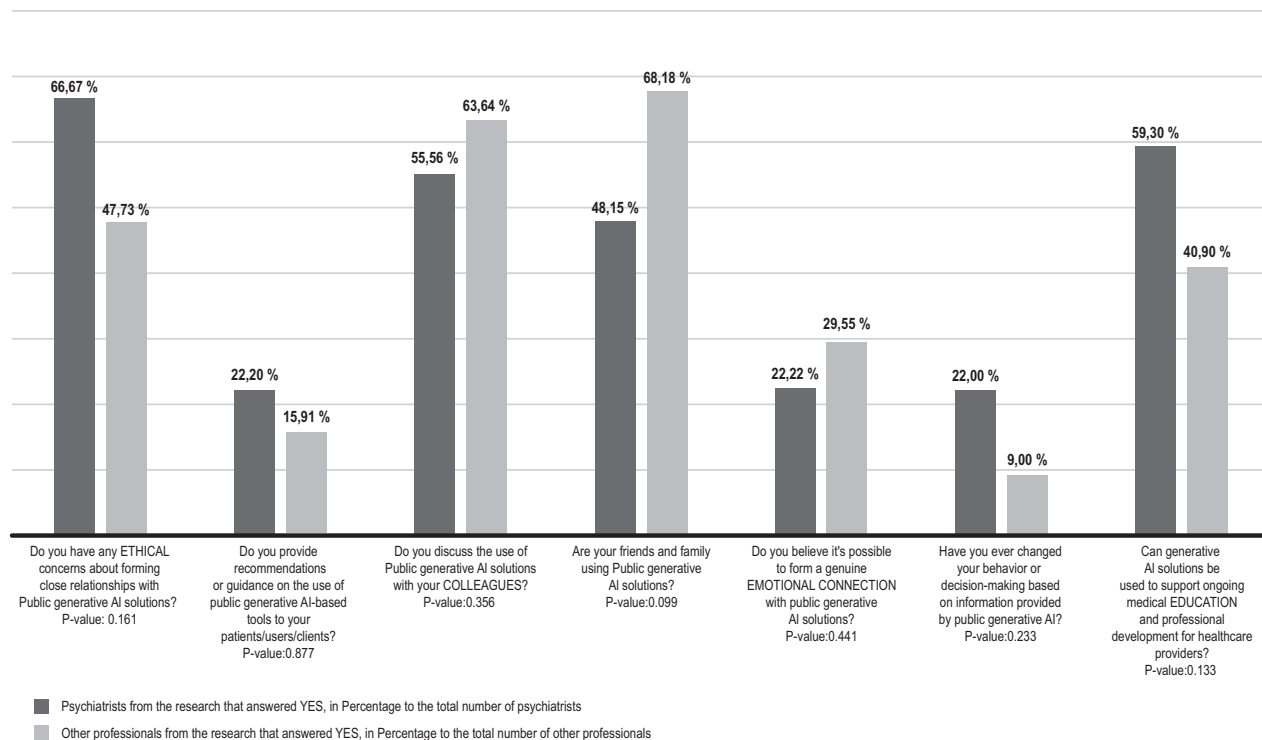


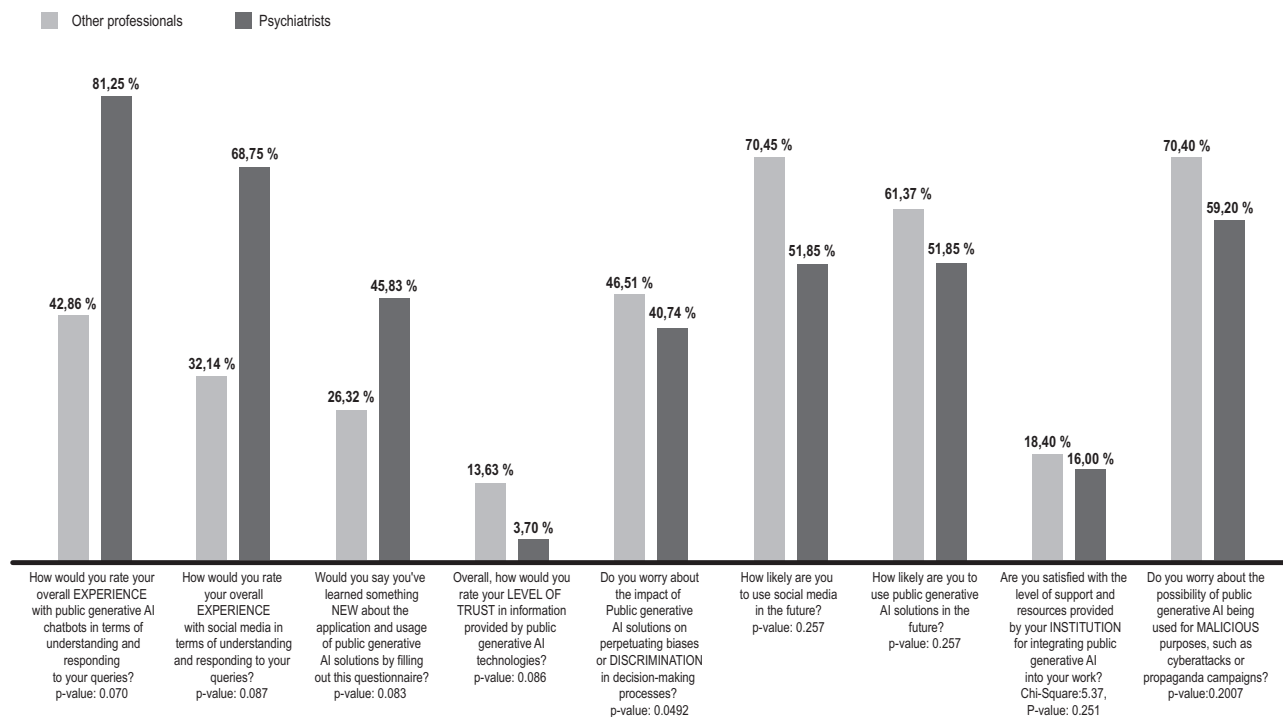
Figure 1. Comparison of positive responses from psychiatrists and other professionals regarding their attitudes and behaviors related to public generative AI solutions.

Bar chart displays the percentage of respondents in each group (psychiatrists vs. other professionals) who answered positively (“yes”) to selected statements related to ethical concerns, guidance provision, peer discussions, emotional connection, behavior change, and educational use of public generative AI. Differences between groups are accompanied by p-values, with  $p < 0.05$  considered statistically significant. Percentages are calculated based on the total number of respondents in each group.

When providing qualitative answers to the question “Do you have any ETHICAL concerns about forming close relationships with public generative AI entities?” participants expressed concerns about the reliability of information provided by AI, including potential biases, lack of accuracy, and issues with trust. There are also concerns about moral and ethical aspects, such as responsibility for decisions made by AI, lack of empathy, and dehumanization. Women in both groups were more likely to highlight issues related to bias, data reliability, and ethical dilemmas regarding AI. Men were more likely to express a more skeptical or neutral stance on ethical issues, focusing more

on technical aspects. Non-binary respondents provided answers that covered a wide range of ethical issues, but with a very limited sample size. Younger respondents more frequently expressed concerns about the technical reliability and potential biases of AI. Older respondents, particularly in the group of psychiatrists, were more focused on ethical and moral dilemmas, including the risk of dehumanization and responsibility for AI decisions.

Percentage distribution of responses among Psychiatrists and Other Professionals, calculated separately for each group based on their respective total number of respondents is shown in Figure 2, together with the level of statistical significance ( $p < 0.05$  to be statistically significant). Statistical analysis was conducted on responses from a Likert scale ranging from 1 to 5. For clarity of presentation in Figure 2, responses from a Likert scale 1-5 have been combined, with values 4 and 5 merged into a single ‘high level’ category and only this “high level” category is shown in Figure 2. Depending on the question, this category includes responses such as ‘high,’ ‘excellent,’ or ‘very much’.



Responses from a Likert scale have been combined, with values 4 and 5 merged into a single 'high level' category. Depending on the question, this category includes responses such as 'high,' excellent, or 'very much'.

Figure 2. Percentage distribution of responses among Psychiatrists (n=27) and Other Professionals (n=44), showing only responses in the “high level” category (combined scores of 4 and 5 on a 5-point Likert scale). For each item, percentages represent the proportion of participants in each group who gave a high rating or expressed high agreement. Questions cover experience with AI chatbots and social media, trust in AI, concerns about discrimination and malicious use, likelihood of future use, institutional support, and learning outcomes. Statistical tests used include Chi-square and p-values are provided below each item; significance was set at  $p < 0.05$ . Values below that threshold indicate statistically significant group differences (e.g., concern about discrimination:  $p = 0.0492$ ).

A statistically significant difference between the groups “Psychiatrists” and “Other Professionals” was found in the responses to the question:

Do you worry about the impact of Public generative AI solutions on perpetuating biases or DISCRIMINATION in decision-making processes?

Scale 1 (not at all) – 5 (very much), Mann-Whitney U test, U statistic: 474.5, p-value: 0.0492.

All psychiatrists from the research: The most frequent rating for concern was 3 (48.15%). A significant portion answered with 5 (25.93%), indicating a high level of concern. A smaller number rated it 4 (14.81%).

Participants of other professions from the research: Ratings of 3 (37.21%) and 4 (34.88%) dominated, indicating greater variability in the mid-range of concern. A rating of 1 was present (11.63%), which was not the case among psychiatrists.

Psychiatrists generally show medium to high concern about the potential of AI solutions to perpetuate bias or discrimination in decision-making processes. Participants from other professions show more variability in

their perceptions, with many giving ratings of 3 and 4, while a smaller number show extreme concern (rating 5) or a lack of concern (rating 1).

Statistically significant difference between the groups “Psychiatrists” and “Other Professionals” to questions about use of generative AI solutions at work was found in the responses to the questions in Figure 3: Do you feel adequately prepared to discuss the BENEFITS and LIMITATIONS of AI in healthcare with your patients/clients? Chi-square: 6.54, P-value: 0.011 and a question: Have you ever changed your BEHAVIOR or DECISION-MAKING based on information provided by public generative AI? Chi-square:5.02, P-value: 0.025

Qualitative responses to the question: “Would you like to receive more PRACTICAL SUPPORT and resources from your institution for integrating AI into clinical practice? If yes, what form of practical support or resources would be good?”.

In the group of “Psychiatrists” answers were: “workshop”, “training”, education of limitations of such models”, “list of resources and evidence-based resources”,

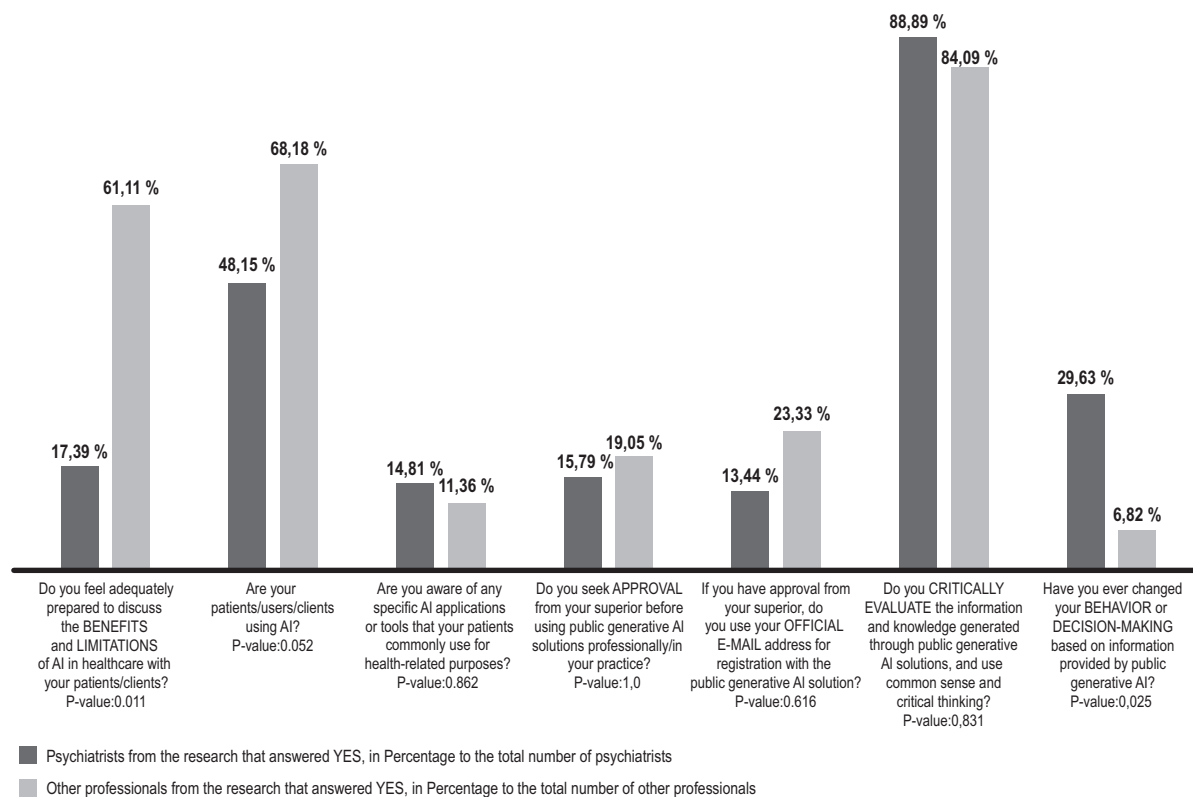


Figure 3. Comparison of positive responses from psychiatrists and other professionals regarding the use of generative AI solutions at work. The chart displays the percentage of participants from each group (psychiatrists in black bars, other professionals in grey bars) who answered “YES” to each question. Statistically significant differences ( $p < 0.05$ ) between the groups are indicated by p-values listed below each question. The questions address topics such as preparedness to discuss AI, patient usage of AI, awareness of AI tools, approval procedures, use of official email for registration, critical evaluation of AI-generated content, and influence of AI on behavior or decision-making.

“information on GDPR issues”, “more reliable AI available to employers”, “access to platforms specialized in AI in research.”

In the group of “Other professionals” answers were: “how it can be used for clinical purposes and decision-making”, “awareness of pitfalls and search optimization”, “for educational matters”, “information about possibilities”, “investing in new solutions”, “guidelines for when to use it and which one” Notably, there were no explicit concerns regarding GDPR compliance from this group, and some participants offered non-responses and uncertain answers, such as “I don’t know” and “I will not use PUBLIC AI solutions.”

Overall, both groups emphasized the need for education and reliable information, with psychiatrists focusing more on GDPR compliance, while participants from other professions expressed interest in practical guidelines and tools for AI use.

## Social Media

Social media usage in all respondents: Facebook 70,42%, Instagram 53,52%, LinkedIn 38,03%, YouTube 29,58%, Twitter 12,68%, Snapchat 12,68%, Reddit 11,27%, Pinterest 8,45%, TikTok 7,04%, Tumblr 1,41%, Be Real 1,41%, None of the Above 1,41%.

For the correlation between experience with generative AI solutions and social media, see to questions in Figure 2, Spearman’s rank test was used, Psychiatrists: Correlation: -0.0516, p-value: 0.8494. This indicates a very weak negative correlation between ratings for AI solutions and social media, without statistical significance. Other professions: Correlation: -0.1209, p-value: 0.5481. The correlation is weak and negative, and not statistically significant. There is no significant association between experiences with generative AI solutions and social media among respondents in both groups.

Qualitative responses to the question, “What are you using social media for?” in categories: Participants from other professions utilize social media primarily for entertainment (65.9%), more than psychiatrists (45.8%). Psychiatrists focus more on communication (25.0%) compared to other professions (11.4%). Both groups use social media for information and news, with psychiatrists at 25.0% and other professions at 18.2%. The category of “planning and events” is less popular among both groups, while “work and research” are utilized similarly. Other professionals show “inspiration and creativity” (9.1%), which psychiatrists do not.

## DISCUSSION

The results of the study are first summarized under thematic subheadings, presenting key findings related to AI usage, its benefits, challenges, institutional support, and social media.

Following this, these findings are discussed under the same subheadings, providing interpretation, context, and implications of the results.

### Summary of the Most Important Results

Total Participants: 71 (Psychiatrists: 27 [38%], Other Professionals: 44 [62%])

Other professions included IT specialists, occupational therapists, psychologists, students, and teachers. Psychiatrists were primarily from Denmark (63%) and Croatia (26%). Psychiatrists: 48.31 years (SD = 11.10), Other Professionals: 42.34 years (SD = 14.33)

### Use of Public Generative AI

Psychiatrists: 55.56% used AI tools, 44.44% did not.

Other Professionals: 63.64% used AI tools, 36.36% did not.

No statistically significant difference in AI usage between the two groups ( $\chi^2 = 0.472$ ,  $p = 0.492$ )

### Types of AI Used

Only ChatGPT: 29.58%, Only Google Assistant: 14.08%, Both Google Assistant & ChatGPT: 4.23%, None of the above: 4.23%, Only Siri: 2.82%, Siri & ChatGPT: 11.27%, Siri & Google Assistant: 1.41%

### Trust in AI

No statistically significant difference between groups regarding their trust in AI-generated information.

Psychiatrists generally exhibited lower trust levels, with none rating it as “excellent” (5), whereas some other professionals gave higher trust ratings.

### Benefits of using AI

Psychiatrists were significantly more likely to feel prepared to discuss AI benefits and limitations with patients ( $p = 0.011$ ).

Psychiatrists were also more likely to have changed their behavior or decision-making based on AI-generated information ( $p = 0.025$ ).

AI was used in both groups to support clinical decision-making, research, and education.

## Challenges of using AI

**Ethical Concerns About AI Relationships:** Participants expressed concerns about: Reliability, accuracy, and potential biases in AI-generated information, Ethical and moral issues, including responsibility for AI-driven decisions, lack of empathy, and the risk of dehumanization in AI interactions.

**Bias and Discrimination Concerns:** Psychiatrists showed significantly higher concern about the potential for public generative AI solutions to perpetuate bias and discrimination compared to other professionals.

**Concern om possibility to form a genuine emotional connection with a public generative AI:** 22,22% of psychiatrists and 29,55 % other professionals in our research believe it's possible to form a genuine emotional connection with a public generative AI.

**Concerns About Malicious AI Use:** No significant difference between groups regarding concerns about AI being used for malicious purposes like cyberattacks or propaganda ( $p = 0.2007$ ).

**Institutional Support in Using AI:** No significant differences were found in satisfaction with institutional support for AI integration ( $p = 0.251$ ).

**Need for Institutional Support.** Psychiatrists emphasized the need for: Workshops, Training, Education on AI limitations, GDPR-related guidance, Access to evidence-based resources and specialized AI platforms for research.

**Other Professionals focused on:** Practical applications in clinical decision-making, Awareness of AI pitfalls, educational resources, Investment in AI solutions, Guidelines on when and how to use AI. GDPR compliance was a key concern for psychiatrists but was not explicitly mentioned by other professionals.

**Job Loss Concerns:** Both groups showed moderate concern about AI-driven job losses, with no significant difference between them ( $p = 0.796$ ).

## Future Use of AI

No significant differences were found in the likelihood of using public generative AI solutions in the future ( $p = 0.257$ ).

No significant differences were found in AI usage by patients, awareness of AI tools used by patients, seeking approval before using AI, or critical evaluation of AI-generated content.

## Social Media Usage

Entertainment was the primary use for other professionals (65.9%) compared to psychiatrists (45.8%). Communication was more common among psychiatrists

(25.0%) than other professionals (11.4%). Information and news consumption was similar in both groups (psychiatrists: 25.0%, other professionals: 18.2%). Planning and event organization had low engagement across both groups. Work and research were used similarly by both groups. Inspiration and creativity were noted among other professionals (9.1%) but not among psychiatrists. **Correlation Between AI and Social Media Experience with AI and social media:**

Very weak, non-significant **negative** correlations were found in both groups, suggesting no meaningful association between experiences with AI and social media.

**Following this, these findings are discussed under the same subheadings, providing interpretation, context, and implications of the results.**

Participants were recruited through open online distribution, primarily via social media platforms. This recruitment strategy resulted in a heterogeneous and non-random sample, including both mental health professionals and individuals from unrelated fields. While the sample cannot be considered representative, such open recruitment is consistent with the exploratory nature of the study.

Given the modest response rate and variability in professional background, this study is best considered a pilot. Despite the limitations in recruitment, conducting such a pilot study is valuable for identifying practical challenges, gauging interest in the topic, and informing the design of a more rigorous, large-scale study. It provides important preliminary insights into how the topic is received across a broad audience and where targeted recruitment efforts might be improved in future research.

Pilot studies are primarily conducted to assess feasibility and are not expected to produce generalizable results. As such, they do not require ideal conditions. Their main function is to identify practical and methodological challenges—such as low response rates—evaluate the usability of research instruments and generate preliminary indications of interest in the research topic (Thabane et al., 2010). Even when based on a small and heterogeneous sample, pilot studies provide valuable insights by revealing aspects that may need refinement, such as recruitment strategies, distribution methods, and the clarity of survey questions (Thabane et al., 2010). Although the data collected may not be representative, it can indicate initial patterns, trends, or ambiguities worthy of further investigation. In addition, a limited response rate may itself offer meaningful information about the accessibility of the target population, the perceived relevance of the topic, or the potential need for alternative methodological approaches (Thabane et al., 2010).

## Use of AI (Artificial intelligence)

Large language models (LLMs) represent a subset of artificial intelligence (AI) systems specifically developed to process and generate natural language (Asbach et al., 2024). Trained on extensive and diverse textual datasets, LLMs are capable of performing a variety of language-related tasks, including translation, summarization, question answering, and text completion. Given a specific prompt or context, LLMs generate fluent, coherent, and human-like responses. In broader terms, AI encompasses capabilities such as problem-solving, language comprehension, learning from data, and decision-making (Asbach et al., 2024).

Public generative AI solutions refer to tools and platforms that apply generative models and are accessible to the general public. These tools leverage advanced machine learning techniques to produce content in multiple formats, including text, images, audio, and code. Common categories include chatbots and virtual assistants (e.g., ChatGPT, Google Bard, Bing AI), content writing platforms (e.g., Jasper, Copy.ai), translation and summarization tools (e.g., DeepL Write, Grammarly), and code generation tools (e.g., GitHub Copilot, CodeWhisperer).

GPT-4, released by OpenAI on March 14, 2023, represents the latest iteration in the GPT model series and is estimated to have been trained on more than one trillion parameters. It demonstrates improved reasoning abilities and better adherence to complex instructions, and it is approximately 40% more likely to generate factually accurate responses compared to its predecessor, GPT-3.5. Nevertheless, GPT-4 still exhibits limitations, including the potential to produce biased, inappropriate, or inaccurate outputs (Asbach et al., 2024).

Recent literature highlights the application of generative AI in statistical analysis, emphasizing its role in supporting data interpretation and workflow automation (Inala et al., 2024). Additionally, ethical and authorship concerns have emerged regarding the use of AI tools in academic writing. According to the ICMJE and COPE guidelines, tools such as ChatGPT do not meet authorship criteria, as they cannot assume responsibility for the integrity or accountability of published work (Sallam, 2023; Stokel-Walker, 2023).

Beyond research and analytics, generative AI has demonstrated utility in educational contexts. For instance, it can support writing and language development by generating ideas, composing essays, summarizing and paraphrasing text, and checking grammar. It can also assist educators by helping create lesson plans, quizzes, and supplementary learning resources (Albadarin et al., 2024).

## Benefits in using AI

Artificial intelligence (AI) holds significant potential to transform the field of psychiatry by enhancing patient outcomes, improving operational efficiency, and reducing healthcare costs (Terra et al., 2023). As interactive systems, AI tools can engage with patients by providing educational content and answering medical queries, thereby promoting greater patient involvement and empowerment (Zhang & Kamel Boulos, 2023). Additionally, generative AI models such as GPT can support the management of electronic health records (EHRs), alleviating administrative workloads and enabling healthcare professionals to dedicate more time to direct patient care (Zhang & Kamel Boulos, 2023).

## Challenges in using AI

Despite the growing potential of artificial intelligence (AI) in healthcare, several challenges remain. These include external systemic factors, internal limitations in strategic change management, and the need to transform healthcare professions and practices (Peterson et al., 2022), as well as sustainability concerns regarding the development and implementation of AI solutions (Li et al., 2022). A major issue is accuracy, as diagnostic or treatment errors may result in serious harm (Terra et al., 2023). In psychiatry, the use of AI raises critical concerns about privacy, confidentiality, and the system's inability to manage emergencies (Kretzschmar et al., 2019; Terra et al., 2023). Over-reliance on AI may also reduce face-to-face interactions and contribute to problematic use patterns (Vaidyam et al., 2019).

Concerns have also been raised about AI's influence on learning environments, particularly the dissemination of false or fabricated information (Fergus et al., 2023). This has led some educational institutions to ban tools like ChatGPT (Nolan, 2023). In a review of 60 records, 96.7% cited issues such as ethics, transparency, bias, plagiarism, hallucinated content, and cybersecurity risks (Sallam, 2023). AI-generated hallucinations—confident yet inaccurate outputs—can be especially dangerous in medical contexts, where they may impact clinical decision-making and patient safety (Alkaissi & McFarlane, 2023; Lin, 2023). ChatGPT, for example, has fabricated sources and citations in academic writing (Alkaissi & McFarlane, 2023). Finally, the computational demands of large language models like GPT present financial and environmental challenges, due to the need for vast data, high-performance infrastructure, and significant energy consumption (Zhou et al., 2021).

## Ethical Concerns in using AI

Research indicates that psychiatrists generally hold a positive attitude toward AI but express reservations related to patient privacy and ethical implications (Asbach et al., 2024). Generative AI tools such as ChatGPT raise numerous ethical concerns, including issues of plagiarism, image manipulation, authorship, copyright infringement, and the creation of fabricated research (Grimaldi & Ehrler, 2023). Although ethical concepts themselves may not be fully expressible through computational models, many ethical problems contain computable elements (Johnson & Verdicchio, 2023).

Another significant concern is the potential for bias within AI algorithms. AI systems inherently reflect the data on which they are trained; if those data are biased, the systems will likely replicate and reinforce such biases (Verma, 2019). This can lead to disparities in treatment, particularly for patients from marginalized communities, thus exacerbating existing inequalities in healthcare (Johnson & Verdicchio, 2023).

Given these ethical challenges, there is an urgent need for collaborative efforts across healthcare education, research, and practice to establish a robust code of ethics that governs the responsible use of AI, particularly tools like ChatGPT, in healthcare and academic settings (Salam, 2023).

## Bias and Discrimination Concerns

According to one systematic literature review, justice and fairness was found to be the most prevalent ethical issue with the use of AI in psychiatry (Li, Ruijs, & Lu, 2022). Justice and fairness were mainly expressed in reference to bias, fairness, discrimination, and equality. This theme is related to the fair distribution of medical goods and services, without discrimination among individuals (Li, Ruijs, & Lu, 2022).

Other research shows the Ethically Aligned Design Framework, that is, according to them, a core concept for ethical AI, guaranteeing that AI systems are consistent with global human rights and social norms (Fukuda-Parr & Gibbons, 2021).

In the previous literature, a novel approach to incorporating ethical reasoning into AI can also be found. Ethical Artificial Intelligence Framework Theory (The Ethical Artificial Intelligence Framework Theory [EAIFT], 2024) emphasizes real-time oversight, open decision-making, bias detection, and the ability to change ethical and legal norms and advocates for establishing “ethical AI watch dogs” that automatically monitor and ensure the ethical

operation of AI systems, together with dynamic compliance algorithms that can adapt to regulatory changes (The Ethical Artificial Intelligence Framework Theory [EAIFT], 2024).

The other previous research presents the methodology developed in the HSE University – Index of Ethics of Artificial Intelligence Systems (Ugleva et al., 2024). The task of developing this Index was to assess real and possible ethical risks arising at all stages of the life cycle of AI systems. The system itself does not possess any “ethics”, while socially acceptable, morally permissible, and necessary may be the actions of developers and data providers in the process of its design, as well as of operators and consumers in the process of piloting and implementation (Ugleva et al., 2024).

The European Union has been in 2019 acknowledged as a leader in establishing a framework for Ethical regulations and rules for AI European Parliamentary Research Service (European Parliament, 2019) and for coordination of actions and national levels because Several Member States have started work on establishing their own national frameworks on ethics and AI in parallel to the EU initiatives (European Parliament, 2019). Examples of rules and regulations are the “Ethics Guidelines for Trustworthy AI” from the European Commission (Ala Pietilä et al., 2019).

The European Psychiatric Association (EPA) also came with several recommendations meant to foster the widespread adoption of evidence-based digital solutions for mental health care in the member states of the EPA (Kalman et al., 2024). To realize the vision of a digitalised, patient-centred, and data-driven mental health ecosystem, a number of implementation challenges must be considered and addressed, spanning from human, technical, ethical-legal, and economic barriers. The list of priority areas and action points our expert panel has identified could serve as a playbook for this process (Kalman et al., 2024).

According to the previous literature, trust, public trust, patient trust, and the adoption of AI in healthcare will eventually depend on transparency and on the betterment of AI systems’ explanation (Li et al., 2022). Transparency refers to the possibility of understanding an AI system’s decision-making process (Zhang & Kamel Boulos, 2023).

The use of AI in mental health diagnoses raises questions about who is responsible for the accuracy of diagnoses and how decisions are made and that is important for AI systems to be transparent about their decision-making processes and for clinicians to understand the limitations and potential biases in AI diagnoses (Murphy et al., 2021).

According the previous literature (Li et al., 2022), to cope with the issue of trust, the strategies presented in the

literature are as follows: inform the patients when and how their data is shared, as part of the research protocols and sharing conditions (de-identification, registration, access control, etc.), improve data privacy and confidentiality to prevent the re-identification of anonymized data with spatial data points to ensure patients' trust in health services and educate healthcare personnel on the basics of AI, including techniques and solutions, to establish trust in AI healthcare providers (Li et al., 2022).

Interestingly, although their level of trust in generative AI technologies is low in the group of psychiatrists and higher in the group of other professionals, our research showed that 29,63% of psychiatrists and 6,82% other professionals changed their behavior or decision-making based on information provided by public generative AI.

Previous studies on AI in psychiatry emphasized its role in augmenting decision-making processes and improving patient care (Asbach et al., 2024) together with that AI can be used to assist clinicians with decision-making. Rather than simply automating tasks, AI is about developing technologies that can enhance patient care across healthcare settings (Alowais et al., 2023).

Findings from other studies have shown high accuracy for potential applications in clinical decision support when using AI for Cross-Diagnostic Prediction of Mental Disorder Diagnosis and Prognosis Using Danish Nationwide Register and Genetic Data (Allesøe et al., 2023).

Previous research show that future integrations could see AI functioning as a supportive in clinical decision-making, complemented by a 'human in the loop' system, which also serves to alert clinicians to the high probability of inaccurate assessment but that is essential for mental health professionals to receive education on the complexities of AI in clinical practice, encouraging a critical yet objective stance in interpreting AI-generated outcomes (Elyoseph et al., 2024).

Previous research also shows that "ChatGPT already uses the Moderation API, an AI-powered moderation system, to block discriminatory and hate speech (Tae Won, 2023).

Thus, if a question is asked that is not appropriate, it will refuse to respond to discriminatory, offensive, or inappropriate questions, including racist, sexist, homophobic, transphobic, or otherwise discriminatory or hateful questions (Tae Won, 2023).

Many predicted that 'man and machine' would increasingly collaborate in undertaking clinical decisions, with mixed opinions about the benefits and harms of such an arrangement (Blease et al., 2020).

On the other side, previous research has shown that technical breakthroughs have raised serious ethical

problems, including bias in AI-driven choices (Trotta et al., 2023) together with that the paternalistic AI model ignores patients' preferences, not just harming patients' autonomy but also their dignity (Li, Ruijs, & Lu, 2022).

In addition, the training data used as inputs, especially inappropriate and poorly representative training data for AI models, represent another factor contributing to the issue of bias. Such input biases can arise when the input data used for training the model do not represent the full spectrum of the target population or when the system has incomplete data (Li, Ruijs, & Lu, 2022).

For instance, an AI algorithm used in the United States of America to predict accused persons' future recidivism rates showed that the risk scores for an African American with minor crimes were higher than a white American who had committed multiple crimes (Paulus et al. 2020).

## **Concerns of AI being used for malicious purposes**

In addition, according to our study, most respondents, regardless of their group, show high concern about the possibility of public generative AI being used for malicious purposes, such as cyberattacks or propaganda campaigns.

Previous research show that most AI-based intervention studies have been conducted by their designers, who may have a personal monetary stake in the outcome, leading to potential biases in the benefits of AI in the field of psychiatry (Luxton, 2016).

Current AI language models do not produce statements reaching beyond the content of their training sets, we should ask ourselves whether this is a fundamental feature of the technology or just a temporary limitation (Grimaldi & Ehrler, 2023).

According to Practical recommendations from the European Psychiatric Association (EPA) Real-world data containing highly sensitive personal information must be handled securely in compliance with data protection frameworks, such as the General Data Protection Regulation of the European Union (GDPR) and national laws (Kalman et al, 2024).

Information and consent forms must be standardized to allow data exchange and use across healthcare providers (Kalman et al, 2024).

Previous research has also shown that one of the main limitations is that GPT models are based on a statistical approach that learns patterns from a large data set of text, which can perpetuate biases and stereotypes present in the data (Dale, 2017). This means that the model may generate offensive or harmful output (Dale, 2017).

Additionally, GPT models are not able to fully understand the context and meaning of the text they generate, and they are not able to perform well in tasks that require common sense reasoning or logical reasoning which is not covered in the training data (Strubell et al., 2019).

Therefore, it is important to be aware of these limitations and to use GPT responsibly (Lund & Wang 2023). Previous research shows that there is a lack of guidelines specific to the various forms of assistance provided by mental health professionals who deliver AI services, and laws are not defined to hold software developers accountable for glitches that occur due to technology malfunction (Johnson & Verdicchio, 2023).

According to the previous literature, to deal with patient safety and cyber security, the following strategies need to be addressed (Li et al., 2022): Develop AI systems in a regulated manner together with clinicians and computer scientists, vet and review AI tools through legally selected regulatory committees before using them, update regulations, codes of conduct, and standards continuously, cooperate with stakeholders involved in the AI develop process to help the project team establish a responsible ethics model and ensure patient safety and the rights and interests of users, foresee undesirable results and avoid adverse consequences of AI techniques by taking proper action to ensure cyber security, ensure that the AI system is robust enough to protect the user's data from being destroyed by the operational or system interacting agents and develop explicit standards or policies of data management with security and privacy, and implement them to preserve data confidentiality and identification in healthcare (Li et al., 2022).

Also, other research has shown that it is important to consider the data privacy and security implications of using ChatGPT (Lund & Wang 2023).

Together with that AI systems process and store large amounts of sensitive personal information, and there is a risk that this information could be used for unintended purposes or accessed by unauthorized individuals (Johnson & Verdicchio, 2023).

The model has the ability to generate highly sensitive information, such as personal data, financial data and even medical data. In light of these concerns, it is important to use these models responsibly and with caution, and to consider appropriate measures to mitigate any potential risks (Lund & Wang 2023).

## **Concerns about the possibility of forming a genuine emotional connection with a public generative AI**

One previous study found that AI-generated messages made recipients feel more heard than human-generated messages and that AI was better at detecting emotions (Yin et al., 2024). However, recipients felt less heard when they realized that a message came from AI (vs. human). Finally, in a follow-up study where the responses were rated by third-party raters, compared with humans, AI demonstrated superior discipline in offering emotional support, a crucial element in making individuals feel heard, while avoiding excessive practical suggestions, which may be less effective in achieving this goal (Yin et al., 2024).

Moreover, another study shows that future GPT advances that incorporate empathy, emotion recognition, personality assessment, and detection of mental health warning signs are essential for its effective integration into psychiatric care (Cheng et al., 2023).

Another research shows that psychiatrists were skeptical that technology could replace human empathy (Blease et al., 2020).

Emotional connections with AI are for example also depicted in films "Her" and "Ex Machina". "Her" (2013) is a science-fiction romantic drama where a lonely writer develops a deep emotional relationship with an artificially intelligent operating system named Samantha. Samantha evolves to meet Theodore's needs, leading to a unique and complex love story that explores themes of loneliness, technology, and the nature of human relationships (Wikipedia 2024a).

"Ex Machina" (2014) is a science fiction thriller that follows a young programmer who meets a highly advanced humanoid robot with artificial intelligence and should evaluate her human qualities through a series of interactions, and while doing this he begins to question the nature of consciousness and the ethical implications of AI. The film explores themes of power, manipulation, and the boundaries between human and machine (Wikipedia 2024a).

Questions of consciousness in AI were raised already in 1966, when a researcher at the Massachusetts Institute of Technology introduced ELIZA, a computer program that simulated a psychotherapist in the Rogerian tradition, rephrasing a patient's words into questions according to simple but effective scripts (Tononi & Raison, 2024).

The original myth of Pygmalion – the sculptor who carved the ideal woman Galatea out of ivory and hoped to bring her to life – is even more apt: does the creation of AI portend artificial consciousness, perhaps even superhuman consciousness? According to the dominant

computational/functionalist stance in cognitive neuroscience, the answer is yes (Butlin et al., 2023).

### **Concern about job losses caused by AI**

Previous research shows the anticipated impact of AI on the world of work: technological unemployment, algorithmic management, platform work and the politics of AI work (Deranty & Corbin, 2024).

One previous study shows that current large language models (LLM), such as GPT-4, can also understand people's mental states (Bubeck et al., 2023). Recent studies suggest that such models can generate responses that exhibit even higher levels of empathy than those from human experts (Zhao et al., 2023) and that responses by Large language models to patients were rated by outsiders as more empathetic than responses by physicians (Ayers et al., 2023).

According to previous research, conversational agents, such as Apple's Siri or Amazon's Alexa, have the look and feeling of interacting with a human, despite being run by an automated software program (Henson et al., 2019). There is some evidence that people can develop therapeutic relationships with digital technologies (referred to as "digital therapeutic alliance" (Henson, Wisniewski, Hollis, et al., 2019). A therapeutic alliance with an in-person therapist is related to more positive outcomes in mental health treatment (Tremain et al., 2020).

According to a study conducted in 2021, AI is unlikely to fully replace psychiatrists because the field relies heavily on human abilities such as empathy, understanding, and the therapeutic relationship between patient and psychiatrist (Brown et al., 2021).

Careful reflection is needed when integrating sentiment and emotion analysis into chatbots for eks. depression intervention (Denecke & Gabarron, 2024). Balancing risk factors is key to leveraging technology in mental health in a way that enhances, rather than diminishes, user autonomy and agency (Denecke & Gabarron, 2024).

### **Institutional support in using AI**

Other research shows also that there is a lack of guidelines specific to the various forms of assistance provided by mental health professionals who deliver AI services, and laws are not defined to hold software developers accountable for glitches that occur due to technology malfunction (Johnson & Verdicchio 2023).

A high percentage of psychiatrists (37.5%) in our research, reported learning something NEW about the application and usage of public generative AI solutions by filling out this questionnaire compared to respondents from other professions (15.79%). This may indicate lack of knowledge among psychiatrists but also a greater motivation or interest in AI topics.

### **Social media**

The relationship between social media and mental health has received much attention from not only the academic literature, but also the traditional media and general public (Solomon, 2024; Sellman, 2024). Frequently accessed via smartphone apps and connecting people from their own devices to global networks of friends, information, and health resources, social media can represent both a means to quantify mental health as well as a source of both positive and negative interactions (Torous et al., 2021).

Previous research shows that social media can also be used as a therapeutic tool. For example, the PRIME app (Schlosser et al., 2018) is designed to help people with schizophrenia through the promotion of functional recovery and the mitigation of negative symptoms (e.g., amotivation) through a supportive and personalized network (Schlosser et al., 2018).

The Moderated Online Social Therapy (MOST) platform is another example of an innovation that offers personalized therapy combined with social connections among other features (Alvarez et al., 2020).

It is noteworthy also that social media is not without risk (Torous et al., 2021). Disinformation (Hao, 2020) and stigma on social media are forces that cannot be ignored. Stigma on social media is common (Robinson et al., 2019). Using social media for mental health work also remains a catalyst for ethical tensions, and a recent review offers a practical taxonomy of these tensions as well as guidance for navigating through these ongoing challenges (Chancellor et al., 2019).

Both groups of participants in our study answered in high percentage that it is likely that they are going to use AI solutions and social media in the future, this is also shown in previous literature where it is expected that the number and relevance of asynchronous interactions such as communication via email, the management and evaluation of the data originating from patients' digital devices or other providers will continuously and significantly increase in the future (Kalman et al., 2024).

## Limitation of the study

This study has several limitations that should be acknowledged. First, the sample size was relatively small ( $N = 71$ ), which limits the generalizability of the findings. The sample was also highly specific and heterogeneous, consisting of both mental health professionals and individuals from unrelated professional backgrounds.

Participants were recruited using convenience sampling. A link to the online survey (hosted on Google Forms) was distributed through various social media platforms, including Facebook, LinkedIn, and Twitter/X, and shared through personal and professional networks. No targeted advertising or demographic filtering was applied. As a result, the sample may be subject to selection bias and cannot be considered representative of the wider population.

Of the 71 participants, 27 were psychiatrists (38%) and 44 represented other professional roles (62%), such as computer scientists, IT managers, software engineers, occupational therapists, psychologists, students, and teachers. Additionally, 22 participants (31%) were employed within Region Hovedstaden Psykiatri (Central Region Psychiatry in Denmark).

The recruitment strategy, based on open online distribution, resulted in a non-random sample. While this limits statistical generalizability, it aligns with the exploratory nature of a pilot study. The limited response rate may reflect a broader lack of engagement with the topic, possibly due to limited use of or interest in generative AI technologies among certain professional groups. Notably, the invitation emphasized that individuals without prior AI use were also encouraged to participate, yet uptake remained modest.

The small sample size increases the risk of both Type I and Type II errors, reducing statistical power and limiting the robustness of the findings. Additionally, due to the limited number of participants, results may be sensitive to the influence of outliers. Although non-parametric statistical tests were applied to mitigate these effects, the results should be interpreted with caution.

Practical significance must also be considered alongside statistical significance. Given the small and heterogeneous sample, observed differences between groups should be viewed as indicative rather than conclusive. Further studies with larger and more representative samples are needed to validate these findings.

A common challenge in technology acceptance research is the difficulty in generalizing results, particularly when recruitment relies on social media. This study also faced barriers to engaging healthcare professionals, many of whom may have been unavailable or uninterested due

to demanding work schedules. Nevertheless, their inclusion was intentional, as their perspectives are critical to understanding how generative AI may be adopted within healthcare settings.

Despite these limitations, the pilot study offers valuable contributions. It identifies practical challenges in recruitment, reveals varying levels of interest and engagement, and provides important guidance for designing future large-scale studies.

## CONCLUSIONS

This study suggests that publicly available generative AI solutions may hold significant potential for supporting professional development, with notable differences observed across professional backgrounds. Understanding these variations can inform more effective and context-sensitive implementation strategies, helping to ensure that AI is adopted as a meaningful and constructive tool.

In addition, differences in attitudes, opinions, and experiences regarding AI technologies highlight the need for further research and dialogue on the ethical implications of AI use, as well as the diverse perceptions and concerns related to its impact on professional decision-making.

Although generative AI tools are already in use and there is expressed interest in expanding their application, this interest is tempered by a cautious approach. Participants reported limited knowledge and moderate levels of trust in these technologies, underscoring the need for continued research and targeted educational efforts.

Despite the small and heterogeneous sample, this pilot study offers valuable insights by identifying practical challenges, gauging initial interest in the topic, and providing guidance for the design of a more comprehensive future study.

**Acknowledgments:** None

**Conflict of Interest:** 'None to declare'

The authors have no financial or other connection to OpenAI.

This study was conducted entirely on a voluntary basis. Some of the results and discussion from this study was presented in a poster format at: 12th European conference of mental health ECMH, Krakow, Poland, 9-11.9.2024 and at European Association of Phenomenology, Psychopathology and Psychotherapy (EAPPP) Conference, Copenhagen 26-27.9.2024

**Authors Contributions:** Ema Nicea Gruber: conception or design of the study, literature searches and analyses, statistical analyses, interpretation of data, manuscript writing, drafting of the manuscript, final approval of the version to be submitted, agreement to be accountable for all aspects of the work. Lucija Gruber Zlatec: questionnaire design, qualitative and quantitative data processing, graph and figure creation, translation, critical discussion, text edit-

ing and proofing, acquisition of the data, drafting of the manuscript, final approval of the version to be submitted, agreement to be accountable for all aspects of the work. Sanja Martić Biočina: analysis or interpretation of data, critical revision of the manuscript for vital intellectual content, final approval of the version to be submitted, literature searches and analyses, interpretation of data, agreement to be accountable for all aspects of the work

## References

- Albadarin, Y., Saqr, M., Pope, N., & Tukiainen, M. (2024). A systematic literature review of empirical research on ChatGPT in education. *Discover Education*, 3, 60.
- Alkaissi, H., & McFarlane, S. I. (2023). Artificial hallucinations in ChatGPT: Implications in scientific writing. *Cureus*, 15(2), e35179.
- Allesøe, R. L., Thompson, W. K., Bybjerg-Grauholm, J., & Kruse, F. (2023). Deep learning for cross-diagnostic prediction of mental disorder diagnosis and prognosis using Danish nationwide register and genetic data. *JAMA Psychiatry*, 80(2), 146–155.
- Alowais, S. A., Alghamdi, S. S., Alsuhebany, N., Alqahtani, T., Alshaya, A. I., Almohareb, S. N., et al. (2023). Revolutionizing healthcare: The role of artificial intelligence in clinical practice. *BMC Medical Education*, 23(1), 689.
- Arshad, H. B., Butt, S. A., Khan, S. U., Javed, Z., & Nasir, K. (2023). ChatGPT and artificial intelligence in hospital-level research: Potential, precautions, and prospect. *Methodist Debakey Cardiovascular Journal*, 19(5), 77–84.
- European Parliament. (2019). Artificial intelligence: Opportunities and challenges for the EU [PDF]. Retrieved November 11, 2024, from [https://www.europarl.europa.eu/RegData/etudes/BRIE/2019/640163/EPRS\\_BRI\(2019\)640163\\_EN.pdf](https://www.europarl.europa.eu/RegData/etudes/BRIE/2019/640163/EPRS_BRI(2019)640163_EN.pdf)
- Asbach, M., Menon, R., & Long, M. (2024). AI in psychiatry: Changing the landscape of mental health care. *Psychiatric Times*, 41(3).
- Ayers, J. W., Poliak, A., Johnson, A., et al. (2023). Comparing physician and artificial intelligence chatbot responses to patient questions posted to a public social media forum. *JAMA Internal Medicine*, 183, 589.
- Blease, C., Locher, C., Leon-Carlyle, M., & Doraiswamy, M. (2020). Artificial intelligence and the future of psychiatry: Qualitative findings from a global physician survey. *Digital Health*, 6, 2055207620968355.
- Briganti, G. (2023). Artificial intelligence in psychiatry. *Psychiatria Danubina*, 35(Suppl 2), 15–19.
- Brown, C., Story, G. W., Mourão-Miranda, J., & Baker, J. T. (2021). Will artificial intelligence eventually replace psychiatrists? *British Journal of Psychiatry*, 218, 131–134.
- Bubeck, S., Chandrasekaran, V., Eldan, R., Gehrke, J., Horvitz, E., Kamar, E., et al. (2023). Sparks of artificial general intelligence: Early experiments with GPT-4. *Computational Science and Computer Languages*, 2023 Mar 22.
- Butlin, P., Long, R., Elmoznino, E., Bengio, Y., Birch, J., Constant, A., et al. (2023). Consciousness in artificial intelligence: Insights from the science of consciousness. *arXiv*.
- Cansel, N., Alcin, Ö. F., Yılmaz, Ö. F., Ari, A., Akan, M., & Ucu, İ. (2023). A new artificial intelligence-based clinical decision support system for diagnosis of major psychiatric diseases based on voice analysis. *Psychiatria Danubina*, 35(4), 489.
- Chancellor, S., Birnbaum, M. L., Caine, E. D., et al. (2019). A taxonomy of ethical tensions in inferring mental health states from social media. *Conference on Fairness, Accountability, and Transparency (FAT '19)*, ACM, New York, NY, USA, 10 pages.
- Cheng, S. W., Chang, C. W., Chang, W. J., Wang, H. W., Liang, C. S., Kishimoto, T., et al. (2023). The now and future of ChatGPT and GPT in psychiatry. *Psychiatry and Clinical Neurosciences*, 77(11), 592–596.
- Dale, R. (2017). NLP in a post-truth world. *Natural Language Engineering*, 23(2), 319–324.
- Denecke, K., & Gabarron, E. (2024). The ethical aspects of integrating sentiment and emotion analysis in chatbots for depression intervention. *Frontiers in Psychiatry*, 15, 1462083.
- Deranty, J.-P., & Corbin, T. (2024). Artificial intelligence and work: A critical review of recent research from the social sciences. *AI & Society*, 39, 675–691.
- Elshawi, R., Al-Mallah, M. H., & Sakr, S. (2019). On the interpretability of machine learning-based models for predicting hypertension. *BMC Medical Informatics and Decision Making*, 19, 1–32.
- Elyoseph, Z., Levkovich, I., & Shinan-Altman, S. (2024). Assessing prognosis in depression: Comparing perspectives of AI models, mental health professionals, and the general public. *Family Medicine & Community Health*, 12.
- Eriksen, A. V., Möller, S., & Ryg, J. (2024, January 1). Use of GPT-4 to diagnose complex clinical cases. *NEJM AI*, 1(1), AIp2300031.
- Ex Machina (film) [Internet]. (2024). *Wikipedia*. Retrieved November 11, 2024, from [https://en.wikipedia.org/wiki/Ex\\_Machina\\_\(film\)](https://en.wikipedia.org/wiki/Ex_Machina_(film))
- Fergus, S., Botha, M., & Ostovar, M. (2023). Evaluating academic answers generated using ChatGPT. *Journal of Chemical Education*, 100(4), 1672–1675.
- Fukuda-Parr, S., & Gibbons, E. (2021). Emerging consensus on 'ethical AI': Human rights critique of stakeholder guidelines. *Global Policy*, 12(S6), 32–44.

- Grimaldi, G., & Ehrler, B. (2023). AI et al.: Machines are about to change scientific publishing forever. *ACS Energy Letters*, 8(1), 878–880.
- Hao, K. (2020). Nearly half of Twitter accounts pushing to re-open America may be bots. *MIT Technology Review*. Retrieved October 16, 2024.
- Hassija, V., Chamola, V., Mahapatra, A., et al. (2024). Interpreting black-box models: A review on explainable artificial intelligence. *Cognitive Computation*, 16, 45–74.
- Henson, P., Wisniewski, H., Hollis, C., et al. (2019). Digital mental health apps and the therapeutic alliance: Initial review. *BJPsych Open*, 5, e15.
- Inala, J. P., Wang, C., Drucker, S., Ramos, G., Dibia, V., Riche, N., et al. (2024). Data analysis in the era of generative AI. *arXiv*.
- Johnson, D. G., & Verdicchio, M. (2023). Ethical AI is not about AI. *Communications of the ACM*, 66, 32–34.
- Kalman, J. L., Burkhardt, G., Samochowiec, J., Gebhard, C., Dom, G., John, M., et al. (2024). Digitalising mental health care: Practical recommendations from the European Psychiatric Association. *European Psychiatry*, 67(1).
- Kretzschmar, K., Tyroll, H., Pavarini, G., Manzini, A., & Singh, I. (2019). Can your phone be your therapist? Young people's ethical perspectives on the use of fully automated conversational agents (chatbots) in mental health support. *Biomedicine & Biomedical Informatics Insights*, 11, 117822261982908.
- Lee, P., Bubeck, S., & Petro, J. (2023, March 30). Benefits, limits, and risks of GPT-4 as an AI chatbot for medicine. *New England Journal of Medicine*, 388(13), 1233–1239.
- Li, F., Ruijs, N., & Lu, Y. (2022, December). Ethics & AI: A systematic review on ethical concerns and related strategies for designing with AI in healthcare. *AI*, 4(1), 28–53.
- Lin, Z. (2023). Why and how to embrace AI such as ChatGPT in your academic life. *Royal Society Open Science*, 10, 230658.
- Lund, B. D., & Wang, T. (2023, February 14). Chatting about ChatGPT: How may AI and GPT impact academia and libraries? *Library Hi Tech News*.
- Luxton, D. D. (2016). An introduction to artificial intelligence in behavioral and mental health care. In *Artificial intelligence in behavioral and mental health care* (1st ed., pp. 1–26).
- Murphy, K., di Ruggiero, E., Upshur, R., Willison, D. J., Malhotra, N., Cai, J. C., Lui, V., & Gibson, J. (2021). Artificial intelligence for good health: A scoping review of the ethics literature. *BMC Medical Ethics*, 22, 1–17.
- Nolan, B. (2023, January 30). Here are the schools and colleges that have banned the use of ChatGPT over plagiarism and misinformation fears. *Business Insider*. Retrieved March 20, 2025.
- OpenAI. (2024, November 21). GPT-4 [Internet]. San Francisco: OpenAI.
- Pavlov, M., Barić, D., Novak, A., et al. (2024). From statistical inference to machine learning: A paradigm shift in contemporary cardiovascular pharmacotherapy. *British Journal of Clinical Pharmacology*, 90(3), 691–699.
- Robinson, P., Turk, D., Jilka, S., et al. (2019). Measuring attitudes towards mental health using social media: Investigating stigma and trivialisation. *Social Psychiatry and Psychiatric Epidemiology*, 54, 51–58.
- Rosoł, M., Gąsior, J. S., Łaba, J., Korzeniewski, K., & Młyńczak, M. (2023, November 22). Evaluation of the performance of GPT-3.5 and GPT-4 on the Polish Medical Final Examination. *Scientific Reports*, 13(1), 20512.
- Sallam, M. (2023). ChatGPT utility in healthcare education, research, and practice: Systematic review on the promising perspectives and valid concerns. *Healthcare (Basel)*, 11(6), 887.
- Sarker, I. H. (2022). AI-based modeling: Techniques, applications, and research issues towards automation, intelligent and smart systems. *SN Computer Science*, 3, 158.
- Schlosser, D. A., Campellone, T. R., Truong, B., et al. (2018). Efficacy of PRIME, a mobile app intervention designed to improve motivation in young people with schizophrenia. *Schizophrenia Bulletin*, 44, 1010–1020.
- Sellman, M. (2024, December 1). Instagram algorithm helps self-harm networks grow, study finds. *The Times*. Retrieved March 20, 2025.
- Sheskin, D. J. (2004). Handbook of parametric and nonparametric statistical procedures (3rd ed.). Boca Raton, FL: Chapman & Hall/CRC.
- Solomon, A. (2024, September 30). Has social media fueled a teen-suicide crisis? *The New Yorker*. Retrieved March 20, 2025.
- Strubell, E., Ganesh, A., & McCallum, A. (2019). Energy and policy considerations for deep learning in NLP. *Proceedings of the Annual Meeting of the Association for Computational Linguistics*, 57, 3645–3650.
- Tae Won, K. (2023). Application of artificial intelligence chatbots, including ChatGPT, in education, scholarly work, programming, and content generation and its prospects: A narrative review. *Journal of Educational Evaluation for Health Professions*, 20, 38.
- Terra, M., Baklola, M., Ali, S., & El-Bastawisy, K. (2023). Opportunities, applications, challenges, and ethical implications of artificial intelligence in psychiatry: A narrative review. *Egyptian Journal of Neurology, Psychiatry, and Neurosurgery*, 59(1), 1–15.
- Thabane, L., Ma, J., Chu, R., Cheng, J., Ismaila, A., Rios, L. P., Robson, R., Thabane, M., Giangregorio, L., & Goldsmith, C. H. (2010). A tutorial on pilot studies: The what, why and how. *BMC Medical Research Methodology*, 10(1), 1–10.
- The Ethical Artificial Intelligence Framework Theory (EAI FT). (2024). A new paradigm for embedding ethical reasoning in AI systems. *International Journal of Multidisciplinary Research*, 6(5).
- Tononi, G., & Raison, C. (2024). Artificial intelligence, consciousness, and psychiatry. *World Psychiatry*, 23(3), 163–165.
- Torous, J., Bucci, S., Bell, I. H., Kessing, L. V., Faurholt-Jepsen, M., Whelan, P., et al. (2021). The growing field of digital psychiatry: Current evidence and the future of apps, social media, chatbots, and virtual reality. *World Psychiatry*, 20(3), 318–333.
- Tremain, H., McEnery, C., Fletcher, K., et al. (2020). The therapeutic alliance in digital mental health interventions for serious mental illnesses: Narrative review. *JMIR Mental Health*, 7, Article e17204.
- Trotta, A., Ziosi, M., & Lomonaco, V. (2023). The future of ethics in AI: Challenges and opportunities. *AI & Society*, 38, 439–441.

- Ugleva, A. V., Shilova, V. A., & Karpova, E. A. (2024). Index of 'ethicality' of AI systems in medicine: From theory to practice. *Ethical Thought*, 24(1), 144–159.
- Vaidyam, A. N., Wisniewski, H., Halamka, J. D., Kashavan, M. S., & Torous, J. B. (2019). Chatbots and conversational agents in mental health: A review of the psychiatric landscape. *The Canadian Journal of Psychiatry*, 64, 456–464.
- Van Dis, E. A. M., Bollen, J., Zuidema, W., Birk, R., Van Rooij, R., & De Rijke, M. (2023). ChatGPT: Five priorities for research. *Nature*, 614(7947), 224–226.
- Verma, S. (2019). Weapons of math destruction: How big data increases inequality and threatens democracy. *Vikalpa*, 44, 97–98.
- Zhao, W., Chen, L., Zhang, H., & Li, Y. (2023). Is ChatGPT equipped with emotional dialogue capabilities? *arXiv*.
- Yin, Y., Jia, N., & Wakslak, C. J. (2024). AI can help people feel heard, but an AI label diminishes this impact. *Proceedings of the National Academy of Sciences*, 121(14), e2319112121.
- Zhang, P., & Kamel Boulos, M. N. (2023). Generative AI in medicine and healthcare: Promises, opportunities, and challenges. *Future Internet*, 15(9), 286.
- Zhou, X., Chen, Z., Jin, X., & Wang, W. Y. (2021). HULK: An energy efficiency benchmark platform for responsible natural language processing. *Proceedings of the 16th Conference of the European Chapter of the Association for Computational Linguistics: System Demonstrations*, 329–336.

*Correspondence:*

Ema Gruber  
Mental Health Centre Sct. Hans, R4,  
Boserupvej 2, 4000 Roskilde, Denmark  
emagruber2000@yahoo.com

Published under 

<https://creativecommons.org/licenses/by-nc-nd/4.0/>