

How Can Transformer Models Shape Future Healthcare: A Qualitative Study

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Abstract. Transformer models have been successfully applied to various natural language processing and machine translation tasks in recent years, e.g. automatic language understanding. With the advent of more efficient and reliable models (e.g. GPT-3), there is a growing potential for automating time-consuming tasks that could be of particular benefit in healthcare to improve clinical outcomes. This paper aims at summarizing potential use cases of transformer models for future healthcare applications. Precisely, we conducted a survey asking experts on their ideas and reflections for future use cases. We received 28 responses, analyzed using an adapted thematic analysis. Overall, 8 use case categories were identified including documentation and clinical coding, workflow and healthcare services, decision support, knowledge management, interaction support, patient education, health management, and public health monitoring. Future research should consider developing and testing the application of transformer models for such use cases.

Keywords. transformer models, deep learning, healthcare, applications

1. Introduction

In recent years, transformer models have emerged as a game-changing innovation in the context of artificial intelligence technologies. First introduced by Vaswani et al. in 2017 [1], they have already significantly changed the landscape of natural language processing (NLP). A transformer model is a deep learning algorithm that learns context and thus meaning by tracking relationships in sequential data, e.g. words in a sentence. Originally designed for language-related applications, transformer models, e.g. BERT (Bidirectional Encoder Representations from Transformers) or GPT (Generative Pre-trained Transformer), have showcased remarkable capabilities in understanding and generating human language. They demonstrated great success in NLP, for tasks such as machine translation, document summarization, document generation and named entity recognition [2]. Recently, the models gained in popularity due to ChatGPT-3 in 2022.

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Especially in healthcare, transformer models could offer various advantages in automating time-consuming tasks to optimize clinical outcomes. There are already several applications in healthcare, e.g. in image classification, segmentation, and disease detection [3]. However, we are still at the beginning of applying transformer models in healthcare. So, the research goal of this paper is to identify future use cases of such models in healthcare by conducting a qualitative study involving 28 experts. This way, we provide a research agenda for developing applications based on this technology. To the best of our knowledge, this is the first study exploring experts' opinions on how transformer models could be used in the health domain.

2. Methods

To achieve our goal, we conducted an online e-survey among experts, precisely experts in the field of NLP in healthcare. All experts were actively recruited by email from the IMIA Participatory Health and Social Media Working group, the authors' peer networks or by contacting researchers authoring papers on transformer models in healthcare. The questionnaire comprised a set of demographic questions and 1 open-ended question: "*Which use cases of transformer models do you envision?*". A brief definition of transformers was provided to the participants to ensure that they not only envision ChatGPT, but the underlying technology. The questionnaire was open to be answered for three weeks starting April 10– May 1, 2023. No reminders were sent.

All responses to the open-ended question were analyzed by the authors using a simplified thematic analysis [4]. After conducting the survey, one author (KD) read the responses, familiarized with them, and grouped the responses into categories of use cases addressing a similar use case. Categories were reviewed to ensure consistency and simplicity (themes included all coded factors (inclusive) and two categories could not be assigned to a response (exclusive)). Finally, names and definitions were created for each category. The final groups and assigned responses were reviewed by a second researcher (OR). For reporting the results of the survey, considering size restrictions, we followed the CHERRIES checklist [5] and COREQ for qualitative studies [6].

3. Study results

3.1. Participants' background

The panel comprised 28 experts (25% female, $n=7$). A response rate cannot be reported since we allowed experts to forward the survey link. 46.4% participants had a background in computer science/engineering, 39.3% in health informatics, 28.6% in medicine, 3.6% in nursing, 10.7% other health sciences and 7.1% selected "other" as their background. 85.7% of the participants had more than 10 years of working experience while 10.7% had less than 5 years and 3.6% 5–10 years of experience. Most participants belong to academia (92.9%); 17.9% are working for the public health sector and 7.1% for the private health sector. The participants originate from Europe (75%), Australia and Oceania (10.7%) and North America (14.3%). 10.7% claimed to be experts in transformer models, 25% use their basic functions regularly, 28.6% know how they work and 32.1% tested ChatGPT, but have only basic knowledge on the underlying

technology. 1 person had no knowledge on transformer models – we excluded the response of this person for reasons of validity.

3.2. Use case categories

The free-text answers revealed 8 categories (C) of use cases (see Figure 1).

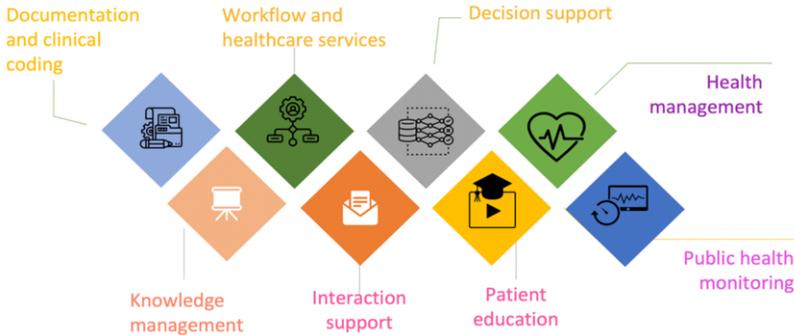


Figure 1. Use case categories of transformer models for future healthcare application.

C1: Documentation and clinical coding. This category consists of three topics: Automatic transcriptions and summarization of conversations, summarization of clinical information, structuring clinical information. For instance, the discharge summary could be summarized in patient-centered language for patients or caregivers. Information could be summarized for healthcare professionals (HCP) by extracting relevant information. Another subtopic is structuring clinical information, e.g. “*language models [...] can assist health professionals by summarizing lengthy medical records, making it more efficient for them to review and extract key information about a patient's medical history*” (female person with medical background).

C2: Workflow and healthcare services. The corresponding use cases include subtopics such as patient triage (e.g. symptom checking) and process guidance. A male expert with >10 years of experience in computer science/engineering provided the following example: “*Automate the first relations with the patient e.g., processing the symptoms reported by the patient, answering questions, providing advice and automatically detecting the most serious cases that require action by the professional*”.

C3: Knowledge management. This category consists of applications that could include medical education and training, updating of knowledge for life-long learning, access to information and generation of new knowledge. For example, transformers could be used to provide an “*interactive medical knowledge resource to support physicians*” (expert in computer science/engineering and health informatics with >10 years of experience) or “*guidelines can be generated automatically based on the evidence available in the published scientific literature, almost in real time*” (expert in computer science/engineering with >10 years of experience).

C4: Interaction support. Care processes involve interactions among HCP, HCP with patients and caregivers with patients and HCP – supported by transformer models. For example, “*clinical notes could be summarized for patient handover to a new clinician or nurse*” (expert in health informatics, >10 years of experience). A platform for HCP for collaboration and information sharing could make such aggregated information easily

accessible. Written communications “*could be edited and improved in terms of structure and language*” (expert in medicine, >10 years experience).

C₅: Patient education. In the context of patient empowerment and getting informed consent from patients regarding the treatment plan, patient education and information provision to patients is essential. Transformer models could help in developing systems that support this. For example, “*virtual assistants based on transformer models could be built to answer patient questions, provide general health information and could teach patients in self-management*” (example provided by a participant with medical background, <5 years of working experience). The language could be automatically adapted to the health literacy level of the user.

C₆: Health management. Another category concerns health management comprising self-management and patient-centered management. A system could automatically follow-up with patients with chronic diseases: “*not only quantitative results from sensors could be analyzed, but also responses to questionnaires on health status, fatigue, well-being, activity, diet, etc.*” (expert in computer science/engineering with >10 years experience). This would provide a more complete picture of patient health and could be used for personalized support and disease management.

C₇: Public health monitoring. Different aspects of public health could be monitored automatically using transformer-based models, e.g. outbreaks of diseases. Additionally, it “*reports for epidemiological surveillance or statistical purposes could be generated automatically*” (experts in health informatics, >10 years experience).

C₈: Decision support. Transformer model-powered decision support systems could help in diagnosing diseases or health conditions and in defining the treatment. An expert with medical background, >10 years experience mentioned that transformers could be “*used to build predictive models that can identify patients at risk of certain conditions based on their medical history and other factors.*”

4. Discussion and conclusions

For most use case categories, we already found support in existing literature: Documentation and clinical coding (C₁) is in line with previous studies that explored how AI could impact on clinical documentation. For instance, Luh et al. [7] found AI had the potential to reduce this burden in radiation oncology. Transformer models have demonstrated significant performance gains for medical problem summarization tasks [8] and clinical coding [9]. Moreover, the category focusing on workflow and healthcare services (C₂) is strengthened by promising results reported for triage [10]. Transformer models are also already applied for clinical knowledge management (C₃) [11], e.g. regarding diabetes [12]. There are some research studies presenting insights of the use of transformer models for facilitating interactions among actors involved in the healthcare process (C₄), e.g. in speech emotion recognition [13]. Education and empowerment (C₅) are in line with several recent research that reported relevant results using these models to empower patients [14]. Public health (C₇) could also benefit from the use of transformer models, e.g. in the context of drug events [15] or fake-news detection [16]. Finally, decision-making (C₈), particularly in diagnosis and treatment plan definition, is supported by the use of transformer models for computer-aided diagnosis [17] and predicting synergistic drug combinations [18]. Surprisingly, we could not find research results or concrete implementation examples for transformer systems supporting health management (C₆). Nevertheless, we strongly encourage the future

investigation of this research field including the feasibility, risks and relevance of the use cases.

Potential limitations of our study are the small sample size and the participants' expertise (32.1% just used ChatGPT without further technology knowledge). The recruitment process could be biased by manually selecting experts in the field of medical NLP. Further, the e-survey provided limited information and might lead to misinterpretations. Overall, we presented valuable results of a qualitative study involving an expert panel on the identification of potential use cases in which the use of transformer models could be beneficial for the health domain. 8 use cases were identified based on the participants' opinions. In future work, we plan to assess the feasibility, perceived practical relevance and impact of each use case from clinical experts. Since use of technology goes along with risks and benefits, we plan to explore detailed information about potential benefits and risks of using transformer models in each use case.

References

- [1] Vaswani A, et al. Attention is All you Need. *Advances in Neural Inform Proc Systems*. 2017;30:1–11.
- [2] Gillioz A, Casas J, Mugellini E, Khaled OA. Overview of the Transformer-based Models for NLP Tasks. In: *MCCSI*; 2020, p. 179–183, doi: 10.15439/2020F20.
- [3] Dai Y, Gao Y, Liu F. TransMed: Transformers Advance Multi-Modal Medical Image Classification. *Diagnostics*. 2021;8:1384, doi: 10.3390/diagnostics11081384.
- [4] Braun V, Clarke V. Using thematic analysis in psychology. *Qual. Res. Psychol*. 2006;3(2):77–101, doi: 10.1191/1478088706qp063oa.
- [5] Eysenbach G. Improving the Quality of Web Surveys: The Checklist for Reporting Results of Internet E-Surveys (CHERRIES). *JMIR*. 2004;6(3):e34, doi: 10.2196/jmir.6.3.e34.
- [6] Tong A, Sainsbury P, Craig J. Consolidated criteria for reporting qualitative research (COREQ): a 32-item checklist for interviews and focus groups. *IJQHC*. 2007;19(6):349–357
- [7] Luh JY, Thompson RF, Lin S. Clinical Documentation and Patient Care Using Artificial Intelligence in Radiation Oncology. *JACR*. 2019;16(9):1343–1346, doi: 10.1016/j.jacr.2019.05.044.
- [8] Gao Y, Miller T, Xu D, Dligach D, Churpek MM, Afshar M. Summarizing Patients' Problems from Hospital Progress Notes Using Pre-trained Sequence-to-Sequence Models. In: *COLING*; 2022, pp. 2979–2991, doi: 10.15439/2020F20.
- [9] Coutinho I, Martins B. Transformer-based models for ICD-10 coding of death certificates with Portuguese text. *JBI*. 2022;136:104232, doi: 10.1016/j.jbi.2022.104232.
- [10] Ding X, Barnett ML, Mehrotra A, Miller TA. Classifying Electronic Consults for Triage Status and Question Type. In: *ACL*; 2020, pp. 1–6, doi: 10.18653/v1/2020.nlpmc-1.1.
- [11] Zhang S, Fan R, Liu Y, Chen S, Liu Q, Zeng W. Applications of transformer-based language models in bioinformatics: a survey. *Bioinforma. Adv*. 2023;3(1): vbad001, doi: 10.1093/bioadv/vbad001.
- [12] Yu Z, et al. Identify diabetic retinopathy-related clinical concepts and their attributes using transformer-based natural language processing methods. *BMC Med. Inform. Decis. Mak*. 2022;22(3):255, doi: 10.1186/s12911-022-01996-2.
- [13] Wang Y, et al. Multimodal transformer augmented fusion for speech emotion recognition. *Front. Neurobotics*. 2023;17:1181598, doi: 10.3389/fnbot.2023.1181598.
- [14] Yeo YH, et al. Assessing the performance of ChatGPT in answering questions regarding cirrhosis and hepatocellular carcinoma. *Clin. Mol. Hepatol*. 2023:1–31, doi: 10.3350/cmh.2023.0089.
- [15] El-Allaly E, Sarrouti M, En-Nahnahi N, Ouatik El Alaoui S. An attentive joint model with transformer-based weighted graph convolutional network for extracting adverse drug event relation. *JBI*. 2022;125:103968, doi: 10.1016/j.jbi.2021.103968.
- [16] Alghamdi J, Lin Y, Luo S. Towards COVID-19 fake news detection using transformer-based models. *KBS*. 2023;274:110642, doi: 10.1016/j.knosys.2023.110642.
- [17] Gong R, Han X, Wang J, Ying S, Shi J. Self-Supervised Bi-Channel Transformer Networks for Computer-Aided Diagnosis. *IEEE JBHI*. 2022; 26(7):3435–3446, doi: 10.1109/JBHI.2022.3153902.
- [18] Hu J, et al. DTSyn: a dual-transformer-based neural network to predict synergistic drug combinations. *Brief. Bioinform*. 2022;23(5): bbac302, doi: 10.1093/bib/bbac302.