Using Equitable Generative AI in Type-2 Diabetes healthcare.

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ABSTRACT

Healthcare is an umbrella term capturing various (medical) attempts to strengthen and/or restore physical or mental bodily needs with the goal of improving health. It is an essential part of life, and good healthcare is often correlated with good quality of life. While it is mostly preventative, some healthcare is remedial and this can be life-long. Diseases like Type-2 diabetes (T2D) require live-long healthcare that includes significant changes to the patient's lifestyle. Technological healthcare interventions have long proven to be effective in the short and long run, and Generative Artificial Intelligence (GenAI) models show potential in providing tailor-made healthcare solutions to each patient according to their individual needs. We examine the use of such models in generating stories and images. T2D patients can use these as part of their behavioural change tools as they develop and/or maintain new lifestyles to manage the disease. Two GenAI models are used, Dolphin-Mistral to generate stories, and Stable Diffusion Lightning to generate the accompanying images that patients can use in their Diabetes management. We present a method for these models to capture and interpret contextual and cultural prompts. The generated stories and images are measured for their contextual and cultural appropriateness. We find that while there are a lot of challenges, these models are able to produce contextual and culturally appropriate material, even for low-resource contexts and cultures which don't contribute much to the models' training.

INTRODUCTION

Imagine Travis, a 19-year-old University student, meets with Nurse Lee to discuss lifestyle changes to manage T2D, particularly smoking cessation. They develop strategies for each that Lee uses to seed a story that helps Travis remember his cognitive prompts when he needs to turn away from smoking. Travis keeps the story on his phone and watches it before he goes out to keep his motivation high. At a follow-up appointment, Travis says he is using the story as an aid, but he doesn't relate to the character. He wants a character that looks like the future version of himself once he is in control of his diabetes. They work to imagine his appearance and generate that character together. The story is then remade. [9] Stories like Travis' can become a reality, with huge potential to improve lives of T2D patients worldwide. This study (study or project?) seeks to develop and test a software system that would assist Healthcare providers (HPs) like doctors, nurses, and patient carers to generate stories and accompanying images that help the patient. Participants from Uganda and United Kingdom interact with the system and provide feedback presented in this study. Previous work from Aggarwal et al. [1] has highlighted the benefits of technologies like Artificial Intelligence (AI) in Healthcare using text (Chatbots). This study presents a new approach by combining both text and images into one coherent multimedia package. This has the potential to improve both the quality and accessibility of such healthcare interventions. We attempt to find out if GenAI can be used to create culturally appropriate material for patients in the Global South. The objectives are:

1. Test the cultural awareness of stories made by GenAI.
2. Test the cultural awareness of images made by GenAI.
3. Explore some cultural proxies that GenAI responds to.
4. Explore some cultural proxies that participants respond to.

The study contains a review of existing literature below, followed by the system and experiment design. We then present the testing results, discuss it, and conclude with some recommendations for future work in these areas.

LITERATURE REVIEW

healthcare

Healthcare encompasses a wide gamut of practices from preventing to treating people with various needs. These include non-communicable diseases such as Type-2 Diabetes which is a life-long condition where the patient's body has too much sugar circulating in it. T2D is reported to make up about 90% of all Diabetes cases in the United Kingdom.[10] and can be managed with medication. However, given its nature, the patient is often recommended lifestyle changes that offset majority of the high-risk symptoms. [11] Unfortunately, people often have challenges with lifestyle changes, especially those that are out of necessity rather than desire.

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Technology in healthcare

Previous literature has shown technology to be a useful tool in Healthcare, bringing improved healthcare delivery, and saving costs. It has also sped up on-job upskilling, increased access to services, and enabled better decision-making.[6]

One of the biggest potential benefits is the ability to customise healthcare solutions for each and every patient. This is currently costly and in many cases, infeasible. Technology solutions like Artificial Intelligence (AI) can be adapted to healthcare needs to help provide tailor-made care for everyone accessing these services. [4, 3, 15]

Artificial Intelligence

AI is generally regarded as the machine's ability to exhibit intelligence, as decided by human operators. While it has been present in one form or another, recent developments in the area have quickly increased its utility and therefore its adoption in both personal and corporate spaces. Machine Learning (ML) algorithms in particular are one such development. These are ways by which machines can be programmed to 'learn' from information given to them without having to be explicitly programmed on each of that information. [7, 16]

Generative AI

Further progress in the AI field has resulted in a subset of technologies called Generative AI (GenAI). GenAI works by using ML methods to generate new synthetic information that is based on what it was trained on. It is noteworthy in its ability to create synthetic samples that are believable, and many times indistinguishable from real-world samples. [17] GenAI can create text, images, video, and sound from similar inputs. For example, ChatGPT can be given a text prompt to explain and illustrate a children's story about kindness. It then generates a story in text form, and generates storybook images too, in response to the prompt it was given. [13]

GenAI models are typically categorised as follows:

1. Autoregressive models
2. Generative Adversarial Networks (GANs)
3. Variational AutoEncoder Transformer (VAEs)
4. Diffusion models
5. State Space Models (SSMs)

Define and give an example of each?

GenAI for healthcare

These GenAI models can help cut healthcare costs associated with creating story and image content at a large scale. They would also drastically shorten the delivery time of such interventions because of their near-real-time results and 99% up-time [7]. This is currently neither possible nor economically feasible using traditional means such as human writers and cartoonists. One of their biggest benefits is their ability to be flexible in creation of responses, and iteration after feedback, would make it easy to customise healthcare to each patient's needs. [12, 1]

However, there are ethical concerns around the information used to train these models, and compensations for the information owners. This is especially true where the models are used by another party for profit. Because of their probabilistic design, GenAI models can be unpredictable in their responses. [5] This poses a challenge in use-cases like healthcare where we need clear control over generation, and consistent, high quality results. Lastly, while these models have relatively-low operational costs, they are expensive to train, requiring large capital investments and highly-skilled personnel. [2]

GenAI, if applied appropriately, could unlock benefits in the quality and scale of healthcare. In this study, we consider those models that generate text (Text-to-Text, or T2T) and those that generate images (Text-to-Image, or T2I). T2T models would generate custom stories for each patient and T2I models would generate custom images to go along with the stories.

Previous AI use in healthcare

In practice, GenAI has been utilised in healthcare with benefits. When evaluating the feasibility, efficacy, and intervention characteristics of AI chatbots for promoting health behaviour change, [1] found that "The participants also reported that AI chatbots offered a nonjudgmental space for communicating sensitive information." [7] reported similar results with conversational agents. [6] also reported that "Overall, users showed favourable acceptance of these chatbots for self-managing chronic illnesses." When investigating whether AI chatbot interventions were effective in changing physical activity, healthy eating, weight management behaviours, [12] found that "Chatbots may improve physical activity", although in a broad sense, they couldn't make "definitive conclusions regarding the efficacy of chatbot interventions on physical activity, diet, and weight management/loss." This study adds more insights to this body of work, to help clarify when and how GenAI can best be utilised in healthcare.

Culture in AI

One of the biggest criticisms of AI technology, and GenAI in particular, is bias. Bias occurs when the training information influences the AI's results. This happens most often as a probability of outcome. As an example, if an image generator GenAI system is trained on more men than women, it's results will be more frequently (and accurately) male than female. In commercial systems that are trained on multiple information sources, some well-digitised sources like the Western world will contribute more information than other locations. add the refs

Another way to look at the bias problem is to present it as difficulty to control the responses of the GenAI systems. For example, models that are trained on information from American popular culture will respond to all queries based on the same culture. The challenge is that when these models are used in a different culture, it is more difficult to get an appropriate response. add the refs

Culture in LLM

needs rewriting In a qualitative study, [14] (1) failing to recognise cultural subjects: generated imagery fails to depict a culture's subject matter, (2) amplifying cultural defaults: culture's subject matter in generated images defaults to particular hegemonic cultures; and (3) perpetuating cultural tropes: generated images contain stereotypes and tropes associated with particular cultures. capturing "elements of culture" and using them as markers for prompting and for output evaluation. Subject-action-verb, Person-action-location.. Values Survey Module (VSM) from Geert has questionnaire modules to use for determining culture. intro article here. VSM here. CulturePark paper [8] uses culture-specific agents to generate more useful cultural dialog and samples (useful in finetuning) based on updated VSM13.

- talk about defining culture (mtd I used is via proxies)
- talk about previous lit approach to culture

Culture in T2I

type it out culture in T2I... check Mendeley for refs, add the notes here.

- borrowing defining culture from LLM, what proxies were same, what changed
- talk about prompting with culture - 'visual culture' prompts

Human-centered approaches to AI

type it out check Mendeley for refs, add the notes here. add paper I got today Tue.

- responsible design choices in models.
- system design always dependant on human decision-making at key points
- talk about cognitive load (technostress) of the system.

STUDY DESIGN:

type it out key concepts: culture. story. image. healthcare. t2d.

Other studies have tested GenAI systems text generation (list some with refs) and image generation (list some with refs). This study aims to combine both text and image generation as a unified result. Other studies have also generated images with different goals such as composition of the image, etc (find some). This study also takes into account these goals, but its main focus is the cultural appropriateness of the resulting images. Maybe also generation time? needs rewriting

System design:

In this subsection, we present the system design and the motivations behind it. The next subsection details the experiment design and how we evaluate the responses from the system and its testers.

From a technical standpoint, the proposed system is comprised of three parts. Two models, an LLM and a T2I, run in the background, and are connected by a user-facing API. From a user perspective, system use is described in four steps. The first is the Patient input, followed by the HP's input. The third is the system's output, and the final part is the feedback loop.

The Patient input allows for the submission of relevant patient details like name, age, and physical appearance, as well as cultural proxies like location and income status. There are more attributes that aren't included but can help customise the responses even further. These include the patient's preferred language, preferred output (text, image, sound, etc). Others are the patient's close contacts that shape familiar characters in the story generation, and common locations the patient attends that can form story and image generation.

Figure 1. needs system design image

The HP's input is where an HP directly inputs "doctor's notes" that relate to the patient's current health status, needs, and next steps. This information can be broken down further into the latest health advice, and any history of previous health advice. This information from the HP is combined with the Patient details and run through the system to return a story and accompanying image prompts.

After this, the HP can request images from the system which are also returned after their generation. Theoretically, the HP can generate any other medium, e.g., an audio of the text can be generated from a text-to-speech (TTS) model.

The final step in this process is an human-centered feedback loop that ensures the system is fully controlled by the user. This is present at every system output step, so that responses can be edited by the HP and regenerated until they are satisfactory. The feedback that is useful is two-fold; patient-facing and healthcare-facing. Patient-facing feedback adjusts the system's response to accommodate the patient's needs and context. An example of this is telling the system the patient has an ankle injury at the moment so it can regenerate exercises the patient can do given this new change in circumstances. Healthcare-facing feedback ensures the system gives appropriate health advice. An example can be the HP informing the system that an appropriate exercise it generated won't work for a patient due to other factors. Currently, the system receives both types of feedback for each story it generates, and regenerates accordingly. Future versions can store this feedback as part of the patient's preferences history.

- mention prompting and RAG, and why you ignored RAG

Experiment design:

testing two scenarios: as the patient and as the HP needs rewriting

As the patient:

type it out

- interpret the images without accompanying story
- deduce culture from the images without the story
- interpret the images with accompanying story

As the HP:

type it out

- input notes that guide the LLM

- generate a story from the LLM
- deduce culture from the generated story
- edit story and/or accompanying image prompts
- generate images from the story using the T2I
- edit image prompts and regenerate images
- deduce culture from the generated images

RESULTS

pending

DISCUSSION

pending

CONCLUSION

pending

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