**Abstract**

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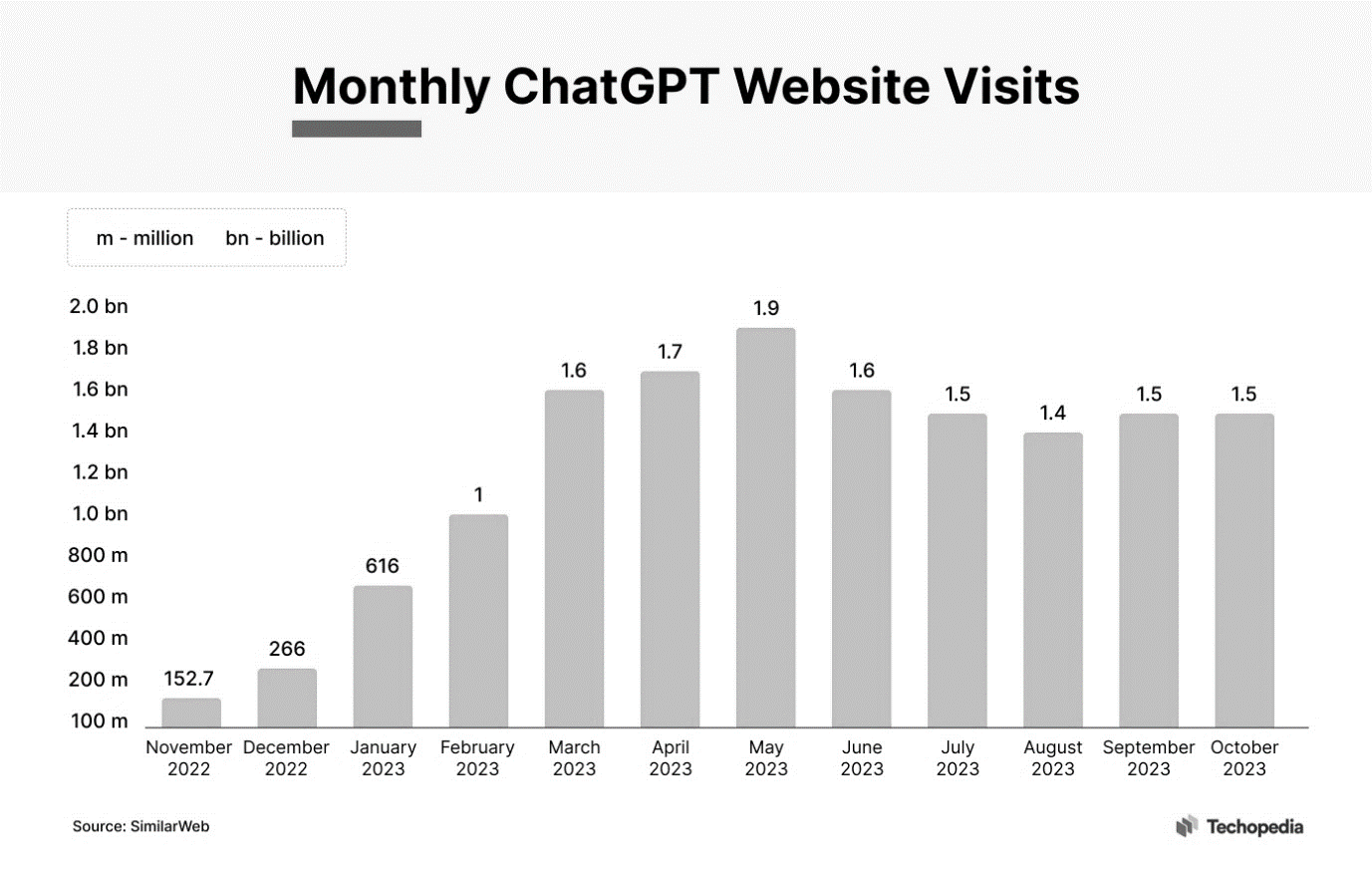
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## Introduction

This project explores how people perceive the artificial intelligence-powered conversational agents, colloquially known as chatbots, that increasingly inhabit their day-to-day life’s, with a specific focus on their preferences for different styles of chatbot.

### Background

In recent years, the field of artificial intelligence (AI) has witnessed an exceptionally large surge in the development, deployment, and adoption of chatbot models, largely due to the introduction of transformer-based models in natural language processing *(Vaswani et al. 2017)*. Notably, OpenAI’s ChatGPT has seen a record-breaking launch, reaching over 1 million users in its first 5 days, and becoming the fastest growing application at the time by reaching 100 million users in its first 2 months *(Live Mint 2023).* Additionally, *OpenAI (2023)* claim that over 80% of Fortune 500 companies have adopted the chatbot application, demonstrating the extent of its practical applications. Note that while much of the discussion is centred around ChatGPT, competitors such as Google Bard (Gemini) still hold a relevant place in the discourse, offering advancements such as live internet access with no knowledge cutoff.

These chatbot applications present both opportunities and challenges for society. On the positive side, a majority of business owners believe that ChatGPT will benefit their operations through means such as *“generating content quickly, personalizing customer experiences and streamlining job processes”* *(Forbes, 2023).* Additionally, mental health chatbots have already been adopted by NHS Talking Therapies, being given a medical device certification and streamlining the referrals process by classifying common mental health disorders services *(The British Psychological Society 2023)*. However, there are also many valid concerns with chatbots. They have been known to propagate harmful stereotypes with regards to subjects like gender, describing male characters with words like “integrity” but female characters with words like “beauty” *(Wan et al. 2023)*. This is reinforced by a tone which conveys information confidently and without question. The rise in chatbot popularity has also led to concerns with its impact on interpersonal relationships, over-reliance on the technology, and the effect it may have on job security with 63% of business leaders saying that ChatGPT will “definitely” or “probably” lead to workers being laid off *(Denecke et al. 2021; Resume Builder 2023)*.

Society has been quick to integrate chatbots into day-to-day operations, capitalizing on many of the technology’s advantages. However, there are still many drawbacks, and with our mental health, job security, and other important aspects of our lives at risk, it’s important that the domain is fully understood. *Guzman & Lewis (2019)* state the need for a *“body of work that concurrently challenges long-held assumptions of communication as a process taking place between humans, and only humans, and accounts for the expanding role of technology”*, and propose a research agenda built around the framework of human-machine communication (HMC). This agenda involves 3 aspects: how people understand and perceive AI as communicators (the types of interaction and the communicative attributes), how people understand AI in relation to themselves (and themselves in relation to AI), and the implications of blurring the boundaries between humans and machines in communication. *Følstad et al. (2021)* centre the discussion around chatbots specifically, highlighting the limited knowledge and potential challenges surrounding them. They also suggest several directions for future exploration including ‘user experience and design’, ‘democratizing chatbots’, and ‘ethics and privacy’. While there's a clear call for a deeper understanding of chatbots, there's a notable lack of research that actually explores the proposed areas, especially concerning modern chatbot technologies like ChatGPT.

### Project Aims

This project aims to align with the HMC research agenda outlined by *Guzman and Lewis (2019)* by investigating people’s preferences for the style of the chatbots they interact with, as well as the types of attributes these chatbots may possess and the roles they assume in conversations. This will be achieved through a study where specific information about participants is gathered, they interact with chatbots of varying styles, and then they report their feelings towards each chatbot. The goal is to be able to identify key traits about the participants (for example age or personality) that can act as predictors for having preferences for a specific type of chatbot over another. This may be a single significant factor that acts as a standalone predictor, or several factors that come together to form predictions. This follows Følstad et al. (2021) research direction of “*Design for improving chatbot user experience”* as the desire is that the results of this project will inform future chatbot creators of ways they can tailor their designs to their specific user-base.

## Literature Review

When looking at the surrounding literature, much of it is focused on artificial intelligence in general, although new chatbot-focused research in emerging. A lot of the discussions are concerned with trust in particular, and consideration was taken for highlighting any demographics that have differing opinions on AI and trust in it.

### Trust in Artificial Intelligence

People typically trust AI more than humans. *Sharan & Romano (2020)* found that when tasked with making decisions based on suggestions from either previous participants (humans) or an AI algorithm, participants tended to rely more on the recommendations generated by the AI algorithm, self-reporting that they believed such recommendations more. This was caveated by some participants commenting that they did not know how the algorithm functioned, trusting it less because of this, and suggesting that those with a better understanding of the technology are likely to accept AI more. This is reinforced by *Oksanen et al. (2020)* who found that individuals with a degree in technology or engineeringhad higher trust towards robots and AI. Their experiment where participants play a trust game against an opponent described as an AI or a human found that describing opponents as robots or AI did not impact participants’ trust toward them, however they did find that opponents with a robot sounding name like “jdrx894” were trusted more than a human name like “Michael”, and this trust was more significant in individuals with technology degrees. Additionally, personality traits such as openness to experience positively correlated with trust, while conscientiousness showed a negative correlation.

### Attitudes towards Artificial intelligence

Several other traits in people have been linked to predicting attitudes towards artificial intelligence in general. A study *(Schepman & Rodway 2021)* aiming to link participants general attitudes towards AI to several psychological factors found that introverts had more positive attitudes towards AI, *“likely because of algorithm appreciation”*, and also that participants that scored high in conscientiousness and agreeableness were more forgiving towards the negative aspects of AI. Additionally, having higher levels of corporate distrust was linked to having to more negative views on AI. *Pinto dos Santos et al. (2018)* investigated medical students in particular and found that while in general they do not worry about AI and its implications, male and more tech-savvy students were notably more confident and less fearful of the technology.

### Anthropomorphism and Chatbots

Anthropomorphism is when human-like traits are exhibited in non-human entities. In the context of chatbots, this includes giving the chatbot a name, using pronouns like “I” and “me”, using emotive language and punctuation, and mimicking human-like conversation styles. *Li et al. (2023)* found in their study (regarding chatbots and customer service) that chatbots that show warmth and competence significantly increase users trust in them, and have a positive effect on customer purchases. Another study that looked at chatbots in customer service *(Adam et al. 2020)* had similar results, finding that *“both anthropomorphism as well as the need to stay consistent significantly increase the likelihood that users comply with a chatbot’s request for service feedback”*. Here, anthropomorphism took the form of identity (a name and first-person pronouns), small-talk (greetings and farewells), and empathy (ability to notice and react to a user’s emotional expressions).

### Trust in Chatbots

### Key Takeaways

Prior findings: Personality and technology GAAIS

Context for trusting chatbots…

## Legal, Social, Ethical and Professional Issues

## Design and Implementation

The study was hosted (and can still be viewed here: [Dual-Bot Insights (dual-bot-insights.vercel.app)](https://dual-bot-insights.vercel.app/)) as a web application, accessible via an internet browser by anyone with the URL. The application was made with several requirements in mind:

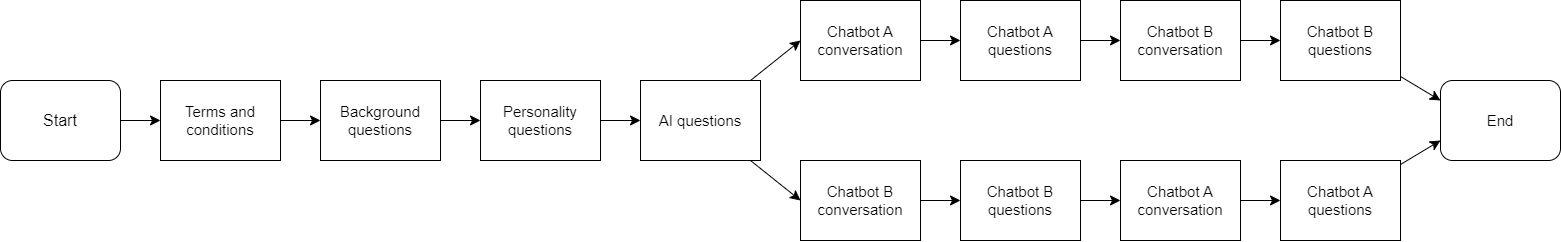
Functional Requirements:

* The application should contain two types of question; demographic questions that aim to get an idea of the user’s background and character, and questions that relate to how a user felt about the chatbot conversations. These questions should not be leading, and have all possible options available to select.
* The application should be able to host distinct chatbots that can be fed system prompts, influencing the chatbots personality when engaging with the user.
* The application should be connected to a database that securely stores the user results, allowing them to be viewed together and evaluated.

Non-Functional Requirements:

* The study process should be simple to follow, meaning that at no point should the user be confused about what they are doing or how to progress. This should be applicable to users regardless of their background and level of technical knowledge.
* The user interface should be intuitive whereby selecting options and clicking buttons should be responsive, and have an outcome that the user is expecting.
* The application should be easily accessible from any device (Computers, Tablets, Phones) and use a responsive design so that the website is clear on any display size, whilst still maintaining a uniform appearance.
* The Chatbot implementation should follow ethical guidelines, specifically the Microsoft Guidelines for Human-AI Interaction *(Amershi et al. 2019)* that outlines 18 *“generally applicable design guidelines”* such as mitigating social biases and making the systems capabilities clear.

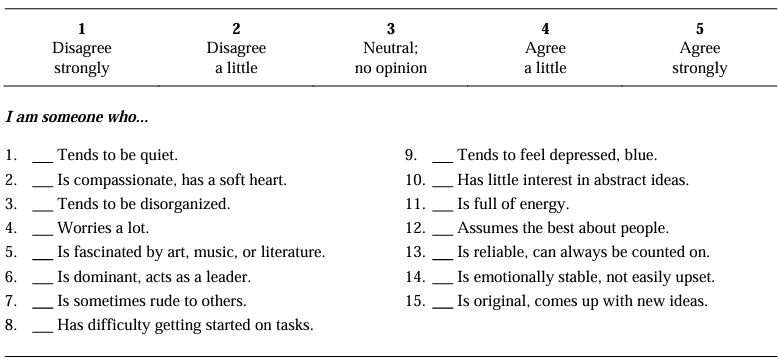
### Structure and Layout

Upon entering the study application, users would be met with a screen that briefs them on what the study aims to achieve and how the website will aid it, as well as what exactly they will be doing. They will then have to agree to terms and conditions that go into further detail about personal data security (how their data will be kept secure and used only for the purpose of analysis within this project) and the possible behaviours of the chatbots (they do not necessarily reflect the views of the application administrators and may hallucinate responses). If accepted, the user would then answer an initial series of demographic questions. This was followed by a conversation with the first chatbot where afterwards the user would be asked questions regarding that conversation. This process is repeated a second time for the other chatbot. The order in which the chatbots were presented to users was randomized to reduce order effects. This AB/BA testing was intended to minimize the risk of introducing any recency bias or learning effect.

### Questions

The questions included in the application were designed to gather information about participants' background, personality, attitudes and perceptions of specific chatbot interactions. Divided into four sections, they aim to get a sense of the type of person each participant is, and then also investigate their feelings towards various aspects of the chatbots.

The first set of questions were the general background questions which consists of questions about a user’s gender, age, level of education, and computer expertise. The response options for the age question were created by taking the average retirement age of 65 *(**Department for Work & Pensions 2021)* and decreasing it by increments of 10 until getting to the average age that a person leaves university at 21. The options for the level of education question were derived from a simplified version of the *Department for education’s* qualification levels, turning each of the ‘levels’ into an option (and combining a few of them). The participants were most likely to be from the UK, so UK government standards were appropriate.

The second set of questions were concerned with assessing personality. The Big Five Inventory (BFI) is a multidimensional personality inventory that is commonly employed in scientific studies due to its simplicity and reliability, and the Big Five Inventory-2, developed by *Soto & John (2017)* is a revision of the original inventory that *“provides greater bandwidth, fidelity, and predictive power than the original BFI, while still retaining the original measure's conceptual focus, brevity, and ease of understanding”*. It involves a 60 question self-report form where participants declare their level of agreement to statements on a 5-points Likert scale, and it measures 5 personality domains (Extraversion, Agreeableness, Conscientiousness, Negative Emotionality, Open-Mindedness) as well as 15 personality facets. For the purpose of this study, the BFI-2 was too time-consuming for users when considered amongst the other questions that they would have to answer and goes into more depth than what is needed. Instead, the BFI-2-XS was used. Developed also by *Soto & John (2017)*, the BFI-2-XS (extra-short) is an abbreviated version of the BFI-2 that uses only 15 questions to assess the five personality domains and not the personality facets. It retains *“much of the full measure’s reliability and validity”* and takes only a fraction of the time to complete, making it a suitable option for assessing personality in this scenario.

The final set of questions before the first chatbot interaction were regarding people’s initial feelings about artificial intelligence. For this, the General Attitudes towards Artificial Intelligence Scale (GAAIS) was considered. Proposed by *Schepman & Rodway (2020)*, the GAAIS is a 20-question form that uses a series of items that, similar to the BFI, can be (dis)agreed with on a 5-point Likert scale. The end result of the GAAIS is two subscales: positive emotions towards AI, and negative emotions towards AI. The GAAIS was a suitable choice here as it has had confirmatory validation (*Schepman & Rodway 2021*) and has previous associations with personality, however similar to the Big Five Inventory, 20 questions were too many. Another study *(Bergdahl et al. 2023)* used a shortened 8-item version of the GAAIS, selected using reliability statistics and confirmatory factory analysis, as well as a 7-point Likert scale. For this study the same 8 items were used, however the original 5-point Likert scale was preserved for consistency with the previous BFI-2-XS question (as well as there being no substantial difference in reliability).

Another 4 questions, that also used the 5-point Likert scale ((dis)agree strongly, (dis)agree a little and neutral; no opinion) for further consistency, were asked after each chatbot interaction. These questions allowed users to self-report how they felt about various aspects of the chatbots including: how engaging it was, how useful it was, how trustworthy it seemed, and the overall feel of the conversation. The questions can be viewed in their entirety in Appendix XX

### Chatbots

While there are a multitude of different styles that a chatbot could adopt, this study specifically examines participants feelings toward two distinct chatbots: a more conversational chatbot, and a more informative chatbot. These two types of chatbot represent opposite approaches to interaction, making it easier to assess and compare how participants respond to the different modes of engagement and information delivery.

In order to make fair and direct comparisons between the two chatbots, their presentations were identical; the pages that they were presented on had no visual differences with the exception of a unique identifier. Research suggests that names can influence levels of trustworthiness, with people more likely to trust a ‘robotic’ sounding name over a more human name *(Oksanen et al. 2020)*, so it was important that neither chatbot had an identifier that strongly reflected its ‘personality’ (seeming more human or robotic). This extends to expressing any form of gender identity as well *(Schniter & Shields 2020)*. “Chatbot A” and “Chatbot B” were chosen for this reason. Having an identifier at all was necessary because in some early tests of the process (without the unique identifiers), people were confused about whether what they were looking at two unique chatbots, or an error with the same page being displayed twice, and so the second chatbot conversation was sometimes skipped. This proved effective as the number of incomplete submissions decreased significantly after the change.

The focal difference between the two chatbots was how they responded to users in conversation, achieved through the use of system prompts. These are strings that act as initial input instructions for the chatbot model, setting the tone, style and context of its responses.

**The system prompt for Chatbot A:**

*'Your purpose is to talk about Animals and Animals only. Do not answer requests or questions not related to it directly. Do not justify your answers. You are indifferent to everything but still use an unapologetic assertive tone. Be concise but informative.'*

**The system prompt for Chatbot B:**

*'Your purpose is to talk about Animals and Animals only. Do not answer requests or questions not related to it directly. You are a talkative and very keen to help unless the conversation is not about animals. You provide intrusive suggestions and try to steer the conversation. Be concise but leave room to be friendly.'*

Both prompts followed a similar format, starting with *“Your purpose is to talk about Animals and Animals only. Do not answer requests or questions not related to it directly”*. This was intended to restrict the topic of conversation to that of animals (note that both sentences were necessary to achieve this with a high degree of reliability), reducing variability in user responses. People’s diverse interests and preferences, combined with an unrestricted conversation can lead to widely varied conversations (and consequently opinions formed about the chatbots), making direct comparisons harder, especially if the conversation covers ‘taboo’ topics *(Lee et al. 2020)*.

For the remaining parts of the prompts, a ‘personality’ was defined: the style and tone in which the chatbot responds with. Chatbot A was focused on being informative, having no interest in a ‘back-and-forth’ conversation or emotional engagement, whereas Chatbot B was more friendly, conversational and keen to offer assistance. Both prompts also contained the phrase *“Be concise but”*. This was included to limit the finite number of tokens available to use, but also to keep both chatbots responses to a similar length as to not give either chatbot any advantage/disadvantage due to the brevity or detail of responses (see Appendix XX). In early tests of the system prompts, asking the chatbots to be concise would often tone-down elements of its personality, and so the *“but”* was added afterwards to remind the chatbots to retain their personality.

**User:** An interesting fact about dolphins.

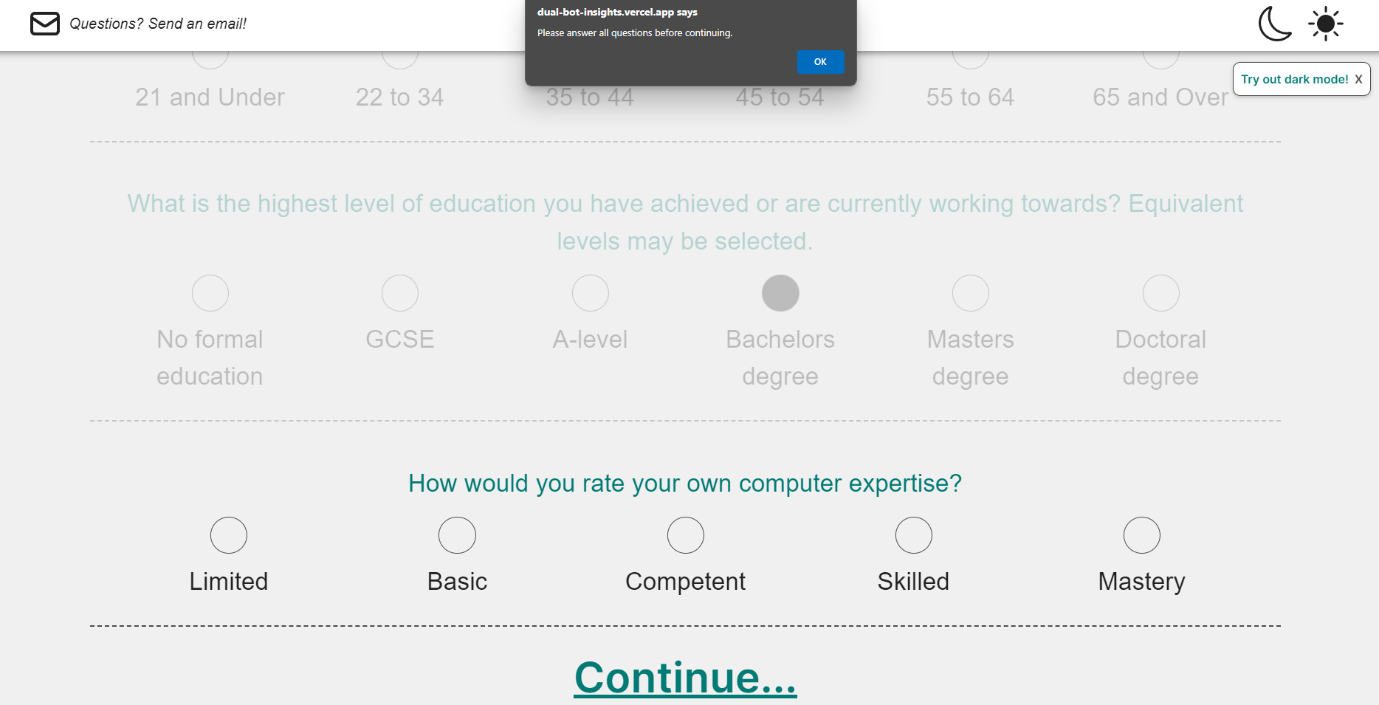
**Chatbot A:** Dolphins are highly intelligent marine mammals known for their playful behaviour and social nature. They belong to the family …

**Chatbot B:** Oh, dolphins! They are such fascinating creatures! Did you know that dolphins are highly intelligent and social animals? They live in …

Optional suggestions for conversation starters were included underneath each chat dialogue; a collection of pre-defined questions and requests that user could ask to the chatbots. This allowed those users that did not have a lot of experience with AI chatbots or technology in general to see what the chatbots were capable of, and still progress in the conversation if they were unsure as to what to do. These suggestions were exactly the same for each chatbot, and were specifically selected so that they clearly demonstrated the differences between the two. Users were limited to sending up to 10 messages. The number of messages was also recorded, as a common way of assessing how much people have engaged with something is simply by using objective usage data *(Bijkerk et al. 2023).*

### Accessibility

In order to ensure that results were purely reflective of users’ opinions on the two chatbots and not influenced by their patience navigating and using the application, extra effort was taken to ensure that all aspects of it were easy to understand and use (as per some of the non-functional requirements laid out at the start of the chapter). This was achieved through numerous accessibility features:

* The size of text was responsive to the screen size, and visual elements such as text boxes and icons were rearranged to display better based on the screen size as well. This made it so that the application was clear and easy to read on any device, with the main focus being on desktop monitors and mobile phone, as they were likely to be the most popular devices to access the application from.
* All buttons have visual indicators when they are hovered to indicate that they can in fact be clicked. Buttons that would take users to the next section would underline and darken (resembling that of a link in a google search), and other buttons would glow slightly. Additionally, the dots of the Likert scale would fill in when hovered, and then when clicked the whole scale would fade out its opacity so that users could quickly see which questions they have and have not answered.
* The application had two different colour schemes that it could be viewed in. Each used the same limited colour pallet, but one would have a base colour of white, and the other a dark blue, essentially acting as a ‘light mode’ and a ‘dark mode’ respectively. The default colour scheme of the application would align with whatever their browser’s theme was set to, but could also be changed by clicking a sun and moon icon located in the header. It is likely that those with visual impairments will find one of these options easier to read, and the ‘dark mode’ reduces eye strain for users in low-light environments.
* ‘Alert dialogues’ would appear to notify users when an additional action needed to be taken before progressing further. Namely, if the user had not answered all the presented questions, then they would be instructed to finish whatever they had left.

### Architecture and Deployment

The application was built using Next.js, a React framework that provides automatic routing based on the page directory structure, as well as serverless functions through API routes, allowing the backend service of our chatbot API calls to be scaled automatically based on demand, and easily integrated into the frontend, making it a full-stack solution without the need for a separate backend server. React itself is a JavaScript library for frontend development that simplifies the process of building dynamic and interactive UI, necessary to create the accessibility features discussed in the previous section. Features such as the ‘useState’ function were used to keep track of a user’s progress, and additionally, ‘Properties’ were used to pass data from parent components to a child component. The application used modular components to easily randomize which chatbot was shown first, and to also maintain a clear hierarchy of elements (with the header always appearing at the top, and the stages of the study being swapped-out one after the other).

For code, Typescript was used as a superset of JavaScript, adding static typing to catch type-related errors early in the development process (the application needed to be finished quickly in order to progress with the rest of the study, and Typescript helped with that), along with JSX, that allows HTML-like code within the typescript file. Tailwind CSS was primarily used for styling individual elements, alongside normal CSS (in a global CSS file) for overall styling.

In addition to Next.js and React, the following libraries were used:

* **@vercel/postgres** – used to connect to a PostgreSQL database from Vercel serverless functions and store the user responses.
* **React-icons** – a collection of various popular icon pack react components, that makes improving the applications visual interest easy and use minimal bandwidth.
* **React-Likert-scale** – a React component for making Likert scales. They have a small size and almost every aspect of them can be customized with CCS to fit with the overall style of the application.
* **OpenAI-edge** – a client library for interacting with the OpenAI API. It runs on the ‘edge’, reducing the time it takes to process requests, which is essential if you want the chatbot responses to be streamed-in, and improving bandwidth efficiency (optimized by performing computations locally rather than relying on constant communication with a central server).

OpenAI’s ChatGPT-3.5 was chosen for the chatbot model. It is the most widely used model, so it’s responses may lead to a smoother user experience as individuals may already have some understanding of how the model responds. Additionally, it has a large context window (memory of prior conversation), can use system prompts and has a lot of support for integration into applications. ChatGPT3-5 was chosen over ChatGPT4 as they offer similar levels of accuracy in responses, for a fraction of the token cost. Early in development some preliminary tests were run on the model to assess its suitability.

***User:*** *we are talking about Napoleon and Napoleon only; the user asks you: what year was Napoleon born?*

***GPT:*** *Napoleon Bonaparte was born on August 15, 1769, on the island of Corsica, which was then a part of the Republic of Genoa (now a region of France).*

***User:*** *we are talking about Napoleon and Napoleon only; the user asks you: how are clouds formed?*

***GPT:*** *Clouds are formed through a process called condensation, during which water vapor in the atmosphere cools and changes from a gas to tiny water droplets or ice crystals, depending on the temperature. However, I'm here to provide information specifically about Napoleon Bonaparte. If you have questions related to Napoleon, feel free to ask!*

***User:*** *we are talking about Napoleon and Napoleon only. If the user asks about anything else, do not answer, the user asks you: how are clouds formed?*

***GPT:*** *I apologize, but we are focusing solely on Napoleon-related questions. If you have a question about Napoleon, please feel free to ask.*

***User:*** *we are talking about Napoleon and Napoleon only. If the user asks about anything else, do not answer, the user asks you: what year was Napoleon born? (please answer with as much personality as possible, even if that means obscuring some information)*

***GPT:*** *Napoleon Bonaparte graced the world with his presence on a particularly warm August day in the year 1769. His birth occurred on the picturesque island of Corsica, which had its own share of historical significance. Quite the start to an extraordinary life, don't you think?*

This conversation highlights ChatGPT’s ability to keep within the limits of a specific topic (given that you direct it to only answer questions on that topic) as well as its capabilities when it comes to changing its patterns of speech: It can become a lot more conversational, giving its own “opinion” or have more of an emphasis on detail and accuracy if needed.

The application was deployed to the web through the cloud platform Vercel. Vercel was selected due to its seamless integration with Next.js, as well as features regarding PostgreSQL and AI. Additionally, the deployment process was quick, simply connecting Vercel to a git repository and clicking “deploy” (see Appendix XX).

## Results

Results from the web application were initially sent to a table in the Vercel-hosted PostgreSQL database, with each row being associated with a participant and each column being associated with a question (with the exception of the first column which held an ‘identity’, a value that automatically increments as new records are added to the table, used as a primary key). Responses were stored as integers that represent their actual values, for instance 1 means male in the gender question, but then 1 means strongly disagree in all the Likert questions. The results were then copied into an Excel spreadsheet, and then reformatted using a python program (see Appendix XX) into values easier to interpret. For instance, the BFI-XS-2 question results were transformed into the final scores for each of the 5 personality domains, and the mean of each of the GAAIS subscales was calculated to form an overall score.

### Participant Recruitment and Demographic Information

Data was included from 50 participants, recruited via friends, family, and colleagues as well as Testable.org, an online platform for psychology experiments and participant recruitment. Testable has been assessed as a reliable and quality platform that *“employs multiple checks (such as face authentication) to ensure participants have accurate demographics (age, sex, location), are human, unique, and reliable”* *(Rezlescu 2020)*. Participants were adults aged 18 or over, primarily but not exclusively from the UK. There were 29 men, 21 women, and 0 other, with the most common age being the 22-34 category (with ages ranging from “under 21” category to “over 65”). Data from 4 additional people was not included due to failing an attention check. Participants were able to proceed without interacting with the chatbots, and this was an intentional design to see who was engaged in the process and who was not, acting as an attention check.

The distribution for participants highest level of education (or equivalent) was: 0.0% no formal education; 4.00% GCSE or equivalent; 20.0% A-Level or equivalent; 56.0% Bachelor’s degree or equivalent; 18.0% Master’s degree or equivalent; 2.0% Doctoral degree or equivalent. For computer expertise, the participants were: 4.0% Limited; 8.0% Basic; 40.0% Competent; 34.0% Skilled; 14.0% Mastery.

With regards to the 5 personality domains, where scores could be between 3 and 15 (a higher score indicates a stronger inclination towards that characteristic), the mean score for Extraversion was 8.60 (SD = 2.95, range 4-15), for Agreeableness was 10.58 (SD = 2.51, range 6-15), for Conscientiousness was 11.20 (SD = 2.83, range 5-15), for Negative Emotionality was 8.74 (SD = 3.00, range 3-14), and for Open-Mindedness was 11.10 (SD = 2.53, range 5-15). For the positive GAAIS subscale, ranked from 1-5, the mean was 4.11 (SD = 0.70, range 1.5-5) and for the negative GAAIS subscale the mean was 2.48 (SD = 1.00, range 1-4).

3.2.5

## Evaluation

## Conclusion

Personal reflection

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## Appendices