School of Computing, Engineering and Technology

Hons Project Report

Adaptive User Interfaces in Educational Apps: A Machine Learning Approach for Older Students

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This report is submitted as part of the requirements for the degree of

BSc (Hons) Computing (Application Software Development)

I confirm that the work contained in this Honours project report has been composed solely by myself and has not been accepted in any previous application for a degree. All sources of information have been specifically acknowledged and all verbatim extracts are distinguished by quotation marks.

Abstract

The rising global life expectancy has significantly increased the number of older adults seeking lifelong education, highlighting the urgent need for inclusive and adaptive digital learning environments. As educational technology rapidly evolves, ensuring that user interfaces (UIs) accommodate the diverse needs of older learners is critical. This research hypothesized that Machine Learning (ML)-driven Adaptive User Interfaces (AUIs) could enhance accessibility, usability, and engagement for learners aged 65 and above by dynamically personalizing key UI elements such as font size and image scaling.

A prototype educational application was developed using Flask, integrating a Random Forest Regression model trained on demographic and interaction data. Structured testing sessions combining quantitative metrics and qualitative user feedback demonstrated that ML-adapted interfaces reduced task completion times and improved subjective comfort and readability compared to default interfaces, supporting the initial hypothesis.

Beyond the immediate findings, this research contributes to the field of Human-Computer Interaction (HCI) by demonstrating how lightweight, real-time personalization strategies can bridge accessibility gaps without compromising usability or security. It also underscores the transformative potential of ML in the educational sector, suggesting that adaptive UIs can foster greater inclusion, improve digital engagement, and promote equity for under-represented demographics such as older adults. Moreover, by moving beyond purely theoretical models, this project offers a practical framework for real-world ML implementation in user-centric applications, inspiring future discoveries and research in lifelong learning systems and adaptive design across wider demographics.

Contents

Chapter 1

Introduction

1.1 Background

The trend towards digitisation and the development of educational technologies in higher education has been ongoing, with a significant acceleration following the COVID-19 crisis. The transition to digital learning spaces has modified systems, roles, dynamics, and the learning environment beyond the physical in higher education institutions [Bygstad et al., 2022]. These changes aim to improve the student experience and learning process. However, these rapid technological advancements in the education sector can present challenges for older adult learners. This population often faces factors or conditions that can cause difficulties when interacting with digital platforms and mobile devices [Taipale et al., 2024].

During the academic period of 2021-2022, there were 605,675 university students aged 30 or over (see Figure 1.1), totalling approximately 22.29% of UK higher education students [HESA, 2022].

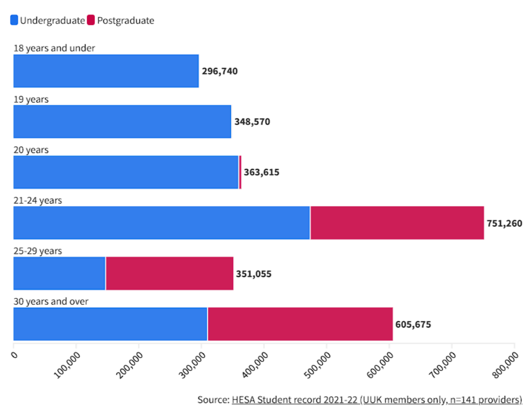


Figure 1.1: HESA, 2021-2022. UK domiciled students by age

Moreover, data collected from the Universities and Colleges Admissions Service (UCAS) show that in 2017, 12% of students entering undergraduate programmes were aged over 40 [UCAS, 2017]. The studies and statistics highlight an overlooked area in the educational sector regarding older adults' ability to keep up with an ever-evolving digital world.

1.2 Project Motivation

In recent years, there has been several studies evaluating the interaction between mobile phones and older adults. A study conducted by Nasrin Navabi and Jannat-Alipoor [2016] with 328 Iranian adults aged over 60, indicated that a majority of participants used mobile phones for basic communication and held unfavorable attitudes towards the devices, highlighting a technological barrier. Nevertheless, according to the Pew Research Center [2024] investigation on mobile phone usage patterns guided in the US "Mobile Fact Sheet", there is a growing dependency among older adults towards mobile phones B.1. In 2023 16% of the participants over the age of 65 reported living with a smartphone dependency in compliance with the survey.

Furthermore, the study by Pirhonen et al. [2020] suggests that older adults actively engage with technology, recognizing both benefits and complications. They appreciate social connections and access to information but manifest concerns about exclusion and loss of control. This infers that digitization can exacerbate inequalities if not designed inclusively.

Similarly, a more recent study [Taipale et al., 2024] suggests that older generations tend to have a "Narrow" usage of mobiles phones. Despite this, deeper analysis reveals an increased usage of mobile phones among older adults within the 7 countries where the research was being carried out.

Taking in consideration these insights, it is important to explore UI technologies that adjust specifically to older adults, enhancing their interaction with technology avoiding implementations that could confuse or scare them. This project aims to contribute to bridge the gap between mobile technology and older users by developing a more inclusive UX (user experience), ultimately fostering greater digital engagement and reducing inequalities within the education sector.

1.3 Problem Definition

In today's educational context, blended learning—integrating face-to-face and online methods—is often identified as the most effective learning approach implemented by higher education institutions since the pandemic, COVID-19, strongly enhancing engagement and flexibility. However, new challenges have emerged, including access to technology, digital literacy, and training for educators.[Imran et al., 2023]. These challenges are likely to impact older adults due to psychological, physical or socioeconomic factors.

Older adults, often face digital exclusion from limited access to resources, unfamiliarity with digital tools, and various socioeconomic barriers. Tomczyk et al. [2022] highlight the importance of providing educators with resources and formal training to promote digital inclusion among marginalized groups, such as older generations, in the academic sector. whilst this study lacks quantitative data, it offers valuable insights when compared to similar research by Caliandro et al. [2021] that suggests that older adults often exhibit network privatism—using technology primarily to maintain private social connections—rather than technophobia. they tend to be cautious with smartphone use, favouring practical applications over social or entertainment purposes. This approach is considered as a strategic and private form of social connection, rather than a fear or limitation for using technology.

Despite the ongoing debate regarding whether older generations' limited technology use origins from a lack of inclusion or practicality, it is common for them to experience Technophobia and technology anxiety—the fear or discomfort associated with interacting with digital devices or systems [Kim et al., 2023]. Thus this project aims to implement Adaptive Machine learning in older adult engaged in education for improving their interaction with educational apps and smartphones, As well as researching on existing tools to identify the most effective approaches.

1.4 Aim and Objectives

1.4.1 Aim

The aim of this project is to develop an adaptive user interface system that enhances digital accessibility for older adults by implementing machine learning to automatically adjust font sizes and image/icon scaling. This system will collect user interaction data, analyse usage patterns, and make personalised interface adaptations to improve the user experience

1.4.2 Objectives

- Investigate current adaptive user interface (AUI) technologies for older adults, assessing strengths and weaknesses related to accessibility, focussing on font and image scaling
- Identify user needs for adaptive UI/UX by gathering insights from older adult learners (65+) on their experiences with educational apps, specifically their preferences with font and icon scaling
- Develop and implement a machine learning model that dynamically adjusts user interfaces based on user preferences and age
- Design a prototype featuring adaptive font size and image scaling, then test it using user feedback to evaluate the employability of machine learning for Adaptive UI.

- Assess the machine learning model based on feedback to determine its adaptability and accuracy for older users specific preferences, based on user testing feedback.

1.4.3 Prototype Overview

As part of this project, a prototype educational application will be developed using Flask, a Python-based web framework for server deployment. The prototype will integrate adaptive UI principles and a separate machine learning (ML) model designed to enhance UI/UX for older adults in educational applications. The key components of the prototype include:

- **Adaptive UI Implementation:** Develop a user-friendly educational app prototype that applies best practices in adaptive user interface design.
- **Machine Learning Integration:** Implement an ML model that analyses user interaction data to provide personalized recommendations for font and image scaling.
- **Dynamic Font and Image Scaling:** Adjust text and image sizes based on user interaction patterns to improve readability and accessibility.
- **User Personalization:** Allow users to manually adjust recommended font and image sizes, with these inputs feeding back into the ML model for continuous improvement.
- **Local Flask Deployment:** Host the prototype on a local Flask server with a web-based interface for testing and demonstration.
- **User Testing:** Conduct evaluations through user testing, interviews, and embedded feedback forms to refine the adaptive UI approach.
- **Data Privacy and Storage:** Store user preferences and interaction data anonymously, ensuring privacy and ethical data collection practices.

This prototype aims to demonstrate the potential of machine learning in enhancing adaptive UI/UX for older adults, optimizing readability and usability in educational applications.

1.5 Methodology Overview

The proposed methodology consists of four stages: literature review, data collection, prototype implementation, and testing and evaluation. The process begins with understanding the problem and identifying all relevant factors. A survey will then be conducted, targeting a wide range of age groups to compare data from various demographics with the target demographic of older adults.

Following this, a prototype will be developed using Python libraries such as Flask and Scikit-learn. This prototype will serve as a sample educational platform and will integrate a machine learning model built using the survey data. The model will be designed to predict user interface element sizes based on user information.

Finally, the prototype will undergo one-to-one testing sessions to gather both qualitative and quantitative feedback. These insights will help evaluate the success of the project and identify areas for improvement.

1.6 Significance and Impact

Older adults represent a growing demographic for higher education institutions, yet many are at risk of being excluded from digital education due to design inadequacies and accessibility barriers. This project's focus on machine-learning-enabled adaptive interfaces has potential for profound social and educational impacts. It promises to improve participation in lifelong learning, foster engagement, enhance the well-being of older users, and significantly reduce existing inequalities and impediments in the educational sector.

Chapter 2

Project Scope

The aim of this project is to develop a system that enhances digital UI/UX for older adult students, aged 40 and above, Implementing ML-powered technology solutions. The scope includes evaluating current AI-driven Adaptive UIs, with a focus on ML-powered designed. learning, analysing their strengths and weakness, usability and accessibility. Subsequently, reviewing relevant literature in older adults' digital interactions, machine learning applications for Adaptive UI generations for a personalized experience (e.g., font size adjustments, personalized layout changes, brightness and more.), and how machine learning can be implemented in mobile phones, mobile applications and the education sector.

The project will conduct a comprehensive evaluation of existing UI Improving technologies includable in educational settings, focusing on their effectiveness and accessibility for older adult as learners. This evaluation will analyse the strengths and limitations of current tools, with special attention to usability and accessibility features.

Using these insights, the project will design a prototype shaped for older users, The prototype will provide UI guidance and recommendations, including app suggestions based on usage patterns, settings adjustments tailored to user preferences, and UI changes based on collected data, with caution of not being excluding, difficult or aggravating to users.

Thereafter, rigorous user testing will be conducted to evaluate the prototype's usability, accessibility, and user perception.; To refine the design and discussing the feasibility of an ML-supported solution for the targeted demographic. The project will ultimately deliver guidelines for inclusive digital platforms, with a focus primarily on mobile devices and educational applications, acknowledging limitations such as advanced accessibility and constraints of ML implementation on mobile devices.

2.0.1 Key Phases

The project scope includes the following key phases:

1. Design and Development: the project will involve designing and developing a prototype capable enhancing UX adapted to the specific needs of older adults. The design process will emphasize creating user-friendly, visually accessible interfaces that support intuitive navigation and accommodate age-related considerations using ML algorithms to suggest the most appropriate UI component.

2. User Testing: The project will incorporate user testing with older adult participants to gather feedback on the prototype designs. This feedback will guide iterative refinement of the interface to ensure that it aligns with the preferences and comfort levels of the target demographic. The data collected from the testing and prototype will be handled in compliance with the Data Privacy laws, more detail in F.1.

3. Guidelines and Recommendations: The project will culminate with a set of guidelines and recommendations for both technology developers and users. These recommendations will enhance inclusivity on digital platforms and systems used in education, promoting better engagement and reducing digital inequalities for older adult learners.

4. Literature Review: The following literature review will examine existing research to better understand older adults' interactions with digital technologies, in addition with a focus on machine learning, the applications in mobile technology, the application as educational tools, and user interface design. This review will establish a foundational understanding of barriers, usability challenges, and potential solutions to improve digital accessibility for older adults. The following literature review will examine existing research to better understand older adults' interactions with digital technologies, emphasizing machine learning applications in mobile technology, educational tools, and user interface design. This review will establish a foundational understanding of the barriers, usability challenges, and potential solutions to improve digital accessibility for older adults.

2.1 Literature Review

To understand the factors related to Older Adults, Education, ML and Smartphones. It is essential to synthesise existing relevant research in these topics. This approach will provide a clearer comprehension of the key points studied in this project. Ensuring the application of recent and credible academic sources, Increasing the credibility and impact of this research.

2.1.1 Understanding Older Adults as User Group

As stated by the World Health Organization (WHO) The population aged 60 and over will increase from 1 Billion (forecasted in 2020) to 1.4 Billion by 2024. It is prognosticated that by 2050 the this demographic will reach 2.1 Billion

[World Health Organization, 2024a]. This significant increase in older adults population expectations would suggest a pertinent need to understand the elements and characteristics that influence the living conditions of sexagenarians. Although, life expectancy measures and population growth forecasts are useful for assessing mortality conditions within a population They often overlook unforeseen events like wars or pandemics [Heuveline, 2023]. Some research exhibit alarming analyses regarding life expectancy in UK. By 2020, the UK had fallen to 36th place in the international life expectancy Rank, as shown in Figures B.2 and **??**, suggesting a frightening decline in life expectancy compared to other countries, particularly those with similar economic conditions, and is suspected to be a consequence of rising income inequalities [Hiam et al., 2023]. Similarly, Marshall et al. [2019] emphasizes the concerns about a decreasing life expectancy in the UK, particularly among vulnerable groups and highlighting patterns of death related to drug use and suicide. Notably, this decline was evident before the COVID-19 crisis, which being a abnormal event that could distort life expectancy data. This analysis in academic and scientific sources, indicates a deterioration in the UK quality of life that is being provided to older adults or adults in the vicinity of that age range. This research aims to facilitate the incorporation of this demographic with both the technological and educational sector. Simplifying their inclusion in society and indirectly contributing to an increase in life expectancy.

Older Adults in Education

According to the World Health Organization [2024b], by 2030, one out of six people will be over 60 years old. This highlights the relevance of this demographic in society. However, this group is often isolated within the educational sector. Recent research by the CEDEFOP [2024] showed a 5.6% decline in lifelong learning participation among older adults in several EU countries in 2020. Similarly, in a study conducted between the year 2002 and 2009, with over 3.000 participants aged 50-69, it was revealed a decreased from 49.1% at Wave 1 to 39.7% at Wave 4[Government, 2018] in the number of participants taking engaging in education. This decline reflect different trends in both formal and informal learning. However, according to the Office for National Statistics [2022], there has been an increase in older adults declaring employment status to HMRC during the period 2014 until 2022 (see figure 2.1).

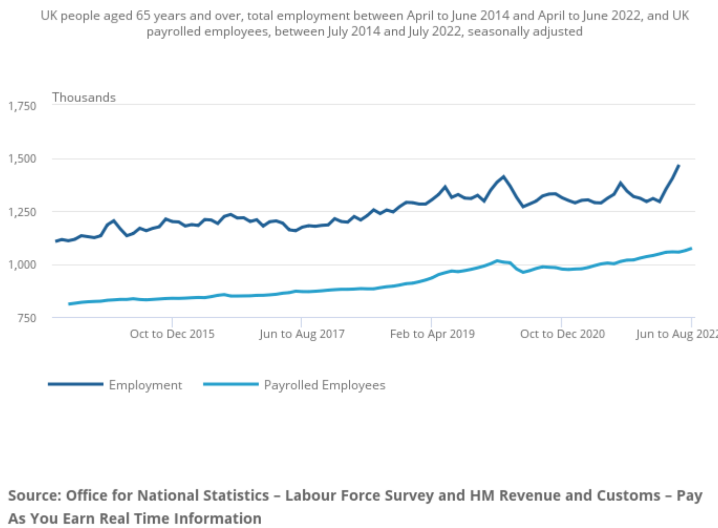


Figure 2.1: Employment of Older Adults (65 years and over) in the UK

This may indicate a societal transition toward older adults being more likely to maintain an active lifestyle due to increased global life expectancy and modern lifestyles.
The global population is ageing rapidly, leading to a growing need for education and learning programs designed for older adults, as indicated by [Boulton-Lewis, 2010]. Moreover, this research suggests that while there is limited empirical evidence proving that education prevents cognitive decline in ageing, it significantly enhances older adults' quality of life. This study also alludes to the absence of research exploring what older adults want and need to learn, relying instead on assumptions made by health professionals and researchers, which may result in ineffective programs, wasted resources, and increased isolation.

Likewise, Ahmad et al. [2022] point out a research gap regarding effective instructional strategies for teaching digital technologies to older adults. emphasizing the lack of systematic reviews on their learning needs and preferences. These literature gaps are particularly concerning given that lifelong learning has been shown to benefit older adults by significantly enhancing their psychological well-being, when implementing goal-oriented and activity-oriented programs rather than a purely learning-oriented approach [Kim, 2019].

Digitalization in the Educational Sector

E-learning has been rapidly adopted globally, with a notably acceleration since the COVID-19 pandemic. Although it has presented challenges for both educators and students, empirical research indicates that digitalization in education has become today's ordinary routine, already adopted for most universities [Rosak-Szyrocka et al., 2022].

Smartphones had been the key factor during this digitalization process, generally demonstrating a positive impact in areas like motivation and learning support. However, presenting new challenges like distractions and dependency[Ubben et al., 2023].

An alarming concern in today's world is the inequality that smartphone usage can create in education, enhancing learning for those with access, widening the performance gap between students with access to smartphones and those without or without technological dexterity to use them [Wang et al., 2023]. Likewise, Education is being influential by the recent advancements in AI technologies, highlighting furthermore the need for evolving the way students are being asses to ensure academic integrity [Pinto et al., 2023]

Older Adults' Interaction with Digital Technologies

The technological adaptability from older adults has significantly grown since the pandemic. Nevertheless, the need for technology reshaping into a more accessible, affordable and amicable designs for older adults have yet to be achieved [Drazich et al., 2023]. The "Digital Revolution" currently transforming the world can represent both a challenge and an opportunity for older people. Digital technology can impact positively older adults' life by decreasing loneliness, increasing social engagement, promoting physical activity, and improve overall health and long-term care. However, a successful implementation requires user training, technical support, and accessible content and features [Vincek et al., 2024].

2.1.2 Machine Learning in today's world

Machine learning is a data analysis method that allows computers to learn from experience using a analytical model by improving their performance using insights of collected data. Deep learning is a specialized branch of ML that uses artificial neural networks to imitate the way human brains work with the aim of providing solution to more complex or elaborated tasks like images or audio recognition or generation[Sharifani and Amini, 2023]. Similar studies emphasize the vast positive impact of ML on society, mentioning that these technologies are being underutilized at present for the fixation on theoretical advancements over real-world applications Rudin and Wagstaff [2014]. Additionally, A wide range of societal problems where machine learning has been successfully applied, including fraud detection, infrastructure maintenance, and weather prediction, among others.

ML and Smartphones

Currently, smartphones face hardware limitations such as power, performance, latency, and energy consumption, which represent challenges for implementing ML algorithms locally in mobile phones. The complications for ML in smartphones can be narrowed down to two main resource-intensive processes: training and inference, this stages are critical in the deployment of ML applications. Training involves sculpting a machine learning model from the available data, while inference utilizes this model to generate predictions based on new data Dai et al. [2020]. Five main approaches have emerged to address this:

1. Cloud inference without training: This method uses cloud-based ML-as-a-service (MLaaS) allowing mobile apps to send data to the cloud for predictions without on-device training.
    - Pros: It's fast and simple to implement
    - Cons: It uses a generic model for all the users. The security relies on the MLaaS provider.
2. Both inference and training in the cloud: In this approach the developers have flexibility from the MLaaS to train custom models via cloud services, accommodating diverse data types and volumes.
    - Pros: Supports customized models and can handle different data types.
    - Cons: Creates security concerns when sending user data to the cloud, especially if data is retained for model retraining—When the algorithm trains itself to be more accurate with new gathered data—.
3. On-device inference with pre-trained models: This method offers maximum privacy because data remains on the device. The app continuously learns from user data, updating its model for improved performance.
    - Pros: Enhances privacy, reduces latency since data is processed locally.
    - Cons: Only applicable for small datasets and simple ML algorithms due to resources limitations
4. Both inference and training on device: This architecture is ideal for privacy, allowing continuous learning from user data.
    - Pros: Ensures maximum data privacy since everything is processed on the device.
    - Cons: Only applicable for small datasets and basic algorithms due to resource constraints.Often requires Model Compression and Acceleration (method to reduce the resource consumption of an algorithm but it reduces accuracy)[Wang et al., 2018]
5. Hybrid approach: This combines cloud and on-device training. A general model is trained in the cloud using large datasets, then refined on individual devices using user-specific data.
    - Pros: Allows for personalized models that can adapt to individual user needs.

- Cons: Increases complexity and maintenance costs due to the dual processing environment.

Currently each model requires a trade-off , Choosing one will depend on the specific application requirements.

AI and UI/UX Enhancing

Artificial Intelligence (AI) is transforming artistic design and interactive digital media, improving both efficiency and creative potential with the application of technologies like generative adversarial networks (GANs), Machine learning and deep learning. Allowing AI to process a vast amounts of data AI enriches design by enabling a diverse, integrated approach, as seen with platforms like Netflix, which unify and personalize user experience [Liu et al., 2024]. This concept is vital to be comprehended as ML is one of the main branches of AI. Similarly, [Xu et al., 2024] Key findings show significant AI adoption in recent years and an incasement of apps leveraging AI for personalization. This personalization suggest a higher engagement, with apps featuring advanced AI seeing a 41% increase in daily active users

Intelligent User Interface and Adaptive User Interface

Intelligent User Interfaces (IUI) are a subset of Adaptive User Interfaces (AUI). AUI is the implementation of UI behaviour modification based on user preferences, needs, or contexts. They can be either user-controlled (adaptable) or system-controlled (adaptive). Similarly, IUI refer to the modification of the user interface applying artificial intelligence considering more factors and providing more personalised experience

2.2 Research Questions

In conclusion, we can reflect on the achievements of machine learning (ML) and its potential implementation for enhancing user interfaces to provide a more personalized experience. This leads us to the scientific question: Can adaptive user interfaces powered by machine learning be applied to improve the inclusion of older adults in education?

Chapter 3

Project Refinement

3.1 Scope and Literature Updates

Following early project development and a deeper engagement with the relevant literature, key refinements were made to both the scope and theoretical foundation of this research. Firstly, the target demographic was clarified to focus specifically on adults aged 65 and over, rather than adults aged 40 and above as initially stated, to better align with current research on digital inclusion challenges faced by older learners. Secondly, the literature review was expanded to incorporate a more detailed examination of educational platforms, particularly the distinction between Learning Management Systems (LMS) and Virtual Learning Environments (VLEs), their role in higher education, and their impact on older adult learners. Additionally, more material was integrated regarding user interface (UI) design principles, emphasizing the importance of perceived ease of use and perceived usefulness, as framed by the Technology Acceptance Model (TAM). These updates ensured a stronger theoretical grounding for the study, sharpened the research question, and reinforced the relevance of investigating machine learning-powered adaptive interfaces tailored to the needs of older adults within educational environments. A full record of these refinements is available in **Appendix A: Project Rescoping and Literature Expansions**.

Chapter 4

Design

This chapter outlines the overall design of the project, detailing the structured approach taken at each stage of this research, covering the main stages, collecting data to demonstrate the challenges older adults face in digital educational interfaces, training an ML model with the collected data, Implementing the ML model into a prototype using the Model in real time interaction and collecting feedback for both evaluation and ML training in a loop for better performance. This chapter provides an overview of the methodological framework, including research strategies, data collection processes, and the development of an ML-driven adaptive UI/UX prototype. Additionally, it introduces the evaluation process, which is further explored in Chapters 5 and 6.

4.1 Requirements

This section outlines the structured and prioritized requirements necessary for both the research and prototype development phases. These requirements were carefully decided to ensure an ethical, and user-centred approach taking in consideration the existing AUI recommendations Raghavendra et al. [2024].

4.1.1 Research Requirements

This phase establishes the prototype's foundation by combining a review of Adaptive UI (AUI) technologies, user studies, and iterative testing. It aims to understand older adults' needs, gather UI preference data, and develop an ML model for UI adaptation.

- **Review AUI Technologies:** Critically analyse AUI literature with a focus on accessibility, highlighting strengths, limitations, and ML-based personalization opportunities.
- **Identify User Needs:** Conduct academic user studies across age groups, prioritizing learners aged 65+, to isolate needs often missed by standard UI designs.

- **Collect UI Preference Data:** Use structured surveys and interaction tasks to gather data on text size, image scale, and UI perception factors Arambepola and Munasinghe [2020].
- **Train an ML Model:** Develop a Random Forest Regression model to predict UI settings based on demographics and usage patterns [Antoniadis et al., 2021].
- **Prototype Educational App:** Embed the model into a mock educational web app to simulate dynamic UI adaptation.
- **One-on-One User Testing:** Observe individual interactions with the prototype for qualitative insights and accessibility validation.
- **Evaluate Model and UX:** Measure model accuracy and UX quality using prediction errors, task times, and user satisfaction.
- **Conclude and Recommend:** Summarize findings and propose future improvements for scalable inclusive design.

4.1.2 Prototype Requirements

Functional Requirements

- **Adaptive UI Implementation:** Dynamically adjust text and image sizes based on ML predictions.
- **Manual Personalization:** Allow manual adjustments to refine model learning iteratively.
- **Feedback Loop:** Enable real-time learning from user interactions.
- **System Architecture:** Use a Flask-based client-server model with a web interface.

Non-functional Requirements

- **Responsiveness:** Ensure smooth, real-time UI adjustments.
- **Scalability and Efficiency:** Maintain a lightweight, scalable Flask backend.
- **Accessibility Compliance:** Follow WCAG guidelines for navigation and readability.
- **Data Privacy and Security:** Store data anonymously in compliance with GDPR.

User Requirements

- **User Testing:** Conduct usability tests and collect embedded feedback.
- **User Control:** Provide intuitive manual font and image size controls.
- **ML-Suggested Adjustments:** Show recommended settings with customize options.
- **Readability and Accessibility:** Tailor the UI for older adults.
- **Testing Support:** Ensure compatibility with observation tools like OBS Studio.

Constraints

- Complete within the project timeline to allow sufficient testing.
- Strict compliance with GDPR and data protection regulations.

4.1.3 MoSCoW Table

This table represents the expectations of the prototype, the priorities of each requirement and things that may be implemented in the future.

Requirement	**Category**
ML model recommending personalised font and image scaling	Must have
Manual adjustment options for font and image scaling feeding back into ML training	Must have
A Flask-based backend hosting the web interface	Must have
Anonymised user data handling compliant with GDPR guidelines	Must have
Suitable for testing in one-on-one sessions for detailed user feedback	Should have
Accurate prediction of recommendations with option of feedback	Should have
A guided testing feature that allows users to test the prototype without the researchers active participation	Should have
Advanced analytics dashboard for user feedback and insights	Could have
Integration with third-party educational platforms	Could have
Responsive design on both web and mobile devices	Could have
Full deployment on a public server	Future Enhancements
Support for complex multi-device synchronisation	Future Enhancements

4.2 Methodology

The methodology section describes the specific research approach and techniques employed in this project. It covers the target population, data collection framework, and the iterative design process used to develop and refine the prototype. This section also discusses the rationale behind the chosen methods, ensuring the reliability and validity of the findings.

4.2.1 Methodology Framework:

The development followed an iterative design methodology allowing continuous refinement of both the machine learning model and the prototype interface based on user feedback. Since the nature and objectives of this prototype prioritizes the successful implementation of the ML model aspect over the aesthetics.

4.2.2 Research Approach

This study adopts a mixed-methods approach, combining quantitative data collection through online surveys and usage analytics with qualitative insights gathered during user feedback sessions. This approach ensures a comprehensive understanding of the challenges faced by older adults in digital educational interfaces and develop an ML-driven prototype for enhanced UI/UX design to simplify this challenge.

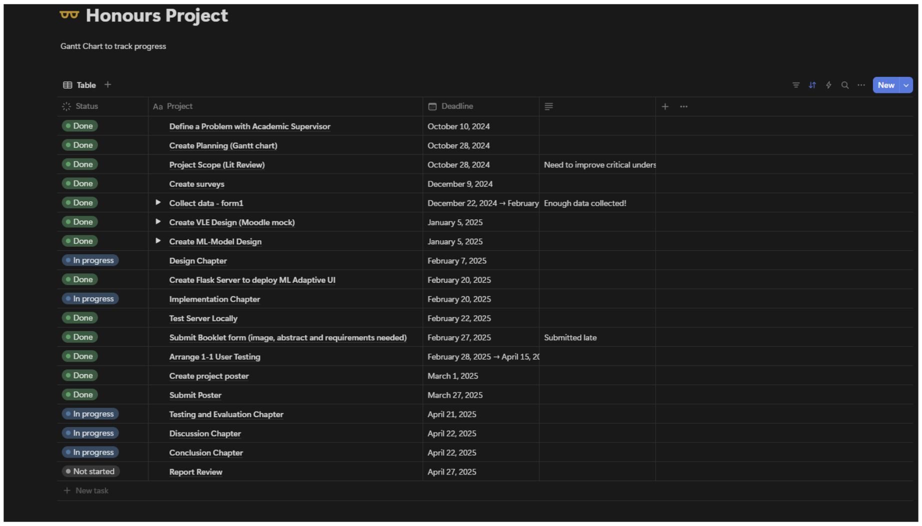
4.2.3 Target Audience

While the primary demographic is older adults aged 65 and above, the study also includes higher education students, educators, and lecturers. This ensures a holistic understanding of the needs and preferences across age groups. However, the primary impact of this research is on older adults using VLEs or educational platforms.

4.2.4 Project Planning

Given the complexity of this research project, it was fundamental to implement appropriate organization and planning methods to efficiently manage tasks and prioritize them. To assist with this, the project management tool selected was Notion[1] (more information available in Appendix E.1) for its simplicity and multiplatform availability, making it ideal for tracking project stages and tasks.

[1] https://www.notion.com/



Honours Project

Gantt Chart to track progress

Table

Status	Project	Deadline	
Done	Define a Problem with Academic Supervisor	October 10, 2024	
Done	Create Planning (Gantt chart)	October 28, 2024	
Done	Project Scope (Lit Review)	October 28, 2024	Need to improve critical unders
Done	Create surveys	December 9, 2024	
Done	Collect data - form1	December 22, 2024 → February	Enough data collected!
Done	Create VLE Design (Moodle mock)	January 5, 2025	
Done	Create ML-Model Design	January 5, 2025	
In progress	Design Chapter	February 7, 2025	
Done	Create Flask Server to deploy ML Adaptive UI	February 20, 2025	
In progress	Implementation Chapter	February 20, 2025	
Done	Test Server Locally	February 22, 2025	
Done	Submit Booklet form (image, abstract and requirements needed)	February 27, 2025	Submitted late
Done	Arrange 1-1 User Testing	February 28, 2025 → April 15, 2(	
Done	Create project poster	March 1, 2025	
Done	Submit Poster	March 27, 2025	
In progress	Testing and Evaluation Chapter	April 21, 2025	
In progress	Discussion Chapter	April 22, 2025	
In progress	Conclusion Chapter	April 22, 2025	
Not started	Report Review	April 27, 2025	

New task

Figure 4.1: Project plan in Notion.

In addition to tool-based organization, regular meetings between myself and my supervisor played a key role in maintaining consistent project planning. These meetings provided an efficient platform to discuss milestones, address challenges, and agree on immediate next steps, ensuring that the project progressed smoothly.

4.2.5 Data Collection Framework

The data collection process is structured into key components, each focusing on gathering valuable insights to inform the design of the adaptive UI.

Survey Design

The survey was ethically designed to gather user preferences for adaptable UI components, focusing on font and image scaling. Special attention was given to simplicity and accessibility to ensure inclusivity for older adults. The questions chosen for the survey and the relevance of each question can be found in Table F.1 in Appendix. The survey workflow and a mock-up of the form interface are provided in Appendix (see Figures F.1 and F.2). The questions used for this survey are listed below.

1. What was your preferred text size?
2. What was your preferred image size?
3. Do you have any challenges when interacting with a digital device? (Select all that apply)

4. Do you have any challenges when interacting with an application? (Select all that apply)
5. What type of device are you using right now?
6. What is your age?
7. How comfortable are you with technology? (1 = Not comfortable, 5 = Extremely comfortable)
8. What device(s) do you primarily use for educational purposes? (Select all that apply)
9. Are you a student in a formal or informal course?
10. What is your highest completed education level?
11. Which educational platforms have you used?
12. Provide feedback on the educational platforms you have used:
    - Blackboard
    - Moodle
    - Brightspace
    - Canvas
    - ATutor
    - Aula

4.2.6 Ethical Considerations

All research activities involving human participants were conducted in compliance with GDPR and institutional ethical guidelines. Participants provided informed consent before participation, and all data collected was anonymized to protect participant identity. The study ensured accessibility and inclusivity for older adults and followed ethical practices in digital data storage and analysis.

Data Privacy

All data collection procedures will adhere to ethical guidelines, ensuring informed consent and rigorous privacy protection measures. Following GDPR principles and always with the consent of the participants.

Dataset

All the data collected for this research is available in the project repository[2] and published as a dataset on Kaggle[3]. Participants were informed about the data usage and provided consent prior to the survey. The publicly shared dataset includes the cleaned and processed information that was used to train the machine learning model.

4.2.7 Prototype Design

The prototype consists of three primary, interconnected components:

1. **Dataset:** Following the processing, cleaning, and vectorization of the survey data, a structured dataset was generated. This dataset is used to train the machine learning (ML) model integrated into the prototype.
2. **Machine Learning (ML) Model:**
    - **Function:** The core component of the system, responsible for analyzing user data (e.g., age, health conditions, technological proficiency) to predict optimal UI element sizes such as font and image dimensions.
    - **Model:** A Random Forest Regression model was selected due to its robustness in handling non-linear relationships, high-dimensional data, and its ability to reduce overfitting. It is particularly suited for deriving personalized features from numerical user data.
    - **Development:** Built using the Scikit-learn library, the model predicts appropriate font and image scaling. A feedback loop was integrated, enabling the model to iteratively refine its predictions based on user adjustments, thereby enhancing both accuracy and personalization over time.

[2]https://github.com/DefoNotGus/ML_for_Adaptive_UI
[3]https://www.kaggle.com/datasets/defonotgus/ml-for-adaptive-ui

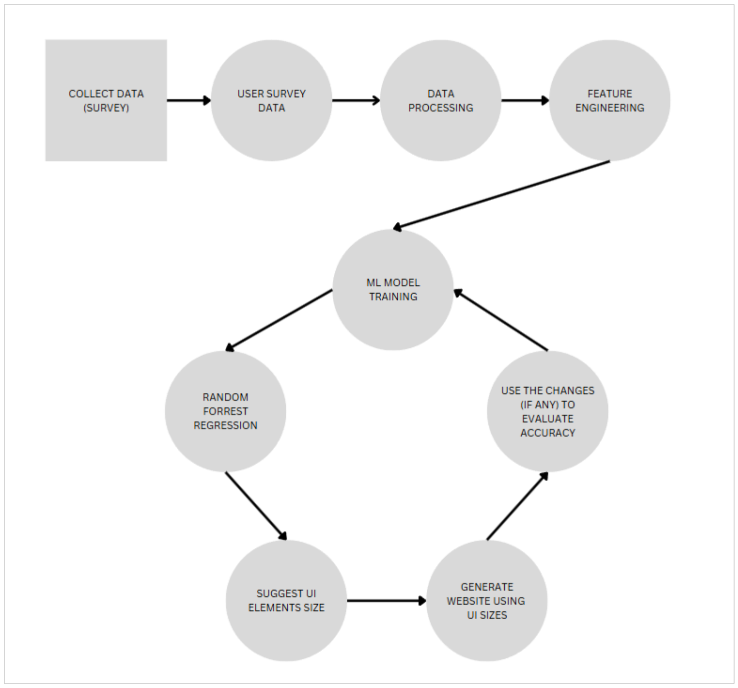


Figure 4.2: Machine learning process diagram

3. **Adaptive User Interface (AUI):**
   - **Wireframe and Design:** The design of the Adaptive UI is not very demanding but rather flexible as this research prioritizes the implementation of the ML technologies and functionality for testing. However an ideal design must provide a very basic design (see figure 4.3)
   - **Function:** The user-facing component of the system, implemented as a web-based educational platform. It demonstrates the personalization capabilities driven by the ML model and provides mechanisms for users to adjust the suggested settings.
   - **Aim:** To dynamically adapt font and image sizes based on ML predictions, thereby enhancing the accessibility and usability of the platform.
   - **Key Features:**
     - Displaying ML-recommended font and image sizes.
     - Allowing users to manually adjust these settings to better suit their preferences.
     - Capturing user feedback on adjustments and feeding this information back into the model for continuous improvement.

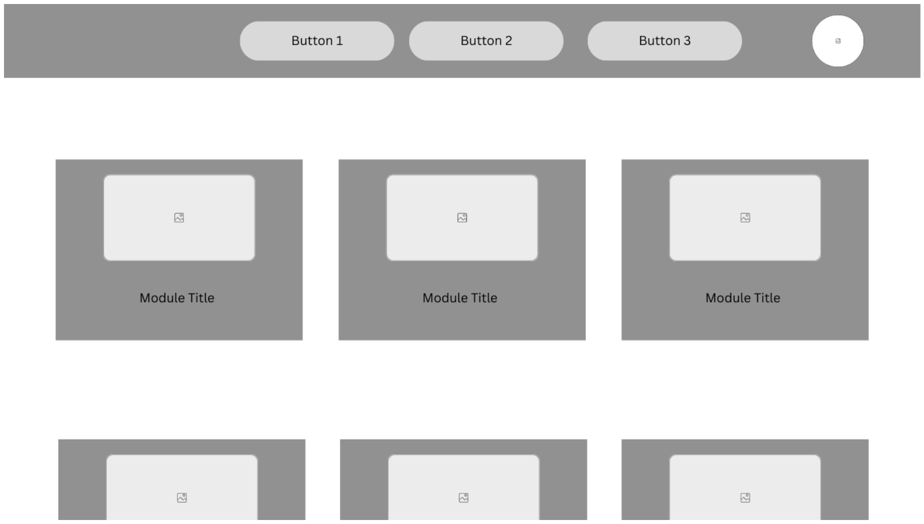


Figure 4.3: Webpage Wireframe

- **Development Stack:**
  - **Backend:** Developed using the Flask framework, selected for its scalability and lightweight design.
  - **Frontend:** Constructed with HTML, CSS, and JavaScript to support a responsive, real-time adaptive design.
- **System Architecture:** The system follows a client-server architecture. A Flask application hosts the website and serves as the API endpoint. User data submitted through the client interface is processed by the API, which applies the pre-trained ML model to generate personalized UI attributes and returns them to the client.
- **Deployment:** The artifact can be deployed using free-tier platforms that support Python or Docker applications. Render (more information available in Appendix E.1) was selected due to its accessibility, ease of integration, and strong reputation within the software development community [Saldana, 2024].

Prototype Functionality

The prototype operates systematically to apply machine learning predictions in real-time to adapt the user interface. Figure 4.5 presents a simplified representation of this process.

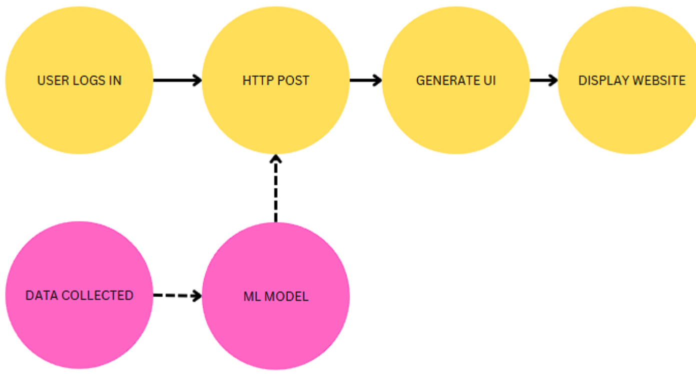


Figure 4.4: Simplified process diagram.

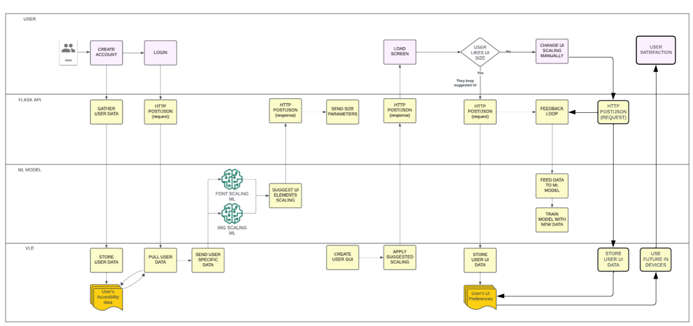


Figure 4.5: Detailed process diagram. For the full size, see Appendix C.1.

4.2.8 Testing and Evaluation

User Testing

One-on-one user testing sessions will be conducted using tools such as *OBS Studio* and *Google forms* to capture interaction data and real-time user feedback. This information will be recorded through video as well as survey forms or checklists to document performance and feedback. All recordings will be obtained with the users' informed consent and used exclusively for measuring the time of completion in the given tasks. Similarly all the forms will provide user anonymity and comply with GDPR

Post-Test Qualitative Questionnaire

- **1. Participant Background:** Are you currently a student or are you considering going back to education?
- **2. Prototype Impressions:** What aspects of the prototype did you like the most?
- **3. Areas for Improvement:** Were there any parts of the prototype you found confusing, uncomfortable, or would improve?
- **4. UI Preference:** Which UI style did you prefer overall — the default (standard) UI or the ML-adapted (personalized) UI?
- **5. Font and Image Size Feedback:** Which font and image size felt most comfortable for you while reading and navigating?
- **6. Usability Experience:** Did you encounter any difficulties when using the prototype? If so, what were they?
- **7. Smart UI Opinion:** How do you feel about the idea of a smart UI that automatically adjusts pages to your preferences?
- **8. Physical Comfort:** Did you experience any tiredness, eye strain, clicking difficulties or discomfort using either the default or personalized UI?
- **9. Perceived Helpfulness:** Do you believe a smart, adaptive UI could make learning platforms easier or more enjoyable to use?
- **10. Final Comments:** Any additional comments, suggestions, or ideas you would like to share about your experience?

Evaluation

Evaluation combined quantitative metrics, such as task completion time and recommendation accuracy, with qualitative assessments of usability and user satisfaction.The prototype was assessed using a combination of:

- **Quantitative metrics:** including task completion times and comparison of performance across similar tasks under default versus ML-adapted settings.

- **Qualitative feedback:** collected through user surveys and informal interviews to assess usability, accessibility, and perceived satisfaction.

Additionally, the adaptive artifact itself will be evaluated based on its ability to personalize user interface elements effectively, its responsiveness to user feedback, and the consistency of the improvements over multiple interactions. Findings from the evaluation phase will provide future recommendations, such as refining the machine learning model, exploring additional personalization features, applying the findings to diffent demographics and improving the user feedback loop for faster model adaptation.

Summary

This chapter outlined the structured design approach undertaken for this research, including requirement specification, methodological planning, prototype development strategies, and evaluation planning. The project was organized into the following phases:

- Initial Research and Literature Review
- Data Collection and Survey Deployment
- Machine Learning Model Development
- Prototype Implementation
- User Testing and Evaluation

These phases structured both the research process and the development timeline of the project. The next chapter describes the implementation phase, showcasing how the designs were realized into a functional adaptive learning platform.

Chapter 5

Implementation

This chapter presents the technical creation of the prototype, covering system architecture, module development, machine learning model implementation, frontend integration, testing, and deployment. Each section outlines the process, tools, and decisions made during development.

5.1 System Architecture

The system employs a lightweight client-server architecture based on Flask, serving two purposes:

- Hosting the user interface through rendered HTML templates and static assets.
- Delivering machine learning predictions via API endpoints for real-time personalized UI adjustments.

The folder structure to use for this project workflow is the available in the appendix C.2

5.2 Development Environment

Development was carried out on Ubuntu 22.04 LTS and Windows 11 (see full list in Appendix E.2). Ubuntu was selected for server-side Python compatibility, while Windows was used for frontend and general development tasks.

Key tools included:

- **IDE:** Visual Studio Code — lightweight, cross-platform, with strong Python and GitHub integration.
- **Version Control:** GitHub — for secure versioning and collaboration.
- **Deployment:** Render free-tier — for fast, cost-free hosting and GitHub integration.

- **Design:** Canva[1] and Sora[2] — used for wireframing and UI prototyping.
- **Testing:** Postman — for API validation, and OBS Studio — for recording usability sessions.
- **Planning:** Notion and Google Docs — for task management and project documentation.

5.3 Technologies and Tools Used

The core technologies for system development included:

- **Flask:** For modular, lightweight backend development.
- **HTML/CSS/JavaScript:** For dynamic, adaptable frontend design.
- **Scikit-learn:** For machine learning model training and evaluation.
- **Pandas and Numpy:** For efficient data cleaning and preprocessing.
- **Joblib:** For fast serialization and deployment of ML models.

5.4 Module Design and Development

The project was modularized into:

- **Routes Module:** Webpage rendering and API management.
- **ML Model Module:** Loading and serving predictions.
- **Feedback Module:** Capturing user adjustment data.
- **Results Module:** Displaying outcomes.

5.5 Data Collection Form Development

Data was gathered using a JavaScript-enhanced Google Form designed for accessibility and clarity (see form in Figure 5.1). The corresponding code snippet is available in Appendix D.1.

[1] `https://canva.com/`
[2] `https://sora.chatgpt.com/explore`

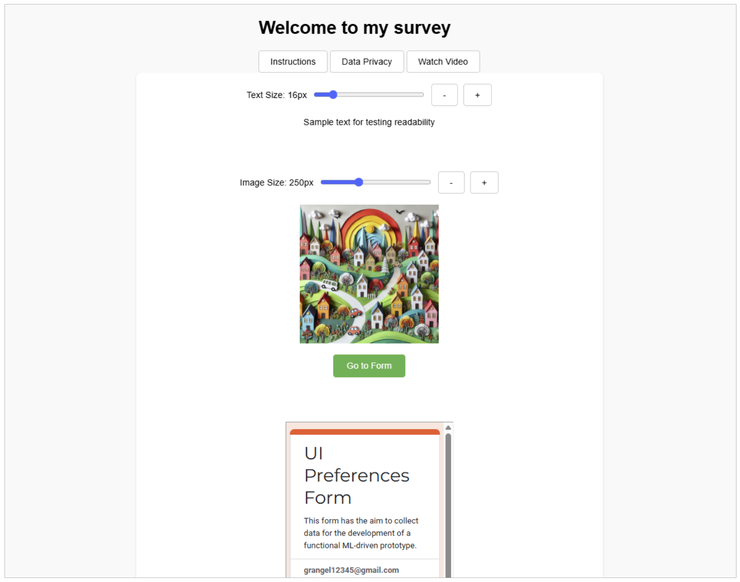


Figure 5.1: Survey Form Workflow

5.6 Data Cleaning and Preprocessing

Collected data was cleaned and preprocessed using Python and Pandas. The full data cleaning script is provided in Appendix D.2.

5.7 Machine Learning Model Training and Serialization

Separate Random Forest models were trained for text and image size prediction. The training code is provided in Appendix D.3.

5.8 Routing and User Flow

The Flask server defines multiple routes to manage navigation and enforce session controls. Example routing code is provided in Appendix D.4.

A simplified routing diagram is presented below:

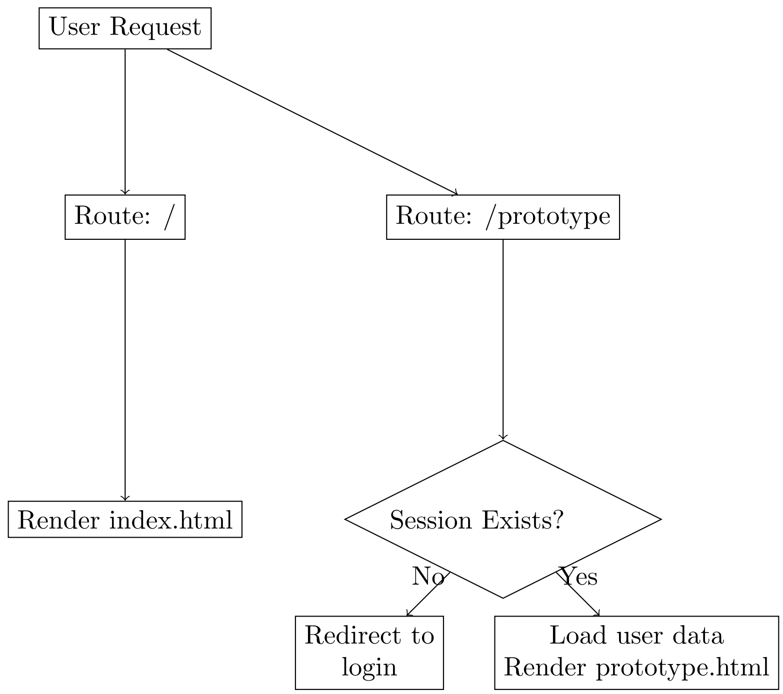


Figure 5.2: Flask Routing and Session Control Example Diagram

5.9 API Endpoint for ML Model Predictions

The server offers a RESTful web API that allows educational applications to integrate adaptive UI features seamlessly. By sending a JSON payload containing user attributes such as `age`, `Digital_Challenges`, `Application_Challenges`, `Education_Level`, and `Current_Device`, client applications receive a personalized UI configuration in return, specifically recommended values for `Text_Size` and `Image_Size`. This enables external systems to dynamically adjust their interfaces based on user needs, without requiring internal access to the ML models or training data.

API prediction endpoint code is available in Appendix D.5. Postman testing examples are shown in Figure 5.3 and Figure 5.4.

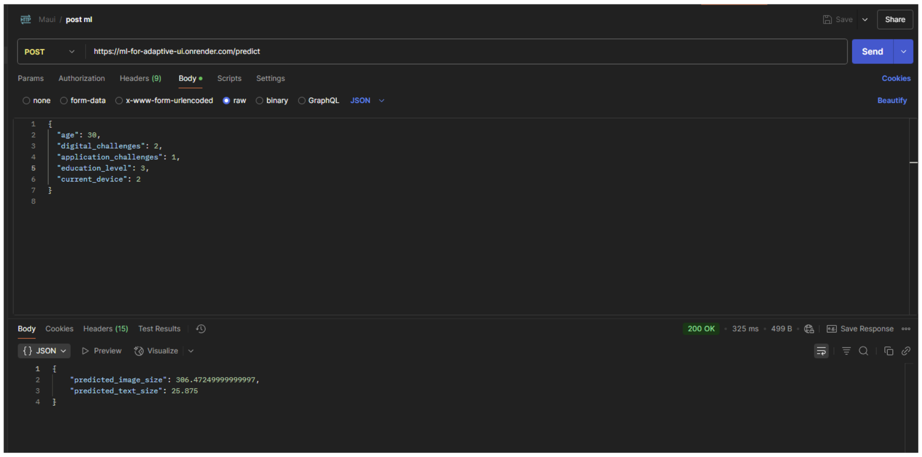


Figure 5.3: Testing API Endpoint with Postman

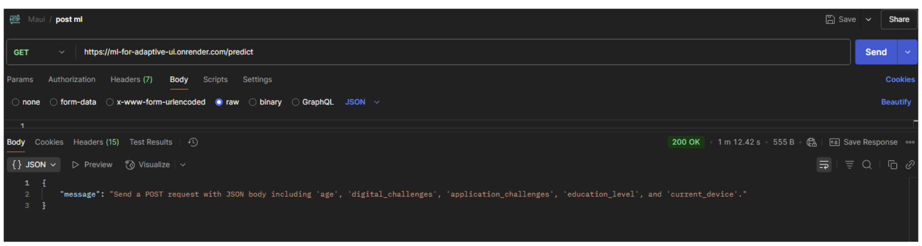


Figure 5.4: Testing GET HTTP with Postman

5.10 Frontend Integration

The frontend dynamically adapts text and image sizes based on ML predictions. Additionally, the prototype includes a toggle option that allows users to switch between the predicted UI settings and a default layout, supporting comparison and personal preference. This design choice reflects the variability of text presentation across existing educational platforms, as discussed in Appendix A.1. The CSS integration snippet is available in Appendix D.6.

5.11 Data Privacy and Security

Privacy was maintained by anonymizing data and hashing user identifiers using SHA-256. The hashing function is included in Appendix D.7.

Key measures included:

- Minimal required data collection.

- Anonymized data storage.
- User control over personal data.
- Frequent data purging.

5.12 Deployment

Deployment to Render required a `Procfile` (provided in Appendix D.8) specifying Gunicorn server configurations.

Deployment steps:

1. Connect GitHub repository to Render.
2. Configure build and start commands.
3. Deploy manually or automatically on Git push.

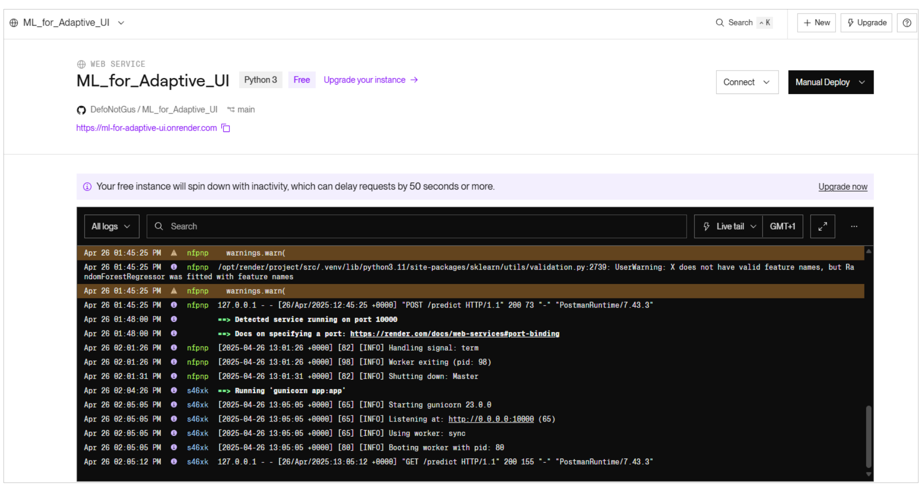


Figure 5.5: Deployment of Flask Application using Render

5.13 Integration and Testing

Testing procedures included:

- API verification with Postman.
- End-to-end manual testing.
- User testing with OBS Studio.

Performance metrics:

- Prediction accuracy.
- UI responsiveness.
- Server stability under multiple requests.

Summary

This chapter detailed the full technical implementation of the project, including system design, model training, backend/frontend development, and deployment. Strong attention was given to ethics, scalability, accessibility, and user-centric design.

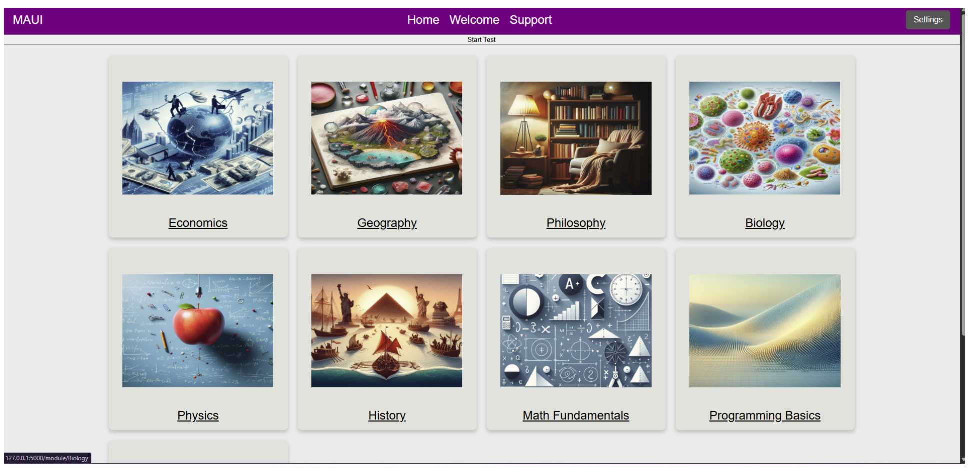


Figure 5.6: Final Adaptive UI Prototype Interface

The completed prototype (Figure 5.6) integrates a trained machine learning model with a Flask backend and a responsive web interface. It allows users to experience dynamically personalized UI settings based on their demographic and interaction data, including text and image scaling. A toggle feature enables switching between predicted and default UI states for comparative usability testing. The prototype was successfully deployed and tested, showing strong usability outcomes and validating the model's effectiveness. Its modular, open-source design further enables replication and future extension, highlighting the project's technical and research value.

Chapter 6

Testing and Evaluation

6.1 Result Hypothesis

It was hypothesized that a machine learning (ML)-driven adaptive UI would improve subjective comfort, readability, and navigation efficiency compared to default educational platform interfaces. It was expected that ML-adapted configurations would reduce eye strain and task completion times during sustained reading tasks [Wang et al., 2017].

6.2 Testing Methodology

Participants took part in one-to-one structured sessions, alternating between ML-adapted and default UI settings across three rounds. Each round involved common educational tasks, such as locating dashboard content and navigating lists. To mitigate bias, UI scaling presentations were alternated between rounds.

Participants were given a brief familiarization period with the prototype to customize settings before testing began. Afterward, a qualitative questionnaire collected feedback on usability, comfort, and UI scaling perception.

6.3 Prototype Deployment

To ensure testing consistency, the prototype was deployed locally on controlled machines, although it was also available online[1]. A fully integrated ML backend enabled real-time switching between UIs.

User interaction and timing data were logged automatically, with additional observation supported via OBS recordings to supervise participant behavior and timing accuracy.

[1] `https://ml-for-adaptive-ui.onrender.com`

6.4 Results

6.4.1 Task Completion Time

The ML-adapted UI consistently reduced task completion times compared to the default UI, as shown in Table 6.1.

Round	Average ML Time (s)	Average Default Time (s)	Difference (s)
Round 1	11.0	13.6	-2.6
Round 2	10.9	12.6	-1.7
Round 3	9.6	11.7	-2.1
Overall	**10.5**	**12.63**	**-2.13**

Table 6.1: Summary of average task completion times for ML-adapted UI vs Default UI across rounds.

Across all rounds, participants completed tasks on average 2.13 seconds faster using the ML-adapted UI. This supports the initial hypothesis that personalized UI scaling can enhance navigation efficiency in educational settings.

6.4.2 Qualitative Feedback

Participant feedback (see Table G.2) provided additional insights into the user experience.

Overall, most participants preferred the ML-adapted UI, citing improved readability and ease of navigation. The clean and simple prototype design was praised, although several participants suggested enhancements such as a search function and more precise scaling controls.

Usability issues were minor, mainly related to large buttons or module name recall during tasks. Physical comfort remained high, though minor eye strain was occasionally reported with smaller fonts.

Importantly, the adaptive UI concept was well-received. Participants appreciated the idea of dynamic personalization to ease navigation and reduce cognitive load, reinforcing the research hypothesis.

Note: Participants were unaware which UI version was machine learning-adapted, ensuring anonymous and unbiased feedback.

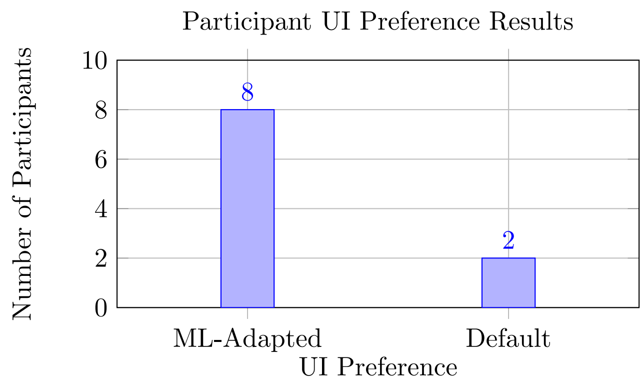


Figure 6.1: Participant preference for ML-adapted UI versus Default UI.

6.5 Evaluation

6.5.1 Research Findings

Testing outcomes strongly support the initial research hypothesis. Key findings include:

- Participants experienced higher visual comfort with ML-adapted UI settings.
- Task completion was faster on the ML-adapted UI across all rounds.
- Personalized scaling improved readability and content accessibility without overwhelming users.

These findings align with prior accessibility research, emphasizing the value of dynamic UI personalization for educational applications.

6.5.2 Prototype Assessment

The prototype successfully demonstrated real-time ML-driven UI adaptation. Strengths identified during testing include:

- Seamless real-time switching between ML and default interfaces.
- Effective improvements to visibility and readability without sacrificing usability.
- User appreciation for the ability to manually override ML-suggested settings.

Areas for future improvement:

- Introducing more personalization options, such as adjustable contrast and color themes.
- Providing enhanced onboarding instructions for new users.
- Expanding testing to larger and more diverse participant groups.

Chapter 7

Discussion

7.1 Interpretation of Results

The testing results strongly support the initial hypothesis: machine learning-powered adaptive UI scaling can significantly enhance both task efficiency and subjective comfort within educational interfaces for older adults.

Participants consistently completed tasks more quickly when using the ML-adapted UI and reported higher levels of satisfaction, readability, and navigation comfort. Qualitative feedback emphasized that dynamic interface adjustments helped reduce visual fatigue and cognitive load.

Overall, the prototype demonstrated that even relatively simple personalization — specifically, font and image size adjustments — can meaningfully improve the usability and accessibility of educational platforms for older learners.

7.2 Limitations

While the findings are promising, several limitations must be considered:

- **Controlled Environment:** The prototype was tested in a controlled setting, which may not fully capture the variability of real-world conditions, such as distractions, diverse hardware, or inconsistent network speeds.
- **Data Privacy Concerns:** Although care was taken to anonymize data, the handling of user information for ML-based personalization introduces potential security and privacy risks that require further mitigation strategies.
- **Small Sample Size:** With a participant group of only $n = 10$, the statistical power of the findings is limited. Broader studies are necessary to generalize the results across wider demographics.

- **Narrow Scope of Adaptation:** The prototype focused exclusively on font and image scaling, without addressing other critical accessibility features such as contrast adjustments, layout density, voice navigation, or adaptive feedback mechanisms.

Future research should address these limitations by expanding participant diversity, evaluating performance in uncontrolled environments, and incorporating a broader range of UI accessibility factors.

7.3 Future Work

Building on the findings and feedback from participants, several avenues for future work are proposed:

- **Expanded Personalization:** Integrate additional UI adaptations such as customizable color themes, adjustable button spacing, contrast enhancements, and animation control to accommodate a wider spectrum of accessibility needs.
- **Live Feedback Integration:** Develop real-time learning mechanisms where the system dynamically refines UI predictions based on ongoing user interactions, improving personalization without the need for manual input.
- **Scalability Testing:** Deploy the system in real-world educational environments with larger and more diverse user groups to assess scalability, long-term engagement, system robustness, and adaptation across multiple devices.
- **Broader Demographic Inclusion:** Extend user studies to include a wider range of ages, educational backgrounds, cognitive and physical abilities, and cultural contexts, ensuring the adaptive system remains equitable and inclusive.
- **Cross-Domain Applications:** Explore the implementation of ML-powered adaptive UIs in different domains, such as workplace platforms, healthcare systems, and entertainment apps, where accessibility and personalization could similarly enhance user experience.
- **Advanced Machine Learning Techniques:** Investigate the use of deep learning models or federated learning to allow more complex, privacy-preserving personalization strategies beyond size adjustments.

These directions offer the potential to significantly strengthen the adaptability, inclusivity, and ethical robustness of ML-driven user interfaces.

7.4 Discussion Overview

This project demonstrated the feasibility and potential impact of using machine learning to personalize educational user interfaces for older adults. Even relatively simple adaptations, such as dynamic font and image scaling, led to measurable improvements in usability, task efficiency, and user satisfaction.

Although the prototype's scope was deliberately narrow to allow focused experimentation, the results point to substantial opportunities for future refinement and expansion. Addressing the current limitations, particularly in terms of scalability, personalization breadth, and data privacy, will be crucial for advancing adaptive UI systems into broader educational and commercial applications.

Overall, the findings validate the promise of machine learning as a tool for creating more accessible, engaging, and inclusive digital environments for lifelong learners.

Chapter 8

Conclusion

This research successfully demonstrated that a machine learning-driven adaptive user interface (UI), personalizing font and image sizes, significantly improved the user experience for older adults engaging with educational platforms. Quantitative results showed enhanced task efficiency, while qualitative feedback reflected greater comfort and satisfaction compared to traditional static interfaces. The project followed a structured workflow: developing a Flask-based prototype, training a Random Forest Regression model on user data, and evaluating it through a mixed-methods approach.

Beyond its empirical success, the study contributes to Human-Computer Interaction by offering open-source tools—including the full codebase, trained models, and a structured dataset—allowing other researchers and developers to replicate, extend, or adapt the system. These resources pave the way for broader investigations into personalization, especially in accessible UI design. Importantly, the work underscores the potential of adaptive UIs to reduce technology anxiety and foster digital inclusion, particularly among older or digitally hesitant populations. Future research can build on this foundation by integrating more advanced machine learning models, expanding adaptive features, and addressing ethical concerns related to user data and personalization. This project affirms the value of accessible, intelligent UI design in shaping equitable digital learning environments.

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Appendices

This section contains supplementary material related to the research project, including relevant figures, development documentation, survey materials, results, and selected code listings.

1. **Appendix A: Project Rescoping and Literature Expansions**
   Corrections to the original project scope, updated research questions, and supplementary literature review covering educational platforms, VLEs, and UI accessibility for older adults.

2. **Appendix B: Relevant Sources**
   Key figures and research statistics related to smartphone usage, life expectancy, and adult education.

3. **Appendix C: Development Resources**
   Diagram outlining the full development process of the prototype.

4. **Appendix D: Code Listings**
   Selected important code snippets referenced in the Implementation chapter.

5. **Appendix E: Development Tools and Resources**
   Overview of software tools, libraries, and datasets used throughout development.

6. **Appendix F: Survey Questionnaire**
   Post-test questionnaire used for collecting qualitative feedback from participants.

7. **Appendix G: Results**
   Raw testing data, timing metrics, qualitative analysis graphs, and participant response summaries.

Appendix A

Project Rescoping and Literature Expansions

This chapter aims to correct errors from the previous chapter and expand on relevant concepts that should have been included to enhance understanding of the research domain.

A.1 Project scope corrections

In the Previous chapter it is stated that the aim of this project is **”to develop a system that enhances digital UI/UX for older adult students, aged 40 and above.”** However, it is important to clarify that the research population are Older Adults, Adults over 65 years-old.

A.2 Literature Review additions

This section contains relevant research material to understand the state of art of Educational apps and relevant concepts.

A.2.1 Educational Platforms and apps

The use of Educational apps, platforms and tools like Moodle, Turnitin, Microsoft Teams , and other digital platforms has become increasingly integral to the higher and further education experience in the UK. While these technologies offer benefits like 24/7 access to information and resources, they also introduce complexity and confusion as institutions adopt a variety of commercial and open-source systems. Challenges include integrating curriculum with computer-assisted learning, reduced interpersonal communication compared to face-to-face classes, difficulty meeting learning expectations, low student motivation and high distractions, and technical issues with devices and connectivity. Addressing these challenges requires institutions to provide training and support, design effective online and blended learning experiences, and leverage analytics to understand and improve student engagement and outcomes.

Learning Management Systems and Virtual Learning Environments

Learning Management Systems (LMS) and Virtual Learning Environments (VLE) serve different purposes in UK education. LMSs function like digital repositories or 'supermarkets', where course materials are stored and managed, providing students with constant access to resources. VLEs, likened to 'airports', offer a more interactive platform focused on collaboration and real-time engagement between students and teachers. While LMSs prioritise content management and progress tracking, VLEs emphasise creating dynamic spaces for active learning and student-teacher interaction [**?**]. Both tools are integral to modern digital education but serve complementary rather than identical purposes.

Virtual Learning Environments in UK

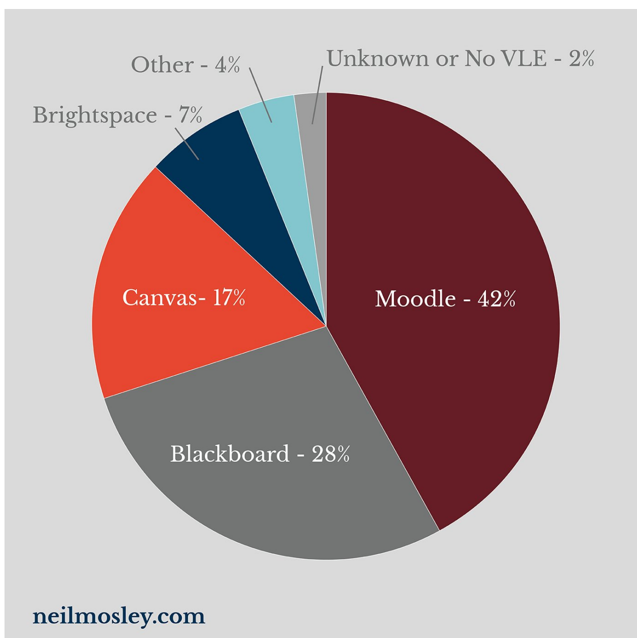


Figure A.1: Distribution of Virtual Learning Environment Market Share in UK Higher Education

Virtual Learning Environments (VLEs) like Moodle, Blackboard, and Canvas have become integral to higher education in the UK, particularly post-COVID-19 as institutions rapidly transitioned to online learning. Research like indicates that VLEs offer flexibility and access to a diverse range of educational resources. The Virtual Learning Environment (VLE) landscape in UK higher education shows a clear dominance of established platforms, with Moodle leading at 42% market share. According to Mosley's comprehensive analysis **?**, the market is primarily consolidated among four major providers: Moodle (42%), Blackboard (28%), Canvas (17%), and Brightspace (7%). This distribution reflects the sector's reliance on proven systems, with Moodle's open-source flexibility and extensive feature set maintaining its position as the preferred choice for UK institutions. The remaining 6% is divided between other solutions (4%) and institutions either without a VLE or with unknown systems (2%), indicating a highly concentrated market with limited diversity in platform adoption.

VLEs User Interface and Older Adults

A comparative analysis of three VLEs-Moodle, Caroline and Atutor—revealed Atutor's superior user interface design [**?**]. Atutor's effectiveness stemmed from its simplicity and personalisation features, specifically:

- Intuitive user control and navigation
- Reduced cognitive demands through simplified tasks
- Consistent interface elements across the platform

However, many VLEs and educational apps present significant challenges for older adult learners. Common barriers include small text sizes, complex navigation systems, and cluttered layouts that can be particularly challenging for users with age-related visual impairments. Furthermore, these platforms often assume technical proficiency that many older users have not developed **?**. The predominant focus on younger, tech-savvy users in VLE design can significantly impact older learners' engagement and educational outcomes, potentially limiting their access to online learning opportunities.

A.2.2 User Interface Concepts

With the rise of digitalization, humanity is in constant contact with computers, which translates into continuous interaction with user interfaces (UIs). This has prompted scientists and businesses to eagerly understand the factors involved in UI design and the way humans perceive them. According to [Ratzer et al., 2014], research proposes that UI perception is influenced by several factors. Initially, the study suggested that gender could be a determining factor. However, the findings revealed that gender does not play a major role; instead, other factors, such as age, education level, and familiarity with similar technologies, have a more significant impact.

In the work of [Alsswey and Al-Samarraie, 2020], it is highlighted that UI elements play a crucial role in user acceptance. However, the major impact is often related to the Technology Acceptance Model (TAM), which proposes that user acceptance of technology is primarily driven by perceived usefulness (PU) and perceived ease of use (PEU), both of which influence the user's intention to adopt the technology. This implies that if the UI design, including elements such as layout, images, colors, fonts, and buttons, is perceived as clear, simple, and culturally aligned, users are more likely to form positive attitudes and intentions toward the application.

A.2.3 Existing VLE's font-size

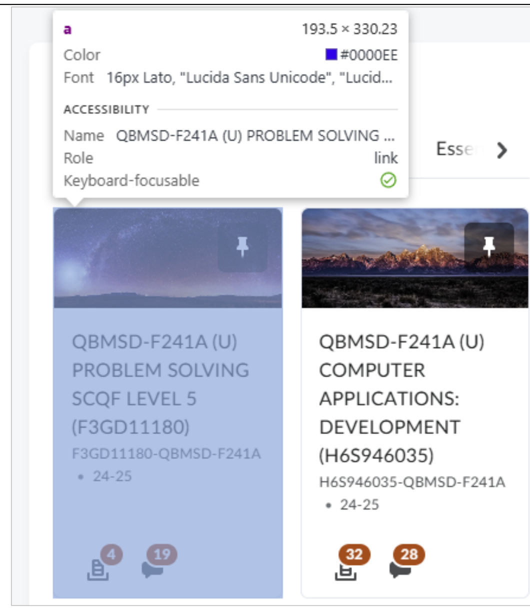
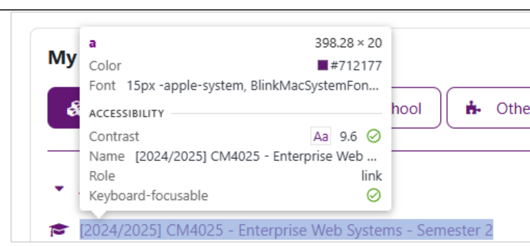
Platform	**Font Size Range**	**Screenshot Example**
Brightspace	16px – 19px	
Moodle	15px – 18.5px	

Table A.1: Font sizes and styles used in major Virtual Learning Environments (VLEs). Decorative or oversized fonts in welcome messages are excluded as they are not representative of main UI.

A.2.4 Existing Image and Icon Sizes

Unlike text styling, image and icon usage across Virtual Learning Environments (VLEs) such as Moodle and Brightspace does not appear to follow any consistent standard in terms of size, placement, or thematic relevance. Images are often decorative rather than instructional, and they frequently bear little to no direct connection with the educational content being presented. Iconography, while present for navigation or tool access, varies significantly in size and resolution depending on the user's device, screen size, and browser zoom settings. This lack of uniformity can contribute to inconsistent user experiences and may impact accessibility, particularly for users who rely on visual cues or require scalable, high-contrast visuals. The observed variability highlights an opportunity for improvement through adaptive UI design that adjusts visual elements more intelligently based on both device context and user needs.

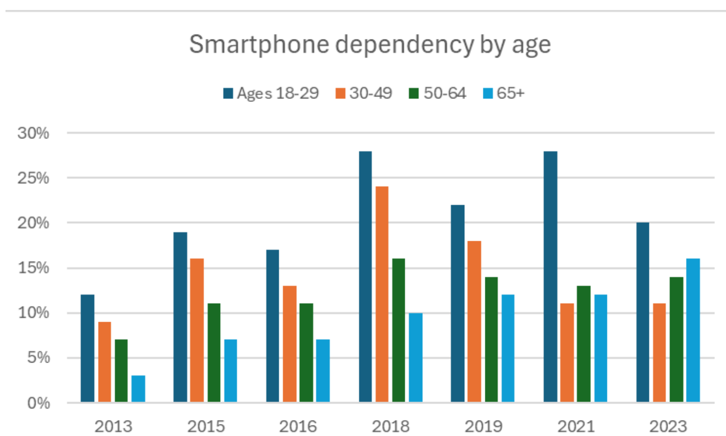
A.3 Research Questions

After deeper consideration from the literature review and the goal of this project, the project scope thrived in into a different path which seeks to answer the following primary question:

> **"Can machine learning-powered Adaptive User Interfaces, focusing on dynamic font and image scaling, improve accessibility and learning outcomes for adults aged 65+ in Virtual Learning Environments?"**

Appendix B

Relevant Sources



Pew Research Center - Mobile Fact Sheet - https://www.pewresearch.org/internet/fact-sheet/mobile/

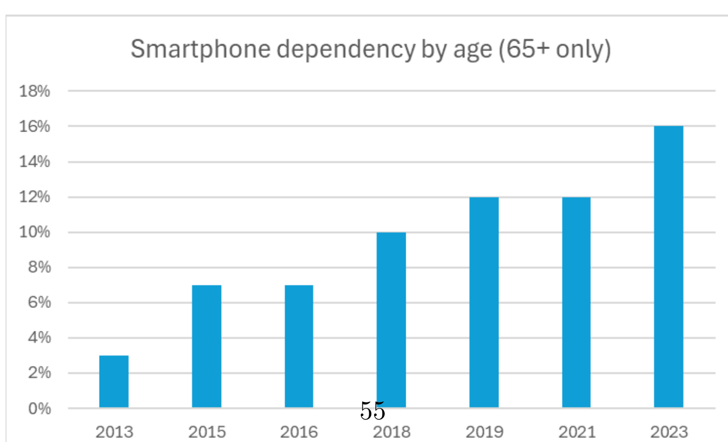


Figure B.1: Smartphone dependency by age, Pew Research Center (2013–2023)

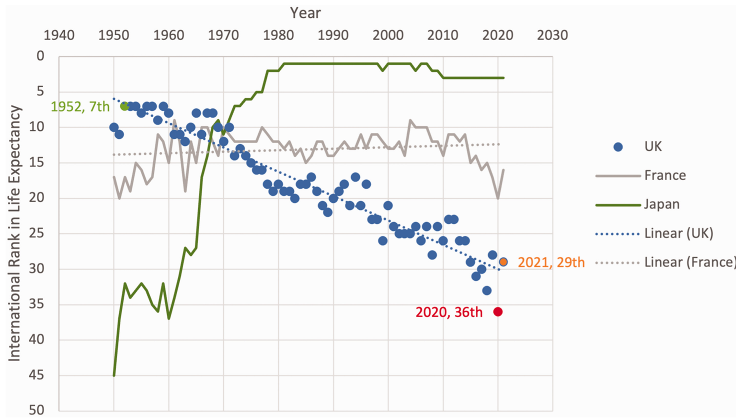


Figure B.2: UK rank in international life expectancy (1950–2021)

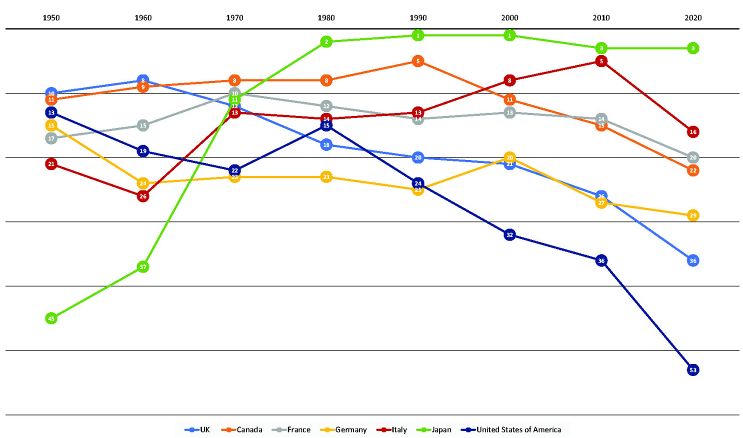


Figure B.3: Life expectancy rankings of G7 countries (1950–2020), UN Population Division

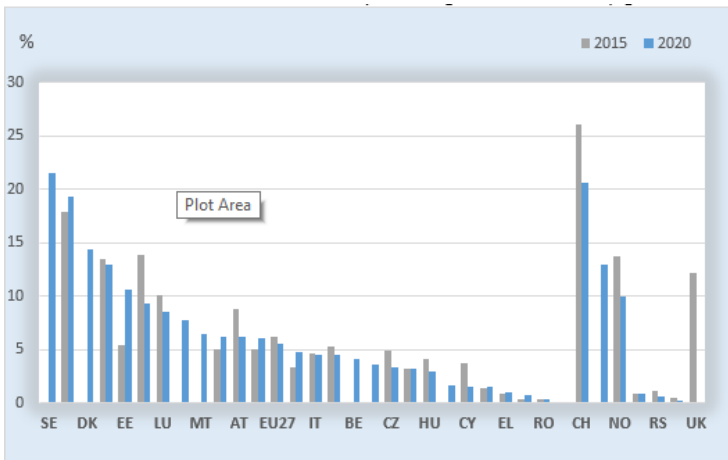


Figure B.4: Older adults' engagement in education and training in the EU

Appendix C

Development Resources

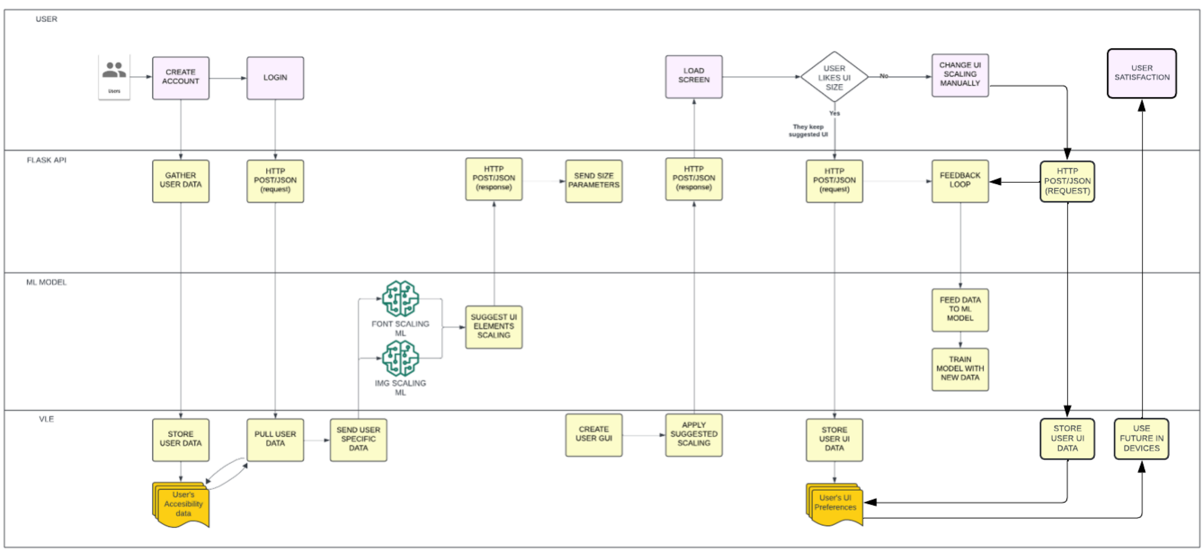


Figure C.1: Full-sized representation of the development process

- app.py
  Main Flask application
- requirements.txt
  Python dependencies
- data/
  JSON user data and course modules
- models/
  ML models, scripts, and datasets
- static/
  Frontend assets: CSS, JS, and images
- templates/
  HTML templates rendered via Jinja2

Figure C.2: Simplified Project Folder Structure with Descriptions

Appendix D

Code Listings

This appendix presents important code snippets referenced throughout the Implementation chapter. Full project code is available in the project repository[1].

D.1 Form Interface Code

HTML snippet of the JavaScript-enhanced Google Form used for data collection.

```html
<div class="controls">
  <label for="textSizeSlider">Text Size: <span id="textSize">16</span>px</label>
  <input type="range" min="10" max="50" value="16" id="textSizeSlider">
  <button onclick="adjustText(-1)">-</button>
  <button onclick="adjustText(1)">+</button>
</div>
```

D.2 Data Cleaning Script

Python script used for cleaning and preprocessing the collected CSV survey data.

```python
# data_processor.py
import pandas as pd
df = pd.read_csv('form1.csv')[['Text_Size', 'Image_Size', ...]]
df['Education_Level'] = df['Education_Level'].map({
    'Primary/Elementary school':2,
    'Secondary/High school/GCSE':3,
    "Bachelor's degree":6
})
```

[1] https://github.com/DefoNotGus/ML_for_Adaptive_UI

```
df.to_csv('data.csv', index=False)
```

D.3 Machine Learning Model Training Code

Python code to train and serialize the machine learning models.

```
# mlmodel.py
data = pd.read_csv('data.csv')
data.fillna(...)
X = data[['age', 'Digital_Challenges', 'Application_Challenges', ...]]
y_text = data['Text_Size']
y_image = data['Image_Size']

rf_text = RandomForestRegressor().fit(X, y_text)
rf_image = RandomForestRegressor().fit(X, y_image)
```

D.4 Sample Routing Code

Example of Flask routing implementation with session checking and rendering.

```
# app.py
@app.route('/')
def index():
    return render_template('index.html', username=session.get('username'))

@app.route('/prototype')
def home():
    if "username" not in session:
        return redirect(url_for("login"))
    users = load_data(USER_DATA_FILE, {})
    username = session.get("username", "guest")
    user_data = users.get(username, {"text_size": 16, "image_size": 100})
    courses = load_data(MODULES_FILE, [])
    response = render_template("prototype.html", course_modules=courses, **user_data)
    response = app.make_response(response)
    response.headers["Cache-Control"] = "no-store, no-cache, must-revalidate, max-age=0"
    response.headers["Pragma"] = "no-cache"
    response.headers["Expires"] = "0"
    return response
```

D.5 API Endpoint Code

Code for the machine learning API endpoint receiving user data and returning predictions.

```python
# app.py
@app.route("/predict", methods=["POST"])
def predict():
    if request.method == "GET":
        return jsonify({
            "message": "Send a POST request with JSON body including 'age', 'digital_challenges', 'application_challenges', 'education_level', and 'current_device'."
        })
    data = request.get_json()
    input_data = np.array([[int(data[field]) for field in fields]])
    return jsonify({
        "predicted_text_size": float(models['text_size'].predict(input_data)[0]),
        "predicted_image_size": float(models['image_size'].predict(input_data)[0])
    })
```

D.6 Frontend Integration Snippet

CSS variable injection to dynamically adapt UI settings based on ML predictions.

```
<style>
:root {
  --image-size: {{ image_size | default(100, true) }}px;
  --text-size: {{ text_size | default(16, true) }}px;
}
</style>
```

D.7 Security Hashing Code

Python function used for hashing user identifiers using SHA-256 for anonymization.

```python
import hashlib
def hash_user_id(user_input):
    return hashlib.sha256(user_input.encode()).hexdigest()
```

D.8 Deployment Configuration

`Procfile` used to deploy the Flask application on Render with Gunicorn.

```
# Procfile
web: gunicorn -w 4 -b 0.0.0.0:10000 app:app
```

Appendix E

Development Tools and Resources

E.1 Tools

- **Notion**: Used for project management and documentation. https://www.notion.com/
- **Render**: Used for backend and frontend deployment. https://render.com/
- **GitHub**: Source code repository and version control. https://github.com/
- **Kaggle**: Hosting of the published dataset for external access and reproducibility. https://www.kaggle.com/datasets/defonotgus/ml-for-adaptive-ui
- **Scikit-learn**: Machine learning model development in Python. https://scikit-learn.org/

E.2 Tools and Their Purpose

Table E.1: Summary of Tools and Their Purpose

Tool / Technology	**Purpose**
Ubuntu 22.04 LTS	Server environment testing; cloud-ready compatibility
Windows 11	Frontend development, general use
Visual Studio Code	Lightweight IDE with strong Python and Git integration
GitHub	Remote version control, backup, collaboration
Flask	Backend development, API creation
Render	Cloud deployment of Flask server
Scikit-learn	Machine learning model training
Pandas and Numpy	Data cleaning and preprocessing
Joblib	Model serialization for deployment
Canva and Sora	Design wireframes, mockups, icons
Postman	API endpoint testing
OBS Studio	Usability testing recordings
Notion	Project management and task tracking
Google Docs	Development log and note-taking

E.3 GitHub Repository

- Complete Project Repository: `https://github.com/DefoNotGus/ML_for_Adaptive_UI`

Appendix F

Survey Questionnaire

F.1 Data Protection Compliance

This survey complies with the Data Protection Act 2018, GDPR, and the Human Rights Act. Personal data will be securely processed solely for research purposes. Participants will be informed of their rights regarding data access, amendment, or deletion. Security measures will be implemented to prevent unauthorized access, and no discriminatory or invasive questions will be included. Paper-trail methods will only be used when absolutely necessary.

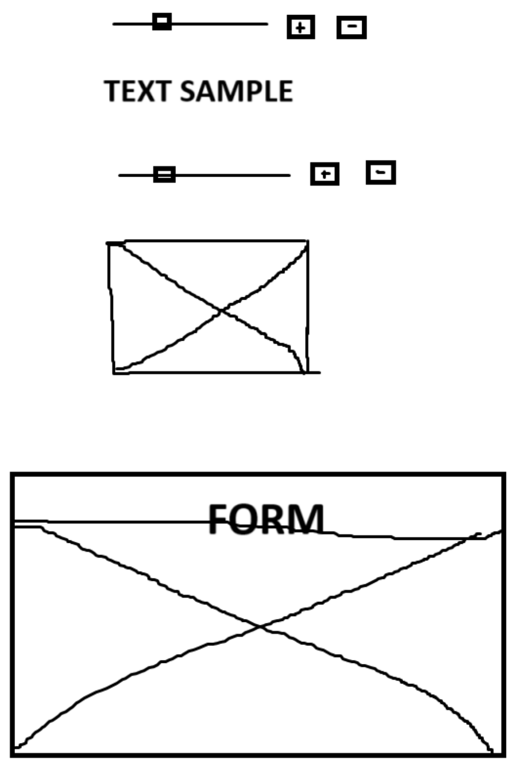


Figure F.1: Workflow of the form design process

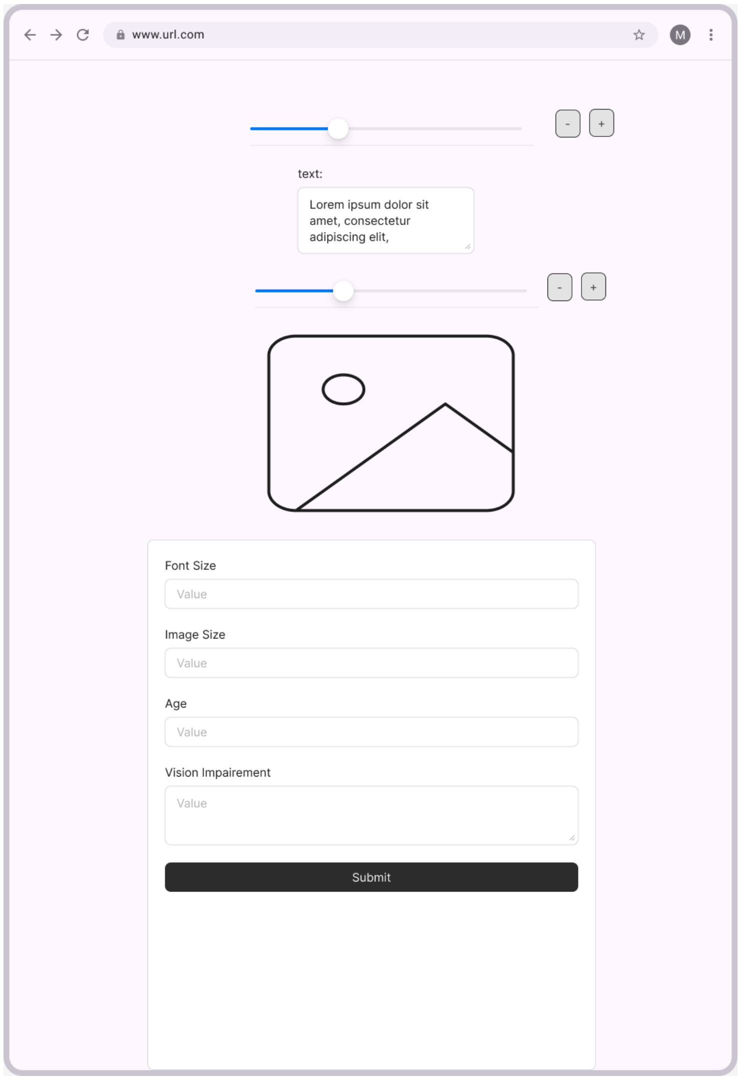


Figure F.2: Mockup of the user interface form

F.2 Survey Question Relevance

Table F.1: Survey questions and their relevance to research objectives

No.	Survey Question	Research Purpose
1	Preferred text size	Assess text readability needs
2	Preferred image size	Assess visual clarity needs
3	Challenges with digital devices	Identify accessibility issues
4	Challenges with applications	Identify usability issues
5	Current device used	Understand device context
6	Age of participant	Demographic categorization
7	Technology comfort level	Measure tech proficiency
8	Educational device usage	Understand learning device preference
9	Student status	Determine formal vs informal learners
10	Education level	Gauge educational background
11	Platform usage	Identify platform exposure
12	Platform feedback	Assess platform satisfaction

Appendix G

Results

Participant	**Age**	**ML-suggested 1**	**Default-size 1**	**ML-suggested 2**	**Default-size 2**	**ML-suggested 3**	**Default-size 3**	**Fails**	**Avg ML**	**Avg Default**	**Difference**
user1	66	7	8	6	9	7	8	0	6.67	8.33	-1.67
user2	63	8	9	7	7	6	7	1	7.00	7.67	-0.67
user3	78	12	18	18	25	10	15	5	13.33	19.33	-6.00
user4	66	15	20	16	14	11	15	3	14.00	16.33	-2.33
user5	70	16	18	18	20	17	20	5	17.00	19.33	-2.33
user6	65	10	12	8	8	9	10	1	9.00	10.00	-1.00
user7	62	8	8	7	8	6	7	0	7.00	7.67	-0.67
user8	67	9	10	7	7	8	9	1	8.00	8.67	-0.67
user9	81	14	17	12	16	13	14	2	13.00	15.67	-2.67
user10	74	11	16	10	12	9	12	4	10.00	13.33	-3.33
Average		11.0	13.6	10.9	12.6	9.6	11.7	22	10.5	12.63	-2.13

Table G.1: Detailed participant results showing ML-suggested and default sizes across rounds.

N°	Background	Prototype Impressions	Areas for Improvement	UI Preference	Font and Image Size Feedback	Usability Experience	Smart UI Opinion	Physical Comfort	Perceived Helpfulness
1	Student	Liked the clean look	Some icons weren't clear	ML-adapted	Preferred the big one	No major difficulties	Good idea	No issues	Potentially helpful.
2	Considering education	Easier to navigate than Brightspace	Search button would be good	ML-adapted	Good sizes	Remembering module names was hard	Very useful	Eyes got tired	Yes
3	Student	Personalized UI interesting	Buttons too big and slow to scroll	ML-adapted	Images too big	Trouble finding button	Open to it	No issues	Potentially helpful
4	Student	Simple design	Hard to scroll down	Default	Smaller text preferred	Easy to use	Convenient idea	No issues	Yes
5	Considering education	Adaptive features were cool	Hard to register	ML-adapted	Bigger text preferred	Difficult to scroll	Would try it	Mouse control difficult	Yes, for sure.
6	Student	Clear, intuitive design	Images too big, text too small	Default	Standard font and images	Easy navigation	Likes idea, wants more customization	No issues	Definitely Yes
7	Student	Good	None	ML-adapted	Larger text and images	Minor issues	Time-saving potential	Felt tired after a while	Helpful
8	Considering education	Easy to use	Test confusing	ML-adapted	Large font and icons	Easy to use	Nice concept	No issues	Definitely!
9	Student	Simple and clean	Clearer instructions needed	ML-adapted	Liked first sizes	No difficulties	Great idea	Small text caused difficulty	Yes, absolutely.
10	Student	Good idea	Features not intuitive	ML-adapted	Wanted a medium size	Test difficult	Liked idea	No issues	Yes

Table G.2: Summary of Participant Feedback on Prototype Usability and Adaptive UI Experience