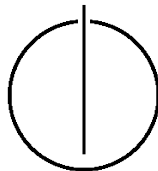# FAKULTÄT FÜR INFORMATIK

DER TECHNISCHEN UNIVERSITÄT MÜNCHEN

Bachelor's Thesis in Informatics

Analyzing Neurodegenerative Diseases with Web Chatbot Typing Behavior

Nicolas Othmar Theodarus

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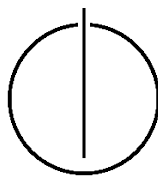
Analyse neurodegenerativer Krankheiten anhand des Tippverhaltens von Web-Chatbots

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I assure the single handed composition of this bachelor thesis only supported by declared resources,

Munich, 03.12.2024   Nicolas Othmar Theodarus

Acknowledgements

Abstract

Neurodegenerative diseases are chronic conditions that destroy and damage part of nervous system of the sufferer over time, especially the brain. This diseases pose a significant challenge for general public health, since the damages are permanent and incurable. This condition happens mainly on elderly people, given that aging is the greatest risk factor. Moreover, early detection of these diseases are inefficient, impractical and only have minuscule success percentage. There is a need for better detection methods that are cost-effective, user-friendly and accurate.

This thesis aims to pave the way of developing the aforementioned better detection methods. In this thesis, a mobile optimized web application to gather typing data from users of different age groups will be developed. A clean and robust architecture structure is utilised to guarantee reliability, scalability and maintainability. It should also be ensured that the application is able to effectively process and save the collected data, so that the data can be used for research purposes. After this thesis, the application can hopefully be developed further with more advanced features in the future. An example of such additional feature would be an analysis functionality, where typing behaviour data of a person can instantly be analysed with a click of a button.

Analysis of the data is done with the goal to find statistical properties. These statistical propertiess hopefully can be used to differentiate between different age groups. Building a robust application that can collect typing data from its users, and then analysing said data to find interesting properties, is the main contribution of this thesis. The conclusion derived from this thesis could give insight into the feasibility of utilising biomarkers to effectively monitor health condition of the user. Specifically, the author hopes that this findings would be beneficials for research on detecting early signs of neurodegenerative disorders effectively with a simple method of collecting typing pattern data.

Zusammenfassung

Neurodegenerative Krankheiten sind chronische Erkrankungen, die im Laufe der Zeit Teile des Nervensystems der Betroffenen, insbesondere das Gehirn, zerstören und schädigen. Diese Krankheiten stellen eine große Herausforderung für die allgemeine öffentliche Gesundheit dar, da die Schäden dauerhaft und unheilbar sind. Sie treten vor allem bei älteren Menschen auf, da das Älterwerden der größte Risikofaktor ist. Darüber hinaus ist die Früherkennung dieser Krankheiten ineffizient, unpraktisch und hat nur einen verschwindend geringen Erfolgsanteil. Es besteht ein Bedarf an besseren Erkennungsmethoden, die kostengünstig, benutzerfreundlich und genau sind.

Ziel dieser Arbeit ist es, den Weg für die Entwicklung der oben genannten besseren Erkennungsmethoden zu ebnen. In dieser Arbeit wird eine für Mobilgeräte optimierte Web-Applikation zur Erfassung von Tippdaten von Nutzern verschiedener Altersgruppen entwickelt. Es wird eine saubere und robuste Architekturstruktur verwendet, um Zuverlässigkeit, Skalierbarkeit und Wartbarkeit zu gewährleisten. Es soll auch sichergestellt werden, dass die Anwendung in der Lage ist, die gesammelten Daten effektiv zu verarbeiten und zu speichern, so dass die Daten für Forschungszwecke verwendet werden können. Nach dieser Arbeit kann die Anwendung hoffentlich in der Zukunft mit fortgeschritteneren Funktionen weiterentwickelt werden. Ein Beispiel für eine solche zusätzliche Funktion wäre eine Analysefunktion, mit der die Tippverhaltensdaten einer Person mit einem Mausklick sofort analysiert werden können.

Die Analyse der Daten wird mit dem Ziel durchgeführt, statistische Eigenschaften zu finden. Diese statistischen Eigenschaften können hoffentlich genutzt werden, um zwischen verschiedenen Altersgruppen zu unterscheiden. Der Hauptbeitrag dieser Arbeit besteht darin, eine robuste Anwendung zu entwickeln, die Typisierungsdaten von ihren Nutzern sammeln kann, und diese Daten dann zu analysieren, um interessante Eigenschaften zu finden. Die aus dieser Arbeit abgeleitete Schlussfolgerung könnte einen Einblick in die Durchführbarkeit der Verwendung von Biomarkern zur effektiven Überwachung des Gesundheitszustands des Benutzers geben. Insbesondere hofft der Autor, dass diese Erkenntnisse für die Forschung zur Erkennung früher Anzeichen von neurodegenerativen Erkrankungen mit einer einfachen Methode zur Erfassung von Tippmusterdaten von Nutzen sein könnten.

Contents

AD Alzheimer's Disease

PD Parkinson's Disease

UI user interface

DAO Data Access Object

DTO Data Transfer Object

LLM large language model

UI user interface

WPM words per minute

IQR interquartile range

Chapter 1

Introduction

Alzheimer's Disease (AD) and Parkinson's Disease (PD), are chronic and progressive neurodegenerative diseases that primarily affect the nervous system. This diseases lead to the degeneration of motoric and cognitive abilities. These diseases are often irreversible and incurable, posing significant public health challenges. As populations age, the risk of such disorders increase substantially, making early detection crucial.

Historically, the diagnosis of neurodegenerative diseases has been done throuh clinical observations, imaging, and biomarkers. Even though medical technologies have improved significantly over the years, there are still many challenges for early diagnosis. One of the main reason for this is because neurodegenerative diseases develop gradually over time. Early symptoms of these diseases can easily be overlooked or mistaken as normal aging [VRW23]. As a result, these early symptons are often ignored until the disease itself has reached a critical stage, where the chance of treatment declines significantly. Furthermore, current diagnostic methods are expensive, invasive, and often inaccessible to a large portion of the population.

A better method is obviously needed to battle these insidious diseases. The rise of technologies such as smartphones open up new possibilities for early detection of these conditions. One example of such possibility is to utilise a phone application as a mean to detect early neurodegenerative diseases. Studies have shown that one of the effect of these diseases, i.e. impairments of motoric functions, will be reflected on how a person types [MFQM18]. This thesis aims to build the required foundation to realise such an application.

1.1 Problem

It is clear from the facts mentioned above, that neurodegenerative diseases are problems that need to be addressed. World Health Organisation estimates that there are approximately 50 million people worldwide affected by these disorders. Most of the sufferer are elderly, since age is one of the main risk factor. As the most common neurogedenerative disorder, AD still lacks an effective cure. It is even harder to treat the more progressive the disease progress. That is why the importance of an effective way to diagnose the disease early cannot be overstated. In the current state, however, misdiagnosis rates are still high, reaching up to 20% [FQS+17]. Not only that, current diagnostic methods are either invasive, costly, or impractical for widespread use.

Similarly, PD, the second most common neurodegenerative disorder, has no cure and limited treatment options. For this disease too an effective mean for early diagnosis is of utmost importance. Since with a successful early detection, the progression of the disease can be slowed significantly, improving the quality of life of patients greatly. The current diagnostic methods for this disease, however, rely mostly on the observation of changes of motoric symptoms. These methods, as previously discussed, are unreliable for many reasons.

In both conditions, early intervention can significantly improve patient outcomes, but existing diagnostic tools fail to provide a practical and accurate solution for early detection. There is a pressing need for non-invasive, cost-effective, and widely accessible methods to detect early signs of neurodegenerative diseases before the onset of significant symptoms.

1.2 Motivation

The motivation for this thesis comes from the urgent need to find better diagnostic methods for neurodegenerative diseases. Finding methods to effectively detect early these diseases would significantly improve general public health. Early detection allows for earlier interventions, which will then slow the progression of the diseases. This would improve treatment outcomes, and ultimately reduce the burden on healthcare systems.

From a scientific point of view, the research on using digital biomarker, i.e. typing pattern, as a mean to detect neurodegenerative diseases is underexplored. This research could give insights into how common tools and activities can be used to improve public health. Typing has became a common daily activity for most modern human, especially with the widespread use of

smartphones and chat applications. This means that it can be a low-cost and non-invasive method to detect subtle motoric or cognitive impairments. In the ideal case, the subject would not notice that they are being monitored for these diseases and can go on about enjoying their daily lives.

Taking advantage of these common daily activities could help reduce the risk of neurodegenerative diseases, by diagnosing them as early as possible. Furthermore, these methods would also be accessible to people that lives in less developed countries with less developed medical technologies. This would ensure equal chances to fight against these neurodegenerative diseases. By developing a mobile-optimized web application that can collect and analyze typing data in real time, it would also become easier to monitor people's condition. Especially the condition of those that are more prone to these diseases, i.e. the elderly.

1.3 Objectives

Developing an application that can capture and analyze typing behavior for early detection of neurodegenerative diseases is an ambitious goal. That goal is unfortunately not in the scope of this thesis. Collecting pathological data that is required for the aforementioned goal requires a lot of process and time, which does not align with the time limitation of this thesis. Another more suitable objective for this thesis would be to explore the possibility of collecting typing pattern data through a mobile-optimized application. The author believe that this thesis will pave the way for a more advanced research on this matter. This thesis wants to show that typing pattern can be collected through a mobile-optimized application.

Specifically, this thesis aims to:

1. Develop mobile-optimized chat application that collects the user's typing data. The main focus is to collect samples from individuals across different age groups.

2. Practice clean architecture and secure coding practices to make sure the application is reliable, scalable, and maintainable. The chat application will be designed to be user-friendly for all age groups, specifically the elderly.

3. Analyze the gathered typing behavior data to identify patterns or statistical distributions that may correlate with the user's age. Metrics such as typing speed, keystroke intervals, and error rates will be examined to determine if they can give indication of the user's age group.

4. Evaluate the accuracy of using typing behavior as a predictor of age. The identified patterns need to be consistent enough to be able to reliably be used to estimate the user's age group.

The goal of this thesis is to built an application that can collect typing pattern data of its users. If this is achieved, the author hopes that this could give insights that would be valuable for future research in user profiling or cognitive assessments. The application could also be further developed to be able to analyse more complex matters, such as early signs of neurodegenerative disorders. Another possible improvement would be adding real-time analysis of the typing pattern and integration with healthcare systems. This would be beneficials for patients and clinicians alike.

Chapter 2

Background

2.1 Mobile-Optimized Applications and Accessibility for Elderly Users

It is crucial that the application is both mobile-optimized and also accessible to elderly users. Since the author wants to use data of people typing on their smartphones, the application needs to be mobile-optimized. Mobile-optimized application ensures that the data gathered by this application captures typing pattern of its users correctly. Irregularities, such as typing mistakes or longer typing interval, should not be caused by the difficulty of using this application. Instead this irregularities should reflect human error, that most likely to happens more frequently with older subjects. Among other thigs, the user interface (UI) design of the application should be clean and minimalist, focusing on essential features and contents. Unnecessary elements and visual clutters should be removed to create an intuitive UI that is easy to navigate on smaller screens. Since there are many types and sizes of smartphones, it is also important to build a responsive web application that is able to adjust to common screen sizes.

The application also need to be accessible for elderly users. This is done to prevent a false positive condition, where significantly more typing errors happen on elderly subjects because of the difficulty of using the application. Designing an accessible UI for the elderly requires some considerations as suggested by Gomez-Hernandez et. al. in their research in 2023 [GHFMVM23]:

1. **Bigger Interactive Elements:** The size of interactive elements, such as buttons and forms, need to be bigger to make them more accessible. This improvement could help with possible vision or motoric impairments.

2. **High contrast:** Another method to help with vision impairment. This could help increase readability.

3. **Font Selection:** The font used should be easily readable, especially on smaller screens.

4. **Spacing:** Enough spacing should be added to improve readability und user experience.

5. **Apropriate color choices**: Avoiding colors like blue, violet, and green, and yellow, which can become harder to distinguish with age due to shifts in color perception.

6. **Centralized content**: Placing key elements in the center of the interface to make them easier to find and interact with.

2.2   Backend Architecture: Java Spring Boot

On the backend side of the application, Java Spring Boot framework is utilised to manage and process data that are sent by the frontend of the application. The Spring Framework is an application framework and inversion of control container for the Java programming language. Spring Boot is an open-source Java framework for applications based on Spring to help project startup and management easier. This framework provides libraries that help to develop a scalable, maintainable and secure web applications. It is important to develop the application in this manner so that new features and improvement could easily be added during or after the writing of this thesis. If the occassion arises, this application would also be ready to be reused for a possible follow-up research on this topic.

Spring Boot provides functionalities that help to ensure clean architecture and adherence to coding principles, such as DRY (Don't Repeat Yourself). Another important feature provied by Spring Boot is RESTful services, that support separation of the client and the server. Other than aiding on building a clean architecture, RESTful services also further ensure the possibility of reusing the code for further researches. This application uses Data Access Object (DAO) and Data Transfer Object (DTO) patterns to manage data efficiently. This separation of concerns between DAO and DTO adheres to clean architecture principles, improving maintainability and testability.

2.3 Database Management: PostgreSQL

PostgreSQL is an open-source, object-relational database system known for its scalability, reliability and support for complex queries. These attributes make PostgreSQL ideal for storing a huge amount typing data and keystroke logs. Features such as JSONB data type that is offered by PostgreSQL also help to simplify data processing and storing, especially data of keystroke logs. Another reason why PostgreSQL is used in this project is its indexing and search capabilities. This will be crucial for fast retrieval of user data, allowing efficient typing pattern analysis that would be useful if instant analysis feature is ever built.

2.4 Large Language Models: Llama3

The Llama3 is the latest large language model (LLM) develop by Meta inc. In addition to Llama3's impressive performance compared to other LLMs, Llama3 is multilingual and can support both english and german language well. This makes Llama3 the perfect language model to use for this thesis. In this thesis, Llama3 will be used to chat with the users in real-time. The language model is prompted to try to get as much response from the users as possible, so that the typing data can be collected.

It is interesting to see whether LLMs such as Llama3 would be able to also analyze the users' typing data. It can potentially help identify changes and irregularities in typing pattern that might indicate the age of the user. If this is possible, a real-time analysis of the typing pattern might be able to be implemented with the help of language models. This topic is, however, not in the scope of this thesis and is only a possible future research.

2.5 Containerization: Docker

To further promotes the scalability of the application, the author utilizes Docker. Docker is a platform for delivering software in packages called containers. Containerization is an important part of deploying a scalable application across various environments. Docker allows applications to be deployed separately (frontend, backend, database and LLM) in their own separated containers. This makes it easier for the application to be reused and rebuild in other environments, such as on the university servers.

2.6 Statistical Analysis of Typing Behaviors

This analysis will be done in three evaluations. In the evaluation, the data will be truncated to eliminate outliers. The first truncation will be done by excluding duration between keystrokes that are more than 5 seconds. This is done to eliminate the possibility of the user being distracted or leaving the application. The second truncation will be done by removing the one-percenth quantile ($<1\%$ and $>99\%$) of duration between keystrokes. This is done to remove outliers of the data.

In a third evaluation, the interquartile range (IQR) method will be used to find outliers of the data. The IQR is a measure of statistical dispersion, often used to detect outliers in data. It represents the range within which the central 50% of the data lies. First, similar to the previous two evaluations, the data will be truncated to exclude duration between keystrokes that are more than 5 seconds. Then, the IQR will be calculated and used to truncated the outliers of the data.

2.7 Privacy in Data Collection

Anonimity and privacy of the users are insured by not collecting any personal data, other than the age of the user. The application will not ask for any personal information, such as name, address, or phone number. This, combined with the fact that the application can be accessed by multiple users at the same time, ensures that the data collected is anonymous.

Chapter 3

Related Work

3.1 Fine Motor Decline and Psychomotor Impairment Detection

Similar research has been done in the work of Kapsecker et al [KOJ22]. In this research, data of typing behaviors are also accumulated, such as typing speed and variation in character usage. Kapsecker's research, however, used a modified version of the iOS default keyboard to able to gather these data. This modified version of the iOS keyboard brings forwards a limitation in this research, specifically that it shows deviation from the standard keyboard which cause more frequent use of backspace due to typos and different typing behaviors in general. Since the default keyboard of iOS devices is highly optimized, even the slightest changes could affect the user significantly. Differences in structure and layout from this default keyboard, however minor, could cause noticeable changes in the behavior of the users and thus the gathered data

This research has three main findings. The first finding show that the uniform statistical property can be found in the subjects' typing patterns, i.e. their typing speed and their associated overall distribution. The second finding is also regarding the typing speed. The results of the research shows that there is a strong consistency in typing speed between healthy subjects regardless of potential impact factors, such as daytime. This implies that the method of recording typing behavior, in this case with a custom keyboard, is suitable for measuring baseline deviations for both short and long term. The third finding shows that there is a high correlation of approximately 0.8 between frequency and average transition time. It implies that subjects show different transition time during typing characters that are rarely used and more often used. The system used in this research seems sensitive enough to

notice these differences.

These findings suggest that it is possible to detect cognitive and psychomotor impairments through recording and analyzing typing behavior. In the effort of extending this research, the author is hoping to achieve similar results while decreasing the limitations, specifically the limitation caused by using custom keyboard.

Van Waes et al. suggested in 2017 that typing tasks might provide a more accessible alternative for both patients and clinicians. Additionally, the research explores the use of keystroke dynamics as digital biomarkers, which could enhance the diagnostic accuracy for detecting fine motor decline associated with neuropsychiatric disorders [VWLME17]. The research highlights how these tasks could serve as a valuable tool in assessing typing and motor skills, which may decline in patients with Alzheimer's disease.

Mastoras et al. suggested in their research in 2019 that typing patterns can be indicative of psychomotor impairment associated with depressive tendencies [MIH+19]. This research contributes to the development of unobtrusive, high-frequency monitoring tools for depressive tendencies, providing a potential method for early detection and intervention in everyday settings. The findings highlight the potential of using everyday interactions with mobile devices as a source of data for mental health monitoring.

A newer research in 2023 by Tripathi et al. showed the recognition of neurodegenerative diseases, such as PD, using typing patterns is an emerging field that leverages keystroke dynamics [TAGG23]. This approach involves analyzing the time it takes for individuals to press and release keyboard keys during typing, known as hold time, as well as the time between keystrokes, referred to as flight time. These metrics can be used to detect signs of PD in an ecologically valid setup, such as at the subject's home.

These researches highlighted the possibility of detecting fine motor decline and psychomotor impairment through typing pattern on a keyboard. They showed that through analysing keystroke dynamics, flight time and hold time, psychomotor impairment can be detected.

3.2 Age Deduction Based on Typing Pattern

In an article published in 1984, Salthouse revealed some interesthing insights on his research on the effect of age on typing pattern [Sal84]. Older typists are generally not slower in overall typing speed compared to younger typists. However, older typists show slower performance in some areas: tapping rate (the speed of repetitive finger movements) and choice reaction time (the time between a stimulus and an action). Older typists tend to compensate this

by being more conscious about characters farther ahead in the text they are typing. This in turn makes it so that older typists are able to maintain a more constant typing speed compared to their younger counterparts.

A similar research has been done by Tsimperidis et al. in 2017 [TRWK17]. According to this research. keystroke dynamics analysis can be used to estimate a user's age based on their typing patterns. It is possible to classify users into age groups with accuracy as high as 89.7% using machine learning algorithms. Keystroke durations appear to play a more important role than digram latencies in age-based user classification. It is noted in this research that while keystroke dynamics show promise for age estimation, it's important to note that other factors such as education level and health status may also influence typing patterns. Further research is needed to refine these techniques and address potential limitations.

To the researcher knowledge, there has not been a study about using typing behavior on a mobile optimized application to infer the age group of a user.

Chapter 4

Requirements Elicitation

This chapter follows the Requirements Analysis Document Template based on Bernd Bruegge's *Object Oriented Software Engineering Using UML, Patterns, and Java* [BD09]. The goal is to illustrate the concepts, taxonomies, and relationships of the application domain independent of the chosen technology and development platform. The following sections provide an overview of the system, describe functional and nonfunctional requirements, and outline important system models.

4.1   Overview

The system being developed has the purpose of collecting typing pattern of its users with the purpose of inferring their age group by analysing their typing patterns. Potential future improvements of the application include the addition of real-time analysis and result. It is also possible to use the system to gather the data for follow-up research on detecting early signs of neurodegenerative diseases with typing pattern. These potential future improvements are, however, beyond the scope of this thesis.

The system's primary objectives are to collect, process and save keystroke data efficiently, so that the data can be analysed. To achieve this, the application also needs to provide a condusive condition for the users, so that they are able to type as they usually would. This means that the application would need to integrate and prompt the LLM to elicit response from the users. The LLM will be prompted to elicit as many response from the users as possible, so that more data can be gathered and the analysis can be more accurate.

User experience is also an important part of the application. The user should feel comfortable using the application as they would usually use another

chatting application. Accessibility, especially for the elderly users, needs to be taken into account. This is important to make sure that differences in typing pattern are only caused by internal factors of the user themselves. Success of this application will be measured by the ability of the system to gather, process and save keystroke data accurately and effectively.

4.2 Requirements

The application will provides a condusive condition for the user to type. Typing pattern of the user will be collected, processed and saved in the database for later to be analyzed. The proposed system will be split into functional and nonfunctional requirements.

4.2.1 Functional Requirements

The functional requirements (FR) define the specific actions that the system must perform. Below is a list of the primary functional requirements:

FR1 **Conducive Typing Environment**: The user should feel comfortable using the system, as they would using other chatting application.

FR2 **Elicit User Response**: The system must be able to elicit response from the users by using LLM.

FR3 **Collect Typing Data**: The system must capture and log keystroke data from the user in real time, including keypresses and timestamps.

FR4 **Store Typing Data**: The system must securely store all captured typing data in the database for future analysis.

FR5 **Store Users' Age**: The system must gather users' age to act as a comparison between infered and actual age group of the user.

FR6 **Ensure Data Anonymization**: The system must anonymize user data before analysis to ensure compliance with privacy standards.

4.2.2 Nonfunctional Requirements

The nonfunctional requirements (NFR) define system constraints, performance criteria, and standards the system must adhere to. These requirements are categorized using the FURPS+ model, as described in Bernd Bruegge's book [BD09], excluding functionality, which was covered in the functional requirements section.

NFR1 **Usability and Accessibility**: The user interface must be easy to use, especially for elderly users. Design of the application should be accessible for the elderly with features such as large fonts, enough spacing, and clear visual indicators.

NFR2 **Reliability**: The system must be able to run and save users' typing pattern without loss of data or functionality.

NFR3 **Performance**: The system should give response to the user within 10 seconds after the user send a message.

NFR4 **Privacy**: The user's information other than their age should be anonym. Chat session of users should be able to be locked, so that it cannot be accessed anymore.

NFR5 **Adaptability**: The system must be able to scale to support more users, e.g. by adding more servers. It should also be possible to add functionalities such as real-time analysis.

Among these requirements, the most challenging to implement is the adaptability and performance requirement. Adaptability requirement is challenging because it involves the system's ability to scale to support more users and functionalities. The system must be designed to be scalable and flexible to accommodate future changes and additions. It is a very time consuming process to design and develop a system that can be easily scaled and adapted to new functionalities. The development process of the application is unfortunately limited by time, which makes it hard to implement this requirement.

The performance requirement is challenging because it involves the system's ability to respond to user input within 10 seconds. It is obvious that the respond time is largely dependent on the response time of the LLM. On practice, the LLM is able to respond within 10 seconds most of the time. However, there are times when the LLM needs more time to respond, e.g. when the response is long. One of the way to solve this problem is to implement a streaming system, where the LLM can send the response in chunks. This way, the user can already see the response while the LLM is still typing the response. Here too, the time limitation of the thesis makes it hard to implement this solution.

4.3   System Models

This section includes key system models for requirements analysis, including scenarios, use case models, object models, dynamic models, and user interface.

4.3.1   Scenarios

A scenario is "a narrative description of what people do and experience as they try to make use of computer systems and applications" [Car95]. The following section will show concrete, focused and informal description of features of the application from the viewpoint of the user.

Visionary Scenarios

The following scenario describes an ideal scenario that might be achieved in a future research.

Scenario name	neurodegenerativeDiseaseDetection
Participating actor instances	bob: User
Flow of events	1. Bob, a man in his late 50s, use a chatting application to chat with his grandson. This chatting application is already integrated with a system to capture and analyze typing pattern.
	2. Even though Bob does not notice it at all, the application records his typing pattern while simultaneously analysing it. After some times, the application notifies Bob that the system has detected with 90% certainty early symptoms of AD on Bob. Bob then seeks medical help to confirm this analysis.

Table 4.1: Neurodegenerative diseases detection using typing pattern analysis.

Demo Scenarios

The following scenario is implemented by the current system. It is the main purpose and functionality of the application.

Scenario name	keystrokeAnalysis
Participating actor instances	bob: User

Scenario name	keystrokeAnalysis
Flow of events	1. Bob uses the application to chat with a LLM. The application logs and stores Bob's keystrokes.
	2. This keystrokes data is then later analyzed. Along with keystrokes data from other users, Bob's keystrokes data is analysed. After the analysis, some interesting patterns of the data are identified.

Table 4.2: Keystroke data collection and analysis.

Scenario name	sessionManagement
Participating actor instances	bob: Researcher
Flow of events	1. Bob is a researcher that wants to collect and analyze typing pattern data of users using the application.
	2. Bob finds some correspondents and asks them to use the application.
	3. During this data collection, Bob opens the admin dashboard page to view how many chat sessions are already created. Bob does not need to access the database directly, since the admin page already shows the data in a user-friendly way.
	4. Some of the correspondents are already finished with the chat session. To protect their privacy, Bob locks the chat session of these correspondents from the admin dashboard page.

Table 4.3: Data collection session management.

4.3.2 Use Case Model

The following use case model show the interactions between the user, the server and the LLM.

Use case name	initialization of chat session.
Participating actors	Initiated by user. Communicates with server and LLM.

Use case name	initialization of chat session.
Flow of events	1. User inputs age and chat ID. 2. Backend server confirms that the ID is valid and accessible. 3. Backend server checks that no corresponding session with this ID has been created and initialises a new chat session. 4. Backend server gives a prompt to LLM. 5. LLM loads and send the first message after it is finished loading. 6. User reads the message from the LLM
Entry condition	• User opens the login page of the application.
Exit condition	• User reads the first message from the LLM.
Quality requirements	• The server should be able to checks that the corresponding chat of the given ID is accessible and has no chat history. • The server should initialise the chat session correctly and save the age user data corresponding to this chat session in the database. • The server should send a prompt to the LLM, wait for the response, and forward the response of the LLM to the user.

Table 4.4: Use case initialization of chat session.

Use case name	loading of an already existing chat session.
Participating actors	Initiated by user. Communicates with server and LLM.

17

Use case name	loading of an already existing chat session.
Flow of events	1. User inputs age and chat ID. 2. Backend server confirms that the ID is valid and accessible. 3. Backend server checks that there exists already a chat session with the corresponding ID. 4. Backend server loads all the messages history of this chat session and sends it to the user. 5. User reads the chat history and continues the chat as they left it.
Entry condition	• User opens the login page of the application.
Exit condition	• User is able to read all of the chat history belonging to the session with the ID given by the user.
Quality requirements	• The server should be able to checks that the corresponding chat of the given ID is accessible and has chat history. • The server should load all chat history of this chat session correctly. • The server should send the chat history data to the user with right information of whether a message is sent by the user or by the LLM.

Table 4.5: Use case loading of an alredy existing chat session.

Use case name	user sends a message.
Participating actors	Initiated by user. Communicates with server and LLM.

Use case name	user sends a message.
Flow of events	1. User types a response to the last message from the LLM. 2. User sends the message. 3. Backend server saves the message and its keystroke data in the database. 4. Backend server sends the message to the LLM. 5. LLM responses to the user's message. 6. Backend server saves the message from the LLM in the database and sends it to the user.
Entry condition	• User is already in a chat session.
Exit condition	• User is able to read the message from the LLM.
Quality requirements	• The server should save the message from the user and its keystroke data in the database correctly. • The server should forward the message to the LLM. • The server should wait for the LLM to response, .

Table 4.6: Use case user sends a message.

4.3.3 Analysis Object Model

The following diagram shows the key objects and their relations with other objects in the application.

Classes: Message, Conversation, Keystroke

Conversation: Represents the whole chatting session with a unique ID. When the user enters an ID, the backend server will look for a conversation that has the same ID. If such object exists, then the server will fetch the conversation along with the Messages that belong to this conversation object. If the object does not exist, then the server will initialise a new conversation object with ID that just has been given by the user. Each conversation object also has age attribute, which give information about the age of the user to whom this object belongs to. To improve privacy, each conversation is also given the attribute deactivated. If this attribute is set, then the conversation will not accessible anymore. This helps prevent unwanted actors to access
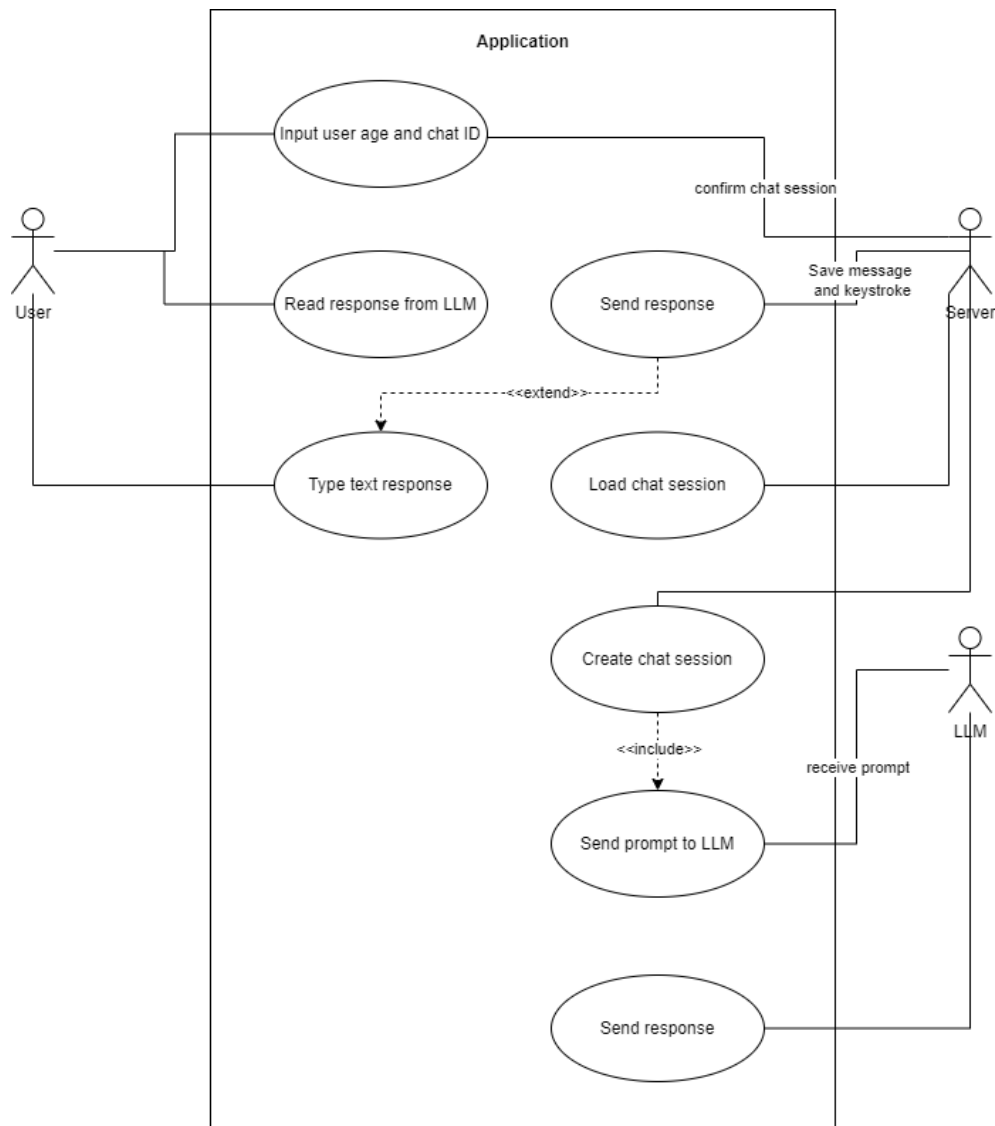
19

Figure 4.1: UML use case diagram of the chatting feature.

chat sessions of users that are already finished.

Message: Represents each message that the user or the LLM sent. Each message object is related to one conversation. Whereas each conversation contains between zero and multiple messages. The messages from the LLM also need to be saved, so that the whole conversation can be loaded again, after the user exits a chat session. As a result, the message objects need to have an attribute to give information, whether this message was created by the user or by the LLM. This information is saved in the boolean attribute
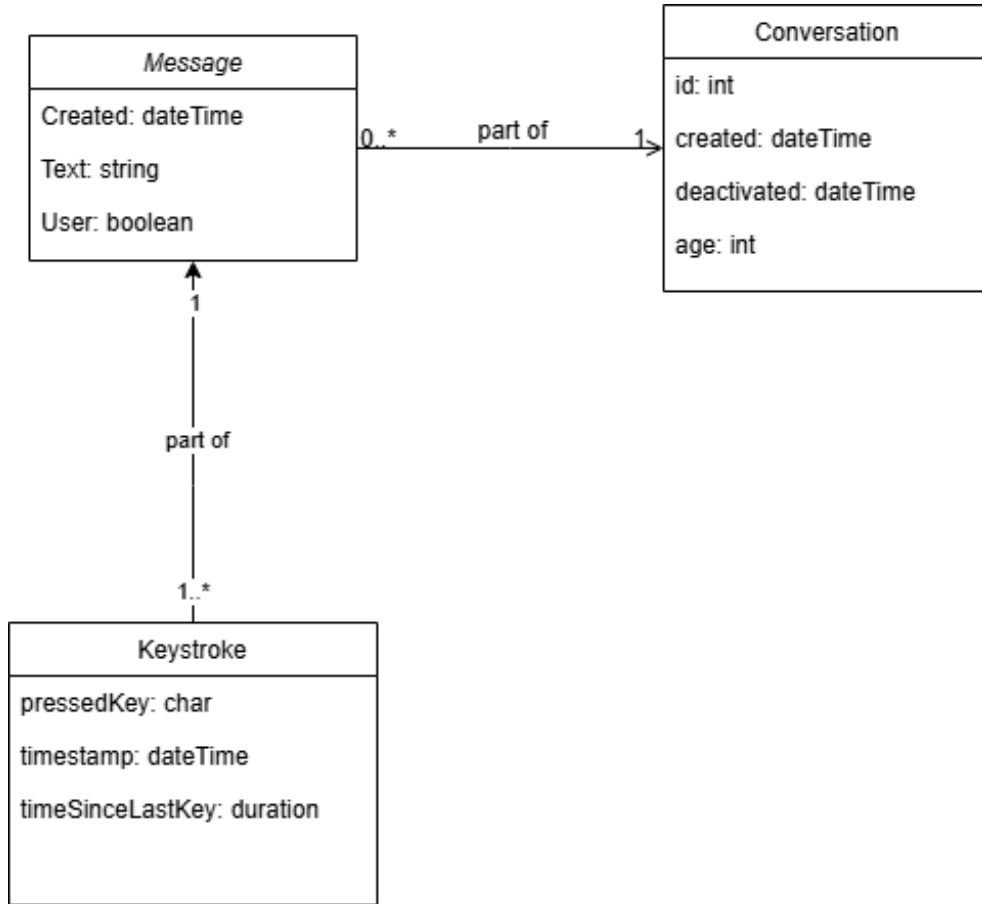
Figure 4.2: UML class diagram of the application domain.

"user".

Keystroke: Represents each keystroke that the user types. Each message object will have between one and multiple keystrokes. The keystroke object is the most important object for this thesis, since the reseach will be focused on the keystrokes of the user. Each keystroke object will have three attributes: pressedKey, timestamp, and timeSinceLastKey. Each key the user pressed will be saved as a keystroke object, such as alphabets, numbers, and control characters, such as backspace or horizontal tab. This information is saved on the attribute pressedKey. The attribute timeSinceLastKey will show the duration between each key presses. Statistical analysis of the keystrokes will be based on the value saved on the attribute timeSinceLastKey.

4.3.4 Dynamic Model

Figure 4.3 depicts UML state diagram of the application. This diagram shows the states the application will be in based on certain triggers. The entry point of the application would be the login page. This will be the first page the user accessed. If the user inputted the correct ID, i.e. accessible ID with the right format, then the second condition will be checked. If the ID is not correct, then a warning will be shown.

The second condition consists of checking whether the chat session corresponding to the ID has been initialised. An initialised chat session means that the chat session has already been accessed before. This chat session possibly already has chat history that needs to be loaded. If, on the other hand, the entered ID is not associated with any chat session, this means that this is the first time the user entered this ID. In this case, the chat session needs to be initialised first. After the chat session is initialised, then a prompt is given to the LLM. The first message from the LLM is then sent to the user.

After either the first message from the LLM or the whole chat history of the chat session is loaded, the application enters the next state. In this state, the application waits for the user to type and send the message. Message that is sent by the user is then processed in the backend server. To begin with, the message is sent to the LLM. The server then waits for the LLM to respond to the text. It should be mentioned here that the server sends the whole chat history to the LLM, so that the context of the previous messages is not lost. After the LLM responded, both the new message from the user and from the LLM are then saved in the database. In the end, the new message from the LLM is forwarded to the user. This bring the application back to the state of waiting for the user to send a message.

4.3.5 User Interface

Technology Stack

React.JS: The application UI for this research is primarily built using the popular Javascript framework, React.JS. React is a free and open-source front-end JavaScript library for building component based UI. This librariy is known for its flexibility and efficiency, which is the main reason why React is being used for this project. React was crucial for the foundation of the application, making it easier to create responsive and interactive elements.

Material-UI: Material-UI, is a React UI library based on Google's Material Design principles. This library facilitates the development of UI by providing pre-designed components like buttons, forms, and avatars. Its
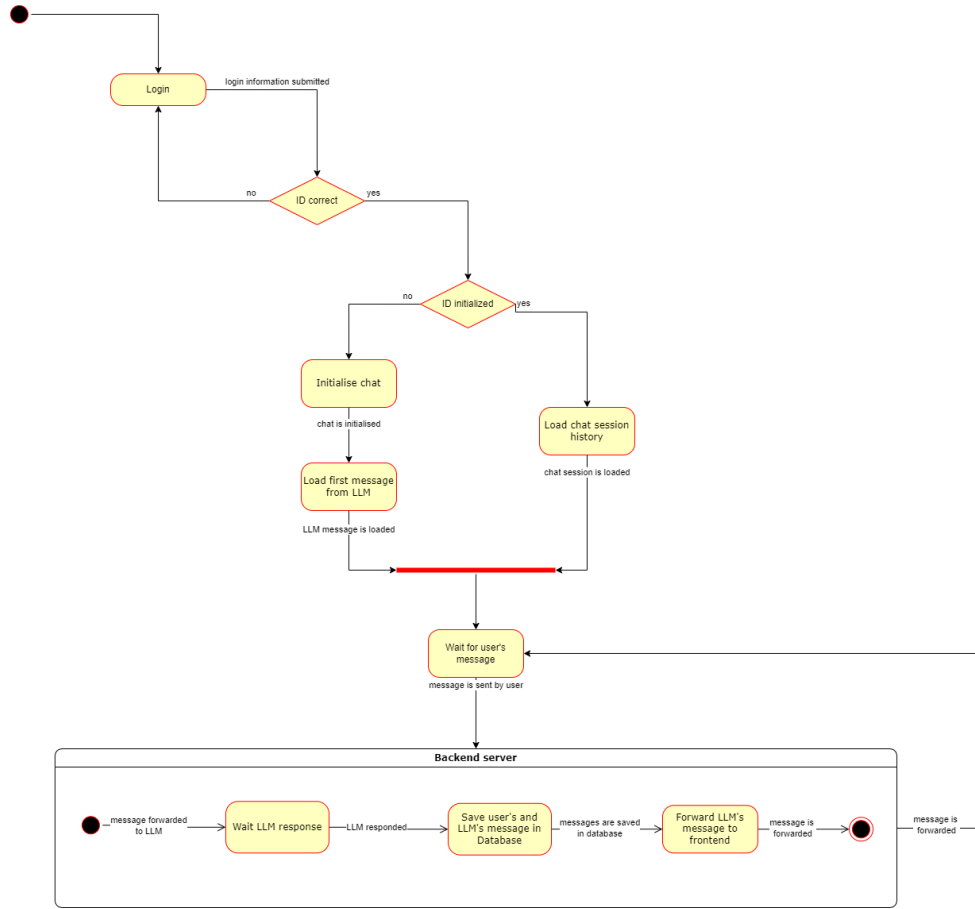
Figure 4.3: UML class diagram of the application domain.

seamless integration accelerates development, making it possible to deliver a polished interface efficiently.

UI Mockup and Design Process

Designing the UI is a crucial first step in developing an application. The design should be intuitive and easy to use for the user. It is even more important for this application, since this application will be used by users from various age groups. The application should be comfortable to use by every age groups, so that the result is as accurate as possible. Early in development, UI mockups is used before the actual implementation. This is done to visualize the design and determine whether the design is suitable for the purpose of the application

It is a widely known fact, that an application, especially mobile application such as the one being used for this project, is harder to use for the elderly. One of the main reasons would be visual impairment that often happen more the older a person gets. To counteract this, the design of the application is focused on UI features, such as bigger interactive elements, high contrast, font selection, spacing, appropriate color choices, and centralized content.
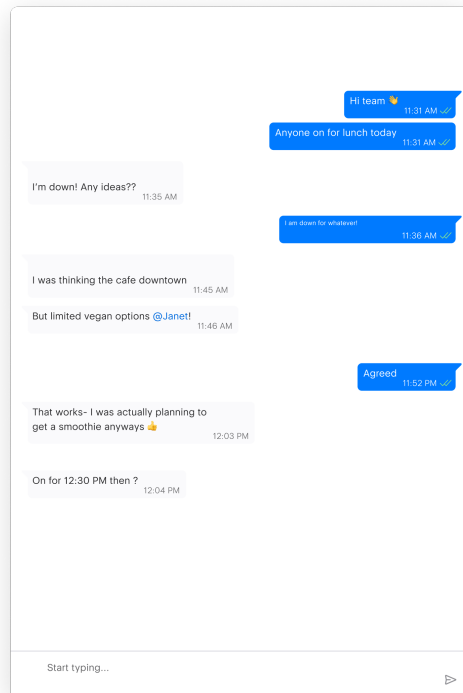

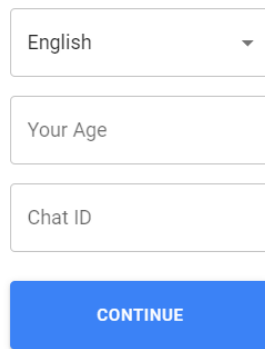**Figure 4.4:** UI mockup of the chat page.

The final UI mockup did not manage to achieve the intended design. Figure 4.4 shows, that the design of the application is not yet user-friendly to the more senior age groups. The font is too small and the text is too cluttered, are some of the problems that this design has. However, this mockup design served its purpose as a base design. Since, as mentioned before, React.JS is known for its flexibility, this problem can easily be solved on the implementation part of the application. This mockup serves as a guideline for the layout of the application, with a message input component at the bottom and color-coded text bubbles based on whether the message was from the user or the system.

This adaptation and improvement from the mockup design demonstrated the value of agile development approach. Changes and adjustments to initial

plan are a common accurance in the world of software development. Many requirements are sometimes missed during planning. This is one of the main reason that a software should be easily adjustable to ever-changing real world constraints and feedbacks. While the mockup played a significant role in early planning, the ability to adapt ensured the final product met practical requirements.

Implementation

Once the mockup is established, the development moves to the implementation phase.

Figure 4.5: Implementation of the login page.

The first component that is implemented is the login page shown in Figure 4.5. Login page is important to ensure that each user gets their own chat session and is unable to access a chat session that has ended. The age of the user is also inputted in this page. After the login button is clicked, the user is then directed to the chat page.

Figure 4.6 shows the chat page. This chat page is where the user can see the chat history and send a message. Design of the chat page has been improved, compared to the mockup design. The font is bigger and the text is more spaced out. These improvements are done to make the application more user-friendly, especially for the elderly. To remove the loading speed during the start of the conversation, the first message from the LLM is a default
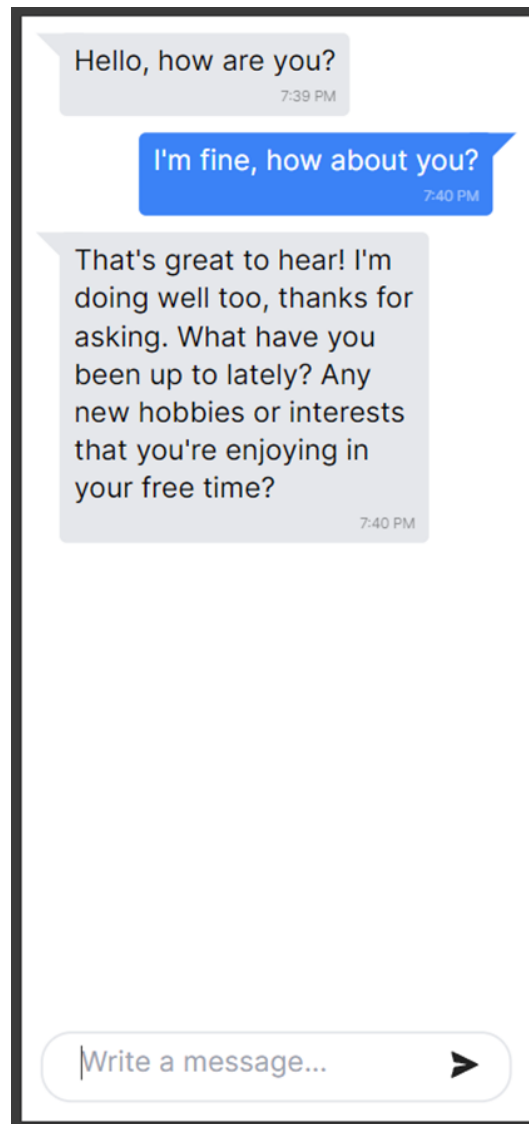
Figure 4.6: Implementation of the chat page.

message set on the frontend: "Hellow, how are you?". At the same time, the backend server sends the LLM the initial message, which is the prompt. This allows the LLM to load, while the user thinks about the reply for the initial message.

Figure 4.7 shows the admin dashboard page. This page is used by the admin to see ID that has been used by the user. From this page, the admin can also deactivate a chat session, making it inaccessible. Some usecases of this feature:

Figure 4.7: Admin dashboard page.

- If the user has finished the chat session, the admin can deactivate the chat session.

- The admin can give the user a new ID, that has not been accessed before.

- The admin has an easy way to see how many conversations have been created and their creation date, without needing to access the database.

- With the date filter, the admin can see how many conversations have been created in a certain date.

Chapter 5

System Design

5.1 Overview

This chapter explains the decision regarding the architecture design of the application. Design of the architecture will be largely based on bridging the conceptual understanding of the application with the concrete technical solution. Requirements of the system and existing constraints are also the main deciding factors of the architecture design. The system aims to address the nonfunctional requirements of the application, such as performance and usability, which were mentioned in earlier chapters. Based on Bruegge and Dutoit's template [BD09], the structure of the system is divided into logical components and subsystems.

5.2 Design Goals

Design goals of the system are derived from nonfunctional requirements. Because of constraints such as time, some of the nonfunctional requirements might not be fulfilled. The design goals are prioritized based on the importance of the nonfunctional requirements. Design goals of the system are as follows:

- **Usability and Accessibility**: One of the most important goal of the system is to be usable and accessible for the elderly. For this goal, the application is designed to be user-friendly for all age groups, specifically the elderly. The UI should be intuitive and easy to use. This is achieved through big buttons, clear visual indicators and enough spacing between elements. Design of the application should be accessible for the elderly with features such as large fonts, enough spacing, and clear visual indicators. This design goal is purely achieved through the frontend of

the application. As such, the only limiting constraint is the time and resources available to develop the frontend.

- **Reliability**: Another most important goal of the system is reliability of the system. Reliability here means that the system should be able to accurately gather, process and store the typing pattern data. Since a faulty or inaccurate data could lead to wrong conclusion, the system should be able to minimize the inaccuracy of the data. Both the frontend and backend of the application play a role in achieving this goal. The frontend should be able to accurately capture the typing pattern data, especially the attribute timeSinceLastKey. This attribute shows information about the time difference between the last key press and the current key press. For this purpose, the built in JavaScript function Date.now() is used.

- **Performance**: Recording the typing pattern data in real-time is not a performance heavy task. This function can easily be achieved by creating an array of keystroke data that is updated every time a key is pressed. The main performance issue of the application is waiting for the LLM to respond to the user's message. The LLM is instructed to try to get as much response from the users as possible, so that more typing data can be collected. This leads to a longer waiting time for the user to get a response, since the longer the response from the LLM, the longer it will take for the LLM to finish the response. One of the possibility of solving this problem would be to stream the response from the LLM. Stream will allow the user to see response from the LLM in chunks, instead of waiting for the whole response to be finished. Unfortunately this feature is not yet implemented in this application due to time constraints.

- **Privacy**: An application that concerns itself with collecting sensitive user data should be secure and able to keep the data private. In this application, a chat session can be accessed by inputting a session ID. As a measure to increase privacy, each chat session can be made inaccessible by changing an attribute in the database. When a user tries to access a chat session that is already closed, the application will return an error message. Another important factor regarding privacy is anonimity. The only information about the user that is saved in the database is the user's age. If another user tries to access chat session of another user that is not yet deactivated, the message history will be shown. However, the user's age will not be shown.

- **Adaptability**: Adaptability means the ease with which a system may be modified to fit changed requirements or environment. Adaptability of the system can be divided into two parts: adaptability of the frontend and adaptability of the backend. The frontend of the application is designed to be easily modifiable by utilising component based design of the React library. Adaptability of the backend is ensured by utilising concepts such as encapsulation and modularity. The backend is divided into several classes, each responsible for a specific task. This allows for easy modification of the backend, since each class can be modified without affecting the other classes. The only limiting factor for adaptability is the time and resources available to modify the system. Docker is used to containerize the application, which allows for easy deployment and scaling of the application.

5.3   Subsystem Decomposition

The system is divided into two main subsystems: the frontend and the backend. The frontend is responsible for capturing the typing pattern data and displaying the chat interface. The backend is responsible for processing the typing pattern data and generating a response from the LLM.

5.3.1   Frontend

User Interface

The frontend of the application of the user interface can be divided into two main components: the login component and the chat component. Figure 5.1 shows the UML class diagram of the frontend architecture of the user interface. The main purpose of the login page is to initialise the chat session and validate the user's input. User inputs their age, the session ID, and the language to chat with the LLM. English and german are the two possible languages that the user can choose.

In the login page, the user can click the "Login" button to start the chat. After this button is clicked, both the session ID and the user's age will first be validated. On the frontend side, the session ID is validated by checking whether the session ID has 6 digits. The user's age is validated by checking whether the user's age is a number and whether the user's age is between 1 and 99. If the validation is successful, the data will be sent to the backend. On the backend side, the session ID is validated by checking whether the session ID is alredy deactivated. The deactivated attribute is a boolean attribute in
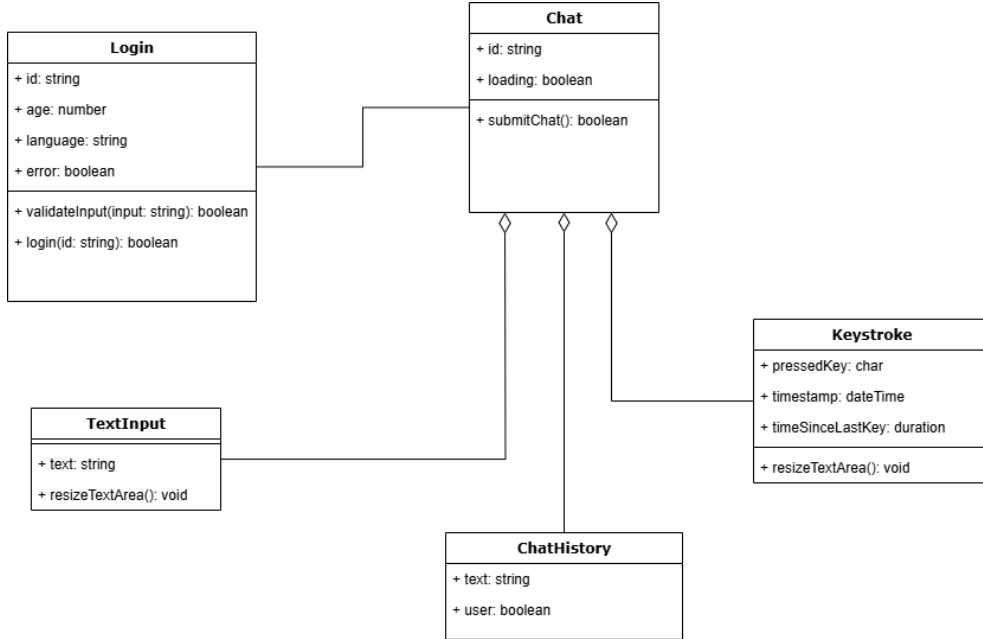
Figure 5.1: UML class diagram of the frontend architecture of the user interface.

the database that can be managed either through the admin interface or by directly changing the value in the database.

In the chat page, the user can see the chat history and type a message. Directly after the user pass the login page, the user will be greeted by the LLM. This initial message from the LLM is actually a default message set on the frontend. This is done to remove the initial loading time of the LLM response. At the same time, the backend will boot up the LLM by sending the initial prompt. This makes it so that while the user thinks about the response to the initial message, the LLM can load. Without this feature, the user would have to wait for the LLM to load before the user can see the initial message.

While the user is typing, the frontend will capture the typing pattern data. Each keypress made by the user is recorded and stored in an array. After the user presses the "Enter" key, the array of typing pattern data will be sent to the backend. The typing pattern data is an array of JSON object that contains the timestamp of the keypress, the pressed key, and the time since the last keypress. Attribute timestamp contains the exact time when the key is pressed, using the JavaScript function Date.now(). Attribute pressedKey. as the name suggests, contains the key that is pressed by the user. Attribute timeSinceLastKey contains the time difference in milliseconds between the last key press and the current key press.
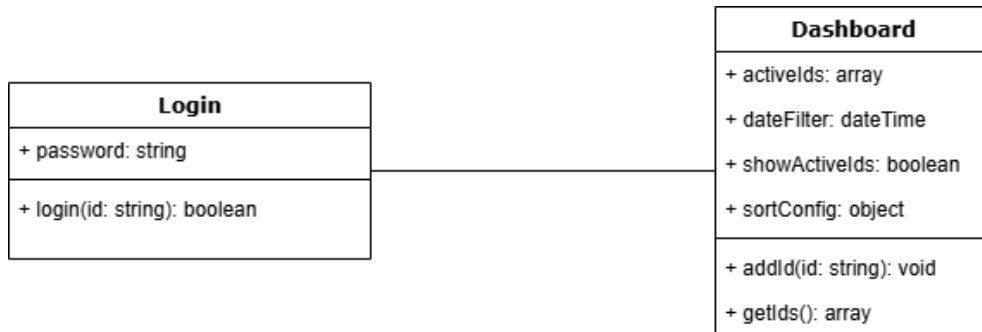
31

Admin Interface

Figure 5.2: UML class diagram of the frontend architecture of the admin interface.

The admin interface is a separate component of the frontend that is only accessible by the admin. Figure 5.2 shows the UML class diagram of the frontend architecture of the admin interface. This admin interface can also be divided into two main components: the login component and the dashboard component. Login page of the admin interface is significantly simpler than the login page of the user interface. The admin only needs to input the admin password to access the admin interface. After the "Login" button is clicked, the inputted password will be checked against the password set in the backend of the application.

The dashboard component helps manage the chat sessions by providing these functionalities:

- View the list of all initialised chat sessions or initialised chat sessions that are still active.

- Deactivate a chat session

- Initialise a new chat session by inputting the ID of the chat session

- Sort the chat sessions by added date, ID, or deactivated date to ease the process of finding a specific chat session

5.3.2   Backend

Main Controller

The backend of the application can be divided into two main components: main controller and admin controller. Figure 5.3 shows the UML class diagram of the main controller. This controller is responsible for handling login, initialisation of a chat session and getting a response from the LLM.
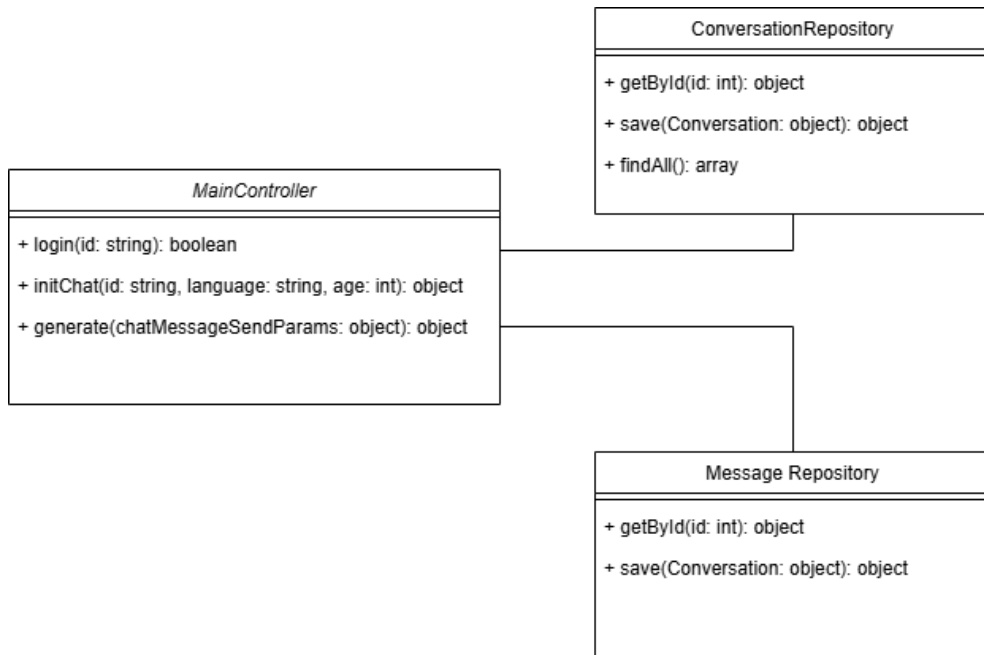
Figure 5.3: UML class diagram of the backend architecture of the main controller.
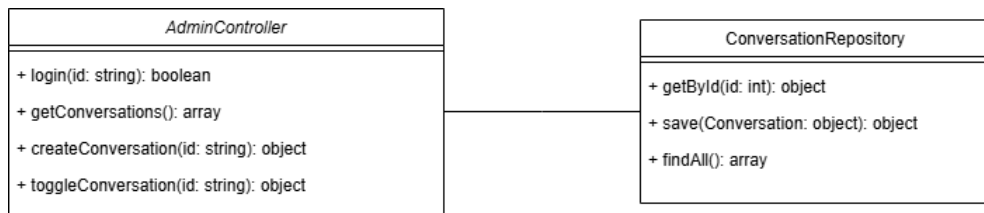
Admin Controller

Figure 5.4: UML class diagram of the backend architecture of the admin controller.

Figure 5.4 shows the UML class diagram of the admin controller. This controller is responsible for handling the admin login and managing the chat sessions. For managing the chat sessions, this controller provides these functionalities: get all chat sessions, deactivate and reactivate a chat session, and initialise a new chat session.

Chapter 6

Evaluation

6.1 Design

The evaluation process was done to assess both the functional and non-functional requirements of the system. This evaluation is done by processing the data collected from the users by the application. The python library numpy and pandas are used to process the data. Numpy is used to perform mathematical operations on the data and pandas is used to visualize the data. If the system was able to collect and store data accurately, then the system is considered to be functioning correctly. Whether the data being saved is accurate or not should be clear through the evaluation process.

6.2 Objectives

The data can be compared to the expected data to see if the system is functioning correctly. An example of this would be to compare the average typing speed from the collected data and average typing speed data from other sources. On average, the typing speed of a person on mobile devices is 36.2 words per minute (WPM) with 2.3% uncorrected errors [PFK+19]. This translate to 331.49 ms average duration between keystrokes, if we consider that on average, there are 5 characters per word.

Typing speed also varies depending ont he age of the user. Age group 10-19 has the fastest typing speed with 39.6 WPM and age group 50-59 has the slowest typing speed with 26.3 WPM [PFK+19]. This translates to average speed between keystrokes of 303.03 ms for 39.6 WPM and 456.65 ms for 26.3 WPM. This is the expected average duration between keystrokes for the data that has been collected by the application.

6.3 Results

Age Group	Conversations	Message Count	Message Length (Mean)
0-24	7	26	19.77
25-39	9	39	53.59
40-59	18	103	48.56
60+	6	30	32.17

Table 6.1: Number of unique conversations, number of messages and average length of the messages of each age groups.
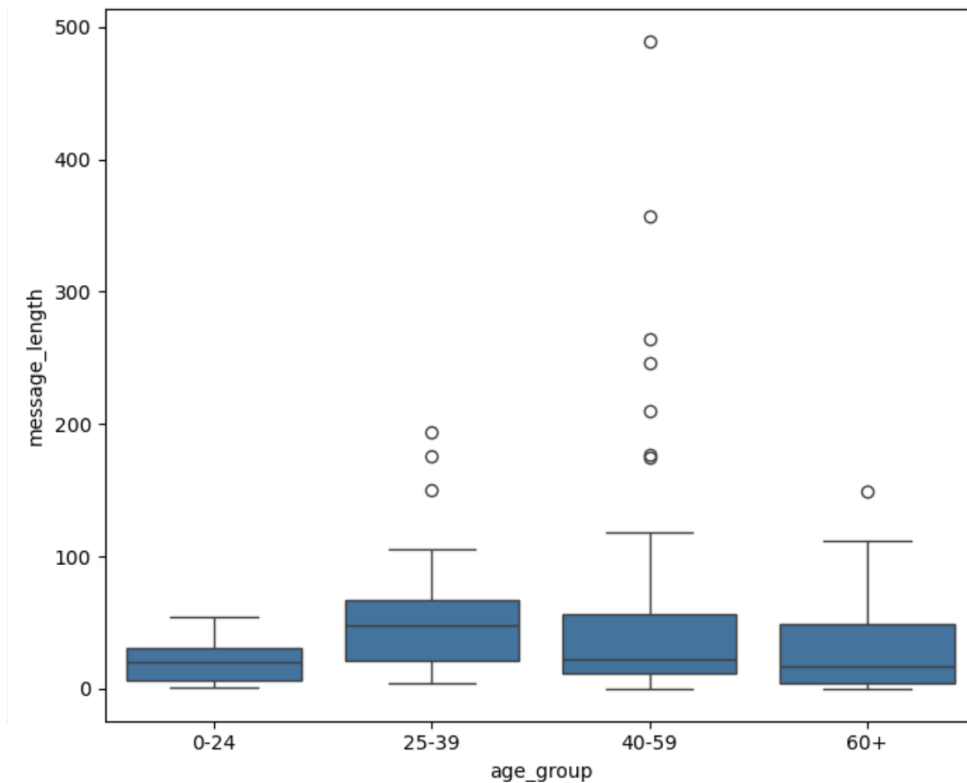

Figure 6.1: Box plot of message length of each age group.

Table 6.1 shows the number of unique conversations, number of messages sent and the average length of the message sent. In total, the application managed to gather data from 40 unique conversations. Age group 40-59 has the most unique conversations with 18 conversations and most message sent with 103 messages. Meanwhile age group 60+ has the least unique

35

conversations with 6 conversations. The least amount of messages sent is by age group 0-24 with 26 messages.

Regarding message length average, age group 25-39 has the longest message length average with 53.59 characters. Age group 40-59 has the second longest message length average with 48.56 characters. Age group 0-24 has the shortest message length average with 19.77 characters.

Age Group	Backspace Percentage (Mean, %)
0-24	6.00
25-39	6.63
40-59	15.93
60+	3.29

Table 6.2: Average of backspace usage percentage of each age groups.

Table 6.2 shows the average backspace percentage of each age group. Backspace percentage is calculated by dividing the number of backspace keystrokes by the total number of keystrokes. Age group 40-59 has the highest backspace usage percentage with 15.93%. Age group 0-24 has the lowest backspace usage percentage with 6.63%.

Age Group	Keystroke Interval	
	Mean (ms)	Std. Dev (ms)
0-24	241.54	199.47
25-39	272.87	128.61
40-59	386.99	188.92
60+	285.72	137.01

Table 6.3: Keystroke interval of each age groups.

During the processing of the data, keysrokes duration that took longer than five seconds are truncated. This is done to remove data that is most likely caused by trivial factors, such as the user being away from keyboard. Table 6.4 shows the average and standard deviation of duration between each keystrokes after the data is truncated.

Age group 0-24 shows the fastest typing speed with an average keystroke interval of 241,54 ms. This age group also shows the highest versatility in typing speed with a standard deviation of keystroke interval of 199,47 ms.

Age group 25-39 shows a slower typing speed than the previous age group. This is, however, the second fastest typing speed with an average keystroke
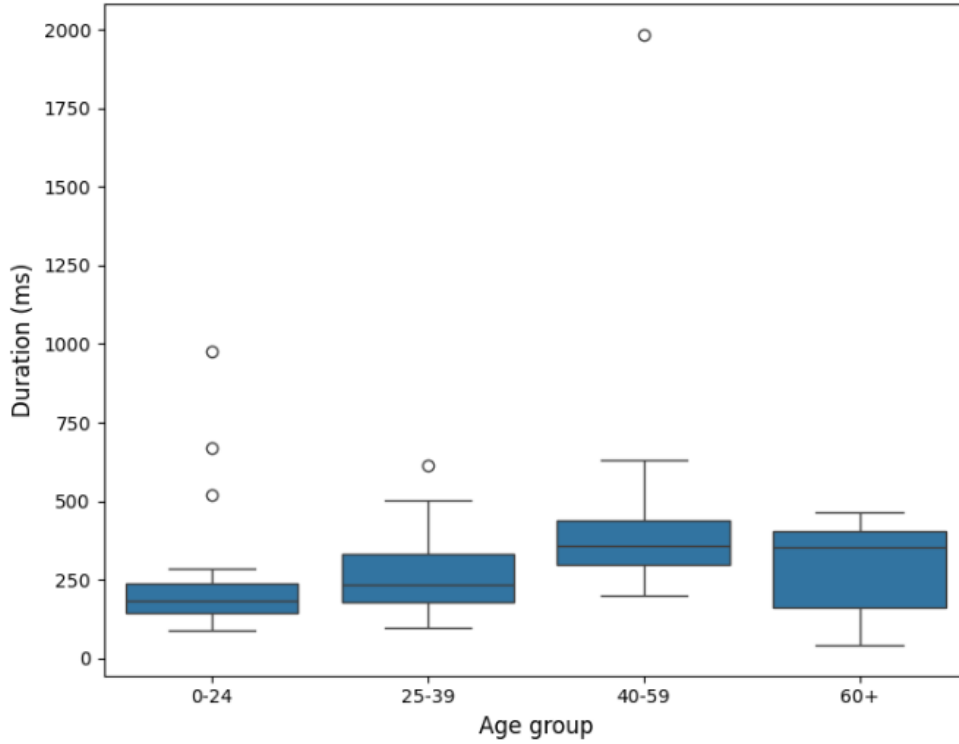
Figure 6.2: Box plot of keystroke interval of each age group.

interval of 272,87 ms. This age group is also the least variable in typing speed with a standard deviation of keystroke interval of 128,61 ms.

Age group 40-59 shows the slowest typing speed with an average keystroke interval of 386,99 ms. This age group also shows high versatility in typing speed with a standard deviation of keystroke interval of 188,92 ms.

Average typing speed of age group 60+ increases compared to age group 40-59. This age group has the second slowest typing speed with an average keystroke interval of 285,72 ms.

Next, the data is truncated further by removing the one-percenth quantile (<1% and >99%) of the keystroke interval. This is done to remove outliers from the data. Table 6.4 shows the average and standard deviation of duration between each keystrokes after data processing is done.

Age group 0-24 shows the fastest typing speed with an average keystroke interval of 226,94 ms. Similar to the previous evaluation, this age group also shows the highest versatility in typing speed with a standard deviation of keystroke interval of 193,75 ms.

Age group 25-39 is slightly slower, with an average keystroke interval of 253,15 ms. This is, however, still the second fastest typing speed. This group

| | Keystroke Interval | |
Age Group	Mean (ms)	Std. Dev (ms)
0-24	226.94	193.75
25-39	253.15	123.82
40-59	357.05	189.69
60+	279.32	132.83

Table 6.4: Keystroke interval of users in different age groups with truncation of the one-percenth quantile.
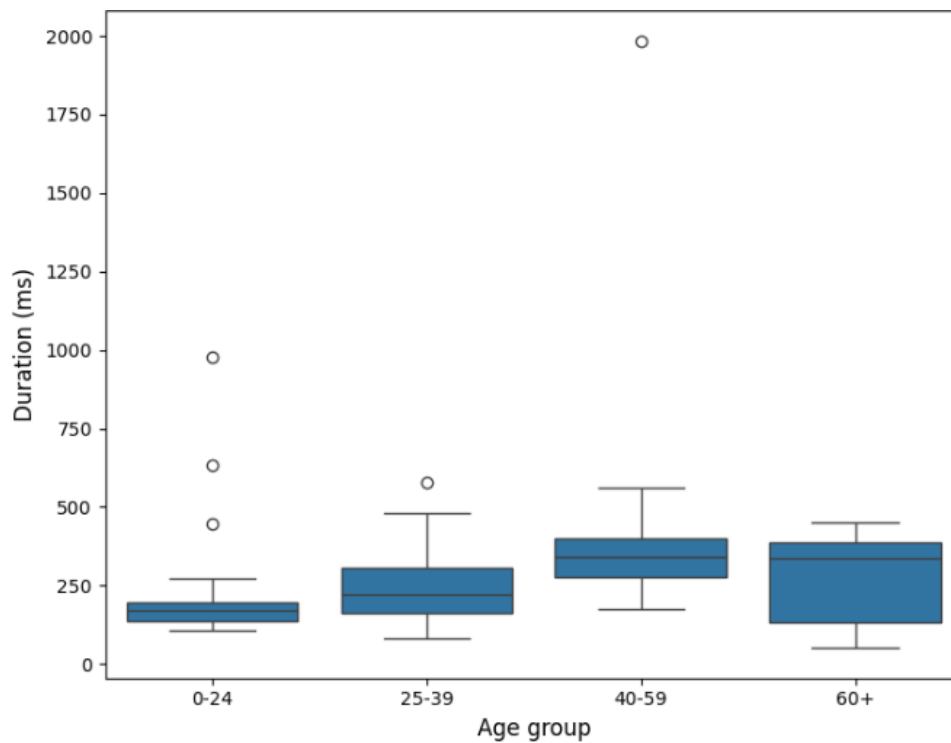

Figure 6.3: Box plot of keystroke interval of each age group with truncation of the one-percenth quantile.

also has the least variable typing speed with a standard deviation of keystroke interval of 123,82 ms.

Age group 40-59 has the slowest typing speed with an average keystroke interval of 357,05 ms. Versatility in typing speed of this group is high with a standard deviation of keystroke interval of 189,69 ms.

For age group 60+ the average typing speed is slightly faster than age group 40-59. This age group has the second slowest typing speed with an

average keystroke interval of 279,32 ms. Versatility in typing speed of this group is low with a keystroke interval of 132,83 ms.

	Keystroke Interval	
Age Group	Mean (ms)	Std. Dev (ms)
0-24	195.69	117.00
25-39	253.84	121.98
40-59	344.07	82.60
60+	274.03	132.96

Table 6.5: Keystroke interval of users in different age groups with truncation based on IQR method.
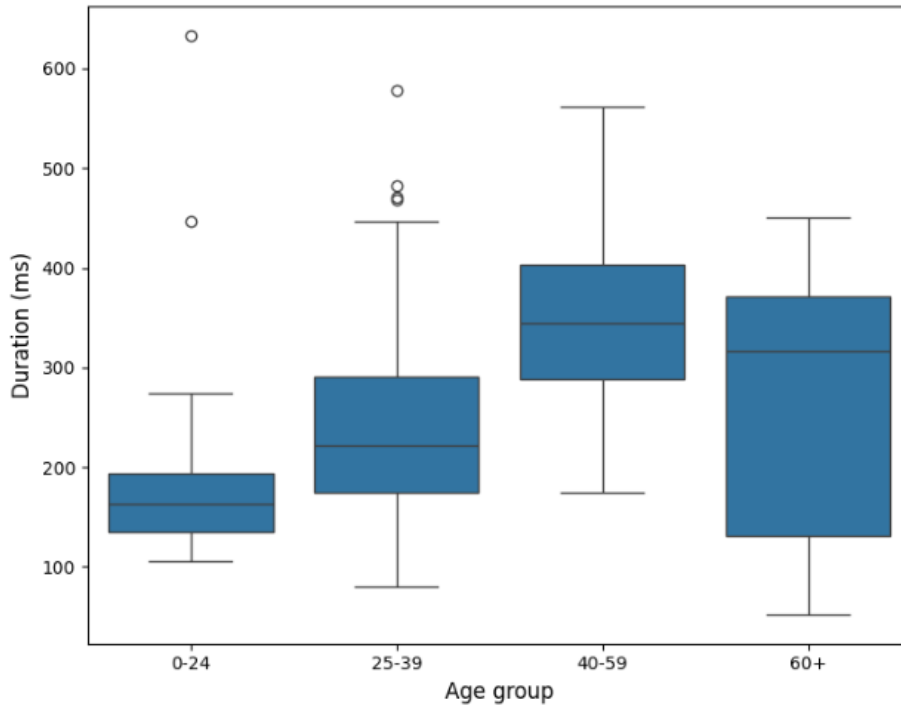

Figure 6.4: Box plot of keystroke interval of each age group with truncation based on IQR method.

In this evaluation, the data is processed by removing the outliers (according to IQR method) from data of duration between keystrokes. This truncation is done after removing keystrokes that took longer than five seconds. The ranking of the age groups in terms of average typing speed remains the same

with the previous evaluation methods. However, the ranking of the age groups in terms of versatility in typing speed changes.

Age group 0-24 that was previously the most variable in typing speed is now the second least variable with standard deviation of keystroke interval of 117 ms. Age group 25-39 that was previously the least variable in typing speed is now the second most variable with standard deviation of keystroke interval of 121,98 ms. Age group 40-59 that was previously the second most variable in typing speed is now the least variable with standard deviation of keystroke interval of 82,60 ms. Lastly, age group 60+ that was previously the second least variable in typing speed is now the most variable with standard deviation of keystroke interval of 132,96 ms.

6.4 Findings

Backspace percentage average increases the older a person is, except for age group 60+. A big jump in backspace percentage average is seen between age group 25-39 and 40-59 from 6.63% to 15.93%. Afterwards, the backspace percentage average decreases to 3.29% for age group 60+.

On all three evaluations, there is a noticeable pattern that the older the person is, the slower their typing speed become. This is consistent with the general knowledge that the older a person is, the slower their reaction time is. There is however an exception with age group 60+. This group has a faster typing speed than age group 40-59 in all of the evaluations. The fact that this group has the least amount of unique conversations might contribute to this result.

On the first two evaluations, i.e. evaluations without the IQR method, if the data for age group 25-39 is left out, there is a trend where the older the age group, the less variable the typing speed is. Age group 25-39 is, however, an exception to this pattern, as it is the least variable group. In the evaluation with the IQR method, this is reversed. In this evaluation, exluding age group 40-59, the older a person is, the more variable their typing speed become.

6.5 Limitations

One of the limitations of the application that becomes apparent during the evaluation is the incapability of knowing whether the conversation is done by typing on the screen or with a physical keyboard. Typing on a physical keyboard is generally faster than typing on a screen [VLH12]. This is a limitation of the current version of the application. Updating the application

to also collect data of the device used while using the application should be considered in the future. This will make sure that the data is more accurate and can be used to make more accurate conclusions.

Another limitation is the fact that the data is gathered from a specific group of people and the small sample size. This specific group of people might not be representative of the general population, thus impacting the generalizability of the result. The small sample size also makes the result less reliable. To improve the reliability of the result, the application should be used by a larger group of people.

Chapter 7

Summary

7.1 Status

The goal of developing a mobile-optimized chat application that collects the user's typing data has been achieved. The application has been designed to be user-friendly for all age groups, specifically the elderly. Clean architecture and secure coding practices have also been practiced to ensure reliability, scalability, and maintainability. However, these characteristics could not be proven yet and still subject to further testing and evaluation. An improvenemt to the application could also be made by collecting data of the device used by the user. This could improve the accuracy of the analysis of the data.

Analysis of the data collected from the application has also been done. The data has been analyzed to conclude interesting findings. Some basic patterns have been identified, such as typing speed, keystroke intervals, and error rates. These features have been examined with basic statistical methods such as mean, median, and truncation of the outlier of the data. There is however still a lot of work to be done to further analyze the data and to identify more complex patterns that could be used to profile the user in an age group.

7.1.1 Realized Goals

Most of the goals set in the beginning of this thesis have been achieved. Among the goals that have been achieved are:

- Developing a mobile-optimized chat application that collects the user's typing data.

  The application has been successfully developed and is able to collect samples from individuals across different age groups. By utilizing the

Llama3 LLM, the application is able to elicit response from the users and collect the typing data. Data of keypresses and timestamps have been collected and stored securely in the database for future analysis. Another information that has been successfully collected is the users' age. Anonimity of the data has also been ensured naturally, since personal information other than the age of the user is not collected. Multiple correspondents have used the application, which further ensures the anonimity of the data, since it would be hard to identify the user from the data collected.

From the evaluation of the collected data, it can be concluded that the data is reliable. The data collected is consistent with the expected data, that was set by taking data from other researches. Some pattern have also been identified from the data that might show some insight into the possibility of using typing pattern to profile the user in an age group.

- Practicing clean architecture and secure coding practices to ensure reliability, scalability, and maintainability.

One of the main focus of this thesis is to develop a reliable application. Reliability of the application can be seen from the evaluation of the collected data. The data collected is consistent with the expected data, that was set by taking data from other researches. Moreover, the application has been used by users from different age groups and seems to be user-friendly for all age groups, specifically the elderly. By utilizing Docker, the application can also be built and hosted on different environments, such as on the university servers, without much trouble.

- Analyzing the gathered typing behavior data to identify patterns or statistical distributions that may correlate with the user's age.

The data collected has been analyzed to identify some basic patterns. The data has been examined with basic statistical methods such as mean, median, and truncation of the outlier of the data. From this processing of the data, some patterns about the average and standard deviation of the typing speed can be seen on the analyzed data. This findings could show some insight into the possibility of using typing pattern to determine or categorize the user in an age group.

7.1.2   Open Goals

Although most of the goals have been achieved, there are still some open goals that need to be addressed. Among the open goals are:

- Evaluating the accuracy of using typing behavior as a predictor of age.

  The accuracy of using typing behavior as a predictor of age has not been evaluated yet. Some improvements are still needed to be made to the application to be able to collect data more reliably. The data collected has been analyzed to identify some basic patterns, but the accuracy of these patterns can not be determined yet. The identified patterns need to be consistent enough to be able to reliably be used to estimate the user's age group. This evaluation is crucial to determine the feasibility of using typing pattern to profile the user in an age group.

- Real time analysis of the typing pattern.

  Because of time limitation, the real-time analysis of the typing pattern has not been implemented yet. The application has been developed to collect data of the typing pattern in real-time, but the analysis of the data is still done offline. Real-time analysis of the typing pattern could be useful to give instant feedback to the user. This is an open goal for the future, which hopefully has been brought closer by this thesis.

- Creating a maintainable and scalable application.

  Even though the application has been developed with clean architecture and secure coding practices, the maintainability and scalability still can not be proven yet. It is not yet clear how easy it would be to maintain or improve the application. The ease of scaling the application by adding more servers or functionalities such as real-time analysis is also still unknown.

- Further analyzing the data to identify more complex patterns that could be used to profile the user in an age group.

  The data collected has been analyzed to identify some basic patterns, but there are still a lot of work to be done to further analyze the data. More complex patterns need to be identified to profile the user in an age group. Metrics such as typing speed, keystroke intervals, and error rates will be examined to determine if they can give indication of the user's age group. This further analysis is crucial to determine the feasibility of using typing pattern to profile the user in an age group.

7.2 Conclusion

This thesis mainly focuses on exploring the possibility of developing an application for early detection of neurodegenerative diseases. To progress towards

this goal, the author has developed a mobile-optimized chat application that collects the user's typing data. The data gathered from the application has been analyzed to identify patterns or statistical distributions that may correlate with the user's age. This can give insights into the feasibility of the aforementioned goal.

The application has been developed with clean architecture and secure coding practices in mind. It is also user-friendly for all age groups, specifically the elderly. Correspondents ranging from age <25 to age >60 have used the application. The data gathered by the application corresponds with the expected data, taken from other research. Evaluation of the data could give interesting insights and ideas for future researchs on what kind of data can be collected by an application and how it can be analyzed. The architecture of the application might also be a reference or inspiration for a more advanced application built for research in this topic.

This thesis contributes by paving the way for a more advanced research on this topic. Some insights or idea from this thesis could be valuable for future research in user profiling or cognitive assessments.

7.3 Future Work

A lot of improvement can be made to the application to further explore the possibility of using application for early detection of neurodegenerative diseases. Some of the possible future work are:

- Gather and evaluate more complete data to be able to make a more accurate analysis.

  An example of this is to collect data of the device used by the user. Different device could affect the typing pattern of the user. Another data that could be evaluated is the time of the day when the user is using the application. This could also affect the typing pattern of the user, since the user might be more tired at the end of the day. The mother tongue of the user could also be an interesting data to be collected and taken into evaluation, since different language could affect the speed of typing of the user. Some other data that could be collected are gender, the user's education level, health status, or even the user's mood. These data could also affect the typing pattern of the user and could be interesting to be evaluated.

- Implement real-time analysis of the typing pattern.

  Real-time analysis of the typing pattern could be useful to give instant feedback to the user. This might also give more interesting insight

towards the end goal, since real-time analysis would be important for early detection of neurodegenerative diseases.

- Categorize the user in an age group based on the typing pattern.

  The data collected has been analyzed to identify some basic patterns, but there are still a lot of work to be done to be able to evalute more accurately. A more accurate evaluation is needed to find a way to categorize the user in an age group based on the typing pattern. Based on evaluated data, an algorithm or model could be developed to make an assessment of the user's age based on the typing pattern.

- Analyze typing pattern to detect early signs of neurodegenerative diseases.

List of Figures

List of Tables

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