# Artificial Intelligence Bootcamp Report- Case Study – The Medical Cannabis Clinics (TMCC)

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## Introduction

Since 1st November 2018, cannabis-based products for medicinal use (CBPMs) have been reclassified under the Misuse of Drugs Regulations 2001 from Schedule 1 to Schedule 2. This means that they are now recognised as having therapeutic value and can be legally prescribed by doctors (NHS, 2019).

As highlighted by PwC supply chains are quite simplistic and unsophisticated for cannabis industries in their emerging state (PwC, 2018). This leads to disruptions in uninterrupted medication flow to patients which can negatively affect patient's quality of life (Trustpilot/ doctor). Such disruptions will only get exacerbated in the face of projected rapid patient growth (Hall, 2021) as seen in Chart 1 and Covid accelerated global supply chain restructuring. Therefore it is vital to resolve any issues before they affect a greater number of patients and to maintain or even increase current dynamic capabilities (Essa, 2022).

The aim if this case study is to investigate how AI can be leveraged to increase dynamic capabilities of a digital CBPM provider in the UK.

The Medical Cannabis Clinics (TMCC) website (see Appendix A) was used to identify current workflow (see Figure 2).

Trustpilot reviews were used instead of interviews to establish existing pain points (see Appendix B).

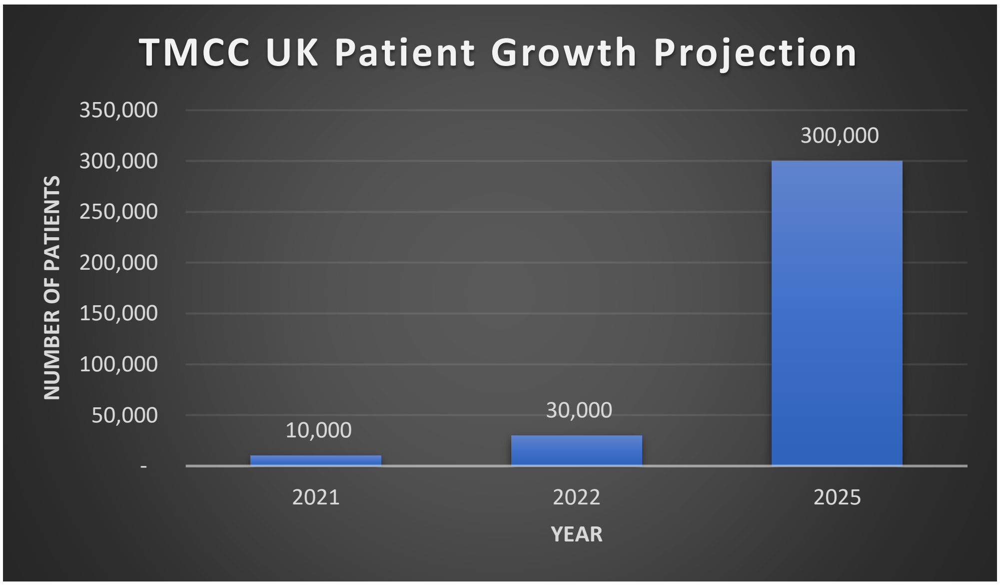


*Chart 1*

## Discussion/Analysis

### SWOT Analysis

SWOT analysis of the companies' automation potential needs to carried out in order to investigate how AI can be used to improve scalability and increase dynamic capabilities (Figure 1).

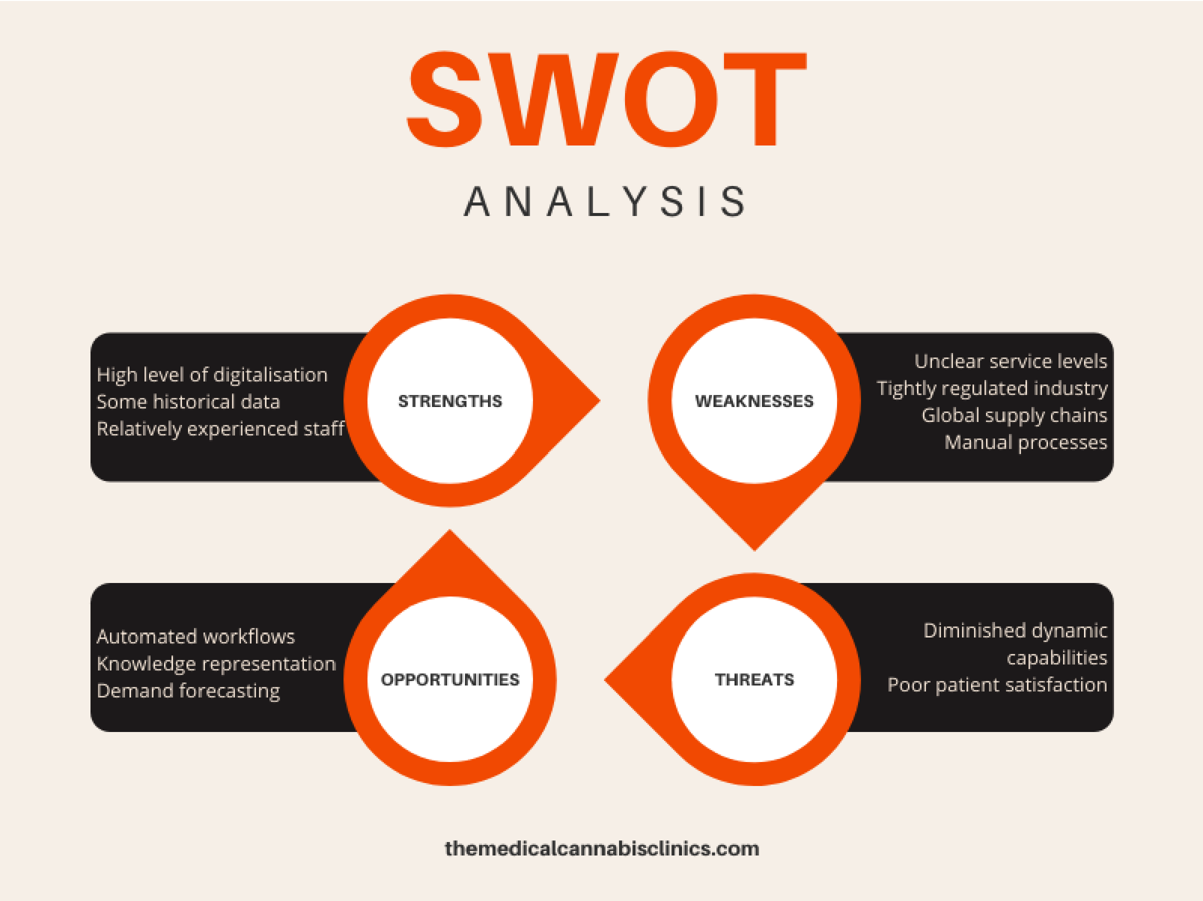


*Figure 1*

### Strengths

The clinic and the dispensary are fully digital from the patients' side. Patient appointments are carried out using telemedicine and the dispensary delivers the medicine to patients' home addresses using 3rd party delivery service. The staff and the clinic have managed to accumulate *some* historical data and expertise however the amount of data is somewhat limited as dates back only as far as 2019 (company inception).

### Weaknesses

Even though the main processes are highly digitalised there is still high reliance on manual administration (initial patient assessment and onboarding, order processing, aftercare, patient queries, etc.).

Lean operational principles will be impossible to apply in some cases due to government regulations (e.g. paper prescription need to be mailed to a dispensary). As the medicine must be currently imported the supply chains are more susceptible to environmental and political influences.

All of the above leads to frequent stockouts and backorders as well as long and inconsistent order fulfilment cycle.

### Opportunities

Having some industry specific data and expertise as well as digital-first patient care approach can provide a good foundation for automation and ML/ AI algorithm application.

### Threats

Dynamic capabilities are significantly restricted by the global nature of the supply chain as well as potential changes in regulations. Lack of adequate service levels will lead to patient dissatisfaction and drop in quality of life or loss of customers (social as well as economic responsibility).

## Main problems

Based on the SWOT analysis and Trustpilot patient reviews (see Appendix B) the main problem is poor service levels. Therefore, the scope of automation should be maintaining an acceptable order fulfilment cycle, minimising stockouts and keeping back-orders at manageable levels as well scaling onboarding and patient support service.

According to Chui et al., the focus should be on data collection and processing as well as predictable physical work in order to achieve maximum automation impact in the healthcare sector while manual effort is best directed at applying expertise and more intricate stakeholder interactions (Chui et al., 2016).

## Current workflow and recent improvements

As seen in Figure 2 current workflow can be divided into three main parts: onboarding, prescription issue and order fulfilment. Several workflow automations and service level improvements have been implemented recently: live finished goods inventory levels, online order tracking portal, email and text notifications/ reminders, aftercare check-ins and consultations as well as call-back requests.

While these measures indicate that the company identifies the current issues and is actively addressing its weaknesses the process is reliant on human-to-human communication (customer service), online forms and booking systems (onboarding, bookings). Digital workflows (order tracking portal) include manual links such as paper prescription mailing which creates bottlenecks. Live stock levels only provide current SKU levels which leads to backorders and stockouts when a monthly repeat prescription need to be issued.

**Current Clinic and Dispensary Order Fulfilment Workflow**

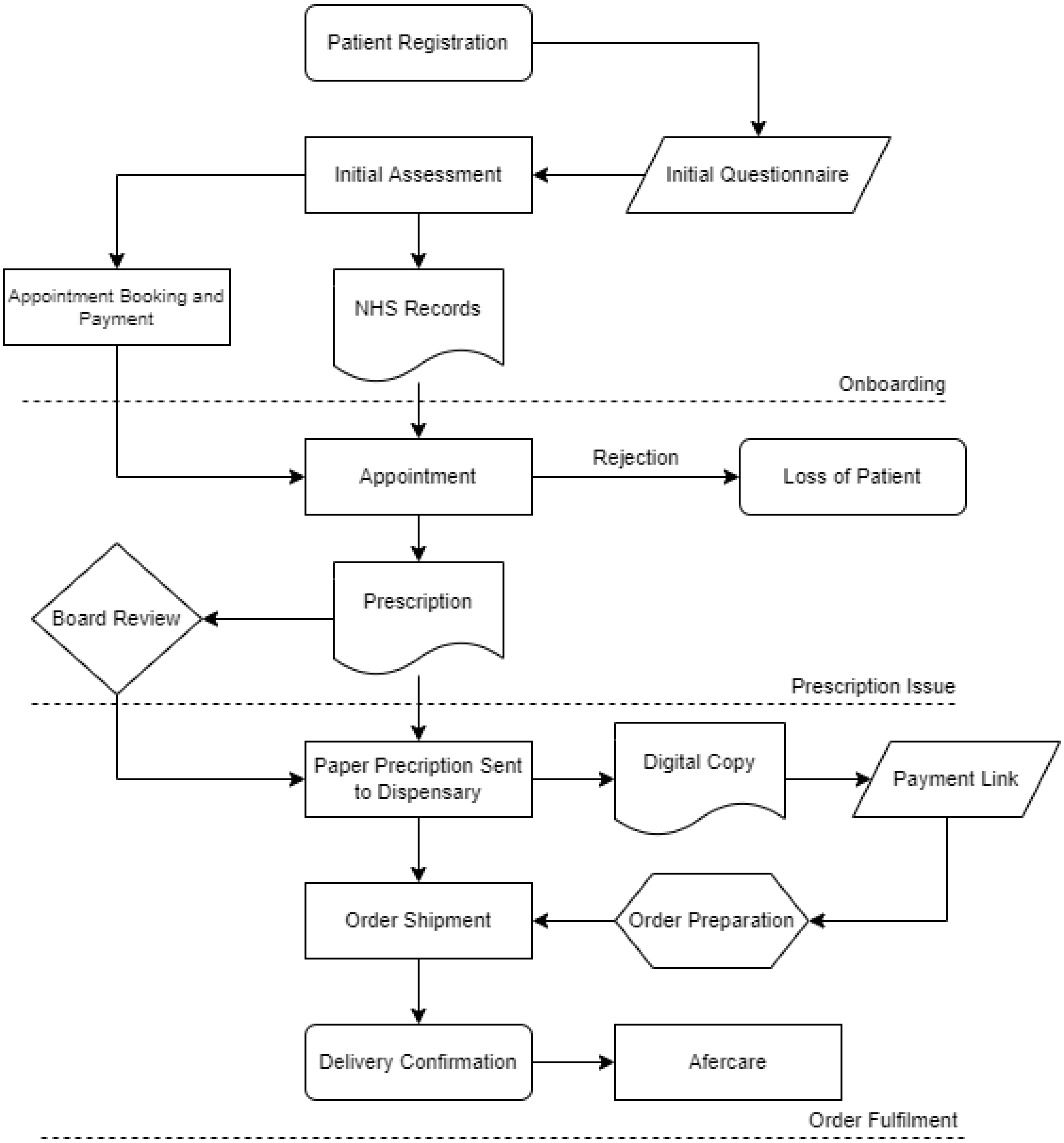


*Figure 2*

## Possible solutions

### Main principles

Human-to-human communication is a major blocker to business scaling as the overall cost of providing customer service will increase with the number of patients. Decreasing the operational cost for client onboarding is even more vital as a significant amount of work time needs to be invested before a patient is accepted or rejected by a specialist doctor (see Figure 2).

Conversational agents can significantly decrease operational costs (Juniper, 2017) therefore it makes sense to explore how a conversational agent can be used in both patient onboarding and customer service.

As “any system designed for people to use should be (a) easy to learn; (b) useful, i.e., contain functions people really need in their work; (c) easy to use; and (d) pleasant to use.” a user-centric approach should be implemented in conversational agent design including: “early focus on users and tasks, empirical measurement and iterative design” (Gould & Lewis, 1983).

### Onboarding

Onboarding is task specific and involves collecting patient’s information, conducting initial assessment and appointment booking. The entire process can be augmented with the help of a frame-based dialogue agent (potentially enhanced by dialogue-state architecture).

A frame-based dialogue system can understand user’s intention and guide through the process from expressing interest all the way to appointment booking. Each *frame* corresponds to a specific task: initial interest, patient registration, initial assessment, appointment booking (see figure 2). In line with the user-centric approach a user can populate multiple slots with a single utterance (e.g. a full name can be parsed into first and last names by the dialogue system using NLTK’s bank of names as a starting point).

Initial patient’s assessment is another important part of the onboarding process. In the case of a false positive result (approved initially but rejected by specialist doctor) patient loses consultation fee which leaves negative impression and the clinic loses valuable resource of applying expertise which is one of the most difficult to automate (Chui et al., 2016). In the case of a false negative result (incorrectly rejected during initial assessment) patient loses access to potentially useful medication and the clinic loses a patient. This makes false positive and false negative results highly undesirable, however false negative results are more detrimental long-term. Therefore, it is vital for the algorithm to be accurate as well as explainable to minimise bias and provide patients with the reason why they had passed the initial assessment but were rejected later.

The problem with statistical machine learning models such as Bayesian algorithms and deep learning models is that although they perform well at classification tasks it is difficult to reason how inputs relate to the output (Launchbury, 2017) which is also referred to as the *AI black box problem* – a big factor in healthcare algorithm evaluation (Agrawal & Prabakaran, 2020).

Symbolic, rule-based AI systems, on the other hand, excel at reasoning as they are based on *crisp* true or false logic (Launchbury, 2017). At the same time, they do not reflect how humans reason as human reasoning usually involves making approximate decisions (i.e., “how many grains constitute a heap?” as illustrated by the *sorites paradox* as can be seen in Appendix C.

One of the approaches applicable to the healthcare sector is fuzzy logic systems. It combines crisp rules with fuzzy sets which does not only enable model explainability but also allows for more accurate classification by being able to "tolerate vague and imprecise concepts that are often embedded in medical entities such as symptom description and test results" (Chen et al., 2021).

### Customer Service

Task-based dialogue systems can be extended to performing administration tasks such as patient account updates, specialist doctor appointment management, repeat prescriptions and payments.

Data volume plays a big role in quantitative demand forecasting (Zhu et al., 2021). This can limit forecasting accuracy and period as the data is only available from 2019 and the amount of patients is relatively low at around 4,000 (Hall, 2021). Furthermore, the supply chains are currently inherently international as medication must often be imported from across the globe due to regulations (Ahsan, 2022). Thus, consistent flow of medication to patients cannot be achieved by demand forecasting alone. Therefore, extra supply chain flexibility is required until regulations change or supply chains mature.

Additional supply chain flexibility can be achieved by setting order fulfilment cycle service levels and dynamically optimising the steps in the order fulfilment cycle that either do not rely on finished goods or come into play as soon finished goods become available.

Stockouts and backorders will persist due do upstream disruptions. Human-to-human interaction should be prioritised to manage these difficulties as according to a survey conducted by Drift 43% of the respondents prefer dealing with real-life assistants (Devaney, 2018). Although the survey is slightly outdated dialogue systems still struggle understanding human sentiment (Barker, 2021) that is why human-to-human communication should be directed to resolving more sensitive issues.

### Order Fulfilment Process and Patient Query Triage

Dynamic order fulfilment cycle service level management can be achieved by breaking down the process into individual steps. A simple rules-based algorithm can track each individual order through the steps and dynamically assign rating from 1 to 5 to each active step based on time elapsed.

One of the downsides of the above method is that it does not take previous fulfilments as well as complaints or queries into consideration. This information can provide important context as even though the current fulfilment cycle can only be slightly behind schedule the fact that the previous cycle was also late could mean that more urgent patient query resolution is required. We can extend the above rule-based method by incorporating historic and additional data such as number of recent queries and recent fulfilment ratings into a *Decision Tree* machine learning model. Such model can produce patient happiness score ranging from 0 to 100 that can be used in automated *triage*.

If patient score drops below certain threshold patient query or incident is automatically generated and assigned to the relevant person based on the current step. This allows for proactive patient complaint management.

Similarly, any patient query is first *triaged* using sentiment analysis and query category classification and then either assigned to an automated agent or a relevant staff member.

Order status updates are currently available via online portal however lack in detail due to poor supply chain visibility. That is why higher level of human-to-human interaction will be required to manage this area until visibility is improved.

# Conclusion

## Summary

Long and inconsistent order fulfilment cycle as well as frequent stockouts and backorders are the main problems currently experienced by medical cannabis patients. Although stockouts and backorders are largely caused by the current regulations and upstream supply chain disruptions, order fulfilment cycle and customer service related dynamic capabilities can be improved and scaled to accommodate forecasted patient increase (see Chart 1).

This can be achieved by using frame-based and dialogue-state architectures to automate those parts of the process that are the most susceptible to automation such as patient onboarding, proactive order management and customer query resolution while directing human resource to applying expertise and handling more intricate stakeholder interactions (complaints, supplier relations, etc.).

AI model explainability plays vital role in any automated patient assessment. Machine learning algorithms such as *Decision Trees* can be used to proactively assess current patient satisfaction level. Patient query sentiment analysis and category classification allow for automated *triage*.

Supply chain improvements are required to improve visibility.

## Solution

Modern chatbots that rely on corpus data require a large number of words for training often in millions or even billions (Jurafsky & Martin, 2009) which might not be available due to recent company inception. Therefore, pre-trained models and hybrid approaches such as dialogue-state architectures should be implemented. At the same time various algorithm training techniques such as *delexicalization* can be used to overcome lack of training data.

All automations can be combined into a single *Virtual Assistant* interface and all patient information including personal data, queries, complaints current and previous fulfilments can be aggregated under a single *Patient ID* profile.

Automated dialogue agents are encouraged as the first point of contact for all patients (see Figure 3). Onboarding process is fully automated. Specialist doctor appointment is the first point of human contact.

Administration duties such as user authentication, personal data updates, appointment management, repeat prescriptions and payments are carried out by *Virtual Assistants.* Patient queries are either resolved by *Virtual Assistants* or assigned to the relevant staff members via automated *triage* system.

Dynamic patient satisfaction score and the current step in the fulfilment process are monitored as part of *Patient ID* profile. *Virtual Assistant* can interact with the relevant staff members regarding any outstanding *Patient ID* tasks or potential complaints.

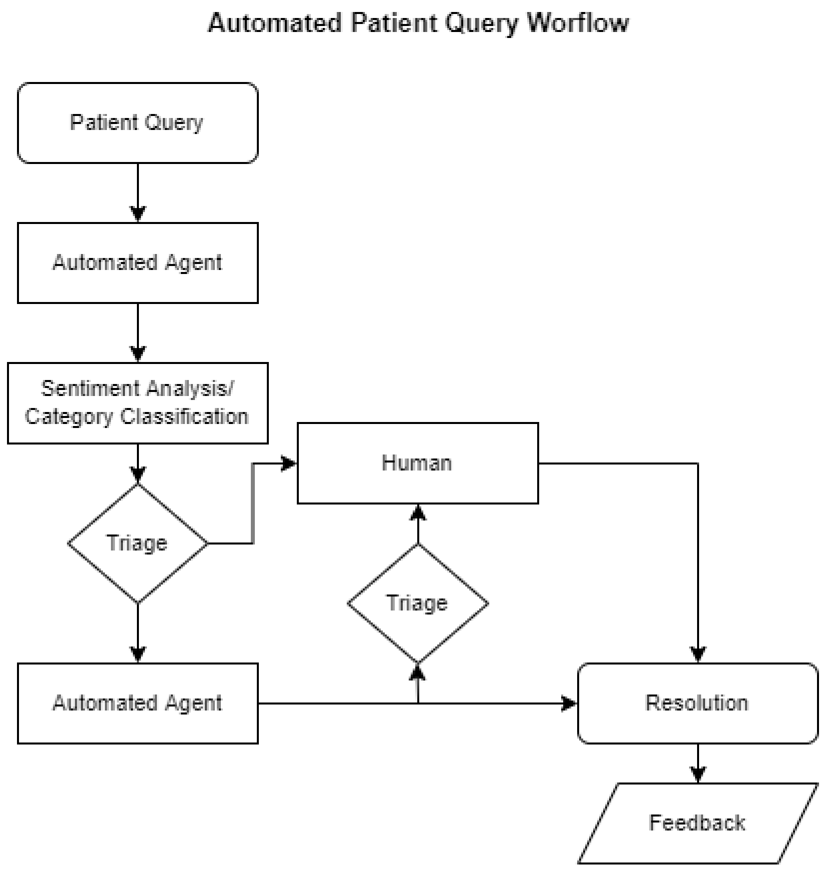


*Figure 3*

## User-centric design

Agile product delivery should be implemented in line with the user-centric design approach as delivering products in an agile way is all about putting the customer first, adapting to their needs quickly and easily, making sure they always have what they need when they need it (Scaled Agile, 2021).

Using cloud-based software systems further increases dynamic capabilities as resources can be scaled accordingly (IBM, 2018).

## References


Agrawal, R., & Prabakaran, S. (2020). Big data in digital healthcare: lessons learnt and recommendations for general practice. *Heredity*, *124*(4), 525-534. https://doi.org/10.1038/s41437-020-0303-2

Ahsan, D. T. (2022). *As a psychiatrist I have been amazed by the power of medical cannabis*. https://cannabishealthnews.co.uk/2022/03/09/psychiatrist-amazed-power-medical-cannabis-mentalhealth/

Barker, S. (2021). *AI Chatbot Implementation Challenges and Benefits*. https://shanebarker.com/blog/challenges-and-benefits-of-ai-chatbots/#2_Understanding_the_Emotions_and_Sentiments_of_Your_Customers

Chen, T., Shang, C., Su, P., Keravnou-Papailiou, E., Zhao, Y., Antoniou, G., & Shen, Q. (2021). A Decision Tree-Initialised Neuro-fuzzy Approach for Clinical Decision Support. *Artificial intelligence in medicine*, *111*, 101986-101986. https://doi.org/10.1016/j.artmed.2020.101986

Chui, M., Manyika, J., & Miremadi, M. (2016). *Where machines could replace humans - and where they can't (yet)*. https://www.mckinsey.com/business-functions/mckinsey-digital/our-insights/where-machines-could-replace-humans-and-where-they-cant-yet

Devaney, E. (2018). *The State of Chatbots Report: How Chatbots Are Reshaping Online Experiences*. https://www.drift.com/blog/Chatbots-report/

Essa, T. S. A. (2022). *5 ways the COVID-19 pandemic has changed the supply chain*. https://www.weforum.org/agenda/2022/01/5-ways-the-covid-19-pandemic-has-changed-the-supply-chain/

Gould, J. D., & Lewis, C. (1983). *Designing for usability—key principles and what designers think* Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, Boston, Massachusetts, USA. https://doi.org/10.1145/800045.801579

Hall, J. (2021). *European Expansion For UK Medical Cannabis Group With Domestic Patient Numbers Set To Hit 300,000*. https://businesscann.com/european-expansion-for-uk-medical-cannabis-group-with-domestic-patient-numbers-set-to-hit-300000/

IBM. (2018). *Benefits of Cloud Computing*. https://www.ibm.com/uk-en/cloud/learn/benefits-of-cloud-computing

Juniper. (2017). *Chatbot Conversations to deliver $8 billion in Cost savings by 2022*. https://www.juniperresearch.com/resources/analystxpress/july-2017/chatbot-conversations-to-deliver-8bn-cost-saving

Jurafsky, D., & Martin, J. H. (2009). *Speech and language processing : an introduction to natural language processing, computational linguistics, and speech recognition* (2nd International edition. ed.). Prentice Hall.

Launchbury, J. (2017). *A DARPA Perspective on Artificial Intelligence*, YouTube. https://www.youtube.com/watch?v=-O01G3tSYpU

NHS. (2019). *Barriers to accessing cannabis-based products for medicinal use on NHS prescription*. https://www.england.nhs.uk/wp-content/uploads/2019/08/barriers-accessing-cannabis-based-products-nhs-prescription.pdf

PwC. (2018). *PwC Canada's cannabis series - Chapter 8 - Supply chain management*. https://www.pwc.com/ca/en/industries/cannabis/pwc-cannabis-series-chapter-8-supply-chain-management.html

Scaled Agile, I. (2021). *Agile Product Delivery*. https://www.scaledagileframework.com/agile-product-delivery/

Zhu, X., Ninh, A., Zhao, H., & Liu, Z. (2021). Demand Forecasting with Supply-Chain Information and Machine Learning: Evidence in the Pharmaceutical Industry. *Production and operations management*, *30*(9), 3231-3252. https://doi.org/10.1111/poms.13426

# Appendix

Appendix A
https://themedicalcannabisclinics.com/

Appendix B
https://uk.trustpilot.com/reviews/6204e993441cb9c247348ecf

Appendix C
https://plato.stanford.edu/entries/sorites-paradox/