International Journal of
Analog Integrated Circuits
ISSN: 2582-3620
Volume 10, Issue 1, 2024
DOI (Journal): 10.37628/IJAIC
https://civil.journalspub.info/index.php?journal=JGGET
Review IJAIC

Pregcare Record Analysis Based on BERT and Anticipatory Computing: A Review

Selva Kumar S.[1]*, Omar Abdulla Sherief[2], Vignesh V.[3], Sreenath M.[4], Dhanashri Shanbhag[5]

Abstract

Development of a sophisticated Medical Pregnancy Care chatbot leveraging state- of-the-art Natural Language Processing (NLP) techniques, specifically the BERT framework. The chatbot offers a seamless user experience with two key functionalities: patient registration and comprehensive medical report generation. New users are prompted to register, providing essential personal details, and subsequently prompted to fill detailed medical reports, ranging from the 1st to the 9th month of pregnancy. The system employs anticipatory computing strategies for dynamic document storage during runtime, ensuring efficient and secure handling of sensitive patient data. The uniqueness of the proposed idea lies in its utilization of the NLP BERT framework to analyse the content of each medical report comprehensively. The system employs anticipatory computing, intelligently predicting and organizing document storage implemented the evolving nature of pregnancy reports. As the user progresses through each month, the chatbot dynamically generates summarized PDF documents for each medical report, incorporating insights derived from NLP analysis. This methodology not only helps in efficient document management but also provides healthcare professionals with concise, actionable information. The domain basically is focused on combining the concept of Anticipatory computing and BERT Framework. The 'EXISTING SYSTEM' already uses technologies using LLM but it is not implemented for document summarization and just involves direct extraction of data from the database unlike the existing system. It is focused on anticipating human/patient needs using text analysis tech like BERT and Anticipating approach.

Keywords: Anticipatory Computing, BERT, QR Code, Document Summarization, LLM, NLP, Interface, CNN

INTRODUCTION

The Medical Pregnancy Care chatbot represents a cutting-edge innovation in the healthcare sector, merging advanced technologies to enhance patient care and streamline medical processes. Leveraging a user-friendly interface, the chatbot offers a seamless experience with two primary functionalities: patient registration and comprehensive medical report management. Upon initiating the chatbot based on paper [1], new users are prompted to register, a process that culminates in the creation of a QR Code encapsulating their detailed medical information. This QR Code serves as an efficient and secure means of storing patient data, ensuring accessibility through a simple scan. The innovative use of QR Codes not only facilitates swift retrieval of patient details but also allows for the extraction of information, enabling the generation of summarized PDF documents. This ensures that pertinent medical information is readily available and easily shareable, fostering better interaction

***Author for Correspondence**
Selva Kumar S.
E-mail: selva.cse@bmsce.ac.in

1- Assistant Professor, Department of Computer Science and Engineering, Bhusanayana Mukundadas Sreenivasaiah (BMS) College of Engineering, India
2- Student, Department of Computer Science and Engineering, Bhusanayana Mukundadas Sreenivasaiah (BMS) College of Engineering, India
3- Student, Department of Computer Science and Engineering, Bhusanayana Mukundadas Sreenivasaiah (BMS) College of Engineering, India
4- Student, Department of Computer Science and Engineering, Bhusanayana Mukundadas Sreenivasaiah (BMS) College of Engineering, India
5- Student, Department of Computer Science and Engineering, Bhusanayana Mukundadas Sreenivasaiah (BMS) College of Engineering, India

Received Date: May 06, 2024
Accepted Date: June 24, 2024
Published Date: June 28, 2024

Citation Selva Kumar S., Omar Abdulla Sherief, Vignesh V., Sreenath M., Dhanashri Shanbhag. Pregcare Record Analysis

between healthcare providers (Doctors) and patients. The heart of the system lies in its anticipatory computing strategy, which optimizes document storage. By employing anticipatory computing, the chatbot intelligently anticipates and adapts to user needs, pre-emptively organizing and storing medical reports based on the pregnancy timeline from the 1st to the 9th month. This anticipatory approach enhances the overall efficiency of the system, reducingthe time and effort required for document retrieval.

Furthermore, the integration of Natural Language Processing (NLP), specifically utilizing the BERT framework,elevates the chatbot's capabilities. The NLP engine analyzes each medical report, extracting valuable insights andtrends throughout the pregnancy journey. This not only aids healthcare professionals in understanding the patient's evolving health status but also enables the system to generate summarized PDF documents for each report. The use of NLP ensures a nuanced understanding of the textual data, allowing for personalized and context- aware healthcare recommendations. Looking ahead, the future advantages of this Medical Pregnancy Care chatbot are profound. Its amalgamation of QR Code technology, anticipatory computing, and NLP not only enhances the efficiency of healthcare services but also fosters a patient-centric approach. The system's ability to generate summarized PDFs based on comprehensive document analysis ensures that healthcare providers receive concise yet informative insights, facilitating quicker decision- making and personalized care. As technology continues to advance, this innovative chatbot paves the way for a more interconnected and intelligent healthcare ecosystem, ultimately improving patient outcomes and experiences. The QR code is an efficient approach to store details of all patients from which only important and necessary details using Pyz-bar Library QR code is generated. And accuracy can be improved by using ANN model at least expected accuracy is 92% according to our research. NLPis also used for avoiding repeated wording's and give an efficient document based on important terminologies which will vary from patient to patient.

Anticipatory computing plays a crucial role in document summarization via a chatbot by enhancing the system's ability to proactively organize, retrieve, and present relevant information. In the context of a Medical Pregnancy Care chatbot, anticipatory computing anticipates user needs and adapts its behaviour based on past interactions and patterns, significantly optimizing the document summarization process.

Literature Survey

Setting up UPAL and launching it in our community has been a positive experience, affirming the potential of health chatbots to enhance health literacy. At its core, UPAL provides caregivers and parents with essential information, aiding them in better understanding the acute needs of their sick child. Through quick, curated, and tailored advice, UPAL has proven to be an effective virtual channel for patient communication. The favourable initial experience is evidenced by high and repeated usage, validating chatbot messaging as a well-accepted communication medium. Public responses have been consistently positive, reflected in high user experience ratings and recommendation scores. Users have expressed that UPAL reduces their reliance on emergency department visits. The author's confidence is in the continued potential of UPAL as they can refine and develop it to address the healthcare needs of the pediatric community.[1]

With the increasing need for telemedicine during the current COVID-19 pandemic, an AI chatbot with a deep learning–based NLP model that can recommend a medical specialty to patients through their smartphones wouldbe exceedingly useful. This chatbot allows patients to identify the proper medical specialist in a rapid and contactless manner, based on their symptoms, thus potentially supporting both patients and primary careproviders.[23] According to paper [4] In addressing various health and well- being issues, from obesity to stressand addiction, behavioural change interventions stand out as a potent approach. The prevailing medical practice involves inducing change through tailored coaching, support, and information delivery. However, the advent of smartphones has ushered in innovative methods for intervention delivery. With mobile phones equipped with an array of sensors and carried by users at all times, therapists now have the capability to not only learn about user behaviour but also influence behaviour through the delivery of highly relevant and personalized information. Thiswork proposes leveraging pervasive computing to not just glean insights from users' past behaviour but also predict future actions and emotional states. The goal is to proactively deliver interventions, assess their impact inreal-time, and, over time, develop a personalized intervention-effect model for each participant.

The above explanation is basically the main idea of our project which basically makes use of Anticipatory computing which tries to analyse or tries to anticipate what patient would want when it comes to document summarization. Paper [16] from our research now introduces the following contents - BERT, an innovative language representation model belonging to the bidirectional representation from transformers category, stands out for its very unique And different design focused on pre processing or pre training deep bidirectional type fromun-labaled text. What sets BERT apart is its ability to consider both for left and the right contexts in all layers, enabling it to achieve remarkable results in various different situation such as question answering and language prediction with minimal task-specific architecture modifications. The strength of BERT lies in its conceptual simplicity and empirical effectiveness, demonstrating exceptional performance across eleven NLP tasks. Notably,it significantly enhances the GLUE score by 7.7% to reach 80.5%, boosts Multiple NLI accuracy or efficiency to86.8% with a 4.6% improvement, elevates SQUAD v1.1 for question answering Test of F1 to a value of 93.2 with a 1.5- point improvement, and achieves an 83.1 Test F1 on SQuAD v2.0markingnotable 5.1-point improvement.Recent advancements in transfer learning with language models emphasize the pivotal role of rich, unsupervisedpre-training in various language understanding systems. The paper contributes significantly by generalizing theseobservations to deep bidirectional architectures, allowing pre-trained models like BERT to effectively tackle a wide array of NLP tasks. Additionally, a study on neural network interpretability showcases that BERT adeptly captures structural properties of the English language, aligning with previous work on the model. The research illustrates that BERT's representations encode intricate syntactic phenomena and convey phrase-level information,showcasing its ability to compose a hierarchy of linguistic signals from surface to semantic features. Notably, deeper layers are found to be necessary for modeling long-range dependency information, and BERT's internal representations reflect a compositional modeling approach akin to traditional syntactic analysis.

Addressing domain-specific challenges, a paper focuses on incorporating medical knowledge into a pre-trained BERT model for clinical relation extraction. While PLMs like BERT demonstrate effectiveness across diverse NLP tasks, applying them to specialized domains like clinical notes can be limiting, requiring additional medicalknowledge. The research systematically explores techniques to integrate medical knowledge, resulting in a modelthat outperforms state-of-the-art systems on the i2b2/VA 2010 clinical relation extraction dataset.

Another paper delves into spatial information extraction, leveraging BERT's effectiveness for the natural languageprocessing-based application. The proposed approach introduces a BERT-based spatial information extraction model, achieving notable improvements in spatial element and spatial relation extraction compared to baseline models. This survey encompasses two core technologies, BERT and Anticipatory Computing, highlighting their significance in the evolving landscape of advanced computing. The observations from papers [1] and [2] emphasize the importance of integrating frameworks like BERT into the rapidly advancing technologicallandscape. The issue of the textual similarity also called (STS) is also addressed, emphasizing the continuous needfor innovation in this area[21-24]. The researchers extensively delved into the realm of general English, yet identified a significant gap in the domain of semantic textual similarity (STS) within clinical contexts, mainly in different languages except English, predominantly Japanese. To avoid this gap, the authors developed a database specifically for Japanese scenario. This database encompasses approximately 4000words pairs derived from Japanese samples, each annotated with the similarity score ranging from 0 (indicating very low semantic similarity) to 5 (reflecting very high semantic similarity).

The authors implemented a solution based on BERT (Bidirectional Encoding forms from Transformers) to extractsimilarity between diverse medical domain areas. In their experiments, they achieved a remarkably high Pearsonscore when comparing the main score with respect to the human score, registering at 0.904 in CR database and consistently around 0.875 for (EMR) database. The study involved a comparison of the performance of the general and medical Japanese version binary encoding models. Despite both of the models demonstrating commendable performance, the generic Japanese model surpassed the clinical Japanese model in the authors' clinical domain database.This discovery predominantly advocates for the application of real-time clinical solutions grounded in the regeneration of the aforementioned paragraph. STS, since very widely now available general domain Bidirectional models would work in a good manner.[18] The basic summary achieved is that the authors have implemented BERT just for text analysis and data extraction and its not been implemented via a medical chatbot. The author have already worked on text analysis via BERT for different language implementations and they havealso checked the accuracy of every iteration. The result achieved is just a general summary of all the contents of a basic report with respect to all the contents of the report without focusing on the important terminologies.

The future work/ research gap analysed is that the summarization of the document is not done for important terminologies in a particular report or prescription. This type of summarization implementation where importantterminologies have to be kept in mind is not implemented still via a medical chatbot.

Table 1: Survey of Methodologies Used

PaperNo.	Methodology	Result
[1],[13]	Setting up a feedback system for user experienand training the chatbot local clinical practice guidelines.	Results indicate strong usersatisfaction, reduced man- power needs, and room for ongoing improvement.
[2]	The study collected cleansed data, trained learning models, evaluated performance to devel AI chatbot for smartpuse in recomme medical specialties bon symptoms.	Transformer models excelled with an AUC of 0.964 and F1-score of 0.768; the LSTM model powers the chatbot on desktops and smartphones for fast, contactless service.
[6]	The paper reviews computational models forsandwich plates and shells, covering various application areas such as heat transfer,mechanical stresses,vibrations, buckling,deflection, damage,and optimization.	Results for thermally stressed sandwich panels demonstrating the effects of variation in geometric and material parameters on the accuracy of the free response and sensitivity coefficients
[8],[9],[10] [11], [12]	The method involves using mac learning reinforcement learning model the impact intervention.	The results emphasize the potential of anticipatory mobile dBCIs for personalizedand scalable behavior changeinterventions.

[4],[5],[7] [15],[16] [18],[19] [20]	The methodology involves pre-training BERT using two unsupervised tasks: Masked Language Model (MLM) and Next SentencePrediction (NSP).	The results show thatBERT achieves state-of-the-art performance onvarious natural language processing tasks.

Methodology

Methodology Work flow

The gap analysed is as explained be low with all the important components. The analysis mainly focuses on howthe summarization is done for that particular report or prescription. The summary is given for all parameters or details on the document irrespective of its important or not using BERT. Just a summary of all the contents of thepaper might not be efficient and a good result for the doctor as well as for the patient. The summary should focus on only the important terminologies of a specific prescription or report.

Dataset/Pre-processing

The data focused is on different patient prescriptions or just a regular report which basically consist of different medical and biological parameters given by doctor's analysis. The dataset will include the data of either the mother or the child after birth.

Proposed Methodology

The focus mainly lies on giving a summary only for important bio medical terminologies for which BERT framework has to be used. Apart from that the summarization, combining of different prescriptions is an important aspect of summarization. The methodology encompasses various crucial componentsof the system. The User Interface serves as the gateway for user interaction with the chatbot, facilitating a seamless experience. The Registration & Authentication module manages the user registration process and incorporates QR Code generation to enhance data security. Anticipatory Computing & Document Organization showcase the system's intelligent capability to organize medical documents systematically, aligning with the pregnancytimeline.

QR-Code Generation

Pyzbar Library from python is used for QR Code generation. This implementation in general is done in other implementations also but, trying to accomplish this same task via a chatbot which could be an efficient manner even for the patient to access data anywhere in India using the QR Code.

Using Anticipatory Computing

Similar to progress in fields like economics, biotechnology and medicine, computing paradigms are developed and improved to meet more social and human needs. Examples include ubiquitous computing, cloud computing and social computing which respectively improve mobility, efficiency and interactivity of people. Each of these paradigms presents an attempt to address a particular implicit/explicit human. Anticipatory Computing marks a progression beyond artificial intelligence, seamlessly merging predictive capabilities with actionable outcomes, poised to deliver substantial enhancements to human comfort and well-being while introducing complex challenges to the realm of computer science. The BERT model works on text embedding and tokenization whereevery alphabet is given a separate sub script for individual identification which help in efficient text summarization and also helps in word analysis. Overview of the Transformer Architecture: The Transformer model is primarily built on the mechanism of self-attention, a system that processes each word of the input sentence in parallel whileconsidering the context provided by the other words in the sentence. The Transformer architecture comprises twomain components: Encoder: The encoder reads and processes the input text. It consists of a stack of identical layers, each with two sub-layers: a multi-head self-attention mechanism and a fully connected feed-forward network. Normalization and residual connections are also applied around each of these sub-layers. Decoder: Thedecoder is responsible for producing the output text. Like the encoder, it is made up of a stack of identical layers.However, each decoder layer has an additional sub-layer that performs multi-head attention over the encoder's output. This structure allows the decoder to focus on appropriate segments of the input text during the generationprocess. BERT for medical report summarization involves several key steps tailored to the specific requirements of the task. Initially, BERT, or Bidirectional Encoder Representations from Transformers, is employed in its pre-trained state. This pre-training occurs on large-scale text corpora, where BERT learns to encode rich contextual representations of words and sentences. Through tasks like masked language modeling and next sentence prediction, BERT gains a deep understanding of language semantics and context, forming a solid foundation for subsequent fine-tuning.

Clubbing the Documents

Anticipatory Computing for PDF'S clubbing and giving a summary for multiple records from the chatbot. Integrate spacy in Text Analysis Module: Create a module or function within your chatbot system that uses spaCyfor text analysis. This module could include the following functionalities:

Tokenization: Breaking down the text into individual words or tokens. Named Entity Recognition (NER): Identifying entities such as dates, medical terms, and relevant information in the text. Part-of-speech (POS) tagging: Understanding the grammatical structure of sentences. Utilize the anticipatory computing results to organize and categorize medical documents based on the pregnancy timeline. For instance, if a date entity indicates the 3rd month of pregnancy, the system can categorize and organize documents related to that timeframe.By integrating spaCy into your anticipatory computing strategy, you leverage its NLP capabilities to extract meaningful information from text data, making your chatbot more intelligent and capable of anticipating user needs based on the content of medical reports. Remember to customize the spacy integration based on your specific use case and the types of information you want to extract.

Fine Tuning with BERT

As BERT is a language model, understanding the input text is an only important factor. Due to this reason only transformer encoders are used in BERT. Hence it is used as an encoder in the summarization model. It require a transformer decoder as well. The decoder is a randomly initialized 6-layered transformer decoder from [8]. This helps us to convert the deep contextual understanding (contextual embedding) achieved by BERT from input textinto a legible text output.

BERT Language Model

BERT is pre-trained language model which comprises of a set of transformer encoders which represents the text at word and sentence level with the help of unsupervised training techniques like masked language modeling andnext sentence prediction. BERT being a pre-trained model, it is trained on 3300M words. To learn contextual relations between words in a text BERT uses a transformer encoder with an attention mechanism. Transformer [9] in their native form consists of the encoder as well as decoder where encoder learns the text input and decoderis tuned to conduct a specific task. As BERT is a language model, understanding the input text is the only important factor. Due to this reason only transformer encoders are used in BERT. Rather than reading the text input sequentially like various directional models [3][5][6][7], the transformer encoder reads the entire sequence of words at once. This functionality of the transformer helps generate context by calculating the relevance of each word concerning the presence of other words in the sentence. The level of contextual understanding is directly proportional to several transformer encoder layers. Fig. 2 shows BERT's architecture. BERT- Base, Uncased is used for the purpose which has 12 transformer layers, 768

Integration of BERT and Anticipatory. (The Proposed System)

The proposed system basically added with anticipatory module so that the summarized PDF'S are present alreadyor are kept ready by the bot even before the patient demand's for it. Here our basic intention is to anticipate basicpatient needs. So that even before patient demand's for the summarized PDF'S the bot understands that the patientin future will demand for the summarized PDF for themselves and for doctor's use so it keeps the PDF'S ready to avoid delay in time and makes it an efficient approach to fetch a understandable document from both Patients and Doctors point of view. Text analysis here is done using BERT model/Framework.

Training in BERT Framework/Module

BERT natively uses masked language models and "next sentence prediction" to train on tokens. In the masked language model, some percentage of the input token is replaced by [MASKED] token. In the case of BERT, it is15%. Then the model is trained by predicting the masked words by only taking help from contextual understanding provided by the rest of the non-masked words as shown in figure 1. In the next sentence prediction, a pair of sentences are passed to the model and it is trained by classifying whether subsequent sentence.

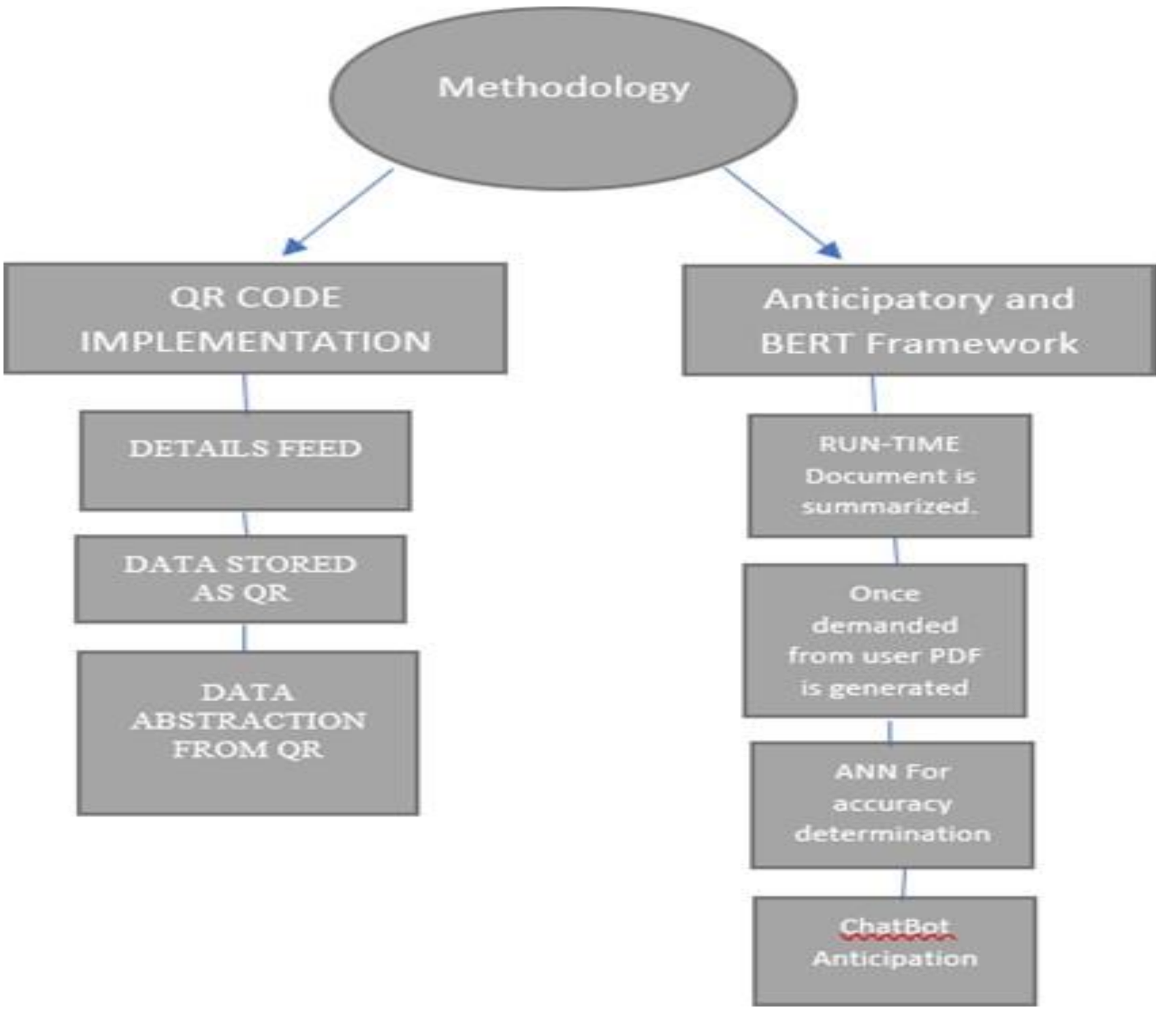

Fig 1 Proposed System

CONCLUSION

In conclusion, this comprehensive review of the BERT framework within the domain of NLP for the specific application of text summarization of monthly pregnancy test reports underscores a significant potential for revolutionizing how medical data is processed and interpreted. Through the analysis, it has been identified that the BERT framework, with its deep learning capabilities, presents an innovative approach to distill complex, verbose medical reports into concise, accessible summaries. This not only enhances the efficiency of medical professionals in monitoring and making informed decisions but also improves the communication channel between healthcare providers and patients, ensuring that critical information is not lost in translation. The surveyhas not only highlighted the strengths and adaptability of BERT in handling domain-specific jargon and nuancesbut also pointed out the existing gaps and challenges in the current methodologies. It is clear that while BERT offers a promising foundation, further research is required to tailor its capabilities more closely to the unique requirements of medical text summarization, particularly in the context of pregnancy monitoring. This involves not just the refinement of models for greater accuracy and reliability but also ensuring privacy, security, and ethical use of sensitive health data. This review aims to catalyze further research in this intersection of AI and healthcare, encouraging innovative solutions that leverage the power of NLP to make pregnancy care more accessible, accurate, and user-friendly. The ultimate goal is to create an environment where technology and medicine work hand in hand to support the health and well-being of mothers and their developing babies, contributing to the broader vision of sustainable, technologically-enhanced healthcare systems.

Acknowledgments

Our heartfelt gratitude goes to our project guide, Dr. Selva Kumar S, whose unwavering guidance, support, and encouragement played a pivotal role in the successful completion of our project and also like to express our appreciation to B. M. S. College of Engineering for providing us with the resources and facilities necessary to complete this project. We would like to extend our sincerest thanks to the doctors of Bangalore Medical Hospitaland Research Institute for their wonderful guidance and insights on the domain knowledge. We would like to acknowledge the contributions of the authors of the research papers that we have referenced. Their work has provided us with valuable information and insights that greatly enhanced the quality of this report. We would liketo thank the developers of the software libraries that we have chosen to include in this project as well as all the open-source communities for their efforts. Finally, we would like to thank our family and friends for their unwavering support and encouragement. This project would not have been possible without their love and support.

REFERENCES

1. Lee, Hyeonhoon, Jaehyun Kang, and Jonghyeon Yeo. "Medical specialty recommendations by an artificial intelligence chatbot on a smartphone: development and deployment." Journal of medical Internet research 23, no. 5 (2021): e27460.
2. Kim, Jin K., Michael Chua, Mandy Rickard, and Armando Lorenzo. "ChatGPT and large language model (LLM) chatbots: the current state of acceptability and a proposal for guidelines on utilization in academic medicine." Journal of Pediatric Urology (2023).
3. Kim, Jin K., Michael Chua, Mandy Rickard, and Armando Lorenzo. "ChatGPT and large language model (LLM) chatbots: the current state of acceptability and a proposal for guidelines on utilization in academic medicine." Journal of Pediatric Urology (2023).
4. Kim, Jin K., Michael Chua, Mandy Rickard, and Armando Lorenzo. "ChatGPT and large language model (LLM) chatbots: the current state of acceptability and a proposal for guidelines on utilization in academic medicine." Journal of Pediatric Urology (2023).
5. Kim, Jin K., Michael Chua, Mandy Rickard, and Armando Lorenzo. "ChatGPT and large language model (LLM) chatbots: the current state of acceptability and a proposal for guidelines on utilization in academic medicine." Journal of Pediatric Urology (2023).
6. Kim, Jin K., Michael Chua, Mandy Rickard, and Armando Lorenzo. "ChatGPT and large language model (LLM) chatbots: the current state of acceptability and a proposal for guidelines on utilization in academic medicine." Journal of Pediatric Urology (2023).

7. Kim, Jin K., Michael Chua, Mandy Rickard, and Armando Lorenzo. "ChatGPT and large language model (LLM) chatbots: the current state of acceptability and a proposal for guidelines on utilization in academic medicine." Journal of Pediatric Urology (2023).
8. Shin, Hyeong Jin, Jeong Yeon Park, Dae Bum Yuk, and Jae Sung Lee. "BERT-based spatial information extraction."
9. In Proceedings of the Third International Workshop on Spatial Language Understanding, pp. 10-17. 2020
10. Noor, Ahmed K., W. Scott Burton, and Charles
11. W. Bert. "Computational models for sandwich panels and shells." (1996): 155-199.
12. Hao, Yaru, Li Dong, Furu Wei, and Ke Xu. "Visualizing and understanding the effectiveness of BERT." arXiv preprint arXiv:1908.05620 (2019).
13. Pejovic,Veljko, and Mirco Musolesi. "Anticipatory mobile computing for behaviour change interventions." In Proceedings of the 2014 ACM International Joint Conference on Pervasive and Ubiquitous Computing: Adjunct Publication, pp. 1025-1034. 2014.
14. Pejovic,Veljko, and Mirco Musolesi. "Anticipatory mobile computing for behaviour change interventions." In Proceedings of the 2014 ACM International Joint Conference on Pervasive and Ubiquitous Computing: Adjunct Publication, pp. 1025-1034. 2014.
15. Nadin, M., 2010. Anticipatory computing: from a high-level theory to hybrid computing implementations.
16. Nadin, Mihai. "Predictive and anticipatory computing." Encyclopedia of computer science and technology, 2nd edn. Taylor and Francis, London (2017): 643-659.
17. Nadin, M., 2000. Anticipatory computing. Ubiquity, 2000(December), pp.2-es.
18. Lin, Chunpei, Guanxi Zhao, Yenchun Jim Wu, and Hailin Li. "Anticipatory computing for human behavioral change intervention: A systematic review." IEEE Access 7 (2019): 103738-103750.
19. Pejovic, V. and Musolesi, M., 2014, September. Anticipatory mobile computing for behaviour change interventions. In Proceedings of the 2014 ACM International Joint Conference on Pervasive and Ubiquitous Computing: Adjunct Publication (pp. 1025-1034).
20. Nadin, M., 2000. Anticipatory computing. Ubiquity, 2000(December), pp.2-es.
21. Devlin, Jacob, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. "Bert: Pre-training of deep bidirectional transformers for language understanding." arXivpreprint
22. arXiv:1810.04805 (2018).
23. Kenton, J.D.M.W.C. and Toutanova, L.K., 2019, June. Bert: Pre-training of deep bidirectional transformers for language understanding. In Proceedings of naacL-HLT (Vol. 1, p. 2).
24. Jawahar, Ganesh, Benoît Sagot, and Djamé Seddah. "What does BERT learn about the structure of language?." In ACL 2019-57th Annual Meeting of the Association for Computational Linguistics. 2019.

