CMP6200
Individual Undergraduate Project
2024 - 2025

A2 - Literature Review and Methods

University Artifically Intelligent Assistant

Course: Computer & Data Science
Student Name: Lewis Higgins
Student Number: 22133848
Supervisor Name: Dr. Atif Azad

Contents

Report Introduction

1.1 Aims and Objectives

This project aims to aid new and existing students alike while they are attending university with helpful information about the university itself, such as university societies, locations/campuses, and policies through the medium of a digital chatbot companion to converse with. Its objectives are to:

- Develop a chatbot capable of accurately answering user queries related to university buildings, policies, and societies with a minimum 95% accuracy rate.
- Conduct a thorough literature review on the surrounding topics, namely AI, LLMs and NLP.
- Create effective documentation for all stages of development, highlighting challenges faced during the process.
- Manage time effectively to ensure all project milestones are met on a consistent and regular timeframe.
- Evaluate the effectiveness of an AI assistant on university student acclimatization.

1.2 Literature Search Methodology

My literature search will be performed using multiple reputable databases for academic papers, including:

- IEEE Xplore
- Scopus / Elsevier
- Google Scholar
- BCU Online Library

By using multiple different databases to source my information from, I can ensure that any potentially relevant literature will be found. Figure 1.1 depicts how in a search for 1685 articles about employee retention strategies and turnover, only 582 (25.7%) appeared in multiple databases (Wanyama, McQuaid, and Kittler, 2022), meaning that the remaining 74.3% of articles were exclusive to the single database in which they were found, emphasising the importance of searching multiple databases.

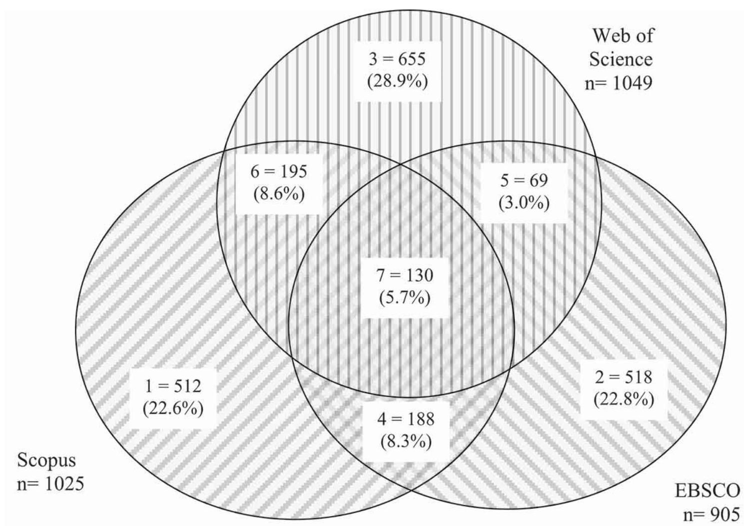

Figure 1.1: Distribution of searched articles across databases. (Wanyama, McQuaid, and Kittler, 2022)

All searches performed for recent literature will have a heavy preference to more recent literature, due to the constantly evolving fields my project is based on. The search terms I will use to retrieve the data I will be studying are:

- Artifical Intelligence / AI
- Natural Language Processing / NLP
- Large Language Models / LLMs
- Chatbots / Digital Assistants

- User Experience / UX

By using these specific terms that are directly relevant to the core themes of my project, I will be ensuring that I only retrieve literature that will be of crucial use in its development.

Literature Review

2.1 Themes

To develop the artefact and conduct thorough background research on relevant literature to further my knowledge of the subject areas, key general themes of the project were identified. From these themes, further keywords to be used in the literature search were derived to ensure that retrieved literature is directly relevant to my research and development of the final artefact. Due to the constantly evolving fields the project focuses on, it will be necessary to limit the results to only those written in recent years (2018 earliest) as there are frequent new developments in the subject areas.

Theme	Description	Keywords
AI	A field of computing dedicated to allowing computers to simulate human learning by training them on large amounts of data so that they can recognise patterns to classify or predict unknown data. AI can only be as good as the data it is trained upon, and can develop biases if it is fed too much data of a certain type.	Generative AI, Human-Centred AI, Explaianble AI, AI Ethics, AI Bias
Natural Language Processing	NLP refers to the use of machine learning to encode and process text to understand it in a similar way to humans, which can be used to allow direct two-way conversation between users and computers.	Deep learning, Tokenization, Sentiment analysis, Entity linking
LLMs	Large Language Models are a type of AI dedicated to the recognition and generation of text. As suggested by their name, they are trained on enormous amounts of text data, which allows them to have active conversations with users. There are many different LLMs, and as their size and complexity increases, so too does the necessary processing power.	Retrieval augmented generation (RAG), Fine-tuning, Prompt engineering, Impact on industry, GPT4o, LLaMA, Gemini, Claude
Chatbot Digital Assistant	Software that simulates a natural conversation between the computer and end user. Many chatbots, including the one I intend to develop, utilise recent developments such as Generative AI and natural language processing (NLP) to interpret and respond to user queries. (IBM, 2024c)	NLP, ChatGPT, Impact on industry
User Experience (UX)	The end user's overall experience of using a system, such as its ease of use and whether it is enjoyable to use (Cambridge Dictionary, 2024). In the context of my project, it will refer to the user's ability to smoothly converse with the chatbot and how human-like it is.	Conversational design, usability, market research, human-computer interaction

2.2 Review of Literature

2.2.1 Artificial Intelligence (AI)

Researchers have always wanted to harness the processing power of computers to act in a similar manner indistinguishable from that of humans, most notably from as long ago as 1950, where the question was posed 'Can machines think?' (Turing, 1950). Ever since, constant innovations were made in computer intelligence and machine learning, from playing games of checkers at a better level than human players (Samuel, 1959) to classifying the contents of millions of images using convolutional neural networks (Krizhevsky, Sutskever, and Hinton, 2012). Recently, AI is used across many disciplines and for different purposes to complete tasks faster than, and in some cases better than, human workers. Wirtz et al. (2018) write that 'service robots' [1] can complete a variety of tangible or intangible actions, such as reading and sending text as a chatbot, seen in Figure 2.1.

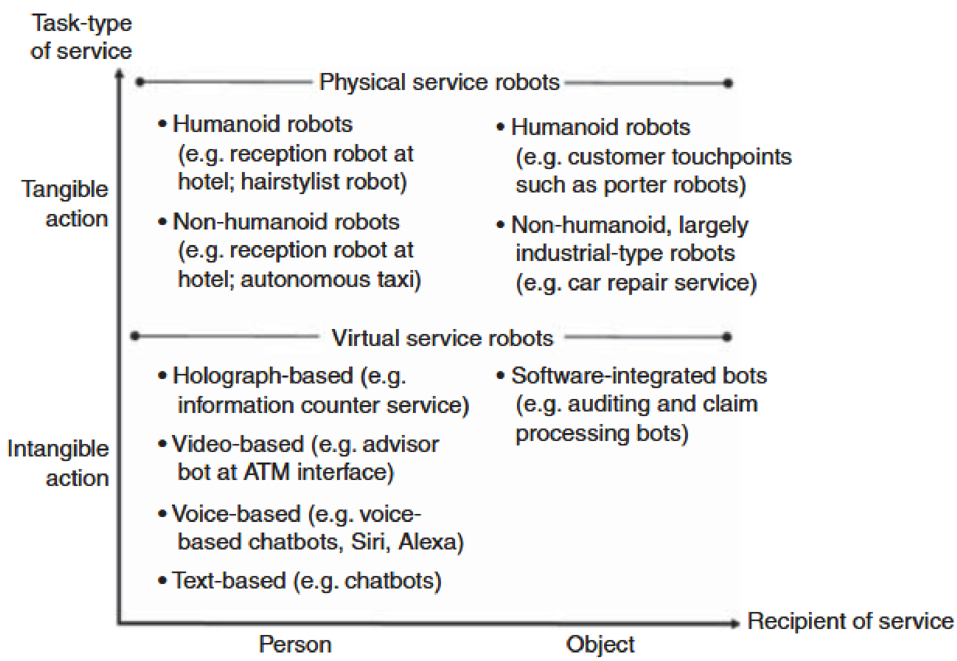

Figure 2.1: Service robots categorization by task-type and recipient of service (Wirtz et al., 2018).

Today, AI is still a constantly evolving field that is seeing bleeding-edge developments on a highly frequent basis, and more recently, is becoming instrumental in many people's work and private lives with the introduction of large language models (LLMs) (Maedche et al., 2019). However, when developing a project that utilises AI, it is important that they are ethical and human-centred in the development process, which is known as Human-Centred AI (HCAI). Another issue is the "black-box problem" - the inability to know an

[1] Defined as "system-based autonomous and adaptable interfaces that interact, communicate and deliver service to an organization's customers" (Wirtz et al., 2018, p.909)

AI's reasoning, meaning that eXplainable AI (XAI) is a growing necessity (Miró-Nicolau, Jaume-i-Capó, and Moyà-Alcover, 2025). In focusing on HCAI and XAI, the focus shifts from the machine executing the algorithms, and instead to the user and their experience using the AI (Shneiderman, 2020). In his article, Shneiderman strongly advocates for the promotion of HCAI for the benefit of both companies and their users, which is a commonly accepted idea due to the ethical risks of using AI. Because AI calculates outcomes from its training data rather than understanding social norms and perspectives, the use of it in sociotechnical systems poses serious risks due to the 'traps' it can fall into, because it cannot account for every possibility such as the personal tendencies and biases of its users (Selbst et al., 2019), and therefore developers require a shift in focus - from the final product at the end of development to the development process itself and end users, which also echoes Shneiderman's views.

2.2.2 Natural language processing (NLP)

The ability for a computer to interpret and understand human language greatly enhances the scale of their capabilities. This was recognised during the 1950s, where machine translation from Russian to English was demonstrated for the first time, albeit in a basic form (Jones, 1994). NLP has persistently been a key topic in computing, and even more so become in recent years, with its applications becoming very wide in scope with modern processing power. performing tasks such as sentiment analysis, which is the classification of the intent of a sentence, whether positive or negative for example, using recent developments in AI such as recurrent neural networks (RNNs) via libraries like TensorFlow (Abadi et al., 2016). Another use of NLP, as previously mentioned in a rudimentary form in the 1950s, is language translation. Back then, there were very limited technical options compared to those that exist today, and with today's AI, translation can be extremely accurate, albeit more computationally intensive. Both of these applications use RNNs, which are neural networks that are often superior to their alternatives such as convolutional (CNNs) and feedforward neural networks (FNNs) when analysing text due to the fact that they can retain information in their internal memory, which can allow them to recall context, allowing them to determine the linguistic relations between sentences within a document (Tang, Qin, and Liu, 2015), which is especially useful in conversational interfaces where the user may say "it" to contextually refer to a previous noun from their last prompt. However, an even better option is a long short-term memory (LSTM), an updated form of an RNN with an even greater memory capacity that allows it to solve problems with long-term dependencies (Hochreiter and Schmidhuber, 1997) that often produce excellent results (Sherstinsky, 2020).

2.2.3 Large language models

LLMs are colossal machine learning models that leverage NLP to generate text. To do so, the training data required is immense, reaching 45 terabytes of pure text data for ChatGPT in 2023 (Dwivedi et al., 2023). This data is harvested from the web (Dubey et al., 2024) and social media due to it being one of the largest repositories of opinionated text data (Wang et al., 2016), such as posts on platforms like Facebook and X. However, meticulous care is taken into the specific sources used to remove Personally Identifiable Information (PII) to minimise privacy and ethical concerns (Dubey et al., 2024). They are currently used widely across an assortment of industries in place of technical support and human resources systems, and can be supplied with text prompts from users which will cause the LLM to generate a response. Vaswani et al. (2017) proposed the Transformer architecture, which became a staple in LLMs due to the major reduction in necessary processing power to produce higher-quality results. The architecture they proposed underpins many massive LLMs today, including ChatGPT (Brown et al., 2020). Even with this revelation, however, LLMs are still extremely performance-intensive, requiring more than 8 top-range server-grade GPUs to run some of the most powerful high-parameter open-source models of today like LLaMA 3.1's 405 billion parameter model (Dubey et al., 2024). However, it is also important to note that the amount of parameters in a model does not entirely account for the quality of its responses, as studied by Ouyang et al. (2022) in Figure 2.2 wherein their surveys revealed their fine-tuned LLM with over 100x less parameters than a 175 billion parameter GPT3 model would often give answers preferred by its human assessors, which reveals that the fine-tuning of an LLM is of vital importance to the quality of its responses, even moreso than the amount of parameters. Another major innovation in LLM came in the form of Retrieval-Augmented Generation (RAG), which allows LLMs to generate answers based on an additional external data source (Lewis et al., 2021), such as a company's own database. RAG therefore allows pre-trained LLMs to be attached to another data source and generate text based on that source, which can help to reduce LLM "hallucinations" (Lewis et al., 2021), which are occurrences where the LLM will fabricate false information as though it were correct, due to the fact that it can retrieve the relevant information it otherwise may not have had.

2.2.4 Chatbots / Digital assistants

Chatbots leverage natural language processing in order to simulate a conversational flow between a user and machine, and have become mainstream products in recent years (Liao et al., 2018), though have existed as far back as 1966 with the creation of "ELIZA" for the IBM-7094 (Weizenbaum, 1966). As time has passed, the capabilities of chatbots have greatly enhanced with developments in AI such as LLMs, and are used widely across industries such as education (Kuhail et al., 2023). However, the use of LLM-based chatbots, especially in educational settings, poses significant risks as studied by Neumann et al. (2024) due to the risk of hallucinations being interpreted as absolute fact, although Shuster et al. (2021) argued that this risk can be greatly reduced through introducing RAG to the backend LLM, which is further backed by the RAG-based chatbot created by Ge et al. (2023), which they found to give superior answers in their medical field of study to those of a general-purpose LLM-based chatbot like ChatGPT.

2.2.5 User experience and Human-Computer Interaction

The way people interact with their devices has drastically evolved over the years, from early MS-DOS command-line interfaces (CLIs) to mouse-based graphical user interfaces (GUIs), to touch screens (Kotian et al., 2024), greatly broadening the userbase of computers as a whole from exclusively those heavily invested in tech to a vast majority of the world's population. As such, inclusive and accessible design is increasingly important to maximise the audience of any software, especially considering the growing disabled population (Putnam et al., 2012). As well as being inclusive, the design should also be user-centred, meaning it should be an iterative process that is constantly taking user feedback into account (Chammas, Quaresma, and Mont'Alvão, 2015). However, there are some barriers in this process when developing chatbots, as studied by Clark et al. (2019) in their survey of university students who stated that they would always view a chatbot as a tool, and would not converse with them in the same way as they would a person, which would limit their potential use and hinder the overall design process. In this same context, it is also important to understand that users may struggle to get the chatbot to respond with information they want, as their prompts may be poorly understood due to issues like overgeneralisation (Zamfirescu-Pereira et al., 2023), and that users can quickly grow impatient after around 2 to 6 failed attempts, often branding the product as poor if this occurs (Luger and Sellen, 2016).

2.3 Theory

2.4 Summary

In conclusion, this literature review has revealed multiple key areas of focus for the development of the chatbot. The overall design of the chatbot must be iterative and human-centred, and user feedback should be obtained at every possible opportunity to ensure the resultant product is high quality. A deep exploration into AI, specifically in its applications in NLP and LLMs, has revealed that the best option for the chatbot will be to leverage a pre-existing powerful cloud-based LLM's RAG capabilities to attach it to a database of university information, as to do so on a local machine would require an infeasible amount of processing power. In doing so, the LLM-based chatbot will be able to give good general answers as well as accurate university-specific answers regarding policies and societies.

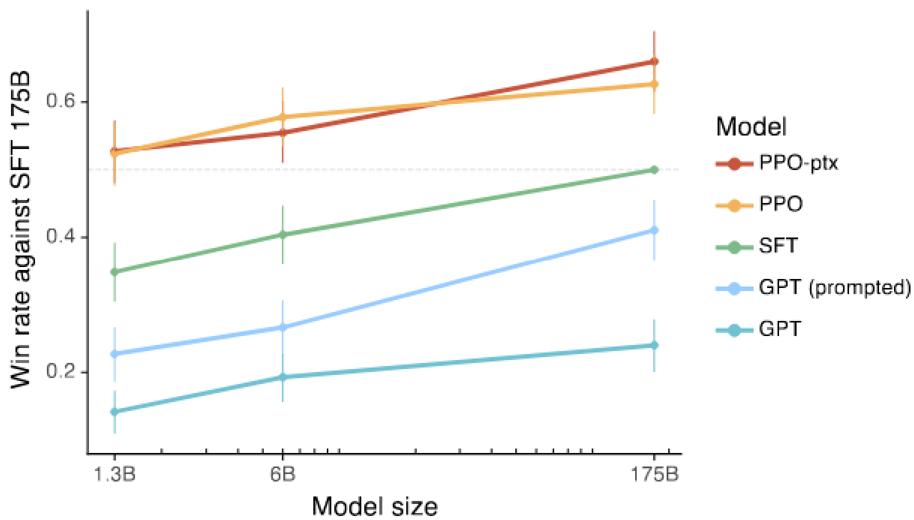

Figure 2.2: Human evaluations of the GPT models produced by Ouyang et al. (2022). PPO and PPO-ptx are their models.

Appendix

Copied from proposal

This will be updated to reflect that the proposal is now done and lit review is in progress.

3.1 Gantt Chart

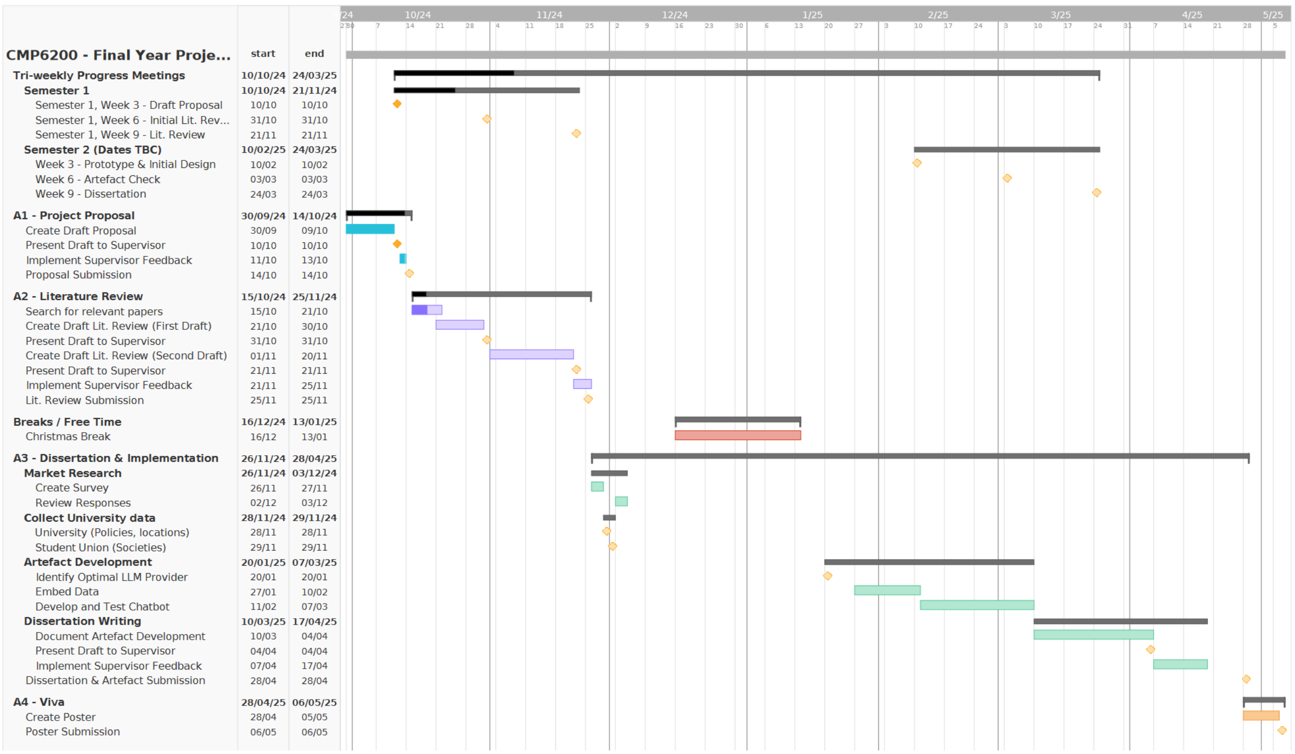

Figure 3.1: The proposed Gantt Chart for the development timeline.

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