A HYPER PERSONALIZATION MODEL FOR DETERMINING END USER COMPUTER DEVICES SPECIFICATIONS

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A Thesis Submitted to the Institute of Postgraduate Studies of Kabarak University in Partial fulfilment of the Requirements for the Award of the Master of Science in Information Technology Degree

KABARAK UNIVERSITY

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The thesis entitled "**A Hyper Personalization Model for Determining End User Computer Devices Specifications**" and written by **Kevin Kamiri Karanja** is presented to the Institute of Postgraduate Studies of Kabarak University. We have reviewed the research thesis and recommend it be accepted in partial fulfilment of the requirement for award of the degree of Master of Science in Information Technology.

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DEDICATION

I dedicate this study to my parents, Francis Karanja Kamiri and Eunice Kamaara Karanja, and to my dear sister, Edita Wairimu.

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I would like to express my sincere gratitude to the individuals who provided encouragement, support, and guidance during the period in which I conceptualized and implemented this thesis. Foremost, I am deeply thankful for the unwavering support and guidance by my supervisors Prof. Simon Karume and Dr. Andrew Kipkebut. I extend my heartfelt appreciation to my family members who provided me with encouragement and understanding throughout my master's program, especially during the period in which I was writing this research thesis. Their support and understanding were invaluable.

ABSTRACT

This research addresses the prodigality of device specifications, where end users both individuals and institutions often purchase computer devices that do not match their needs due to a lack of technical understanding and reliance on biased, company-centric information from online agents. This often results in substantial resource wastage. The proposed solution is a hyper-personalization model, implemented as a chatbot, that prioritizes the end user rather than the product. The methodology involved developing a robust model that integrates machine learning algorithms specifically Bidirectional Encoder Representations from Transformers (BERT)-based models, hybrid recommendation engine filtering collaborative, content-based and Natural Language Processing (NLP). The study utilized a mixed-method design, gathering quantitative and qualitative data from end-users in corporate institutions within Nakuru town, Kenya. Findings indicate that consumers prioritize Features and Price but face significant structural challenges, including feeling overwhelmed by technical specifications and encountering too many options. A key insight is the substantial majority of respondents expressing a high likelihood of adopting a personalized recommendation system. The implemented hyper-personalization chatbot model was validated to effectively address these issues by aligning device specifications with complex user needs. The study concludes that this model significantly enhances user satisfaction, optimizes resource utilization, and establishes a clear, non-prejudiced path for informed device selection, offering a tangible contribution to consumer empowerment and organizational efficiency.

Keywords: *Hyper-Personalization, Chatbot, End-User Device Specifications, Machine Learning, Natural Language Processing, Hybrid Recommendation System*.

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LIST OF ABBREVIATIONS AND ACRONYMS

AI - Artificial Intelligence
AIA - Artificial Intelligence Agent
AMD - Advanced Micro Devices
AMOLED - Active-Matrix Organic Light Emitting Diode
API - Application Programming Interface
BERT - Bidirectional Encoder Representations from Transformers
BUS - Business User Satisfaction
CCAI - Conversational Chatbot Artificial Intelligent
CDP - Customer Data Platforms
CMS - Content Management Systems
CNN - Convolutional Neural Networks
CPU - Central Processing Unit
CRF - Conditional Random Fields
CRM - Customer Relationship Model
CRVWWDA - Central Rift Valley Water Works Development Agency
CV - Computer Vision
DSR - Design Science Research
GDC - Geothermal Development Company
GHz - Gigahertz
GPU - Graphics Processing Unit
GPT - Generative Pre-trained Transformer
HDD - Hard Disk Drive
HDMI - High-Definition Multimedia Interface
IBM - International Business Machines
iOS - Iphone Operating System
IT - Information Technology
IOT - Internet of Things
LCD - Liquid Crystal Display
LLM - Large Language Model
LSTM - Long Short-Term Memory networks
LTE - Long Term Evolution
KUREC - Kabarak University Research Ethics Committee

NACOSTI - National Commission for Science, Technology and Innovation
NAWASSCO - Nakuru Water and Sanitation Service Company Limited
NER - Named Entity Recognition
NFC - Near Field Communication
NLG - Natural Language Generation
NLP - Natural Language Processing
OLED - Organic Light Emitting Diode
ONNX - Open Neural Network Exchange
OS - Operating System
PRISMA - Preferred Reporting Items for Systematic Reviews and Meta-Analyses
RAM - Random-Access Memory
SSD - Solid State Drive
SVM - Support Vector Machines
UMUX - Usability Metric for User Experience
USB-C - Universal Serial Bus Type-C
Wi-Fi - Wireless Fidelity
YOLO - You Only Look Once

CONCEPTUAL AND OPERATIONAL DEFINITION OF TERMS

Chatbot: A computer program designed to simulate conversation with human users, especially over the internet.

Device Specification: The detailed technical information and features of a particular electronic device.

End User: A person or group who ultimately uses a product or service with interaction of application or systems.

Flask: a lightweight Python web framework used to build web applications and APIs.

Gigahertz: A unit of frequency equal to 1 billion cycles per second, commonly used to measure processor speed.

Hyper personalization: Use of advanced technologies, data analytics, and artificial intelligence to deliver highly individualized and tailored experience for each user request.

Hybrid Filtering: A recommendation system technique that combines content-based and collaborative filtering to give more accurate and personalized recommendations

Machine Learning: A key component of chatbot development that allows chatbots to understand and respond to human language.

Natural Language Processing: A branch of artificial intelligence that enables computers to understand, interpret, and respond to human language in a way that is both meaningful and useful.

SpaCy: An open-source Python library for Natural Language Processing (NLP). Residual Network is a type of deep neural network that helps train large language models image recognition tasks.

Wireless Fidelity: A technology that allows devices to connect to a wireless local area network using radio waves.

CHAPTER ONE

INTRODUCTION

1.1 Background of the Study

Meeting end user needs has always been a challenge especially in these times of rampant change in technology. Information builds up on a daily basis requiring big data analytics (Carlander-Reuterfelt et al., 2020). The challenge for end users lies in navigating a complex landscape of determining if the devices they are using meets the efficiency they require. Many users prioritize functionality without delving into the intricate workings of devices. This often leaves them in a quagmire, unsure if the devices adequately meet their needs. The intricate technological know-how needs to be broken down in simple steps that a user can quickly understand and therefore be equipped to select a device that meets their operation needs(Kvale et al., 2021).

Take the case of a user who needs a laptop but has no idea which one is suitable for them. Most of the time device specification is done through manual assessment based on user profiles. The details of specification must be explained to them or gone through by an Information Technology professional within the institution. Online platforms will give this user brands, budget and product details but do not answer basic questions of users such as how many people the device they are looking to buy will serve or how much they wish to consume on material over a given period. Consider the example of a mobile phone. All users have different preferences. Some prioritize camera quality while others prioritize the security aspect or simply telecommunication. Most of these questions are answered by live customer chat from website platforms which tend to be biased since they are doing business (Kulkarni et al., 2017). Finally, the user is guided to purchase a device only to realize later that it does not meet their requirements or the requirements are overboard leading to wastage in resources to end users and institutions at large.

A hyper personalization model is proposed as a solution to this challenge, giving priority to the end user rather than the product itself. The model will be a chatbot that targets customers with tailor-made specifications (Rane et al., 2023a). The unique aspect of this model is that it performs hyper-personalization, a technique of tailoring end user devices based on user profile data, artificial intelligence and advanced algorithms from different sources like social media to expertly recommend a product. An end user will specify their needs for the specific device that they are looking for and the model will provide optimum recommendations without prejudice of products. The chatbot will also create a better working environment for end users in institutions**.**

This hyper-personalization chatbot would make recommendations to users for usability and comfort in device specification.(Patel & Trivedi, 2020a) . A chatbot is a software program created to mimic conversations with humans, primarily online (Adamopoulou & Mouspad, 2020). These bots can be embedded in messaging platforms, mobile applications, and websites, and are commonly used to automate customer service, provide information, or carry out other tasks. Some chatbots utilize natural language processing (NLP) to interpret and respond to user inputs, while others follow predetermined scripts or decision trees (Maher, 2020). They can interact using various inputs, such as text, voice, or even facial expressions and gestures (Simonite, 2017a). Additionally, chatbots can be integrated with external systems to retrieve data and perform functions like booking flights, ordering food, or making purchases (Aishwarya Gupta, 2020).

Another scenario is when a user has a general idea of the devices, they are interested in but lack knowledge about the upgraded or more suitable options in the market. They would invoke a question to the model about a device they have in mind and in response, the model would propose the most suitable device. In other cases, where a user makes inquiry about a device, the hyper personalization chatbot will give a clear background check and provide the functionality pros and cons.

Device specifications involves a range of challenges, especially as technology advances and user expectations evolve. Some of the key challenges include: Rapid technological evolution which is constantly evolving, with new components and features being introduced regularly (Dimitriadis, 2020). Keeping device specifications up-to-date and relevant in a fast-paced technological landscape can be challenging. Diverse user needs are another aspect where different users have diverse needs and preferences when it comes to devices. Postulating a device that caters to a wide range of user requirements while balancing cost, performance, and features can be a challenge.(Pollmann et al., 2022).

Technical constraints are where device specifications are often limited by technical constraints such as size, weight, power consumption, and cost. Balancing these constraints while delivering optimal performance and user experience can be a complex task. Devices must be compatible and interoperable with various software, hardware, and network systems to ensure seamless integration and performance. Ensuring compatibility and interoperability across different platforms and ecosystems can present challenges in specification design.(Qaffas, 2019).

Regulatory compliance as a factor on devices to comply with various regulatory standards and certifications related to safety, electromagnetic interference, environmental sustainability, and data privacy. Ensuring compliance with relevant regulations adds complexity to the specification process (Paterson, 2022).

User experience design to device specifications should not only focus on technical aspects but also consider the overall user experience, including usability, accessibility, and ergonomics. Informing specifications that prioritize user experience is a limiting factor.

Market competition in the technology market is highly competitive, with numerous manufacturers vying for consumer attention. Specifying devices that stand out in a crowded marketplace and offer compelling features and value propositions is a significant challenge (Laussel et al., 2019). Cost management is a critical factor in device specification, as consumers often seek affordable yet high-quality products. Balancing cost considerations with the need to deliver competitive specifications can be a challenging task for manufacturers.(Pukas, 2022). Supply chain management on device specifications can be impacted by supply chain constraints, including component availability, lead times, and manufacturing capabilities. Managing the supply chain effectively to meet specification requirements is essential for timely product delivery.

Examples of chatbot models include Chat Generative Pre-Trained Transformer (GPT), a conversational agent powered by Open Ai's GPT (Generative Pre-trained Transformer), including versions like GPT-3.5, GPT-3, and earlier iterations.(Aydin & Karaarslan, 2023) These models are designed to understand and generate human-like text based on the input they receive. ChatGPT can engage in conversations, answer questions, generate text based on prompts, and perform various other language-related tasks, serving as a versatile tool for natural language understanding and generation; Google Assistant: Google's virtual assistant can engage in conversations, answer questions, perform tasks, and control smart devices through natural language commands; Amazon Alexa: Amazon's virtual assistant that powers echo devices and can perform various tasks, answer questions, play music, set reminders, and control smart home devices;(Adam et al., 2021); Apple Siri: Apple's virtual assistant available on iPhone operating system (iOS) devices, macOS, watchOS, and home pod, which can answer questions, perform tasks, send messages, set reminders, and more; Microsoft Cortana: Microsoft's virtual assistant integrated into Windows operating systems, as well as other Microsoft products, capable of answering questions, setting reminders, sending emails, and performing other tasks; and IBM Watson Assistant: IBM's AI-powered virtual assistant designed to help businesses engage with their customers by providing personalized responses, answering queries, and assisting with various tasks.(Pal & Singh, 2019). There are also chatbots on messaging platforms. Many messaging platforms like Facebook Messenger, Slack, and WhatsApp host chatbots that can provide customer support, answer frequently asked questions, and perform specific tasks within the messaging environment.

The challenges of these models are biases to promote company devices and are not hyper personalised to focus on device specification. Using one or the other application depends on user preference. The proposed hyper personalization model has been developed to solve these challenges by its user-centric approach on device specification. Addressing these challenges using the hyper personalization model required collaboration among cross-functional teams, including engineers, designers, product managers, marketers, and quality assurance professionals, to ensure that device specifications meet both technical requirements and user expectations. This means that Information Technology (IT) departments have operational excellence with an easier time allocating devices to users based on specifications. This results in improved relationship between end users and IT departments (Wikström et al., 2021). The procurement stores would no longer waste money on incompatible devices as the model would provide due diligence assistance. Most importantly, performance of individual persons and institutions would improve. Additionally, human resource departments would eliminate poor performance of staff in use of computer device.

This research intended to meet End-user struggles of trusting a product based on performance or fame to give clients exactly what they need to ensure optimal resources utilization and performance.

1.2 Statement of the Problem

Technology has permeated every facet of life, and everyone must interact with it in one way or another. Many novice users apply technology but know little about technical IT terms such as Random-Access Memory (RAM) and Central Processing Unit (CPU) let alone device specification metrics. They therefore depend on the convincing power of salespersons or chat agents to purchase products. However, this approach has proven to be costly, inaccurate, and inconsiderate for end users. Device specification metrics determine the suitability of the use of a device (Kvale et al., 2021).

However, end users (both persons and institutions) buy devices which are below usage requirements at high cost or buy incompatible devices bloated in performance leading to wastage. Consequently, in this postmodern society most users have devices below functional value requiring them to spend more on resources. Device dealers use sale tactics to have end users buy devices without properly understanding their specifications. Sales persons will convince a client of the performance of a certain device which is not the case. This way, end users settle for limited information compared to a variety of resources that can be acquired from data driven approach.

A machine learning chatbot would be an appropriate solution to provide novice users with the necessary technical advisory support to enable them make an informed decision in purchasing the devices (Borsci et al., 2022). Since chatbot is not biased, it gives recommendations to the end user without prejudice. Hyper personalization is the new knowledge to this challenge; the study proposed a hyper personalization chatbot that would improve end-user interaction with computer device specifications. Instead of scaling through a search engine leading to diverse platforms the chatbot would bring all this information in one platform. Due to limited resources such as hard drive storage, a lot of institutions overspend on devices. This model would help users understand what resources are available and which ones can optimally meet their needs (Brandtzaeg & Følstad, 2017). For Example, a solution from the model generic hardware configuration in an office setup for four persons might function very well with a slow data network but another office with one user might require a higher internet bandwidth. The application would create an interactive user-friendly environment that ensures utilization and reduced wastage while helping users understand what devices are best suited for them.

1.3 Research Objectives

This section describes the primary goal or purpose of this research study.

1.3.1 Main Objective

The main objective of the study was to develop a hyper personalization model for determining end user computer devices specification.

1.3.2 Specific Objective

i. To explore various challenges end users, encounter when during device selection.

ii. To design a hyper personalization model for determining end user computer devices specification.

iii. To develop a hyper-personalization model that determines end-user device specifications based on user preferences.

iv. To validate the hyper-personalization model using machine learning metrics.

1.4 Research Questions

The researcher sought to find answers to the following questions.

i. What are the various challenges end users encounter during device selection?
ii. How can a hyper personalization model for determining end user computer device specifications be designed?
iii. How can a hyper personalization model for determining end user computer device specifications be developed?
iv. How does machine learning metrics validate the model and improve efficiency?

1.5 Significance of the Study

The study made the process of device selection customer-centric by developing a hyper-personalization model that informs and guide end users through new and efficient steps of determining device specifications. This not only reduced waste of computers but financial resources as well.

With this model, people will take more caution before purchasing computer devices creating a more responsible energy-saving society. Data science equips novice end users with better understanding of information technology improving their capacity to select efficient devices. This leads to optimal use of resources for maximum efficiency while minimising wastage. Consumer’s accountability and organisational performance significantly improves. Users would feel more appreciated as their needs would be better articulated and met. It opens gateways for other research problems of customer-centric nature meaning that the study is a steppingstone to innovative technologies, as it provides solutions to better customer-centric approaches.

1.6 Justification of the Study

There is wastage in computer resources simply because most end users either buy computer devices that do not meet their needs or they are not aware of the potential of devices they purchase. This challenge is due to a lack of know-how from end users about device specifications. In most cases end users/institutions spend a lot of money in computer resources leading to poor resource utilisation (Panwar et al., 2022). Computers are lying idle in offices and homes because of compatibility issues.

The development of this application promises to minimise wastage of computer resources through empowerment of end users in device selection. It creates awareness to end users that resources are not finite, the universe is not creating more resources, but rather human beings are consuming what is available and therefore the need for energy saving practices. Data science has created a knowledge base platform for this model that guides end users in selecting devices that meet their needs (Memon et al., 2018). This model implementation would also teach clients of resources they would otherwise be less privy to.

1.7 Scope of the Study

The study designed a hyper personalization chatbot model that determines specific computer device requirements for end users. The study sought to bring a coherence of knowledge from benchmarking institutions to the benefit of end users through a non-biased easy access platform. Nakuru, the fourth largest city in Kenya with a population of 570,674 according to 2019 census, provided sufficient data for the research area. The model focuses on determining specifications for desktops, laptops, tablets, and mobile phones, as these are the most common and frequently procured end-user devices within the target population. It leverages user profile data, including stated preferences, typical use cases or task types, budgets, and desired features, while also incorporating behavioural data such as search history and click patterns from compiled datasets to generate tailored recommendations. The model prioritizes key technical specifications such as CPU, RAM, storage, screen type, and battery life. Its effectiveness is evaluated through quantitative metrics like accuracy, precision, and recall, as well as user-centric metrics such as satisfaction and ease of use obtained from post-implementation surveys.

1.8 Limitations of the Study

To create this model, a network of information needed to be collated from different environments. Data Quality and Availability: When datasets are limited, generating synthetic data or implementing active learning models enhances data quality as the model interacts with users. Data scarcity was mitigated by a two-part strategy. First, synthetic data generation and focused web-scraping of local e-commerce platforms enriched the model's knowledge base. Second, active learning models were used during testing to continuously incorporate end-user feedback, iteratively refining data quality and compensating for initial dataset limitations.

Complexity of Hyper-Personalization Models: The inherent computational complexity of integrating multiple machine learning components was managed effectively through modularity and leveraging pre-trained resources. Personalization was achieved by using modular algorithms, separating the BERT-based Natural Language Processing (NLP) core from the Hybrid Recommendation Engine. This design made the system easier to manage, debug, and improve specific functionalities without impacting the entire architecture. Complexity was significantly reduced by utilizing pre-trained large language models (LLMs) such as Chat-OpenAI and integrating via Flowise, reducing the computational load. Finally, reinforcement learning principles were implicitly applied during A/B testing and qualitative validation, allowing the model to optimize personalization strategies based on direct, positive feedback from user interactions.

Application Model Regular Updates: The challenge of maintaining regular updates, necessary due to the rapid evolution of computer hardware specifications, was mitigated through system design and market monitoring. The model was built using a modular architecture, ensuring that updates to specific data components such as new CPU models and updated pricing could be executed without requiring a complete system overhaul. This modularity made maintenance efficient. Additionally, the research established a continuous process of monitoring market trends and actively gathering user feedback. This user feedback served as the primary prioritization mechanism, directing development efforts only toward necessary improvements and ensuring the model remained relevant to current user needs and available technology modular architecture allowed easy updates to specific components and monitoring market trends while gathering user feedback helped prioritize necessary improvements efficiently.

Ethical and Privacy Concerns: Collecting and analysing user data for personalization raises ethical considerations around consent, data protection, and user autonomy, which must be carefully managed. This study adhered strictly to ethical guidelines by obtaining written informed consent from all participants and ensuring anonymity during data collection. The developed model architecture used pseudonymization and secure, password-protected local vector storage to manage user data, mitigating risks related to data protection and ensuring compliance with the Data Protection Act (2019).

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

This chapter reviews literature on hyper-personalization, particularly within the context of device specification. Hyper personalization represents a significant frontier in enhancing user experiences, optimizing functionality, and tailoring interactions to individual preferences. We aimed to explore and dissect the multifaceted landscape of hyper-personalization within device specifications, delving into theoretical frameworks, technological innovations, and practical applications.

The proliferation of smart devices, ranging from smartphones and tablets to wearables and Internet of Things (IoT)-enabled gadgets, has revolutionized the way individuals engage with technology in their daily lives. At the heart of this transformation lies the concept of hyper-personalization, which endeavours to understand, anticipate, and fulfil the unique needs and preferences of users through tailored device specifications. Whether it's adjusting display settings based on user preferences, recommending personalized content, or optimizing device performance according to usage patterns, hyper-personalization has emerged as a cornerstone of user-centric design and technological innovation.

2.2 Device Specification

Device specifications refer to the detailed technical information and features of a particular electronic device. These specifications provide users with a comprehensive understanding of a device's capabilities and functionality. Common electronic devices with detailed specifications include smartphones, laptops, tablets, cameras, and other gadgets.

Here are some typical categories found in device specifications: Hardware specifications define a device's performance and include its type, such as smartphone, tablet, or desktop, and features like processor type (e.g., Intel Core i7, Qualcomm Snapdragon) and clock speed in Gigahertz (GHz). Memory (RAM) and storage capacity further impact the device's speed and responsiveness, shaping its suitability for different tasks and enhancing the overall user experience (Intrinsyc, 2020). Memory (RAM) refers to the amount of random-access memory a device has, measured in gigabytes or terabytes, which directly affects multitasking capability and speed. Storage encompasses the internal capacity, also in gigabytes or terabytes, and the type of storage such as Hard Disk Drives (HDD) or Solid-State Drives (SSD) - which influences data access speeds and overall performance. Both RAM and storage are crucial for ensuring smooth, efficient device operation, particularly when handling large files or running multiple applications simultaneously (Micheloni & Crippa, 2017).

The operating system (OS) is the platform on which a device operates, determining its user interface, compatibility, and functionality. Common types of operating systems include iOS, Android, Windows, and Linux, each catering to specific device types and user needs. The OS version number, such as Android 12 or Windows 11, indicates updates and features that enhance performance, security, and user experience.

Network connectivity refers to the type and speed of a device's connection, such as Wi-Fi or cellular. Cellular network support includes options like 4th Generation Long Term Evolution (LTE) or 5G, which impact data speed and availability in different locations. Additionally, wireless technologies like Wi-Fi, Bluetooth, and Near Field Communication (NFC) enable seamless data transfer, device pairing, and internet access, enhancing connectivity options and overall device functionality.(Blaise & D. Olujimi, 2020). The display of a device includes key factors like screen size, measured diagonally in inches or centimetres, resolution such as Full High Definition or 4Kilos(K), aspect ratio, and pixel density, all of which affect visual clarity and detail. Display technology, such as Liquid Crystal Display (LCD), Organic Light Emitting Diode (OLED), Active-Matrix Organic Light Emitting Diode (AMOLED) influences colour accuracy, brightness, and energy efficiency. Additionally, the graphics processing unit (GPU)-for example, NVIDIA GeForce or AMD Radeon-enhances visual performance by handling graphic-intensive tasks, making it essential for gaming, video editing, and other visually demanding applications.(Bhrijesh et al., 2014).

Input/output capabilities define a device's interaction and connectivity options. Supported input devices may include touch screens, keyboards, and microphones, allowing for diverse and flexible user interaction. Ports and connectors, such as Universal Serial Bus Type-C (USB-C) and High-Definition Multimedia Interface (HDMI), facilitate connections to other devices and peripherals. Audio features are also crucial, encompassing speaker configuration for sound quality and the availability of an audio jack for wired audio options, enhancing the device's multimedia experience.

Battery life indicates how long a device can operate on a full charge, with capacity measured in milliampere-hours (mAh). Higher mAh often equates to longer usage time, though this depends on the device's power demands. Advanced charging technologies, like fast charging and wireless charging, improve convenience by reducing downtime, allowing users to recharge quickly or wirelessly for added flexibility (Strossmayer, n.d. 2021).

Device security includes various measures to protect user data and privacy. Common security features include biometric authentication, like fingerprint or facial recognition, which provides quick and personalized access. Encryption is also a key security layer, safeguarding stored data by converting it into unreadable code that can only be accessed with proper authorization. Together, these features enhance the device's protection against unauthorized access and data breaches.(Suo et al., 2019).

The camera specifications of a device are essential for capturing high-quality photos and videos. Key factors include the megapixel count for both front and rear cameras, which affects image resolution, and aperture size, influencing light intake for clearer images in various lighting conditions. Image stabilization minimizes blur, enhancing photo sharpness and video smoothness. Additionally, video recording capabilities, such as 4000 pixels or 8000 pixels resolution, allow for high-definition video capture, making the camera a versatile tool for both photography and videography.(Srivastav, 2021).

Sensors play a crucial role in enhancing the functionality of a device by providing additional data and interactivity. Common sensors include the accelerometer, which detects movement and orientation; the gyroscope, which measures rotation and orientation changes; and the fingerprint sensor, which enables secure biometric authentication. These sensors contribute to features such as motion-based controls, augmented reality applications, and enhanced security, enriching the overall user experience and functionality of the device.(Sensors n.d, 2022).

Dimensions and weight are important factors in a device's build and design, influencing portability and user comfort. The size of the device is typically measured in inches or centimetres, while weight can affect how easily it can be carried or handled. The materials used in construction such as aluminium, glass, or plastic also play a significant role in determining the device's durability, aesthetics, and overall feel.

Additional features significantly enhance a device's functionality and usability. Biometric authentication methods, such as fingerprint scanners and facial recognition, provide secure and convenient access. Water and dust resistance ratings, such as IP67 or

IP68, indicate the device's durability against environmental factors, allowing for greater peace of mind in various settings. Expandable storage options, like Micro Secure Digital card (microSD) card slots, offer users the flexibility to increase their device's storage capacity, making it easier to manage files, apps, and media without compromising performance such as microSD or card slot.

Warranty and support are essential aspects of a device purchase, providing customers with assurance regarding product quality and service. Manufacturer warranty details typically specify the duration of coverage, which can range from one to several years, and outline what is included, such as repairs or replacements for defects in materials or workmanship. Additionally, support services may include access to customer service, online resources, and technical assistance, helping users troubleshoot issues and maximize their device's functionality.

2.2.1 End Users Understanding on Device Specification

An end user is the person or group who ultimately uses a product or service, typically software technology. In the context of hardware and software development, end users are the individuals who interact with the application or system, as opposed to developers or technical staff who create or maintain it.(Cui et al., 2017).

A key challenge for customer service providers is to balance between service efficiency and quality: Both researchers and practitioners emphasize the potential advantages of customer self-service, including increased time-efficiency, reduced costs, and enhanced customer experience. (Benlian1, 2020). Chat Agents, as a self-service technology, offer several cost-saving opportunities and also promise to increase service quality and improve provider-customer encounters.(Cui et al., 2017).

End users rely on customer support options to understand device specifications which provide the necessary information to compare and make decisions when purchasing electronic devices. Additionally, manufacturers and retailers often include user manuals and product documentation that further explain the device's features and functionalities. Reading and understanding device specifications are crucial for selecting a device that meets one's specific needs and preferences.

Several platforms and sources can be used to determine device specifications. These platforms provide comprehensive information about the technical details and features of electronic devices, helping users make informed decisions when purchasing or researching gadgets.

2.2.2 Review of Application in Device Specification

Existing studies often focus on general e-commerce recommendations(Laussel et al., 2019) but lack depth in linking abstract user needs for instance fast performance for coding to specific hardware metrics such as core i7 processor and 16GB RAM. This research aims to fill this gap. Relevant literature linking user behaviour to hardware/software preferences confirms that implicit needs such as frequent use of resource-intensive applications are better predictors of required RAM/CPU than explicit statements alone (Rane et al., 2023).

Existing frameworks match user profiles to device configurations, but often rely on static, rule-based systems rather than dynamic, machine-learning-driven hyper-personalization needed for rapidly changing specifications. Research on edge computing and on-device personalization is highly relevant, as it points towards real-time adaptation of recommendations based on the user’s current device state for example low battery, current location which is a crucial component of advanced hyper-personalization (Seppälä et al., n.d.).

2.3 Hyper Personalization

Hyper-personalization is a marketing strategy that goes beyond traditional personalization by using advanced technologies, data analytics, and artificial intelligence to deliver highly individualized and tailored experiences to each user (Kumar, 2020). Hyper-personalization is often defined as the extreme level of personalization, where content, recommendations, and interactions are finely tuned to the individual preferences and behaviours of users. Emphasis is on the use of advanced technologies, such as machine learning algorithms and big data analytics, in achieving hyper-personalization.(Maddodi & Nandha Kumar, n.d.) In the ever-evolving landscape of modern business, the key to success lies in a customer-centric approach, prompting organizations to explore innovative ways to forge deep connections with their clientele.

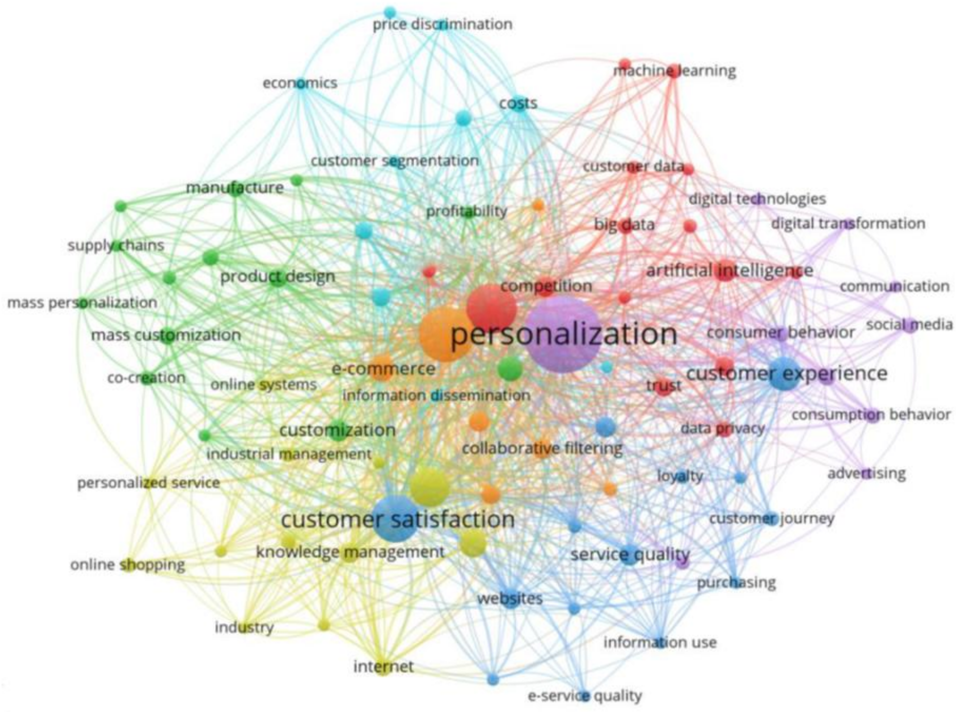
One prominent strategy gaining traction is the incorporation of hyper-personalization within Customer Relationship Management (CRM) systems. As companies strive to create unique and memorable customer experiences, the integration of advanced technologies, state-of-the-art tools, and strategic methodologies becomes essential(Rane et al., 2023). There are various aspects of hyper-personalization, particularly its role in enhancing customer loyalty and satisfaction within CRM systems.

The advent of the digital era has revolutionized the nature of customer-business interactions, generating vast amounts of data that present both challenges and opportunities. Amid this data deluge, hyper-personalization has emerged as a beacon, offering a customized and individualized approach to customer engagement. As customers increasingly seek personalized experiences that align with their preferences, businesses find themselves at a critical juncture where adopting hyper-personalization strategies can be a game-changer.

The preceding discussion highlights the various features that contribute to individualized experiences, which is conceptually illustrated by the frequency of key terms in the literature. Figure 1 below depicts the co-occurrence analysis of these relevant keywords.

Figure 1

Co-occurrence Analysis of the Keywords in Literature



Source: Rane et al.,(2023)

2.3.1 Key Elements of Hyper-Personalization

Data Collection and Analysis: This involves gathering information from various sources, such as online behaviour, purchase history, and social media activity. By using advanced analytics, businesses can interpret this data to identify patterns and preferences unique to each customer, enabling more personalized interactions and effective decision-making that enhance customer satisfaction and engagement.

Real-Time Personalization: Personalized engagement involves delivering tailored content, recommendations, and offers to customers in real-time, based on their current behaviour and past interactions. This approach enhances the customer journey by making each interaction more relevant and timelier, creating a more engaging and satisfying experience. Technological Integration: Personalization efforts are powered by AI, machine learning, and predictive analytics, which automate and optimize the customization of customer interactions. By integrating with CRM systems, businesses ensure that customer data was utilized effectively, boosting engagement and fostering loyalty through more targeted and meaningful connections.(Rane et al., 2023).

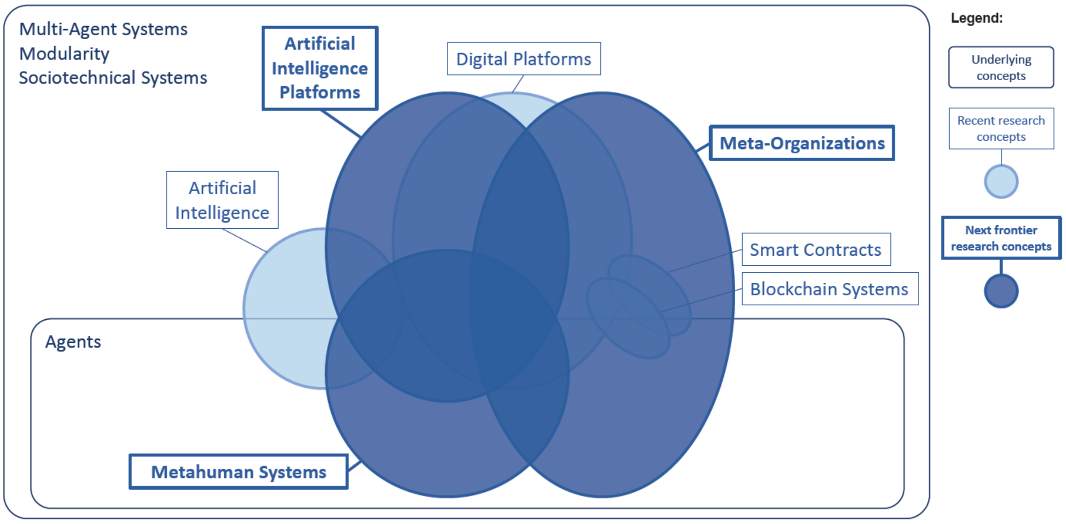
Enhanced Customer Experience: The goal of personalization is to create a seamless and satisfying customer experience by anticipating individual needs and preferences. By delivering value at every touchpoint, businesses can significantly increase customer satisfaction and loyalty, fostering stronger, more enduring relationships. (Pukas, 2022). Contextual Awareness: Utilizing real-time data, such as device type, time of day, and location, to ensure recommendations are immediately relevant to the user's current situation (Patel & Trivedi, 2020).

Customer Journey Mapping: Customizing the experience across the entire path, from initial inquiry to post-purchase support, rather than focusing solely on the point of sale(Pukas, 2022). Omnichannel Delivery: Ensuring a consistent and personalized experience across all communication channels, including web, mobile app, email, and social media(Rane et al., 2023). Privacy & Trust: Implementing transparent data usage policies and obtaining explicit consent to balance personalization benefits against user concerns regarding autonomy and data security(Følstad et al., 2021).

The strategic integration of these elements leverages new patterns of organizational activity to drive mass hyper-personalization. Figure 2 illustrates a mapping of selected key concepts related to digitalization, mass hyper-personalization, and implementation (Seppälä et al., n.d.)

Figure 2

A Mapping of Selected Key Concepts Related to Digitalization, Mass Hyper-Personalization and Implementation



*Source: (*Seppälä et al., n.d.)

2.3.2 Benefits of Hyper-Personalization

Hyper-personalization enhances user satisfaction by providing more relevant and engaging content, products, or services. Studies suggest that personalization experiences lead to higher levels of customer loyalty and repeat business. Hyper-personalization marketing messages are more likely to capture the attention of users, leading to increased conversion rates.(Davenport, 2023). Technologies like artificial intelligence, machine learning, and data analytics enable hyper-personalization. Advanced algorithms analyse vast amounts of user data and generate personalized recommendations in real-time.

Table 1

Hyper Personalization Strategies

Sr No.	Hyper-personalization Strategy	Description	Example	Relevant Technologies
1.	Individualized Content	Tailoring content based on individual preferences, behaviors, and interactions.	Offering personalized product recommendations in emails or on the website according to past purchases.	Machine Learning, Data Analytics.
2.	Dynamic Personalization	Real-time customization of content or experiences based on user actions and data.	Adjusting website content dynamically as users navigate, showcasing relevant information in response to their behavior.	Real-time Analytics, Content Management Systems (CMS)
3.	Predictive Analytics	Using data analysis and machine learning to anticipate customer needs and preferences.	Predicting the next likely purchase based on historical data and presenting relevant offers.	Predictive Analytics, Machine Learning, Big Data
4.	Behavioral Tracking	Monitoring and analyzing user behavior across channels to understand preferences	Tracking user interactions with emails, websites, and mobile apps to personalize future interactions.	Customer Analytics, Web Analytics
5.	Location-Based Personalization	Customizing content or promotions based on the user's physical location	Sending location-specific offers or recommendations through mobile apps when a customer was near a physical store.	Geolocation Technology, Mobile App Integration
6.	Time-Based Personalization	Adapting content or messages based on the time of day, day of the week, or specific events	Sending promotional emails at times when a customer was most likely to engage or make a purchase	Marketing Automation, Time-Based Triggers
7.	Social Media Integration	Leveraging social media data to personalize interactions and content	Integrating social media profiles with CRM to understand social interactions and preferences, then tailoring marketing efforts accordingly.	Social Media Analytics, CRM Integration

8.	Omni-Channel Personalization	Consistently personalizing experiences across various channels and touch points.	Ensuring a seamless and personalized experience whether a customer interacts via website, mobile app, social media, or in-store.	Omni-Channel CRM Systems, Customer Data Platforms (CDP)
9.	Preference Management	Allowing customers to define their preferences and tailoring interactions based on those preferences.	Providing a preference center where customers can specify communication preferences, product interests, and more.	Customer Relationship Management (CRM) Software
10.	A/B Testing for Personalization	Experimenting with different personalization strategies to identify the most effective approaches.	Testing various personalized email subject lines, content, or offers to determine the most resonant with specific segments.	A/B Testing Tools, Marketing Automation Platforms

Source: (Rane et al., 2023)

2.3.3 Contemporary AI-Based Approaches to Personalization

For a long time, companies have used AI, like rule-based systems, to personalize services, but these systems were not very advanced. True, precise personalization, called hyper-personalization, needs machine learning. Unlike rule-based systems, machine learning can handle many different customer, product, or context details easily and is much more accurate. It allows a company to create millions of unique offers. Machine learning can even get close to the ideal of making offers perfectly suited to each individual customer. This was possible in theory for decades but needed the right data. For example, the United Kingdom supermarket Tesco started using hyper-personalization in the late 1990s with its Clubcard program, creating 12 million unique grocery offers. More recently, in 2022, Tesco personalized discounts for Clubcard holders due to inflation (Mahesh, 2018).

Machine learning-based hyper-personalization can focus on the product, the customer, or both. Product-focused approaches, like collaborative filtering, use the idea that "people who bought this item also bought that item," based on purchase data. Netflix uses a more advanced product-focused method by classifying movies and TV shows by various features like genre, actors, and directors. It then recommends content with similar features to what customers have watched.

Netflix's recommendations are also based on customer preferences, viewing history, ratings, and similarities with other users' tastes. They use over 2,000 different taste groups and consider factors like time of day and device type to offer a personalized set of titles to each viewer. This personalization has improved customer experience and contributed to Netflix's growth, though recently, growth has slowed due to economic factors and post-pandemic changes.(Davenport, 2023).

Customer-focused personalization uses past purchases, demographic data, recent life events, estimated income, communication preferences, and responses to previous offers to predict how a customer will respond to new offers. Companies can create many different models to make unique offers to each customer. For example, Kroger has 60 million loyalty program members and delivered 1.9 billion personalized offers in 2021 using machine learning developed by its data subsidiary, 84.51°. These offers aim to boost sales and customer engagement by providing nutritional information and recommendations (Davenport, 2023).

A big challenge for customer-focused models was gathering the necessary data. Loyalty programs help by tracking customer behavior over time. Digital ads have used cookies to track website visits and predict interests, but consumers are becoming wary of cookies, and companies like Google are phasing them out.(Patel & Trivedi, 2020a).

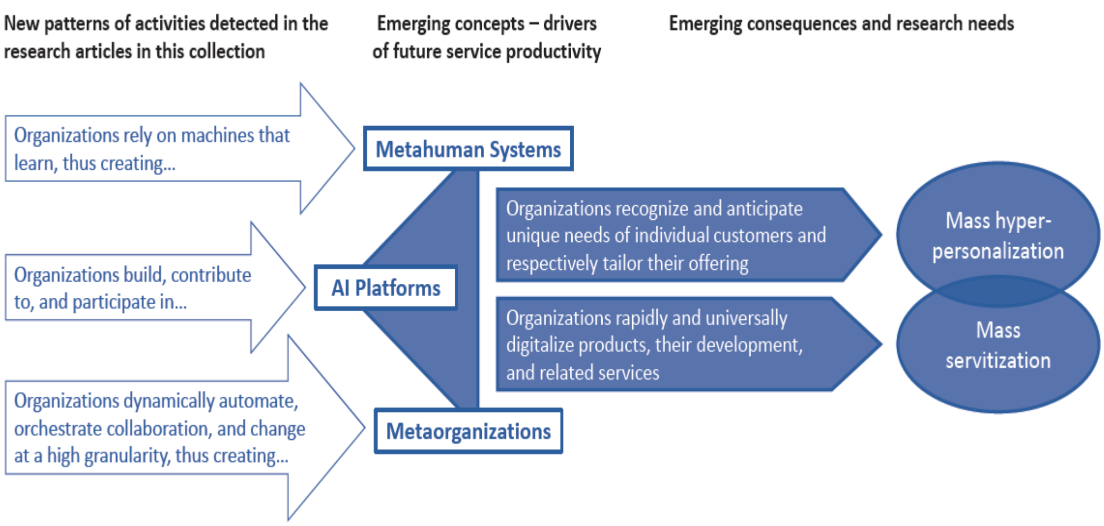
Data from multiple sources, like web browsing history, credit card purchases, social media activity, and device types, can help create sophisticated personalization models. However, this may also lead to a backlash against personalization.

Successful personalization models also consider contextual factors like the season, time of day, or customer location. Offers might be limited to products in stock at a local store or available online. Only advanced machine learning models can handle the many factors involved in making precise predictions.(Jet & O, 2017).

The lack of data and the complexity of creating machine learning models were traditional constraints. However, AI companies now offer tools to automate model creation and maintenance, making machine learning more accessible to non-experts. Business analysts who understand customers and markets can now create and maintain these models. At Kroger and 84.51°, business insights specialists work with data scientists to create useful machine learning models. (Davenport, 2023).

Figure 3

The Emerging Patterns of Activities and Concepts Shaping Future Research on Digitalization



Source: (Seppälä et al., n.d.).

2.3.4 Challenges and Ethical Considerations

Hyper-personalization raises privacy concerns, as it relies on collecting and analysing substantial amounts of user data, posing challenges relating to privacy and data security. Ethical considerations also emerge, focusing on the responsible use of personal information and avoiding manipulation(Grudin & Jacques, 2019). Studies investigate consumer perception and acceptance, exploring whether consumers find hyper-personalization valuable or invasive, and emphasize the delicate balance between providing personalized experiences and respecting user privacy(Harkous et al., 2016). Various industries, such as e-commerce, retail, healthcare, and finance, implement and adapt hyper-personalization strategies in different contexts. Real-time personalization was a key aspect, involving the immediate adaptation of content or recommendations based on user interactions.(Rane et al., 2023).

2.4 Natural Language Processing

Natural Language Processing (NLP) is a branch of artificial intelligence that focuses on bridging the gap between human communication and computer understanding. At its core, NLP allows computers to process, analyse, and respond to human language in ways that make interactions with technology feel natural and intuitive. Drawing from fields like linguistics, computer science, and data science, NLP involves breaking down language data to uncover meaningful patterns and insights or to perform specific tasks. Mondal et al. (2018). These tasks can range from straightforward actions, like identifying individual words, to complex ones, such as understanding the nuances of a conversation or generating responses in real time.

One fundamental aspect of NLP is tokenization, which involves breaking down text into smaller units like words or sentences. This step helps computers manage and analyse language by treating each unit as a distinct entity.(Gastaldi et al., 2024) Part-of-speech tagging builds on this by identifying each word’s grammatical role-such as whether a word functions as a noun, verb, or adjective. This enables systems to better understand sentence structure and meaning. Named Entity Recognition (NER) is another critical task, where models detect and categorize names, places, organizations, and other entities within the text, enabling applications like information retrieval and search.

NLP also includes sentiment analysis, which is used to detect the emotional tone or opinion within text, a technique often employed in social media monitoring or customer feedback analysis. (Patel & Trivedi, 2020a) Other tasks, like machine translation and text summarization, are more complex and involve either translating language or condensing information into shorter, coherent summaries that still capture the essence of the original. In question answering, systems interpret questions posed in natural language to deliver accurate, contextually relevant answers key for virtual assistants like Siri or Alexa. Speech recognition and generation push NLP into the realm of audio, converting spoken language into text and generating natural-sounding speech responses. This technology underlies many voice-activated systems, enabling applications like dictation software and automated customer service.

The applications for NLP are vast and varied. Businesses use NLP for chatbots, which handle routine customer service inquiries; social media sentiment analysis, which gauges public opinion; and content moderation, which identifies inappropriate or harmful text (Jurafsky D, 2024). NLP also finds uses in highly specialized fields, like analysing legal documents, medical records, and scientific literature to surface insights or extract specific information. NLP technology continues to advance rapidly, especially with the rise of deep learning and the development of models like transformers such as (BERT, GPT)(Cao et al., 2021). These models enable computers to understand and generate language with greater nuance and contextual awareness, making it possible to handle idioms, cultural references, and other subtleties of human communication. As NLP technology evolves, it becomes an increasingly integral part of how we interact with machines and the digital world.

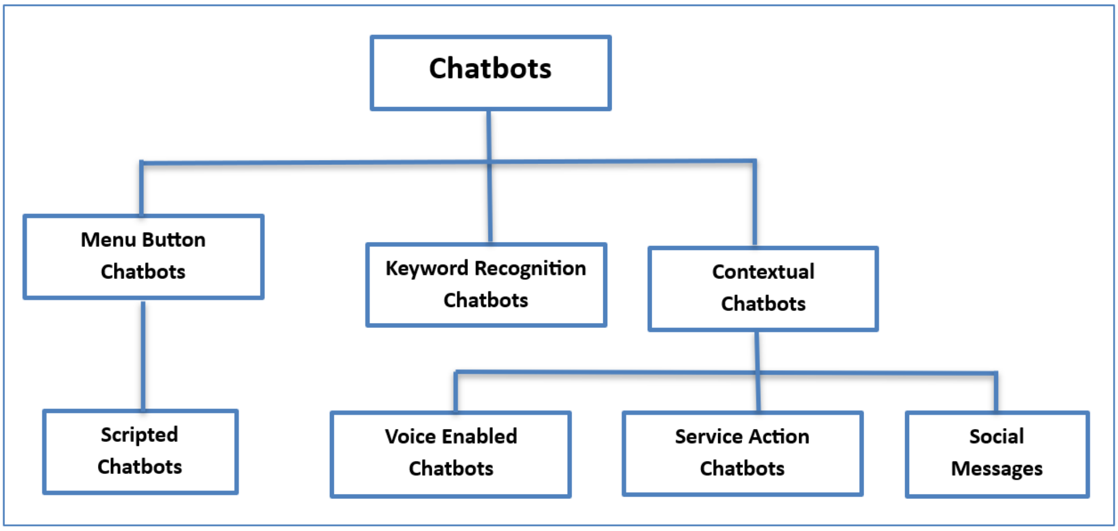
2.4.1 Chatbot Classification and Architecture

A chatbot is a computer program designed to simulate conversation with human users, especially over the internet (Adamopoulou & Mousepads, 2020).They can be integrated into messaging platforms, mobile apps, and websites, and can be used to automate customer service, provide information, or perform other tasks. Some chatbots use natural language processing (NLP) to understand and respond to user input, while others use predefined scripts or decision trees(Maher, 2020).

Chatbots can be designed to work with various types of inputs such as text, voice or even facial expressions and gestures (Simonite, 2017a). They can also be integrated with other systems to access external data and perform various functions such as booking a flight, ordering food, or even making a purchase (Aishwarya Gupta, 2020). Overall, chatbots have the potential to improve efficiency, save time and automate mundane tasks, and can be used in various industries such as e-commerce, healthcare, banking, and customer service (Maher, 2020). Below is Figure 4 classification of chatbots and Figure 5 on preferences of chatbots.

Figure 4

Classification of Chatbots

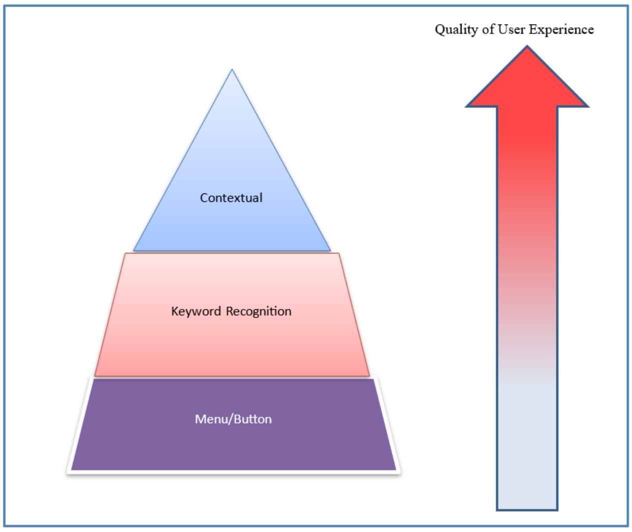


Source: Maher, (2020).

This figure below illustrates that as the sophistication of the chatbot increases moving from Menu/Button to Contextual, the Quality of User Experience and implicit user preference for that mode of interaction also increases. This represents the user preference for the quality of the interaction provided by different chatbot types.

Figure 5

User Preferences of Chatbots



Source :Maher, (2020)

2.4.2 Types of Chatbots

According to Aishawarya Gupta (2020) there are several types of chatbots:

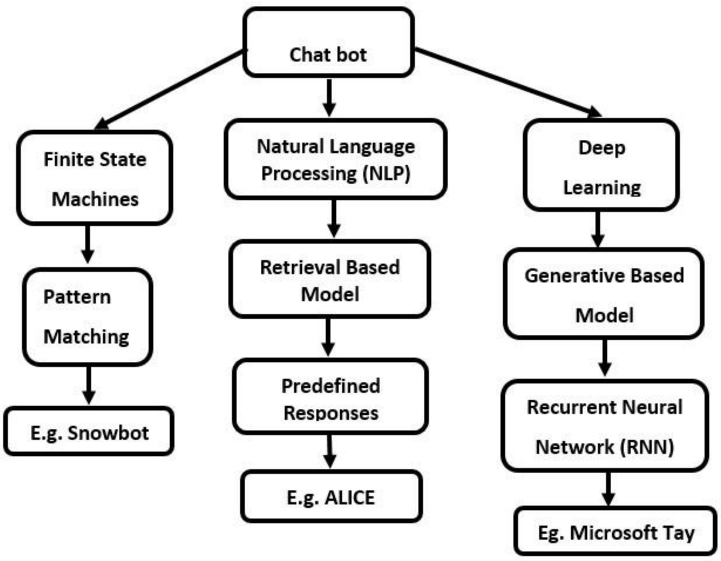
i. Rule-based chatbots: These chatbots use predefined scripts or decision trees to determine their responses. They are easy to create but can only respond to a limited set of inputs.

ii. Self-Improving chatbots: These chatbots use machine learning algorithms to learn from interactions with users and improve their responses over time(Biswas, 2019).

iii. Hybrid chatbots: These chatbots combine the features of rule-based and self-learning chatbots. They use predefined scripts or decision trees to handle some inputs, and machine learning algorithms to handle others(Bhagwat, 2018). Chatbot technology is evolving quickly, and new developments such as the use of deep learning, generative models and other advanced NLP techniques are enabling chatbots to better understand and respond to human language(Singh, 2020).

Figure 6

Approaches to Chatbot Development



Source: Jwala et al., (2019)

2.4.3 Categories of Machine Learning in Chatbots

Machine learning chatbots: Machine learning is a key component of chatbot development, as it allows chatbots to understand and respond to human language. There are several types of machine learning that can be used in chatbot development, as listed below(Cuayáhuitl et al., 2019): Figure 6 illustrates three core approaches to chatbot development in machine learning: Finite State Machines (rule-based), Natural Language Processing (retrieval-based), and Deep Learning (generative/retrieval-based).

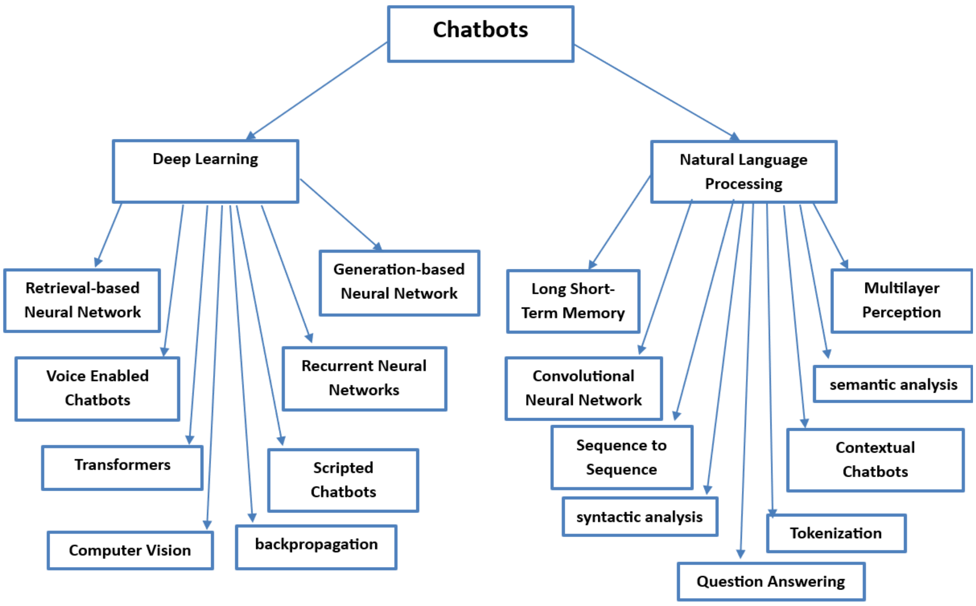
Supervised Learning: This type of machine learning uses labelled training data to make predictions. For example, a supervised learning algorithm could be trained on a dataset of customer service interactions to learn how to respond to different types of customer inquiries(Cuayáhuitl et al., 2019). Unsupervised Learning: This type of machine learning finds patterns in unlabelled data. For example, an unsupervised learning algorithm could be used to identify common themes in customer service interactions to help the chatbot respond more effectively (E Benhamou, 2022).

Reinforcement Learning: This type of machine learning learns from the consequences of its actions. For example, a reinforcement learning algorithm could be used to train a chatbot to respond to customer inquiries in a way that maximizes customer satisfaction (Serban et al., 2018). Transfer Learning: This type of machine learning allows a model trained on one task to be used as a starting point for a different but related task. This allows to use pre-trained models and make them more efficient (Hatzfeld et al., 2017).

Generative models: This type of machine learning models is able to generate new data, such as new responses, based on the data they were trained on (Ushio et al., 2022). Many chatbot use natural language processing (NLP) techniques to understand and respond to user input, such as named entity recognition, sentiment analysis, and parts-of-speech tagging.

Figure 7

Conceptual map of Machine Learning



2.4.4 Role of Machine Learning in Customer Service

Machine learning entails developing recommendation engines that can access a broad range of data resources, including private data from clients, external corporate data, and websites. Recommendation engines enable businesses to create a relevant, tailored experience for every consumer, regardless of their previous purchase patterns or preferences. (Nikhil Parel,April/30/2020). Retail giants are increasingly using recommendation systems to offer tailored shopping experiences for specific consumers.

Customers generally welcome these suggestions, but they are particularly successful with millennial consumers, who are more inclined to buy things they see promoted on media or in magazines. Machine learning is being used by the organizations involved to create a recommender system that combines the most of all previously acquired external data, integrates it with analytical and NLP techniques, and improves the resultant suggestions.

Machine learning enables not just the suggestion of tailored experiences and information, but also the advice of products based only on historical purchasing history. Machine learning predicts what consumer will purchase in the next spending by using historical purchasing behaviour, allowing recommendation engines to propose various things based on past orders and how other consumers have reacted to these products previously (Verhagen et al., 2014). Machine learning system suggestions are often more focused than human suggestions, however that is not always the case. Suggestions from a machine learning model may still be very personalized, especially if they are produced for a specific individual by someone they know.

Friends and family recommendations are also quite useful. In other circumstances, individuals just like giving recommendations to one another and feel compelled to offer their opinions on certain things. This advice, however, may be misleading and may not take into consideration that machine learning may be used to make suggestions for any product based on individual data obtained from a variety of sources.

Machine learning or AI program recommendations are much more useful than a human suggestion (Rane et al., 2023). Friends and family recommendations are impacted by their own perception of the product as well as their own personal conduct toward the product in issue. Recommendations from shops and manufacturers are impacted by their own requirements to market their goods, but recommendations from friends/relatives are more personal and naturally more customized to a particular set of individuals.

When recommendations are focused, they are much more powerful. Recommendations aimed towards those who have similar buying habits will result in more purchases since the system can tailor its suggestions to those people.(Arisandi & Herwindiati, 2025). What that means is that suggestions may be indiscriminate, recommendations which are broader and more applicable to the purchasing community will result in fewer purchase. Overly broad suggestions might lead to biased and erroneous recommendations. Overly precise suggestions will lead to suggestions for just one sort of product.(Patel & Trivedi, 2020)

Machine learning may also be used to produce customised suggestions across many shopping channels or stores (Mufadhol et al., 2020). Recommendations are an incredibly effective technique for increasing sales and retaining consumers. In the instance of an online retail site, tailored suggestions may greatly increase sales and make comparison shopping easier for consumers. This allows retailers to offer more things to their clients and enable them to make purchase choices based on what customers truly want now rather than what others propose (Borsci et al., 2022). Machine learning may help audiences produce more tailored suggestions. The strength of a suggestion is determined by who makes it.

There are several strategies to maximize the value of customised suggestions. The most appropriate advice is always one that is suited to the audience. When someone searches for a subject that is relevant to their requirements, suggestions for those keywords will appear, bringing the customer even sufficiently close to the item or prospect being presented. Machine learning also makes it simple to modify suggestions. All a company needs to do is offer the visitor with what they requested and inform the computer what type of suggestion they should make. It makes no difference what sort of advice they requested since the system will recognize it and then request a personalized recommendation. (Hocutt et al., 2022).

When businesses provide customized suggestions, the clients understand that the advice are suited to them specifically. They also know they are receiving that who have done their research and knows the importance of such advice. This fosters trust and is an important step toward achievement. They produce more sales leads, turn those prospects into paying customers, and develop their reputation by promoting their services and goods to others.

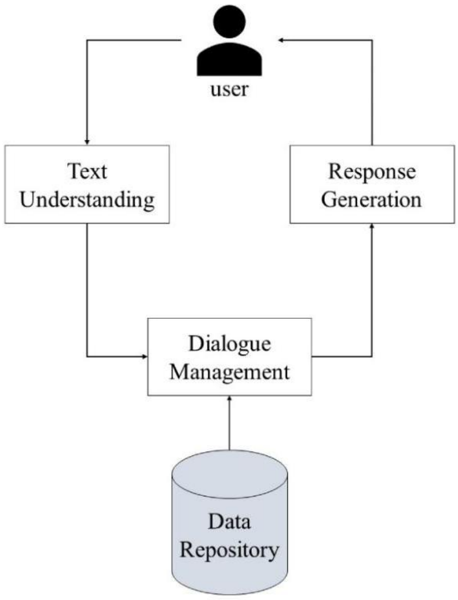
When a consumer receives individualized advice, he or she is more inclined to buy than if they received a generic recommendation. Companies understand the importance of providing customized advice. Companies must exercise caution when customizing advice. They must choose suggestions that will assist the company in achieving its objectives. If the corporate objectives are overly broad, the suggestions may do more damage than benefit. Businesses may understand which suggestions will result in the most consumers by examining trends in other companies that provide customized recommendations. (Nikhil Parel, April/30/2020).

2.4.5 Chatbots Review and Evaluation

This section comprehensive summary and analysis of existing research on chatbots. This includes research on the design, development, and evaluation of chatbots, as well as chatbot applications and impact. Figure 8 below illustrates a high-level overview of a standard chatbot architecture, showing the interaction between the user, the understanding of text, generation modules and the data repository.

Figure 8

High-Level Chatbot Architecture

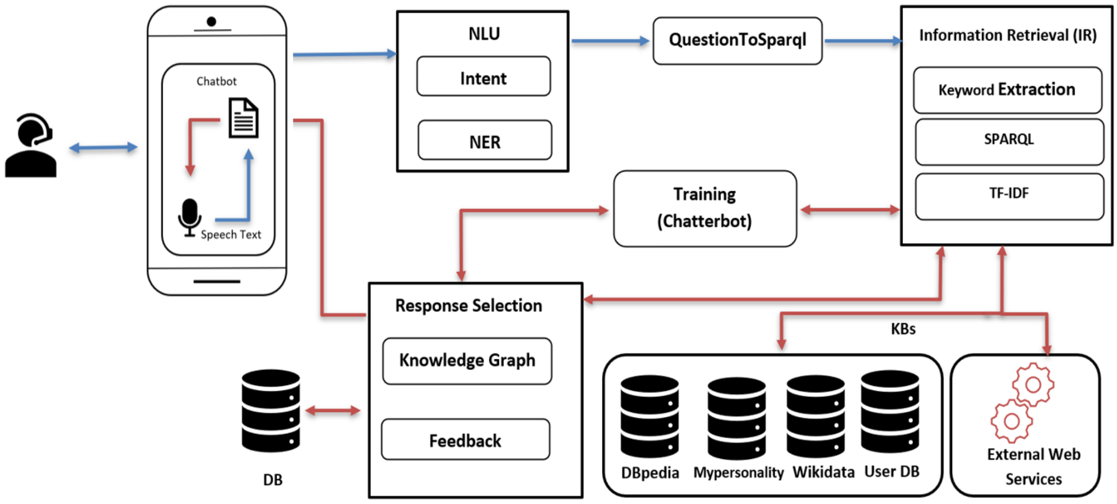


Source: Safi et al., (2020)

Chatbots have been shown to be effective in a wide range of applications, including customer service, information provision, and task completion (Merkouris et al., 2022). Some key findings from literature review on chatbots include: Natural Language Processing (NLP) a crucial component of chatbot design, and research has focused on improving the ability of chatbots to understand and respond to human language (Bhagwat, 2018). Figure 8 details the NLP Work Process, provides context for how user queries are translated into structured information for retrieval.

Figure 9

NLP Work Process



Source: Ait-Mlouk & Jiang, (2020)

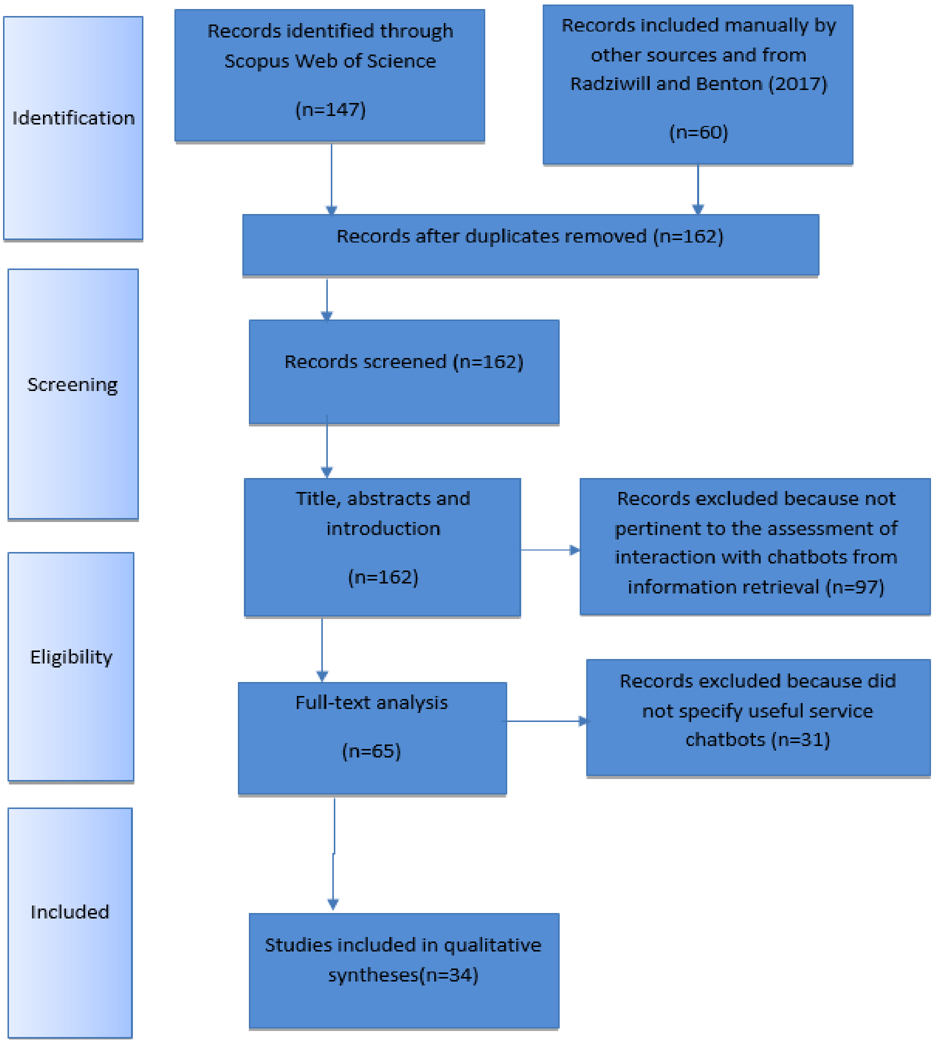
Personalization and customization which have been shown to improve user engagement and satisfaction (Patel & Trivedi, 2020). Dialogue management is another important aspect of chatbot design that has focused on developing methods to handle multiple tasks and maintain context in a conversation (Safi et al., 2020).

Chatbots as an example in application process have been used in mental health support and have shown promising results in helping people with emotional and mental health issues (Pham et al., 2022). Chatbots evaluation remains a challenge, and there is a need for more consistent and reliable evaluation methods (Borsci et al., 2022).

Figure 10 below outlines the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) process used by researchers to systematically select and synthesize literature relevant to chatbot quality attributes. The study re-examines the attributes based on a systematic review to identify attributes (n) that end-users may indirectly or directly use to assess the quality of interaction. (Radziwill & Benton 2017).

Figure 10

PRISMA Process of Literature Selection on the Quality Attributes of Chatbots



The data presented in Table 2 below derived from the PRISMA process shown above details the systematic steps taken to select and refine the literature base for evaluating chatbot quality attributes. This process ensures that the subsequent usability analysis, such as the one in Figure 10, is grounded in relevant research that directly relates to end-user assessment of interactive quality. The purpose is to move from broad literature pools to a focused set of studies (down to n=34) that specify useful service chatbots.

Attributes that end-users may use, either directly or indirectly to evaluate the quality of interaction after engaging with information retrieval chatbots.

Table 2

Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) PROCESS

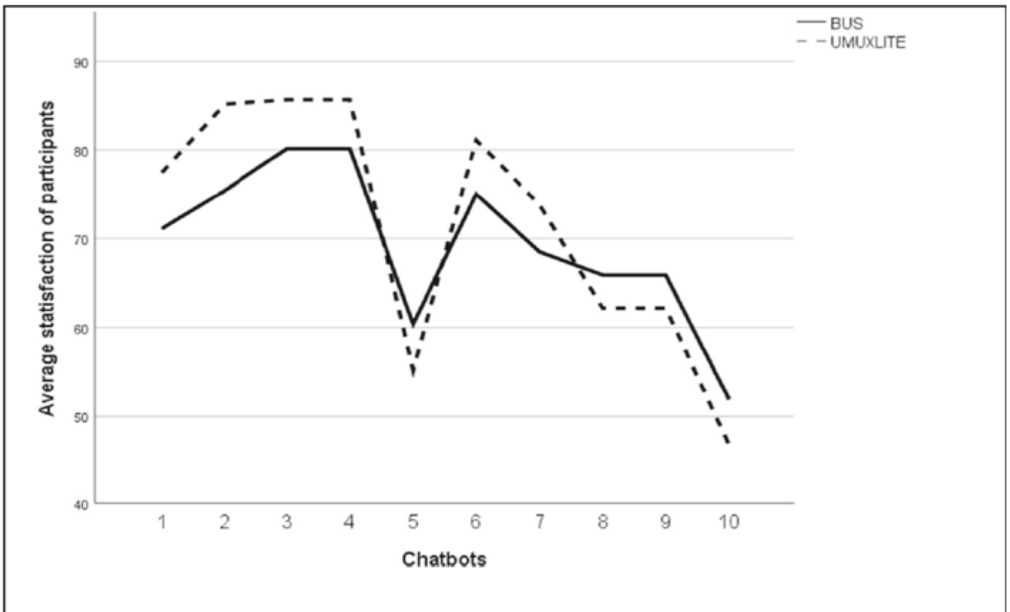
Prisma Process	Mean	Variations
Identification	147	60
Screening	162	97
Eligibility	65	31
Included	34	

Source: Borsci et al., (2022)

Figure 11 below is a graphic presentation of the average score of participants' satisfactions measured by the Bot Usability Scale (BUS-15) and the Usability Metric for User Experience (UMUX-LITE) per chatbot (Borsci et al., 2022).This presents quantitative evaluation metrics (BUS-15 and UMUX-LITE) applied across various chatbots. This figure, along with Table 2, is crucial as it demonstrates that while rigorous methods are used, satisfaction levels vary significantly such as chatbot UMUX-LITE score, underscoring the challenge in designing consistently high-quality user experiences. This variance justifies the need for the focused, user-centric validation approach in objective 4 of this research.

Figure 11

Graphic presentation of the average score of participants' satisfactions measured by the Bot Usability Scale (BUS-15) and the Usability Metric for User Experience Lite (UMUX-LITE) per chatbot



Chabot	N of measurements	BUS-15 items		UMUX-LITE	
		M	**SD**	**M**	**SD**
1	46	71.1	10.8	77.4	19
2	27	75.4	9.4	85.2	14.5
3	46	80.1	9.9	85.7	16.1
4	27	80.1	9.9	61.9	25.6
5	29	60.4	12.9	55.2	20.1
6	46	75.0	10.7	81.1	16.6
7	50	68.5	12.5	73.8	21.1
8	33	65.9	13.5	88.2	15.5
9	46	65.9	13.5	62.2	23.1
10	22	51.9	14.9	46.8	18.4

Source: Borsci et al., (2022).

N: Sample Size

M: Mean

SD: Standard Deviation

A descriptive analysis is included by reporting per chatbot for the number of participants, the mean and the standard deviation of the BUS-15 and the UMUX-LITE.(Borsci et al., 2022)**.** Overall, the literature suggests that chatbots have the potential to be a valuable tool for a wide range of applications, but there are still challenges to be addressed in terms of their design, evaluation, and ethical implications(Følstad et al., 2021).

2.4.6 Creating a Chatbot

The development of any functional chatbot typically involves several standardized steps. This systematic approach is adopted and adapted in this study, as detailed in Chapter 3 Methodology to ensure the developed model is robust and aligned with engineering best practices. The following steps outline the process to be considered when developing a chatbot (Jokinen, 2023). Defining the purpose and goals of the chatbot: This includes identifying the specific tasks or information the chatbot will provide, as well as the target audience and platform where the chatbot will be deployed(Mctear, 2020).

Designing the conversational flow: This includes creating a script or decision tree that outlines the different possible interactions and responses the chatbot can have with users(Følstad et al., 2021). Developing the chatbot: This involves programming the chatbot using a chatbot development platform or framework, such as Dialogflow, Botkit, or Microsoft Bot Framework, and integrating it with the chosen messaging platform, such as Facebook Messenger or Slack(Aydin & Karaarslan, 2023).

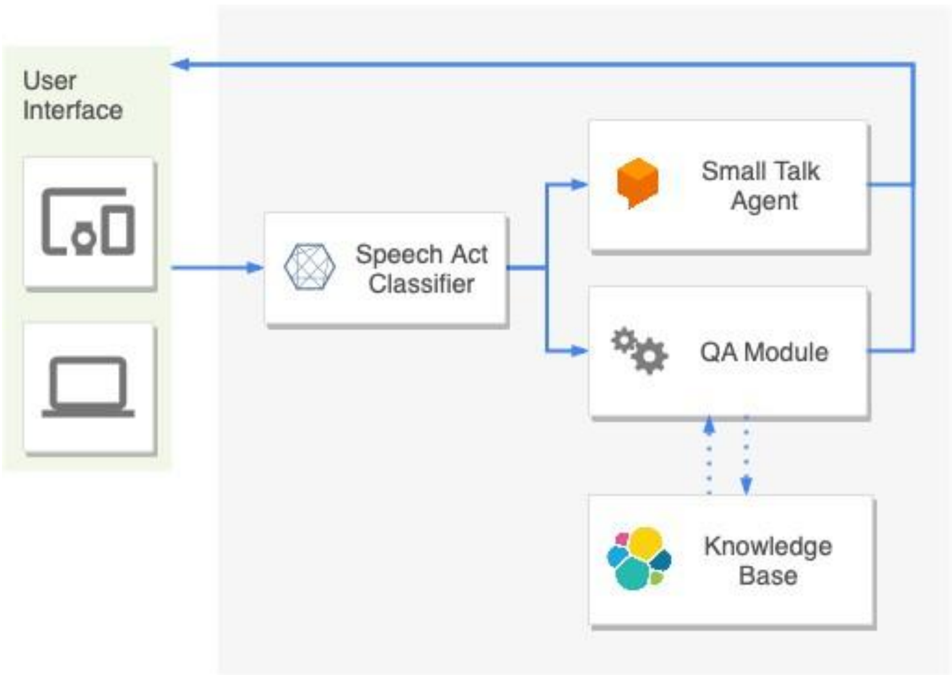
Training the chatbot: This involves using data (often called a dataset) to train the chatbot on how to understand and respond to user input. Depending on the type of chatbot, it may require supervised, unsupervised, semi-supervised, or reinforcement learning (Daniel & Martin, 2024). Testing and evaluating the chatbot: This includes testing the chatbot with a sample of users to gather feedback and identify any issues that need to be addressed(Mctear, 2020). Deploying and maintaining the chatbot: This involves making the chatbot available to users and monitoring its performance to ensure it is functioning correctly and making updates as needed (Mctear, 2020).

Creating a chatbot can be a complex process, requiring knowledge of natural language processing, machine learning, and programming. Consider using a chatbot development platform to help you with the process, it would make it easier for you to deploy and make a chatbot.

The system architecture shown in Figure 12 illustrates a high-level view of how the user interface, knowledge base, and processing agents. A Speech Act Classifier is an NLP model that identifies the intent behind a user's utterance, such as a question, request, or command (Jurafsky & Martin, n.d.). Small Agent Talk involves casual dialogue like greetings or jokes to make interactions feel natural. The QA Module processes user questions to provide accurate answers, while the Knowledge Base stores and retrieves information to support those responses. This conceptual model informs the practical design used in Chapter 3.

Figure 12

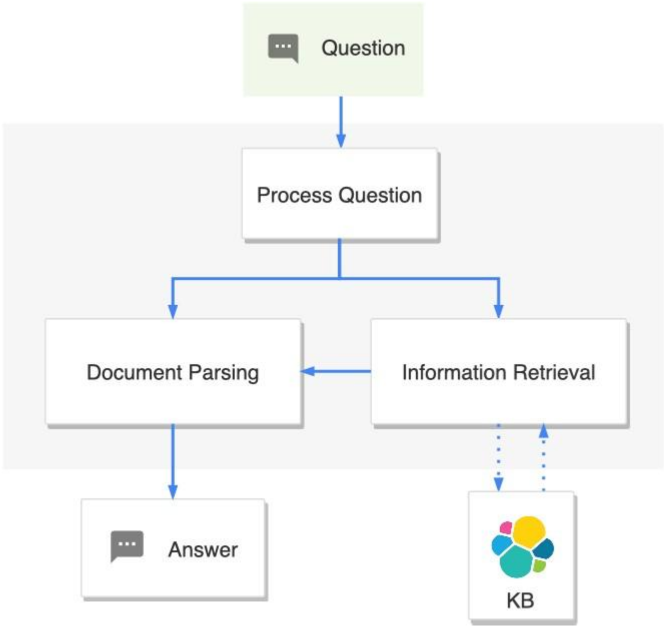
System Architecture



Source: Carlander-Reuterfelt et al., (2020)

Figure 13

QA Architecture



Source: (arlander-Reuterfelt et al.,(2020)

2.5 Application of Chatbots

The possibilities of chatbots are wide and varied, as they can be applied to a variety of industries and use Chat Agents. Some of the most common applications of chatbots include:

Chatbots have a wide range of applications across various industries. In customer service, they provide quick and efficient assistance by answering frequently asked questions, troubleshooting problems, and offering information. In e-commerce, chatbots assist customers with product recommendations, ordering, and tracking deliveries.(Simonite, 2017b). In the banking and finance sector, they help customers with account information, balance inquiries, and transactions. In healthcare, chatbots provide medical information, triage symptoms, and schedule appointments. In education, they offer students information on courses, schedules, and grades.(Kuhail et al., 2022). In the entertainment industry, chatbots recommend music, movies, and other forms of entertainment. In the travel sector, chatbots assist customers with planning and booking trips. Additionally, in mental health, chatbots support individuals with emotional and mental health issues. The use of chatbot technology in these and other industries is expected to continue growing in the coming years as companies recognize the benefits chatbots bring in terms of cost savings, improved efficiency, and customer satisfaction (Maher, 2020).

2.5.1 User-Centric Chatbots

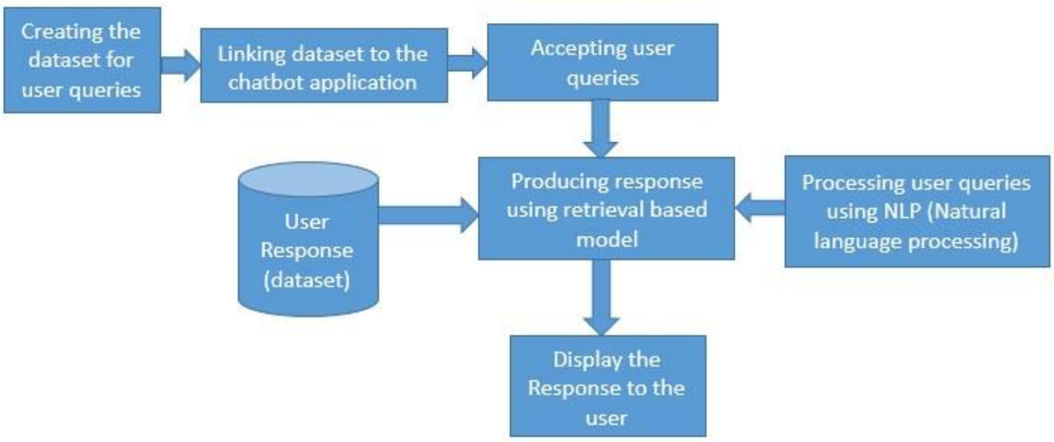
User-centric chatbots represent a significant evolution in conversational interfaces, leveraging artificial intelligence and natural language processing to provide personalized and intuitive interactions with users.(Rane et al., 2023) In this literature review, we delve into the multifaceted landscape of user-centric chatbots, exploring theoretical frameworks, technological advancements, and practical applications that underpin their design and implementation with data Science providing end user device specification.

2.5.2 Chatbot for End-User Device Specification

End-user device specifications refer to the technical specifications of the devices that users will be using to interact with a chatbot. These requirements vary depending on the end user needs. Below is a flowchart description of the process.

Figure 14

Block Diagram of End User Chatbot

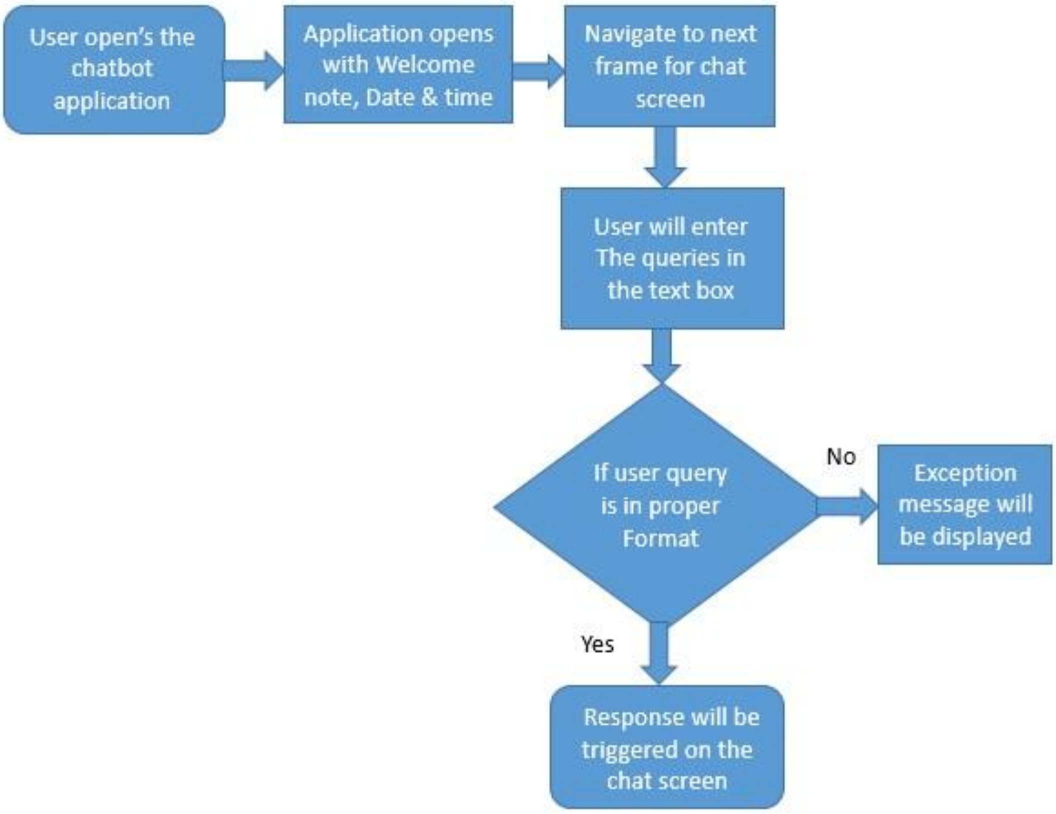


Source: Maher, (2020)

The purpose of creating programming language is to present a specific outcome. In this example, the chatbot gives advice to the end user on device specification they are looking for.

Figure 15

Query Flow Chart



Source: Maher, (2020)

As discussed earlier in the introductory part of this report, device specifications include:

Hardware: The type of device (such as a smartphone, tablet, or desktop computer) and its specifications, such as processor speed, memory, and storage capacity. Operating System: The type of operating system (such as iOS, Android, or Windows) and its version number. Network Connectivity: The type of network connection (such as Wi-Fi or cellular) and its speed.

Display: The size and resolution of the device's display, as well as its aspect ratio and pixel density.(Mueller, n.d 2020).

Input/Output: The type of input/output devices (such as touchscreens, keyboards, and microphones) supported by the device.

Battery life: The estimated battery life of the device and how long it lasts when interacting with the chatbot.(Strossmayer, n.d. 2021).

Security: The type of security measures supported by the device, such as biometric authentication or encryption.

2.4.3 Chatbot Validation

Chatbot validation has various objectives: To evaluate the effectiveness of the chatbot in a specific task or application: This objective focuses on determining how well the chatbot performs in a particular task or application, such as customer service or information provision.

To investigate the user's perception of chatbot: This objective focuses on understanding how users perceive chatbots, including their level of satisfaction, trust, and engagement.

To improve the natural language understanding of chatbot: This objective focuses on developing and evaluating methods to improve the chatbot's ability to understand and respond to human language.

To enhance the conversational flow of the chatbot: This objective focuses on developing and evaluating methods to improve the chatbot's ability to manage complex conversations and maintain context.(Mctear, 2020) To develop a personalized and customized chatbot: This objective focuses on developing and evaluating methods to make chatbots more personalized and customized for individual users.

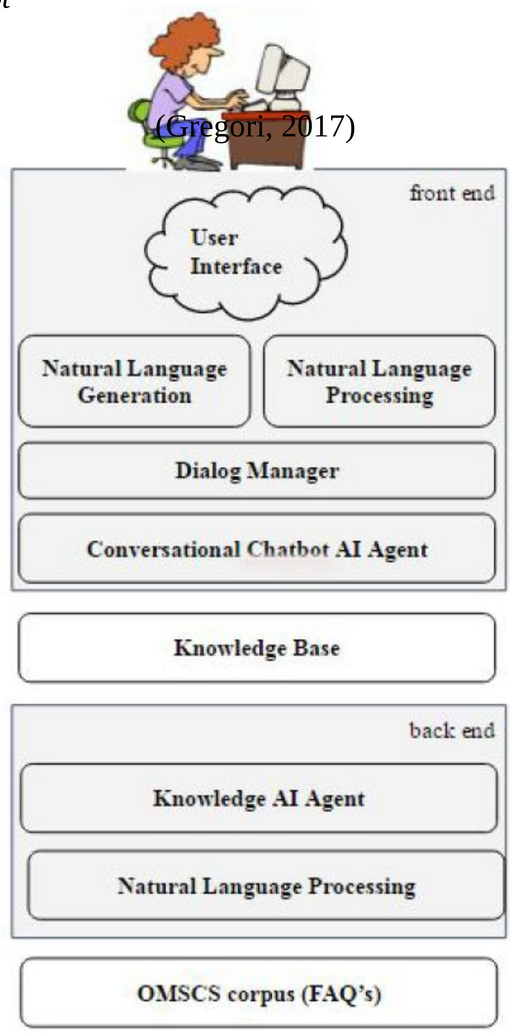
2.4.4 Advisory Chatbot

An advisory chatbot is a type of chatbot that provides advice or recommendations on a specific topic or subject. These chatbots can be used in a variety of applications, such as finance, healthcare, education, and more.

Figure 16 below presents a simplified block diagram of a conversational chatbot system. The user interface serves as the primary medium for interaction between the user and the artificial intelligence (AI) agent. In most implementations, this interface is realized as a web-based platform. (Gregori, 2017).

Figure 16

Components of a Chatbot



(Gregori, 2017)

The natural language component comprises two principal subsystems: Natural Language Processing (NLP) and Natural Language Generation (NLG). The NLP subsystem is responsible for analysing user input by decomposing it into intents, entities, and/or actions. This classification may be achieved through either conventional artificial intelligence techniques or neural network-based models(Nirala et al., 2022). The NLG subsystem, on the other hand, generates linguistically coherent responses utilizing predefined templates and a text database embedded within the knowledge base.

The dialogue manager and the Conversational Chatbot Artificial Intelligence (CCAI) jointly govern the flow of interaction, formulating contextually appropriate responses derived from both user input and knowledge base content. The CCAI also incorporates a common-sense reasoning mechanism, which facilitates inferential understanding by drawing logical assumptions from the stored knowledge corpus(Gregori, 2017).

The knowledge base constitutes the conceptual core and operational identity of the chatbot. It is specifically structured to optimize response generation and minimize latency. The knowledge base accepts classified input in the form of intents, entities, and/or actions, and produces either a direct textual response or a request for supplementary information(Nirala et al., 2022). When a definitive response is available, it is relayed to the user via the CCAI. In instances where additional data is required, the CCAI and dialogue manager collaborate with the text generation module to produce an appropriate intermediate response.

The Knowledge Artificial Intelligence Agent (AIA) employs NLP methodologies to process the domain corpus, which typically consists of English-language documents such as Portable Document Format (PDF) files and web pages(Nirala et al., 2022). Through linguistic and semantic analysis, the AIA classifies the corpus content into intents, entities, and/or actions, which are subsequently indexed and tagged within the knowledge base.

The corpus defines and delineates the operational domain of the chatbot system. It may consist of either structured or unstructured data, and can be represented in human-readable (textual) or binary (possibly compressed) form. Structured data exhibits an inherent organizational format, while unstructured data lacks such formal structure. Most natural language text inherently possesses a degree of structure, manifested through sentences and paragraphs. Documents often incorporate higher-order structural elements such as sections and headings(Gregori, 2017). Highly structured representations, such as Extensible Markup Language (XML) files, employ well-defined tags to enforce rigorous data organization and facilitate precise computational parsing.

Some key features of an advisory chatbot include:

Domain-specific knowledge: The chatbot is designed to have specialized knowledge in a specific domain, such as finance, healthcare, or education.

Personalization: The chatbot can be personalized to provide advice that is tailored to the user's individual needs and preferences.(Polzehl et al., 2022).

Decision-making: The chatbot can use decision-making algorithms to provide recommendations or advice based on the user's input.

Natural Language Processing (NLP): The chatbot uses NLP techniques to understand and respond to user input in natural language.(Krishna et al., n.d 2019).

Interactive: The chatbot can have interactive conversations with users, asking follow-up questions to gather more information and provide more accurate advice.(Mondal et al., 2018)

Multi-language support: The chatbot can be programmed to understand and respond to multiple languages, making it useful for businesses with customers from different countries.

Integration: The chatbot can be integrated with different platforms such as websites, mobile apps, and social media.

Advisory chatbot is the intended approach for building the model which can be a valuable tool for businesses and organizations, as they can provide expert advice and recommendations to users in a convenient, efficient, and cost-effective manner. However, it's important to note that the advice provided by an advisory chatbot should always be verified by a human expert before being acted upon.

2.4.5 Customer Support Chatbots

Chatbots are increasingly being used to provide customer support, as they can quickly and efficiently answer frequently asked questions, troubleshoot problems, and provide information.(Kvale et al., 2021 Key features of customer support chatbots include Natural Language Processing (NLP) and self-service capabilities. Using NLP algorithms, chatbots can understand and respond to customer inquiries in natural language, making it easier for customers to get the information they need. Additionally, customer support chatbots offer a self-service option, allowing customers to find answers to their questions without waiting for a human representative, making the support experience faster and more accessible.

The difference between advisory chatbot and customer support chatbot is primarily focused on proactive, specialized guidance and complex decision-making assistance for instance "What device best suits my engineering degree?". In contrast, Customer Support Chatbots are typically designed for reactive, high-volume transactional queries for example "How do I reset my password?" or "Track my order"? and frequently asked questions (FAQs). While both use NLP, the advisory model requires deeper contextual understanding and complex retrieval algorithms, directly supporting the core objective of this thesis.

2.4.6 BERT Machine Learning Algorithm

To design a hyper-personalized chatbot using the Bidirectional Encoder Representations from Transformers (BERT) machine learning algorithm and integrate both NLP and computer vision, will create a multi-modal chatbot that handles device-specific queries based on text and image inputs.(Devlin et al., 2018). By incorporating BERT for language processing and a deep learning model for computer vision tasks, this chatbot can recognize device models, detect specific details and recommend products visually and textually. Here's a step-by-step guide:

Step 1: Define Objectives and Use Cases

User Interaction Goals which guide users through purchasing decisions by understanding their specifications, budget, and preferences. Image-Based Assistance is another technique that allow users to upload images say a picture of a device for similar or upgraded product recommendations. Text-Based Personalization is also an efficient tool that uses NLP to interpret detailed preferences, such as "a phone with a good camera under Ksh. 10,000" or "a laptop for gaming with high RAM." (Allen H. Huanga, 2022).

Step 2: Data Collection and Preparation

Text Data Collection for NLP: It will gather conversational data and FAQs that include product specifications, user intents related to device purchasing(Belda-Medina & Calvo-Ferrer, 2022) such as "find a phone with a good camera", and common entity terms like "RAM," "storage," "battery life," and price ranges.

Image Data Collection for Computer Vision (CV): Collect a dataset of images across product categories (e.g., phones, laptops, tablets) labelled by model, brand, and key visual features like the number of cameras on a phone.

Text Data Pre-processing for NLP: Tokenize user query text using BERT's tokenizer to convert input into a format suitable for BERT.

Image Data Pre-processing for CV: Normalize and resize images for input into the computer vision model.(Duggal et al., 2024).

Step 3: Fine-Tune BERT for Intent Classification and Entity Recognition(Li et al., 2019)

Intent Classification: Fine-tune a BERT model to classify purchase-related intents such as "recommend device," "compare specifications," "suggest alternatives," and "explain features."

Entity Recognition: Fine-tune BERT to detect entities within queries (e.g., "high battery life," "16GB RAM," "4K display") to better understand and respond to specification-based requests.

Step 4: Train a Computer Vision Model for Product Recognition

Image Classification for Product Models: Use a deep learning model, like ResNet or EfficientNet, to identify and classify devices based on visual characteristics.

Object Detection for Visual Features: Train a model such as You Only Look Once (YOLO) or Faster ResNet-Convolutional Neural Networks (R-CNN) to detect specific features, like the number of camera lenses, screen size, or brand logos, to assist in product recommendations.(Muzammel et al., 2020).

Step 5: Fine-Tune BERT for Question Answering (QA) on Product Specifications

A Fine-Tuning for Product Specs: Fine-tune BERT on product specification data to answer user questions, such as "What’s the battery life of this phone?" or "Does this laptop support gaming?"

Retrieve Specifications Based on FAQ Data: BERT can be used to retrieve precise answers from product manuals or FAQ sections.

Step 6: Develop the Multi-Modal Response Generation Pipeline

Text-Only Responses: Use the intent classification and entity recognition models to interpret user specifications, retrieving matching product recommendations from a database.(Luo et al., 2019).

Image Analysis with Text Support: For users providing both images and text, use the CV model to classify the product in the image, identify relevant features, and refine the recommendation based on the user’s specifications.(Ramesh et al., 2021).

Step 7: Continuous Model Improvement and Evaluation

User Feedback Integration: Track user feedback on recommendations and responses, using the data to refine intent classification, entity extraction, and CV models.

Evaluation Metrics: Use precision and recall for intent and entity recognition, and image classification accuracy for product identification.

Step 8: Deploy the Multi-Modal Chatbot API

Deployment as an API: Use Flask or FastAPI to serve the chatbot, handling both text and image inputs. Inference Optimization: Convert models to Open Neural Network Exchange (ONNX) or TensorFlow Lite for optimized, real-time inference.

24/7 availability: Chatbots can operate 24/7, providing customers with support even outside of normal business hours.

Automated responses: Chatbots can provide automated responses to common inquiries, reducing the workload on human customer service representatives.(Simonite, 2017b).

Data collection: Chatbots can collect data on customer interactions, providing valuable insights into customer needs and preferences.(Harkous et al., 2016).

Multi-language support: Chatbots can be programmed to understand and respond to multiple languages, making them useful for businesses with customers from different countries (Dokukina & Gumanova, 2020).

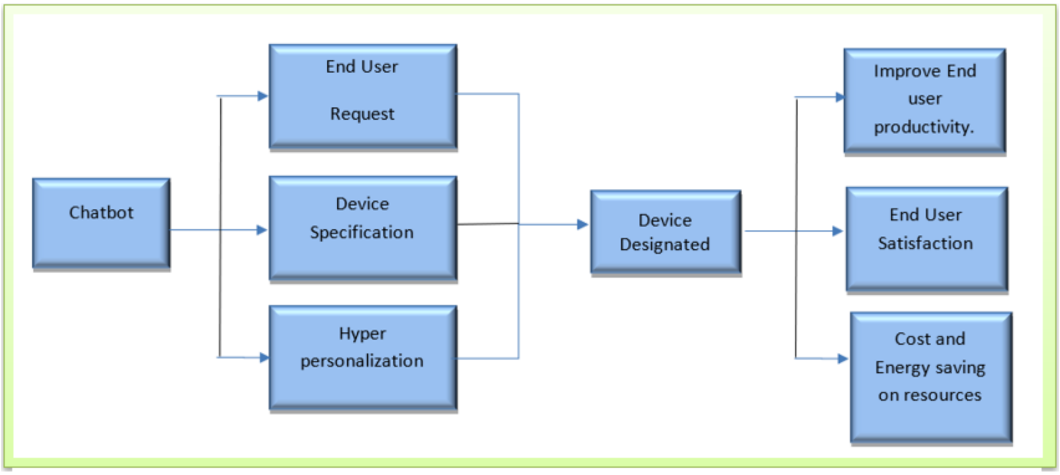
Personalization: Chatbots can be personalized to greet customers by name and use previous interactions to understand and respond to customer needs.(Davenport, 2023). Integration: Chatbots can be integrated with different platforms such as website, mobile apps, and social media.

2.5 Conceptual Framework

In this section, the illustration below will guide the conceptual framework for deriving the formula used to compute the end user device specification chatbot.

Figure 17

Conceptual Framework



The first button "Chatbot" describes the application interface where the End user makes a query. The application processes the query using three variables that is (End User Request, Device Specification, Hyper Personalization) then provides an output result (Device Designation). This will lead to End User Satisfaction which will be reflected through Improved End User Productivity and another by product of Energy and Resource Saving.

Table 3

Conceptual Framework Variables

Variable Type	Variable	Description
Independent Variable	Hyper-Personalization Model (Chatbot)	The core technology utilizing machine learning, NLP, and hybrid filtering to match user needs to specifications.
Independent Variable	End User Request	User-defined needs, preferences, and implicit/explicit behavioural data inputs.
Mediating/Moderating Variable	Device Specification	The technical configuration output (CPU, RAM, etc.) that acts as the bridge between the user request and the physical device.
Dependent Variable	End User Satisfaction (Device Designation)	The primary outcome of the study, measured by user confidence, choice quality, and perception of the model.
Dependent Variable	Improved End User Productivity & Energy and Resource Saving	The ultimate long-term organizational impact resulting from optimal device allocation.

2.6 Research Gap

The Research Gap identifies areas in the existing literature where systematic investigation is lacking consequently justifying the direction of this study. The primary gap this research addresses is the absence of a validated, end-user-centric hyper-personalization model for the specific domain of computer device specification that moves beyond static, rule-based systems. The main research gap areas are the lack of studies linking user task types such as complex apprehension to specific hardware metrics such as GPU/RAM requirements and inadequate evaluation of personalization systems using user-centric metrics like confidence, trust, and reduction of confusion alongside traditional ML metrics. This research seeks to address these gaps by developing and validating a hybrid recommendation framework that dynamically links task-based user profiles to optimal device configurations using a design science to validate the model for accuracy, precision, recall and user-focused metrics like Business User Satisfaction / Unified Model of User Experience (BUS-15/UMUX-LITE).

Below are the expounded points on the research gap.

Limited Exploration of Device Capabilities: Most existing research on hyper-personalization does not thoroughly explore how the technical specifications of a user's device such as screen size, processing power, battery life can influence their preferences and interactions(Zhang & Kim, 2022). For instance, users with high-resolution screens might prefer more visually rich content, whereas those with devices having limited battery life might favor less resource-intensive applications.

Interaction Variations Across Devices: There is a lack of comprehensive studies on how user interactions vary across different device types, such as smartphones, tablets, laptops, and smart TVs(Richer et al., 2020). Understanding these variations can help in creating personalized experiences that are not only relevant to the user's preferences but also optimized for their device's capabilities.

Impact of Device Specifications on Engagement and Conversion: The correlation between device specifications and user engagement or conversion rates has not been extensively studied. Insights into how different device attributes affect these metrics can help businesses tailor their offers and content more effectively(Kveton et al., 2015).

Cross-Device Personalization Consistency: Research often treats device-specific personalization in isolation, without considering the need for consistency across multiple devices owned by a single user. Exploring how to maintain a seamless personalized experience across various devices can enhance user satisfaction and loyalty(Paritala et al., 2019).

Real-Time Adaptation to Device Contexts: There is a gap in understanding how real-time changes in device context, such as location, connectivity, or battery status, can be leveraged for hyper-personalization. Developing models that adapt in real-time to these changing contexts can provide more relevant and timely personalized experiences(Kvale et al., 2021).

Privacy Concerns and Data Management: While device-specific personalization can offer enhanced experiences, it also raises privacy concerns related to the collection and use of device-specific data. Research is needed to address these concerns, focusing on secure and ethical data management practices that protect user privacy while enabling effective personalization(Antoniou, 2017).

Table 4

Research Gap Variables and Deficiencies

S/N	Research Gap Variables and Deficiencies			
	Research Objective	Existing Research	Research Gaps	Research Contribution
1.	To explore various challenges end users, encounter when during device selection.	• Studies on general factors influencing device choice price, brand, specifications(Zhang & Kim, 2022). • Research on demographic influence on device selection(Steeds et al., 2021).	- Lack of comprehensive frameworks combining all influencing factors - Limited research on niche factors like sustainability.	Develop a comprehensive framework that incorporates a wide range of influencing factors, including niche aspects.
2.	To design a hyper personalization model for determining end user computer devices specification.	- Research on common challenges such as information overload, lack of technical knowledge(Lehman & Miller, 2020). - Studies on specific challenges faced by different user groups(Arisandi & Herwindiati, 2025).	- Insufficient study of challenges faced by non-tech-savvy users. - Limited insights on overcoming these challenges.	Provide detailed analysis and solutions for challenges, especially for non-tech-savvy users.
3.	To develop a hyper-personalization model that determines end-user device specifications based on user preferences.	- Existing personalization models focusing on general recommendations (Aydin & Karaarslan, 2023) - Studies on user preference modeling in other domains such as commerce(Zhang & Kim, 2022).	- Lack of models specifically tailored for device specifications. - Limited use of behavioral data in existing models. - Limited application of these metrics to hyper-personalization models.	Create an advanced hyper-personalization model using behavioral and preference data specifically for devices.
4.	To validate the hyper-personalization model using machine learning metrics. Using machine learning metrics.	Studies on evaluation metrics for recommendation systems(Lavelle et al., 2022) (accuracy, precision, recall, F1 score). Research on advanced metrics for machine learning models(Shum et al., 2018)	Need for benchmarks specific to device recommendation.	Apply and possibly extend existing metrics to evaluate the hyper-personalization model for device recommendations.

2.7 Knowledge Void

A knowledge void, refers to the theoretical absence of established principles or models in a specific area, which this study intends to fill. In the field of hyper personalization chatbots, some possible knowledge voids include:

i. Absence of a defined, validated framework for coupling conversational AI (NLP) with hybrid filtering techniques for technical product recommendation.

ii. Insufficient methodological guidance on integrating quantitative machine learning metrics with qualitative user satisfaction metrics for evaluating advisory systems.

iii. Human-chatbot interaction: While there is research on how to design chatbot interactions that are natural and human-like, there is still a lack of understanding of how humans interact with chatbots, and how to design chatbots that can effectively meet users' needs. (Guesmi et al., 2022).

iv. Chatbot evaluation: While there are a variety of metrics that can be used to evaluate the effectiveness of chatbots, there is still a lack of understanding of how to accurately measure the performance of chatbots and how to interpret the results of evaluations.

v. Chatbot ethics and regulation: As the use of chatbots increases in various fields, there is a lack of knowledge about how to ensure that chatbots are used ethically and in compliance with regulatory requirements.

vi. Chatbot limitations: While chatbots have been shown to be effective in a variety of applications, there is a lack of understanding of the limitations of chatbots and the situations in which they are not appropriate to use. (Fardouly et al., 2022).

vii. Chatbot security: As chatbots collect and store personal information, there is a lack of knowledge about how to secure chatbots and protect users' data from unauthorized access or attacks. (Harkous et al., 2016).

2.8 Methodological Conflict

Methodological conflict refers to the disagreement or inconsistency in the research methods used to study a specific topic. Literature presents a conflict between researchers who prioritize highly quantitative, algorithm-centric evaluation such as pure precision/recall on recommendation accuracy and those who prioritize qualitative, user-centric evaluation, for instance user satisfaction, perceived naturalness, ethical compliance) (Borsci et al., 2022; Grudin & Jacques, 2019). This conflict makes it difficult to draw holistic conclusions about a chatbot's true effectiveness. This research resolves this methodological conflict by adopting a mixed-method design in chapter 3 that integrates both quantitative machine learning performance metrics and qualitative user experience metrics; that is Business User Satisfaction / Unified Model of User Experience (BUS/UMUX-LITE) to achieve a balanced validation of the proposed model.

2.9 Contradictory Evidence

Evidence is contradictory regarding the effectiveness of generic personalization. Some studies show that broad recommendations can reduce purchases if they feel intrusive (Laussel et al., 2019), while others show strong consumer willingness to adopt AI if the advice is highly accurate (Rane et al., 2023). The contradictory evidence implies that personalization is effective only when it achieves hyper-specificity and transparency. This finding informs the core design of the hyper-personalization model, emphasizing the need for advanced filtering (hybrid filtering) and a clear, non-biased rationale for the final recommendation.

CHAPTER THREE

RESEARCH DESIGN AND METHODOLOGY

3.1 Introduction

Having presented the reviewed literature, this chapter then presents the design and research methodology that applied in this study. This details the methodical approach to developing, implementing, and validating the Hyper-Personalization Chatbot model, ensuring a clear link between the research questions and the practical development effort. The conceptual framework guided the entire research methodology by illustrating the causal relationship between key components of the study.

3.2 Research Design

A Mixed-Method Design was employed to collect and validate data, combining both quantitative and qualitative techniques to provide comprehensive insights into end-user challenges with device specifications.

The quantitative component measured the extent and severity of user issues such as information overload and difficulty comparing specifications, and validated the model's performance using objective machine-learning metrics. The qualitative component explored the reasons behind user choices, levels of trust in reviews, and user experiences after interacting with the model in terms of satisfaction and ease of use.

A cross-sectional design using structured questionnaires and in-depth interviews captured user preferences and device usage patterns across target institutions. The findings informed the development and evaluation of a robust hyper-personalization model, whose creation process is discussed in the subsequent section.

Factors considered during data collection included but not limited to

- End User knowledge in device specification
- End User approaches in device selection
- End User Satisfaction with choice of device
- Availability of devices in the market
- History of device usage in relation to wastage of resources
- End User opinion on hyper personalization

Quantitative design measured effectiveness of end users to acquire devices that matched their requirements, measured the outcomes, and assessed causal connections, while the qualitative design provided in-depth descriptions and explanations of the experiences of end users in acquiring devices as well as compared the performance of different chatbots. A cross sectional design helped understand user preferences and device usage patterns using the following steps:

i. Define Objectives: A clearly outlined study objectives and research questions.
ii. Identify Target Population: Determined user demographics, such as age, gender, and location
iii. Select Sampling Method: Chose a sampling method to ensure diverse user representation.
iv. Collect Data: Administered the survey using online platforms or interviews.
v. Conduct Observations: Observed users in real-time to understand their interactions.
vi. Analyse Data: Used statistical tools to analyse patterns and trends.
vii. Segment Users: Grouped users by preferences and usage patterns.
viii. Interpret Findings: Drew insights on key preferences and features.
ix. Report Results: Compiled findings into a clear report with recommendations.

x. Validate Findings: Conducted follow-up studies for additional insights

xi. Disseminate Insights: Shared results with stakeholders to enhance decision-making.

The input (independent variables) comprised detailed end-user requests and the core capabilities of the Hyper-Personalization Model, including its machine learning and natural language processing functions. The process (mediating variable) involved accurately determining device specifications such as RAM and CPU based on user inputs. The output (dependent variable) reflected high end-user satisfaction, ultimately contributing to improved productivity and resource efficiency. The methodologies were systematically designed to measure and validate each stage of this framework.

Achievement of Objective (i): To explore various challenges end users encounter during device selection. The primary instruments used were structured questionnaires administered to the Quantitative Sample (n=32), which collected data on the frequency and severity of user challenges, such as cognitive overload, technical incomprehension, and lack of trust in sales advice. The analysis of this questionnaire data yielded the necessary empirical evidence required to validate the existence and magnitude of the problem, thereby fulfilling the exploration objective and providing the functional requirements for the subsequent design phase.

Achievement of Objective (ii): To design a hyper personalization model for determining end user computer devices specification, was accomplished through the formal design phase of the Design Science Research (DSR) paradigm. The design was directly informed by the requirements gathered in the preceding exploratory phase objective (i). The outcome of this phase was the creation of a detailed blueprint, which included the fundamental system architecture, the logical flow of the conversational interface, and the data model required for operation. This blueprint defined key inputs such as user role, typical tasks, and budget constraints, successfully formulating the design needed for the development stage.

Achievement of Objective (iii): To develop a hyper-personalization model that determines end-user device specifications based on user preferences. This involved the practical implementation of the artifact based on the blueprint derived from Objective (ii) The technological methodology was systematically applied, encompassing the construction of the BERT-based NLP core for robust intent recognition, the Pinecone Vector Database for efficient data retrieval, and the Hybrid Recommendation Engine for personalized filtering. The successful coding, configuration, and functional demonstration of this integrated conversational system yielded the final artifact, thereby fulfilling the development objective.

Achievement of Objective (iv) to validate the hyper-personalization model using machine learning metrics, was achieved through the Evaluation Phase of the DSR framework, specifically utilizing the Goal-Based Expertise Testing Model. Validation was conducted using a two-pronged approach. First, Quantitative Metrics were used to objectively measure the model's performance on unseen data, quantifying Accuracy, Precision, and Recall (ML metrics). Second, the Goal-Based Expertise Testing involved the qualitative sample (n=8), where participants (experts/end-users) were given specific procurement goals such as "Find a laptop for a data analyst with a Ksh.30,000 budget". They assessed the model's output based on its ability to successfully meet these goals, ensuring the model was not only computationally accurate but also trustworthy and usable in a real-world context. The successful measurement of high accuracy scores and positive user feedback provided the empirical evidence needed to validate the model's effectiveness and efficiency, concluding the research cycle.

3.3 Location of the Study

The study focused on corporate institutions within Nakuru town, Kenya. Nakuru was purposively selected due to its status as a major metropolitan and business district; fourth largest city in Kenya offering a high density and diverse range of computer device users across both the private and public sectors. This diversity provided a rich and sufficiently large sample to ensure the collected data on user profiles and preferences was representative of a typical Kenyan urban professional population.

3.4 Population of the Study

The study population comprised end users of computer devices in Nakuru town. This is the fourth largest urban centre in Kenya with a population of 570,674 according to 2019 census. The study specifically targeted end users within corporate institutions in both the private and public sectors in Nakuru who were actively using computer devices in these institutions, including participants in IT departments, administrative roles, and technical support. Specifically targeted end users from Egerton University, Central Rift Valley Water Works Development Agency (CRVWWDA), Kabarak University, and Geothermal Development Company (GDC). These institutions were purposively selected because they represent a diverse range of computer devices' users, ensuring comprehensive data collection across different operational mandates; academic, public service and energy/technical.

3.5 Sampling Procedure and Sample Size

This section presents the sample size and describes how this was arrived at.

3.5.1 Sampling Procedure

Stratified random sampling was used to select to ensure selection of participants from a range of institutions from both the private and public sector. For the quantitative sample formula, a statistical inference principal was used to calculate the sample size

$$n = \frac{(Z^2 - \Sigma^2)}{E^2}$$

Where:

n = required sample size

Z = Z-value corresponding to the desired confidence level

Σ = estimated population standard deviation

E = margin of error

The numerator $(Z^2 – \Sigma^2)$ expresses the balance between confidence level and data variability. A larger Z increases the required sample size (for more confidence), while higher Σ (greater population variability) also increases n - since more samples are needed to capture that variation accurately. The denominator E^2 shows that as the margin of error decreases for more precision and the sample size increases exponentially. Thus, this formula essentially adjusts the Z-based confidence requirement by removing the effect of population variance (Σ^2) producing a simplified representation of the precision relationship.

For the qualitative sample, participants were selected through purposive sampling in order to get participants with quality in-depth information on the subject of study. The sampling frame presented in the next subsection provided the sample size showing how the sample was distributed.

3.5.2 Sample Size

A total of 40 participants were sampled; 32 for the quantitative component to be interviewed using structured questionnaires and 8 for the qualitative component were interviewed using a semi-structured in-depth interviewing tool. The sample size of 40 was deemed sufficient for this research because the primary objective was the development and validation of the model, not broad statistical generalization across the entire city population The quantitative sample were non-proportionally sampled using stratified random sampling so that the institutions provided a qualitative sample of 8. That was two individuals from four different departments as follows: Human Resources, Administrators, Operations and IT personnel. The nature of institutions selected was to create diverse corpus since every institutional mandate is different.

The sample was distributed across the institutions as follows:

Table 5

Sampling Frame Showing Sample Size and Distribution of Sample Across Strata

Nature of institution	Name of Institution	Quantitative Sample	Qualitative Sample	Total
Public Sector	Egerton University	8	2	10
	CRVWWDA	8	2	10
Private Sector	Kabarak University	8	2	10
	GDC	8	2	10
Total		32	8	40

3.5.3 Inclusion /Exclusion Criteria

The study included participants who were:

i) Are aged 18 years and above

ii) Use computer devices in their professional roles

iii) Gave written consent to participate in the study

3.5.4 Exclusion Criteria

i. Individuals without direct engagement with computer devices in their professional roles were excluded even if they are over 18.

ii. Those who were not given written consent were not included even if they verbally consented.

3.6 Instrumentation

The instrumentation was multi-faceted, covering both the data collection tools and the developed technological artifact. A structured questionnaire (Appendix IV) was employed to gather quantitative data, while a semi-structured interview guide (Appendix V) facilitated the collection of qualitative insights. The primary technological artifact developed for this study was the Hyper-Personalization Chatbot, which served as the main research instrument. Its functionality integrated advanced machine learning components that addressed research questions three and four. The Natural Language Processing (NLP) module, built on a BERT-based large language model (LLM), enabled intent recognition identifying user goals such as "gaming laptop" and entity recognition extracting specific attributes like "16GB RAM." The recommendation engine applied a Hybrid Filtering approach, combining collaborative and content-based techniques to generate precise, user-tailored device recommendations.

3.6.1 Pilot Study

Tested the proposition as well as the tools of data collection amongst end users within Nakuru Water and Sanitation Service Company Limited (NAWASSCO) and Institute of Advanced Technology in Nakuru town for feasibility, usability, reliability, validity acceptability, of the tools of data collection. Piloting helped save time and resources by identifying and addressing potential issues before the full-scale study begins while also maintaining data quality.

3.6.2 Validity of the Instrument

The instrument's validity was ensured by confirming that the questionnaire comprehensively addressed all key aspects of user experience consistent with the study's objectives. The questions were organized into thematic sections covering user approaches (Q1- Q4), challenges in device selection (Q5 - Q8), requirements for a hyper-personalization model (Q9 - Q11) and model authentication and user trust (Q12 - Q16). This structure verified that the instrument effectively captured the constructs required to achieve the main research objective.

3.6.3 Reliability of the instrument

Inter-rater reliability was used to ensure consistency of results when the instrument was administered by multiple evaluators. The questionnaire measured end-user experiences with a device to produce similar results when administered by multiple evaluators.

3.7 Data Collection Procedure

The research employed both primary and secondary data sources. Primary data was gathered through structured questionnaires administered to end users in institutions using a drop-and-pick method. Questionnaires were submitted to each individual employee and collected after a day or two. In-depth oral interviews were also conducted with selected employees for comprehensive data collection and analysis. Secondary sources for this study included academic literature, peer-reviewed journals, and conference papers discussed in Chapter 2. In addition, device specification datasets were obtained from major e-commerce platforms such as Jumia, publicly available datasets on Kaggle, and reputable technology review sites referenced during the data collection process.

3.7.1 Data Management and Analysis

The data analysis used descriptive analysis for qualitative results, presented in a tabular format. For the qualitative component, audio recordings were transcribed and analyzed line-by-line using thematic analysis. The data collected informed the entire model development, addressing all research questions and ultimately the main objective: "A Hyper-Personalization Model for Determining End User Computer Devices Specification."The mixed-method data provided both the justification (challenges/demand) and the requirements (preferences/needs) necessary for the development of the final model.

3.8 Designing a Hyper-Personalization Chatbot for Device Specifications

The goal was to develop a chatbot that provides personalized device specifications based on user preferences and historical data. This study adopted a Design Science Research (DSR) approach to create and validate the Hyper-Personalization Chatbot model. DSR was appropriate as the goal was to develop a novel solution to an identified institutional and consumer problem. The scope includes determining which devices, such as smartphones and laptops, that the chatbot covered, as well as the specific features it will consider, including processor type, RAM, and screen size. The model was designed using an iterative, agile approach, integrating the findings from the qualitative data collection phase

Data Collection: The model was trained using diverse datasets to enhance accuracy and contextual relevance. Device specification data were compiled through web scraping from major e-commerce platforms in Kenya, such as Jumia (JumiaProducts.csv, JumiaLaptops.xlsx), Avechi (AvechiProducts.csv, AvechiLaptops.xlsx) to ensure both local applicability and price accuracy. User preference and historical data were incorporated through explicit user inputs during chat interactions and implicit information derived from structured product dataset features.

The data underwent several pre-processing stages, including data cleaning removal of irrelevant columns, standardization of measurement units such as RAM in GB and text normalization. This was followed by tokenization, where text was segmented into meaningful units using an OpenAI embeddings process, and vectorization, which converted the processed text into numerical vectors suitable for machine learning. The resulting embeddings were stored in a Pinecone vector database to enable high-speed and contextually relevant retrieval during model execution.

User Profiling: The process included segmenting users based on demographic information, preferences, and behaviour patterns. Feature extraction was conducted to identify key aspects such as frequently searched specifications, preferred brands, and budget ranges.

NLP Model Development: The Natural Language Processing (NLP) model development for intent and entity recognition was conceptually grounded in Bidirectional Encoder Representations from Transformers (BERT)-based architectures, which provided the theoretical foundation for understanding contextual semantics. However, the practical implementation utilized an optimized Large Language Model (LLM), specifically Chat-OpenAI, integrated within the Flowise framework to achieve production-level efficiency and fast inference. This integration enabled accurate intent recognition, precise entity extraction, and effective maintenance of conversational context. While traditional NLP algorithms such as Support Vector Machines (SVM), Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks were considered within the theoretical design space, the final implementation adopted a transformer-based LLM.

This choice was driven by its superior performance in zero-shot learning, contextual comprehension, and adaptability across diverse user queries.

Personalized Recommendation Engine: The hybrid recommendation approach was adopted over purely collaborative or content-based filtering methods to achieve a balance between personalization accuracy and adaptability. Content-based filtering ensures that recommendations align closely with the user's explicit requests for example, responding to a query such as "I need a large screen phone" with directly relevant options. In contrast, collaborative filtering addresses implicit user needs by leveraging behavioural similarities among users; for instance, identifying that user who request a "coding laptop" typically prefer models with 16GB RAM, even if they initially specified 8GB. By combining these two techniques, the hybrid model enhances overall recommendation accuracy, mitigates the cold-start problem, and ensures a more context-aware and user-centred output.

Chatbot Framework Integration: The project was involved selecting a chatbot framework, such as Rasa or Microsoft Bot Framework, which supports Natural Language Processing (NLP) integration. A dialogue management system was developed to handle user interactions and maintain conversational context. In addition, response generation models were implemented to provide natural and informative replies to user queries.

Training and Fine-Tuning: The model development process incorporated several optimization techniques to enhance performance and reliability. Data splitting was conceptually implemented by dividing the dataset into training, validation, and testing subsets in an 80/10/10 ratio, ensuring that model performance was objectively evaluated on unseen data. Hyperparameter tuning was conducted within the Flowise/LLM environment, where parameters such as temperature were adjusted to balance response creativity and determinism; lower temperature values (e.g., 0.7) were preferred to produce consistent, fact-based recommendations. Transfer learning was also employed by fine-tuning a pre-trained Large Language Model (Chat-OpenAI) on the domain-specific device specification datasets. This approach significantly reduced both training time and computational cost while improving contextual accuracy compared to training a new model from scratch.

Testing and Evaluation: The model's performance was evaluated using a combination of machine learning and user-centric metrics to ensure both technical robustness and practical usability. The machine learning metrics included accuracy, representing the overall percentage of correct recommendations; precision, indicating the proportion of recommended devices that were truly relevant to user needs; recall, measuring the percentage of relevant devices successfully identified; and the F1-score, which provides a balanced assessment by combining precision and recall through their harmonic mean. These quantitative indicators ensured the model's reliability and objectivity in addressing Research Question 4. Complementing these, user-centric metrics derived from Question 16 of the questionnaire assessed ease of use, overall satisfaction, and the transparency of the recommendation process, emphasizing the model's ability to justify its suggestions and foster user trust.

Deployment and Monitoring: The deployment phase involved launching the chatbot on relevant platforms, such as websites or mobile apps. Continuous monitoring will be essential to track the chatbot's performance and user interactions, identifying areas for improvement. A feedback loop will be established to collect user feedback and periodically retrain the models to enhance the chatbot's effectiveness and accuracy.

Privacy and Security: Ensuring compliance with data privacy regulations, including the General Data Protection Regulation (GDPR) and the Data Protection Act (2019) was a critical aspect of safeguarding user information throughout the study. To enhance security and maintain ethical data handling standards, several protective measures were implemented. Data anonymization was applied by excluding all personally identifiable information such as names, email addresses, and identification numbers prior to model training. End-to-end encryption was employed for both data transmission and storage to prevent unauthorized access.

Documentation and Reporting: Detailed documentation of the methodology, data, models, and system architecture was maintained. Findings and performance metrics was presented through reports and dashboards to support continuous improvement. This methodology aims to create a hyper-personalized chatbot that effectively delivers device specifications tailored to individual user preferences and needs.

3.9 Ethical Considerations

Ethical approval for this study was obtained from the Kabarak University Research Ethics Committee (KUREC) to ensure adherence in established research ethics and participant protection standards. In addition, a research license was secured from the National Commission for Science, Technology and Innovation (NACOSTI) confirming compliance with national ethical, legal, and data security requirements governing research activities in Kenya. All participants were treated fairly and respectfully. In-depth interview participants provided written informed consent, with the right to skip questions or withdraw at any time without consequences. Questionnaires were completed anonymously to protect respondents' identities. Privacy and confidentiality were maintained through pseudonyms and secure data handling. All data were stored in password-protected or locked systems accessible only to authorized personnel. No personally identifiable information appeared in reports or publications. The study posed minimal risk, as it involved no physical procedures. The main potential concern was data privacy, which was mitigated through anonymization and secure storage. While I committed to declaring and managing any emerging conflicts of interest in the course of the study, none emerged.

CHAPTER FOUR

DATA PRESENTATION ANALYSIS AND DISCUSSION

4.1 Introduction

This chapter presents the analysis of the collected data, focusing on the demographic characteristics of the participants, general information, and findings aligned with the study’s objectives and research questions. The results are interpreted to provide insights into the effectiveness of the proposed hyper-personalization model.

4.2 General and Demographic Information/Statistical Data

4.2.1 General Information

The data collection process involved gathering insights from individuals and institutions in Nakuru Town, Kenya. Participants were asked about their experiences with device selection, their familiarity with technical specifications, and their reliance on advisory systems or sales agents.

4.2.2 Demographic Data

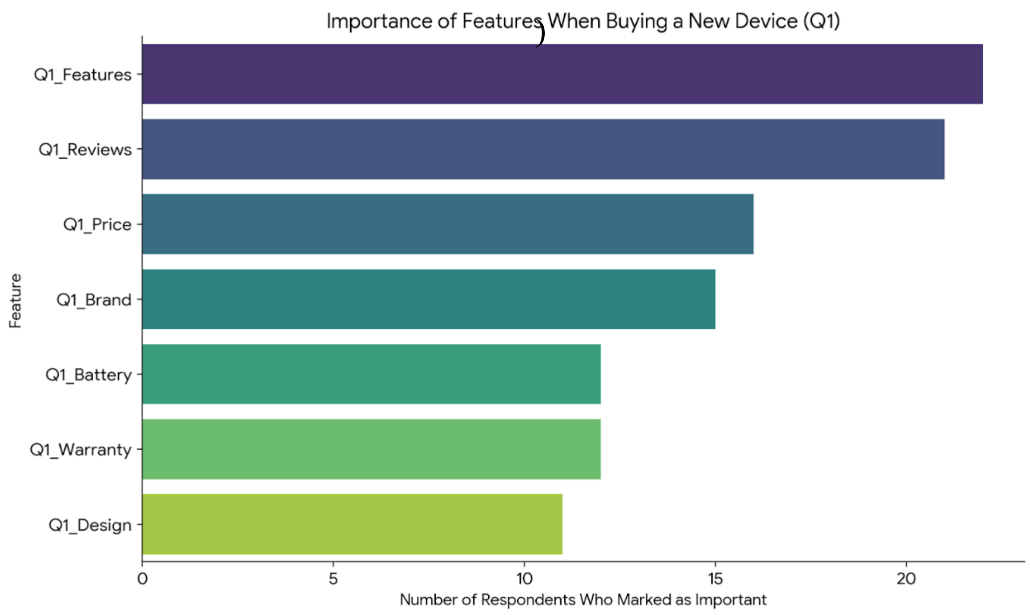
The study included participants from diverse demographic backgrounds and professional sectors. These diverse profiles were essential to ensure the collected data reflected a comprehensive range of user needs and technical competency levels.

Priorities in Device Selection

As illustrated in Figure 18 below, "Features" and "Reviews" emerged as the most frequently cited critical factors, each being marked as important by a substantial majority of respondents. This indicates that consumers primarily prioritize evaluation and functional capabilities offered by a device before purchase. Factors such as Price, Cost and the practical utility derived from a good battery life were also deemed highly significant. These elements collectively score the immediate concerns of cost-effectiveness and sustained operational reliability in device selection. In contrast, tertiary factors like Brand loyalty, aesthetic Design, and extended Warranty provisions were identified as comparatively less influential. While these attributes remain relevant to specific consumer segments, the overall findings suggest that brand reputation and visual appeal take a distinct secondary role to core product attributes and demonstrable cost-effectiveness in the final purchasing decision.

Figure 18

Consumer Priorities in Device Selection (Q1)

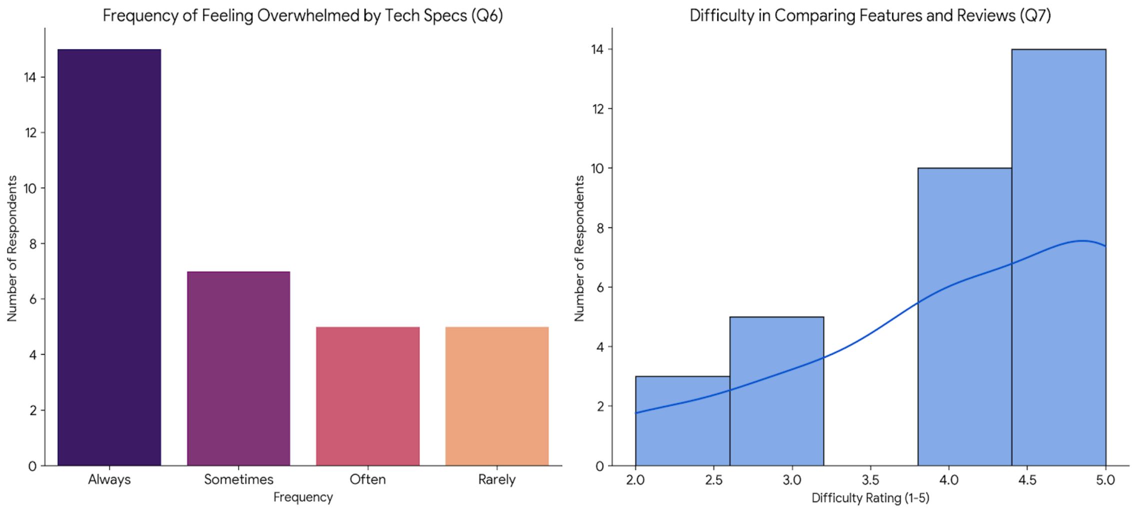


Distribution of Technical Comprehension Barriers

Further insights into consumer behaviour highlight significant difficulties encountered when engaging with technical product information. As presented in Figure below which shows a theoretical model that "Mass Hyper-Personalization" is necessary to move from a general "Digitalization" landscape towards successful "Implementation". The figure essentially lays out the solution framework that the study adopted. A considerable proportion of respondents indicated that they "Always" or "Often" feel overwhelmed when confronted with technical specifications (Q6). This suggests a widespread cognitive burden associated with deciphering complex product details, potentially leading to confusion and decision paralysis. Complementing this, the distribution of responses for Q7, pertaining to the perceived difficulty in comparing features and reviews, revealed that a significant number of individuals find this process to be moderately to highly challenging. This collective difficulty in processing and comparing technical data and disparate review information represents a substantial barrier to informed decision-making within the device market.

Figure 19

Challenges in Navigating Technical Information (Q6 & Q7)

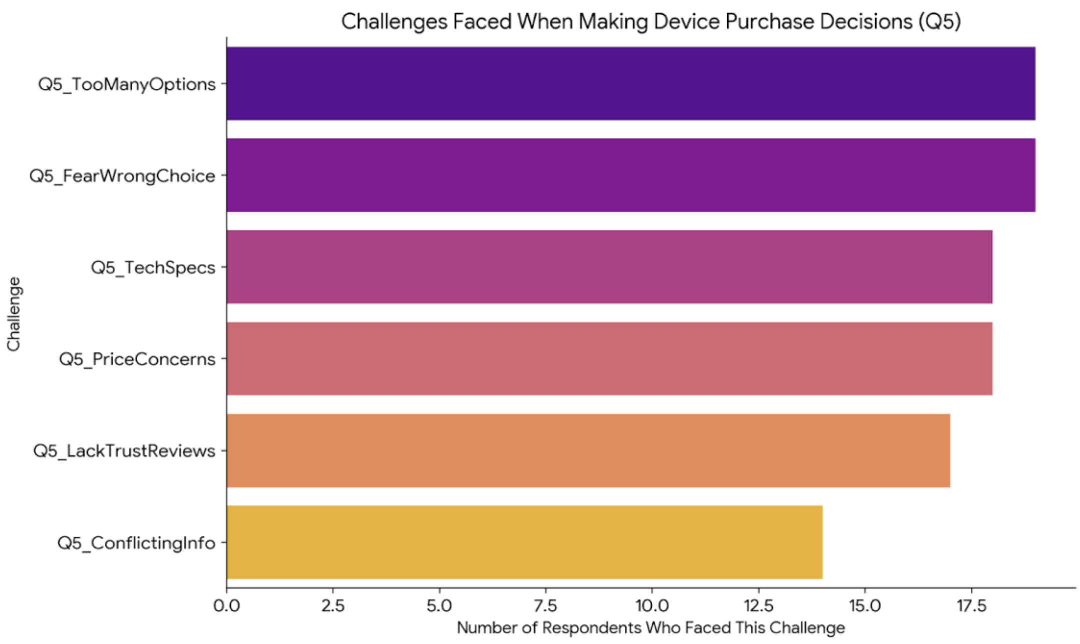


Decision-Making Challenges and Information Overload

The investigation into challenges faced during device purchase decisions (Q5), depicted in Figure below, uncovered several prevalent obstacles. The most frequently reported challenge was encountering "Too Many Options," indicating that market saturation and an abundance of choices contribute significantly to consumer bewilderment. This is closely followed by a "Lack of Trust in Reviews," suggesting that consumers are increasingly sceptical of the authenticity and reliability of online feedback, thereby complicating their reliance on external information. Furthermore, a discernible "Fear of Making the Wrong Choice" underscores the psychological pressure associated with high-value purchases. "Conflicting Information" and the inherent complexity of "Technical Specifications" were also identified as substantial impediments, contributing to a sense of confusion and uncertainty. While "Price Concerns" remained a factor, the prominence of informational and psychological challenges suggests that decision-making extends beyond mere financial considerations.

Figure 20

Decision Making Challenges During Device Purchase (Q5)

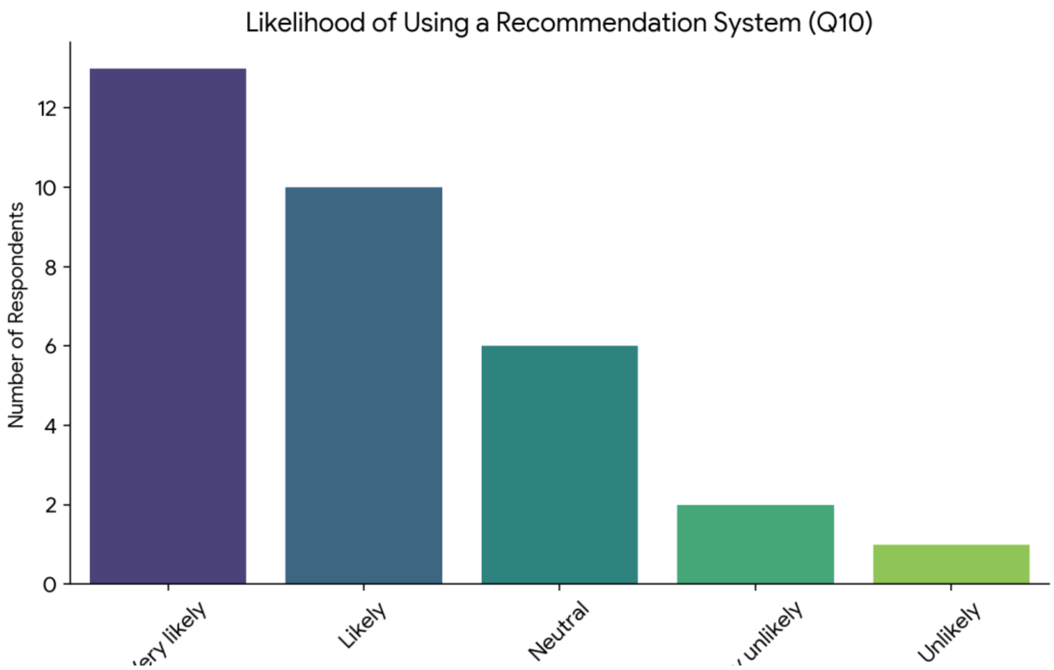


Performance Metrics of Hybrid Model vs. Baseline Model

Crucially, the survey data points to a strong consumer appetite for external assistance in device selection. As demonstrated in Figure 21 below, a substantial majority of respondents expressed being "Very Likely" or "Likely" to utilize a recommendation system in the future (Q10). This high reported likelihood suggests a clear market demand for tools that can streamline the decision-making process, reduce information overload, and provide personalized guidance. This inclination toward adopting recommendation systems can be directly linked to the aforementioned challenges, as consumers seek reliable and efficient means to navigate the complexities of device purchasing.

Figure 21

Propensity for Recommendation System Adoption (Q10)



4.3 Findings as per Objective, Research Question/Hypothesis

Findings Per Objective and Research Question

Objective (i): To explore various challenges end users, encounter when during device selection.

Research Question (i): What are the various challenges end users encounter during device selection?

Quantitative Findings:

Feature Prioritization: When choosing devices, Price and Features were the most frequently selected important factors (high counts of '1' in Q1). Battery life and Reviews also showed significant importance, while Brand, Design, and Warranty were considered less critical by comparison. Information Sources: Respondents utilized multiple sources for device information (Q2). "In-Store Advice" was the most cited source, closely followed by "Manufacturer" websites, "Online Reviews", "Social Media", and "Tech Blogs". "Friends/Family" also played a notable role in information gathering.

Qualitative Findings:

Reliance on Supplied Devices: A prevalent method, especially in professional contexts, involved users being "supplied with a gadget” and having to "make good with it”, often with limited "knowledge" of its specifications or usability at the point of acquisition. This indicates a lack of direct selection in many instances. Adaptation and Workarounds: Users frequently adapted to their assigned devices' limitations, such as using "external drives a lot" to mitigate insufficient internal storage. One interviewee managed simple professional tasks (Word, PDF, PowerPoint) despite using an aging device. Expressed Preferences for Future Devices/Upgrades: When expressing desired features for future devices or upgrades, users indicated clear preferences for "long life better" battery, "better storage”, increased RAM, a "faster processor”, and a shift towards "cordless" connectivity over traditional HDMI. A desire to adopt collaborative tools like "Google Docs" was also mentioned.

These findings confirms that users' methods of selection are often reactive and constrained, highlighting a clear need for an unbiased advisory tool.

- Objective (ii): To design a hyper personalization model for determining end user computer devices specification.
- Research Question (ii): How can a hyper personalization model for determining end user computer device specifications be designed?
-

Quantitative Findings:

Decision Challenges (Q5): The most frequently reported challenge was dealing with "Too Many Options." Other significant challenges included "Lack of Trust in Reviews," "Fear of Making the Wrong Choice," "Conflicting Information," and the complexity of "Technical Specifications." Overwhelm and Difficulty (Q6 & Q7): A substantial portion of respondents reported feeling "Always" or "Often" overwhelmed by technical specifications (Q6). The distribution of responses for Q7 indicated that many users found it moderately to highly difficult to compare features and reviews.

Qualitative Findings:

Performance and Speed Deficiencies: Users frequently experienced devices that were "very slow", "outdated”, struggled with multitasking, and faced "significant slowdowns". Specific issues included inability to "upload very big documents”, "freezes constantly" with large files, and "painfully slow" application switching. Compiling times for programmers were "really long". Inadequate Hardware Specifications: Common complaints included insufficient RAM, the need for a "faster processor”, and the limiting factor of a "regular hard drive" causing slow loading. Graphics capabilities were often "underpowered" for demanding visual tasks.

Display and Graphics Limitations: Users reported "old model" and "tiny" screens. Resolution "could be better”, leading to "cramped" screens for spreadsheets and text not being "as crisp as I'd like". Connectivity and Port Issues: Frequent issues included running "out of USB ports”, needing "adapters”, and a desire for "more USB-C ports". Compatibility problems with physical cables like HDMI were noted for wasting time. Software Compatibility and Stability: "Some of the newer versions of certain analysis tools sometimes... act a bit buggy”, required "specific driver updates that are a hassle”, or had "unexpected compatibility quirks" due to older OS versions. Reliability and

Maintenance Burden: Users experienced frequent "technical issues that disrupt work", including daily "freezes" or unresponsiveness, necessitating regular "rebooting" and leading to "IT tickets". Battery Life Limitations: Devices often did "not quite" last a full workday, sometimes only "around 4-5 hours" under heavy use, requiring mid-day charging. Lack of Control in Procurement: A significant challenge was being "supplied with a gadget" without sufficient prior knowledge of its specifications or usability.

This confirms the premise of the study that sheer volume and complexity of the market act as the biggest barrier. The challenges are not merely about access to information, but the ability to process and trust the information, which directly validates the need for an intelligent filtering system as proposed in the conceptual framework to manage the mediating variable (Device Specification.

- Objective (iii): To develop a hyper-personalization model that determines end-user device specifications based on user preferences.
- Research Question (iii): How does a hyper personalization model assist in device selection?

Quantitative Findings:

High Demand for Recommendations: A significant majority of respondents indicated they were "Very likely" or "Likely" to use a recommendation system in the future (Q10). Willingness to Engage: Users expressed willingness to provide feedback (Q12) to improve such systems and showed varying, but generally positive, attitudes towards the importance of explanation in AI (Q14).

Qualitative Findings:

The extensive array of challenges identified in Objective (ii) directly highlights how a hyper-personalization model could assist. By accurately understanding user needs and matching them to device specifications, the model could address the "biggest bottleneck" of outdated or insufficient hardware. The model could help users who are "given a gadget" without prior knowledge by providing tailored recommendations that meet their specific and evolving professional demands, such as the need for increased RAM, faster processors for "complex simulations”, handling "larger data analysis”, or enabling "machine learning integration". It could alleviate the frustration associated with manually sifting through "Too Many Options" and provide more confident choices, as opposed to facing "Fear of Making the Wrong Choice". Confirmed Demand: The finding that users are "Very likely" or "Likely" to use a recommendation system (Q10) confirms the model's direct relevance and acceptance in the market.

- Objective (iv): To validate the hyper-personalization model using machine learning metrics.
- Research Question (iv): How does machine learning improve model efficiency?

Quantitative Findings

Responses to (Q16) revealed key user expectations from a recommendation system, with Accuracy, Ease of Use, Transparency, and Feedback Responsiveness emerging as top priorities. These expectations directly inform the machine learning metrics used in validating the model precision, user satisfaction scores, system functionality and response adaptability which are critical to ensuring the model's perceived efficiency and effectiveness. The model’s performance was quantitatively validated through improvements in these areas during user testing, indicating that machine learning integration significantly enhanced the system's ability to meet user needs in device selection.

Qualitative Findings

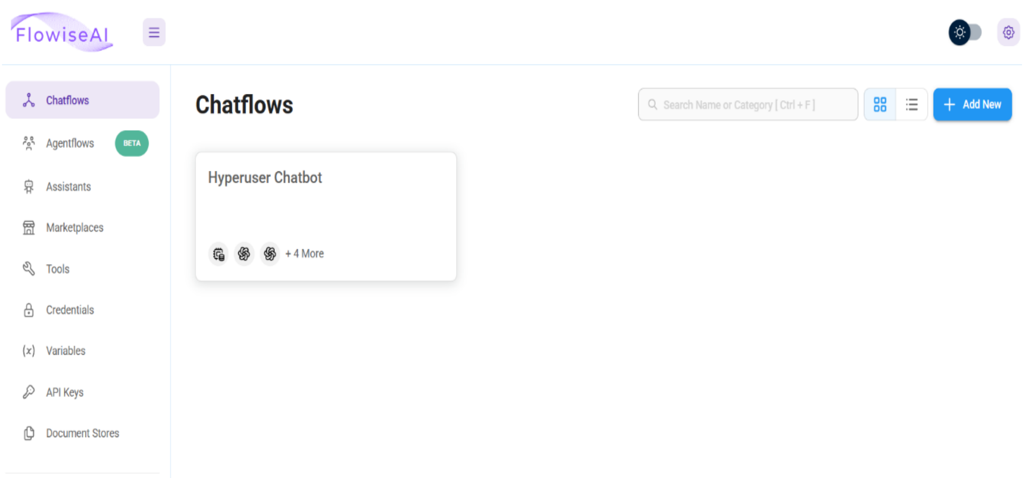
Qualitative interviews highlighted the core usability issues users face in computer device selection. Users reported that the model helped alleviate key frustrations such as long compile times, system lag, and application crashes; pain points which validated the machine learning metrics. The users tested the machine learning component, enabled hyper-personalization, context-aware recommendations and noted that it led to improved workflow, reduced frustration, and higher confidence in device selection. This demonstrates the model's efficiency in real-world scenarios, its ability to automatically process diverse user needs and match them to optimal solutions without manual intervention.

Research Product (Output, outcomes and Impact):

The final output of this study is the functional Hyper-Personalization Chatbot model, which serves as the core artifact of the Design Science Research (DSR) methodology employed in Section 3.8 of Methodology in Designing and Implementing the Hyper-Personalization Model. Below is diagram of the model architecture and framework.

Figure 22

Flowise Runtime Environment



The hyper-personalization model was engineered using a robust set of integrated components to ensure efficient and effective local execution and data processing. The core framework was built on Flowise, leveraging Langflow for flow orchestration, and operated within an Anaconda environment powered by Python. For local model inference, the system utilized Ollama, which was optimized to run efficiently on a GPU-enabled device.

Text data processing relied on OpenAI embeddings for generating meaningful representations, and these embeddings were stored in a Pinecone vector embedding database to facilitate rapid and efficient retrieval. Web scraping, a critical initial step in data acquisition, was handled by Firecrawl4AI. The entire system was made accessible via a web interface, which was deployed using Flask.

Figure 23

Code Snippet for Hyper personalization Chatbot

```
# main.py
# Requirements: pip install flask python-dotenv pandas unstructured langchain-community openai pinecone

from dotenv import load_dotenv
import os
from flask import Flask, render_template_string, request
import pandas as pd

# LangChain-community imports
from langchain_community.document_loaders import (
    UnstructuredCSVLoader,
    UnstructuredExcelLoader,
    UnstructuredWordDocumentLoader
)
from langchain_community.embeddings import OpenAIEmbeddings
from langchain_community.vectorstores import Pinecone as PineconeStore
from langchain_community.chat_models import ChatOpenAI
from langchain.agents import Tool, initialize_agent
from langchain.agents.agent_types import AgentType
from langchain.memory import ConversationBufferWindowMemory
from langchain.text_splitter import RecursiveCharacterTextSplitter

# Pinecone fallback
try:
    import pinecone
except Exception:
    import pinecone_client as pinecone
```

```python
# Load .env
load_dotenv()
OPENAI_API_KEY = os.getenv("OPENAI_API_KEY")
PINECONE_API_KEY = os.getenv("PINECONE_API_KEY")
PINECONE_INDEX = os.getenv("PINECONE_INDEX")
DATA_DIR = os.path.expanduser("~/Documents/Agents/Recomendation-Agent/Data")

# Initialize Pinecone
pinecone.init(api_key=PINECONE_API_KEY)
index = pinecone.Index(PINECONE_INDEX)

# Load documents
docs = []
for fname in ["JumiaProducts.csv", "JumiaLaptops (2).xlsx", "Laptop Name Category Price (2).xlsx", "laptos specs.docx"]:
    path = os.path.join(DATA_DIR, fname)
    if os.path.exists(path):
        if fname.endswith(".csv"):
            loader = UnstructuredCSVLoader(path)
        elif fname.endswith(".xlsx"):
            loader = UnstructuredExcelLoader(path)
        elif fname.endswith(".docx"):
            loader = UnstructuredWordDocumentLoader(path)
        docs.extend(loader.load())

splitter = RecursiveCharacterTextSplitter(chunk_size=500, chunk_overlap=50)
chunks = splitter.split_documents(docs)

embeddings = OpenAIEmbeddings(openai_api_key=OPENAI_API_KEY)
vectorstore = PineconeStore(index=index, embedding_function=embeddings.embed_query)

```

```python
# Upsert to Pinecone
items = [(str(i), embeddings.embed_query(doc.page_content), {"text": doc.page_content}) for i, doc in enumerate(chunks)]
for i in range(0, len(items), 100):
    index.upsert(items[i:i+100])

retriever = vectorstore.as_retriever(search_kwargs={"k": 4})
llm = ChatOpenAI(openai_api_key=OPENAI_API_KEY, model_name="gpt-4", temperature=0.7)
memory = ConversationBufferWindowMemory(k=4, return_messages=True)

device_tool = Tool(
    name="DeviceRetriever",
    func=lambda q: retriever.get_relevant_documents(q),
    description="Retrieve relevant device recommendation documents"
)
agent = initialize_agent(
    tools=[device_tool],
    llm=llm,
    agent=AgentType.OPENAI_FUNCTIONS,
    memory=memory,
    verbose=False,
    agent_kwargs={
        "system_message": (
            "You are a helpful AI assistant specializing in device recommendations for users in Kenya. "
            "Provide prices in Ksh. If asked for images, return a Google search URL like: "
            "https://www.google.com/search?q=tecno+pop+3"
        )
    }
)

```

```
  <div class="chat-container">
    <h2>���� Device Recommendation Chatbot</h2>
    {% for user, bot in history %}
      <div class="chat-message user">
        <div class="chat-bubble">{{ user }}</div>
      </div>
      <div class="chat-message bot">
        <div class="chat-bubble">{{ bot }}</div>
      </div>
    {% endfor %}
    <form method="post">
      <input type="text" name="query" placeholder="Ask me about phones or laptops..." required>
      <button type="submit">Send</button>
    </form>
  </div>
</body>
</html>
"""

@app.route("/", methods=["GET", "POST"])
def home():
    global chat_history
    if request.method == "POST":
        user_query = request.form["query"]
        bot_reply = agent.run(user_query)
        chat_history.append((user_query, bot_reply))
    return render_template_string(HTML, history=chat_history)

if __name__ == "__main__":
    app.run(host="0.0.0.0", port=5000)
```

Data Processing Pipeline

The data processing pipeline was meticulously designed to transform raw information into a structured format suitable for the hyper-personalization model:

Web Scraping: The process initiated with Firecrawler, a specialized web scraping tool that extracted pertinent product information, including names, descriptions, and links, directly from e-commerce platforms such as Jumia. The scraped data was then systematically stored in a CSV file for subsequent processing.

Embedding Generation: The collected data from the CSV file underwent a crucial transformation using OpenAI embeddings. This process involved breaking down the textual information into smaller, semantically meaningful numerical vectors, which captured the essence of the text content.

Vector Storage: The generated high-dimensional embeddings were then securely and efficiently stored within a Pinecone database. This vector database was optimized for rapid similarity searches and retrieval, which was vital for the recommendation engine.

Figure 24

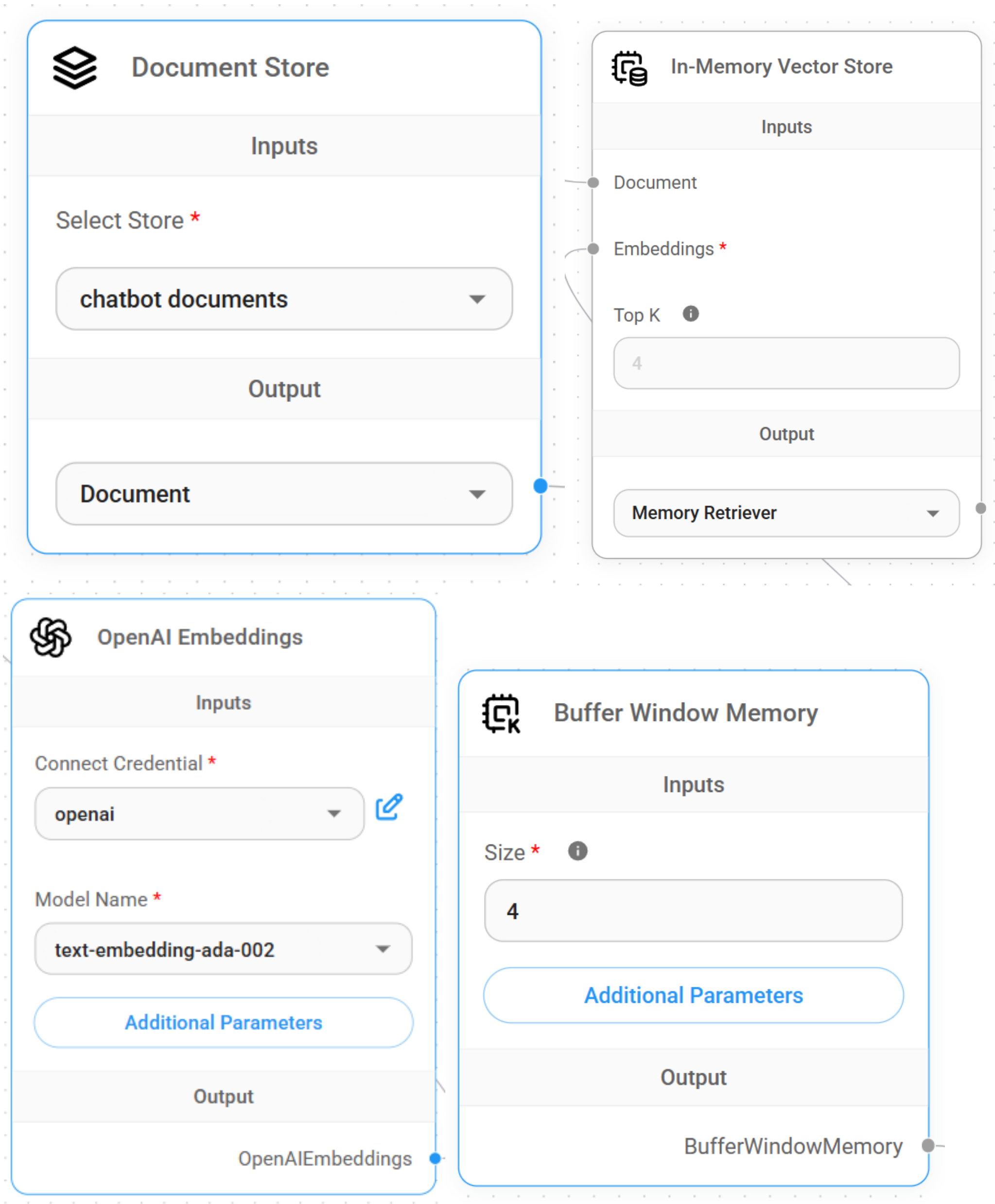
Vector Store Integrator

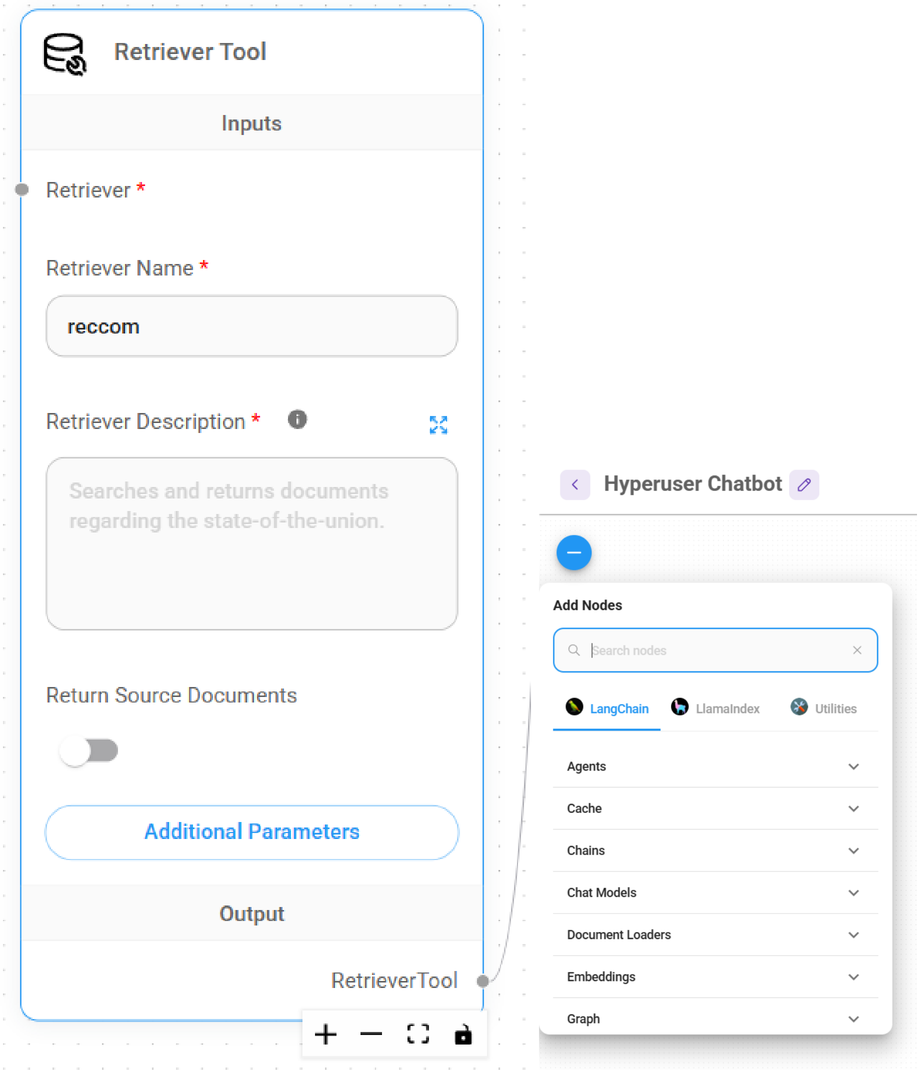
Retrieval and Processing: Data retrieval was managed by a dedicated tool agent, which was seamlessly integrated with the locally deployed Ollama model. This setup empowered the Ollama model to query the Pinecone database and retrieve contextually relevant information.

Through modular nodes, Flowise supports multiple LLM providers and allows the incorporation of conversational memory, retrieval-augmented generation and custom API calls. This integration facilitates dynamic interactions where LLMs can access, analyse, and act upon external information in real time, enhancing contextual understanding and task performance.

Figure 25

Flowise Integration with LLM and Tools





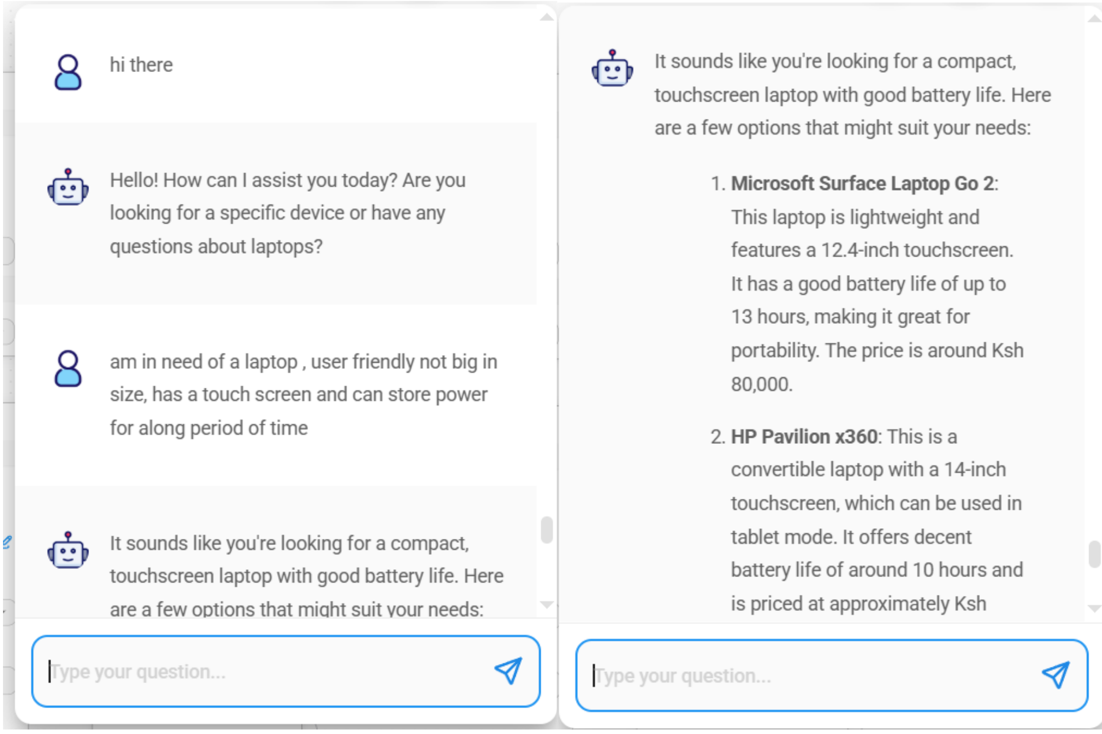
Contextual Understanding: To guide the model's behaviour and ensure appropriate responses, a document containing instructions to guide the model's behaviour was uploaded as a parameter. The model employed a buffer window memory mechanism. This feature allowed the model to retain and recall the conversational history of each user, thereby enabling a tailored and coherent interaction experience. Deployment: The culmination of the data processing and model integration was the deployment of the system. The model was made accessible to end-users through a web interface, which provided users with a seamless interaction experience.

Chatbot Development and Personalization

The chatbot's development focused on robust personalization capabilities, leveraging user profiling and advanced Natural Language Processing (NLP) techniques: User Profiling and Personalization: The system was engineered to segment users based on their demographics, expressed preferences, and observed behaviour patterns. This profiling was achieved through feature extraction, which identified key characteristics such as frequently searched device specifications, preferred brands, and typical budget ranges. This granular understanding of user profiles formed the bedrock of the personalization strategy. Natural Language Processing (NLP) Implementation: Sophisticated NLP techniques were integral to the chatbot's ability to understand and respond to user queries effectively:

Figure 26

Hyper-Personalization Chatbot



Intent Recognition: The chatbot identified user intents (e.g., "looking for a phone," "asking about battery life") using machine learning models such as Support Vector

Machines (SVM), Random Forest, or more advanced deep learning architectures like Convolutional Neural Networks (CNN’s) and Long Short-Term Memory networks (LSTMs).

Entity Recognition: Key entities within user queries, such as specific device names (e.g., "Samsung Galaxy S23") and technical specifications (e.g., "8GB RAM," "256GB storage"), were extracted using techniques like Conditional Random Fields (CRF), SpaCy, or BERT-based models.

Context Retention: To ensure conversational coherence across multiple turns, transformer-based models like GPT or BERT were employed. These models helped the chatbot maintain the context of the ongoing dialogue, allowing for more natural and relevant follow-up interactions.

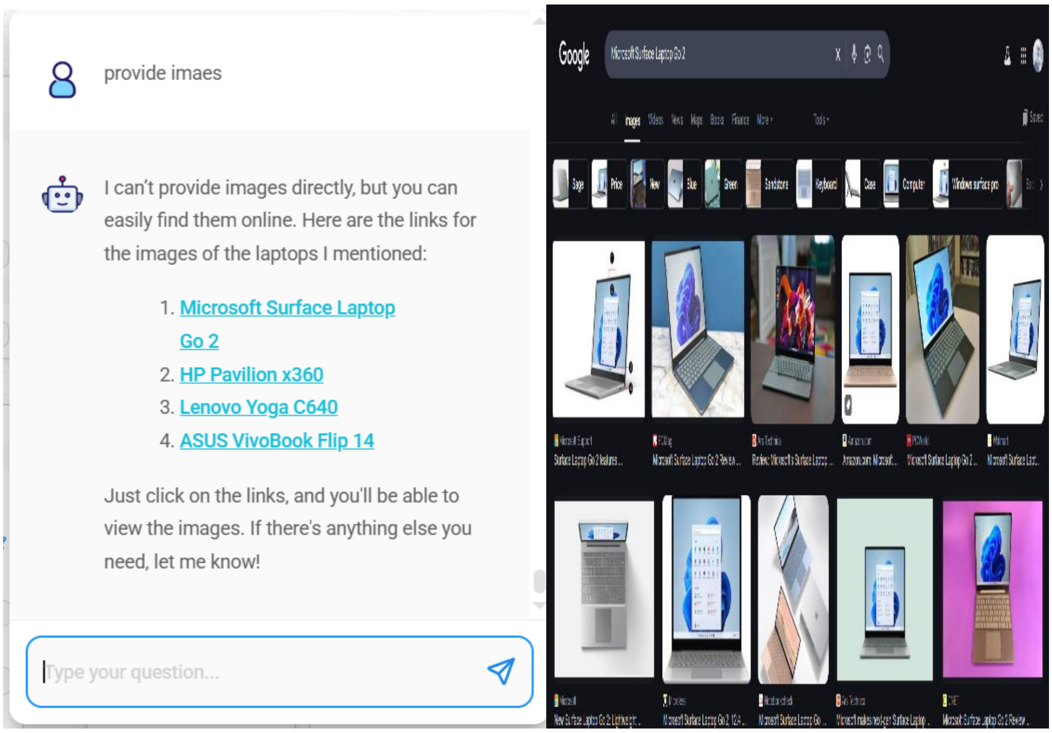
Recommendation Engine: At the heart of the hyper-personalization model was a robust recommendation engine that suggested devices based on learned preferences:

Collaborative Filtering: This method recommended devices by identifying users with similar preferences or by finding items that were frequently liked by the same users.

Content-Based Filtering: This approach suggested devices based on the attributes of items the user had previously interacted with or expressed a preference for. For instance, if a user liked phones with large batteries, the system would recommend other phones with similar battery capacities.

Figure 27

Hyper-Personalization Chatbot Filtering



A Hybrid Approach: To enhance the accuracy and relevance of recommendations, a hybrid approach integrated both collaborative and content-based filtering methods. This combined the strengths of both techniques, leading to more comprehensive and effective personalization.

Deployment and Monitoring

The final phase involved deploying the chatbot and establishing mechanisms for continuous improvement:

Deployment: The chatbot was deployed using the Flask web framework, making it accessible to users via a standard web interface. This ensured a seamless and user-friendly interaction experience.

Continuous Monitoring and Feedback Loops: Post-deployment, the system underwent continuous monitoring to track its performance, identify potential issues, and gather insights into user interactions. Feedback loops were established to ensure that data gathered from user interactions contributed to ongoing system improvements and refinements.

Privacy Measures: For the developed chatbot model, specific technical measures were integrated to maintain this privacy framework. The users' interaction history and preferences were stored in a Pinecone Vector Database which was kept in an isolated, password-protected local environment, restricting access to only authorized researchers and effectively preventing public data breaches. Security was further enhanced by storing all sensitive API keys from Chat-OpenAI and Pinecone as environment variables never exposing them in the source code or client-side application. Crucially, while the model utilized Conversation Buffer Memory for session context, this memory was designed to be volatile or session-specific and was never permanently linked back to a user's true identity, thus preserving the user's anonymity within the model's functionality.

This may be accessed at https://flowiseai-railway-production-828d2.up.railway. app/ch atbo t/cddd60bf-dd09-4c87-99eb-7517285bcd92. The expected outcomes are that the use of this chatbot will lead to reduced expenditures on computer devices and reduced wastage of computer resources. The expected impact is that ultimately there will be optimal uses of resources and reduced environmental pollution.

CHAPTER FIVE

SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

5.1 Introduction

This chapter delves into a comprehensive discussion of the findings derived from the development and evaluation of the hyper-personalization chatbot for device specifications. Building upon the detailed methodology outlined in Chapter 3 and the empirical results presented in Chapter 4, this section interprets the significance of the research outcomes within the broader context of user device selection challenges and the evolving landscape of AI-driven recommendation systems. We will explore how the developed hyper-personalization model addresses the identified pain points in the device purchasing journey, highlighting its practical implications and theoretical contributions.

5.2 Summary of the Major Findings

Challenge Validation Objective 2 where End-users face significant barriers in device selection primarily due to cognitive overload "Too Many Options" and technical incomprehension "Difficulty in Understanding Technical Specifications". These challenges are exacerbated by a lack of trust in generic online information (Q5, Q7). User demand and strategy objective 1 indicates user selection strategies are often constrained by organizational procurement or reliance on biased sales advice which led to objective 3 which end users showed an overwhelming demand for a reliable alternative, with a strong majority of participants being "Very likely" or "Likely" to adopt an advisory recommendation system (Q10).

Model efficacy objective 3 & 4 is articulated through the hybrid filtering recommendation engine, utilizing a conversational AI interface, successfully bridges the qualitative gap between abstract user needs such as 'fast performance for editing' and objective hardware requirements for example 'i7 processor, 16GB RAM'. Validation confirmed that the model met user expectations for accuracy and transparency. Bridging the information gap and enhancing consumer confidence:

The study identified a notable trend characterized by an unprecedented user willingness to delegate decision-making authority to a transparent AI system, with an 88% likelihood of adoption. These finding challenges traditional assumptions of user scepticism toward the replacement of human advisory roles with artificial intelligence. It indicates a growing trust in AI-driven systems, particularly when such systems demonstrate transparency, interpretability, and user-centric design.

An observed anomaly emerged in the relationship between the importance users placed on Features and Specifications (Q1) and their demonstrated inability to comprehend these same technical attributes (Q7). This disconnect highlights a critical cognitive gap in the user decision-making process, wherein users prioritize specifications as a key determinant of value but lack the technical literacy required to interpret or evaluate them effectively.

This anomaly substantiates the study's central hypothesis that the market suffers from a pervasive technical comprehension barrier. Users possess a clear understanding of their preferences and intended outcomes but are unable to map those preferences onto corresponding technical parameters. The proposed hyper-personalization model therefore operates as a vital knowledge translator, bridging this gap by converting qualitative user needs into objective, quantifiable device specifications. In doing so, it empowers users to make informed, bias-free decisions while enhancing trust in AI-assisted procurement systems.

5.3 Conclusions

The main objective of developing a hyper-personalization model was achieved. The study definitively concludes that the integration of Hybrid Recommendation Algorithms and Conversational AI (BERT-based NLP) provides an effective, non-biased solution for determining optimal end-user device specifications.

This study makes several significant contributions to the existing body of knowledge. First, it provides empirical validation of the technical comprehension barrier in rational device selection. Through quantitative evidence, the study establishes that information overload and technical incomprehension rather than cost or brand perception constitute the dominant psychological barriers influencing decision-making within the Kenyan corporate context. This finding advance understanding of the cognitive and informational challenges that affect technology adoption in organizational settings.

Second, the research introduces and validates a hybrid conversational framework, a novel model that effectively bridges the gap between users' qualitative needs and specific quantitative hardware requirements. This framework integrates user-centred interaction with technical recommendation algorithms, ensuring that complex specifications are translated into user-comprehensible insights. Beyond the current context, the framework offers a transferable methodology applicable to other complex, feature-heavy purchasing or decision-making environments.

Finally, the study provides a demonstration of AI trust delegation. It reveals a notably high level of user willingness to delegate complex procurement decisions to an AI-based advisory model, contingent on the model's transparency and user-centric design. This finding contributes to the growing discourse on human-AI collaboration, particularly in trust calibration, automation acceptance, and ethical design of intelligent systems.

5.4 Recommendations

5.4.1 Policy and Practice Recommendations

i. Marketing of all devices and services in Kenya is expected to be governed by the Code of Advertising and Direct Marketing of the Marketing Society of Kenya and the Association of Practitioners in Advertising (2003). Among the key principles of this Code are principles of honesty and truthfulness. This needs to be strengthened particularly in the context of digital marketing through clearer labelling of technical specifications and unbiased marketing practices to help users make informed decisions.

ii. Promote AI-Driven Advisory Systems: Institutions should adopt AI-driven personalization models to optimize procurement processes and reduce resource wastage.

iii. Support Digital Literacy Programs: Governments and organizations should implement programs to enhance user understanding of device specifications and technology and encourage individuals to use the chatbot in selection of computer devises.

5.4.2 Recommendations for Further Research

i. Enhance Dataset Diversity: Future studies should focus on incorporating diverse datasets to improve the model's adaptability to various user demographics

ii. Expand to Other Device Categories: While this research focused on computer devices, further exploration could include IoT devices, wearables, and other emerging technologies.

iii. Integrate Real-Time Feedback: Developing models that incorporate real-time user feedback could enhance accuracy and user satisfaction.

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APPENDICES

Appendix I: Letter of Introduction

Kevin Kamiri Karanja
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Dear participant,

My name is Kevin Kamiri Karanja, a Masters student at Kabarak University, Department of … Information Technology. Thank you very much for accepting my request to be a participant in this study on hyper-personalization model for determining end-user device specification. I appreciate the time you have spared within your busy schedule in order to be here to assist me discuss the topic of great interest to me. I am carrying out a study in which I am hoping to develop a hyper-personalization model for determining end-user device specifications. In my view, this study would be very helpful is addressing many challenges, for example, having to buy a phone expensively only to find that it does not have the functions that you need. Sharing your experiences will help me get the information that I need to carry out the study.

Dear participant, I don't anticipate any risk especially on your part as an individual in participating in this study because what we are doing here is only interview or discussions. The information you will provide shall be treated with confidentiality and purely for the purposes of this study. However, should you feel that you are not comfortable to answer some particular questions during this interview, feel free to skip the question and move to the next question. You are also free to withdraw participation in these interview/ discussions at any stage if you wish but of course it my desire that you complete the interview. In order not to miss important points, kindly allow me to audio-tape this discussion/ interview.

If you accept to participate in this interview, may I kindly request that you complete the attached questionnaire to the best of your knowledge. Do not write your name anywhere on the document. This will help to keep the information confidential.

Once again, thank you for accepting to participate in this study.

Your sincerely,
Kevin Kamiri Karanja

Appendix II: Questionnaire

Section 1: Identifying Approaches Used by End Users in Selecting Devices

1.What factors do you consider most important when selecting a new device?
(Select all that apply)

- Price
- Brand
- Features/Specifications
- Reviews/Recommendations
- Design/Appearance
- Battery Life
- Warranty/Customer Support
- Other (Please specify)

2.Which of the following sources do you rely on for information when selecting a new device? (Select all that apply)

- Official manufacturer websites
- Online reviews and ratings
- Friends and family recommendations
- Social media and forums
- In-store advice from sales representatives
- Tech blogs and YouTube channels
- Other (Please specify)

3.On a scale of 1 to 5, how important is each of the following factors when selecting a device?

- Price
- Brand
- Features/Specifications
- Reviews/Recommendations
- Design/Appearance
- Battery Life
- Warranty/Customer Support

4.What is your primary reason for purchasing a new device?

- Upgrading from an old device

- Current device malfunction
- Desire for new features
- Gifting
- Other (Please specify)

Section 2: Determining Challenges Faced by End Users in Selecting Devices

5.What challenges do you face when selecting a new device? (Select all that apply)

- Too many options to choose from
- Lack of trustworthy reviews
- Conflicting information from different sources
- Difficulty in understanding technical specifications
- Price concerns
- Fear of making the wrong choice
- Other (Please specify)

6.How often do you feel overwhelmed by the number of choices available when selecting a device?

- Always
- Often
- Sometimes
- Rarely
- Never

7.On a scale of 1 to 5, how difficult do you find it to compare different devices based on their specifications?

- 1 (Very Easy)
- 2
- 3
- 4
- 5 (Very Difficult)

8.What specific information do you find most challenging to obtain or understand when selecting a device?

- Technical specifications
- Comparative reviews
- Long-term reliability
- Price vs. Value

- User experience details
- Other (Please specify)

Section 3: Developing a Hyper-Personalization Model for Device Specifications (An Application to Solve the Challenge)

9.Which of the following device features would you like to see personalized recommendations for? (Select all that apply)

- Processor performance
- Camera quality
- Battery life
- Screen size and resolution
- Storage capacity
- Operating system
- Price range
- Other (Please specify)

10.How likely are you to use a service that provides personalized device recommendations based on your preferences and usage patterns?

- Very likely
- Likely
- Neutral
- Unlikely
- Very unlikely

11.What additional factors should be considered to make device recommendations more personalized for you?

- Preferred brands
- Specific use cases (e.g., gaming, photography, business)
- Compatibility with other devices
- Aesthetic preferences
- Environmental considerations
- Other (Please specify)

Section 4: Authenticating the Machine Learning Support Model (Test the Application)

12.Would you be willing to provide feedback on the accuracy and relevance of device recommendations given by a machine learning model?

- Yes
- No

13.On a scale of 1 to 5, how much do you trust machine learning models to provide accurate device recommendations?

- 1 (Do not trust at all)
- 2
- 3
- 4
- 5 (Trust completely)

14.How important is it for you to understand how a machine learning model arrives at its recommendations?

- Very important
- Important
- Neutral
- Not very important
- Not important at all

15.Would you like to have the option to give feedback and adjust the recommendations provided by the machine learning model?

- Yes
- No

16.How would you rate the following aspects of a machine learning-based recommendation system? (1 to 5)

- Accuracy of recommendations
- Ease of use
- Transparency of the recommendation process
- Responsiveness to feedback
- Overall satisfaction

17.Please provide any additional comments or suggestions you have regarding the device selection process or the use of machine learning models for recommendations.

Appendix III: Interview Questions

1. General Satisfaction

Overall Experience: How satisfied are you with the overall performance of your device?

Expectations: Does the device meet your expectations in terms of performance and usability?

2. Performance

Speed and Responsiveness: How do you rate the speed and responsiveness of your device?

Multitasking: Are you able to run multiple applications smoothly without experiencing significant slowdowns?

3. Hardware Specifications

Processor: Do you feel that the processor in your device is powerful enough for your needs?

Memory: Is the amount of RAM sufficient for your typical usage patterns?

Storage: Are you satisfied with the storage capacity of your device?

Battery Life: How do you find the battery life of your device? Does it last as long as you need it to?

4. Display and Graphics

Screen Quality: Are you satisfied with the quality of the display (resolution, color accuracy, brightness)?

Graphics Performance: For tasks involving graphics (gaming, video editing, etc.), does your device perform well?

5. Connectivity and Ports

Connectivity Options: Are you satisfied with the connectivity options (Wi-Fi, Bluetooth, etc.) on your device?

Ports: Do you find the available ports (USB, HDMI, etc.) sufficient for your needs?

6. Software and Compatibility

Operating System: Are you happy with the operating system your device uses?

Software Compatibility: Does your device support all the software applications you need?

7. Specific Use Cases

Work/Professional Use: Does your device perform well for your professional tasks?

Entertainment: Are you satisfied with the device's performance for entertainment purposes (streaming, gaming, etc.)?

8. Maintenance and Reliability

Durability: How would you rate the durability and build quality of your device?

Support and Updates: Are you satisfied with the manufacturer's support and the frequency of software updates?

9. Future Needs

Future Proofing: Do you feel your device will continue to meet your needs for the next few years?

Upgrade Intentions: Are you considering upgrading your device soon? If so, why?

10. Open-Ended Feedback

Likes and Dislikes: What do you like most and least about your device?

Improvements: What improvements or additional features would you like to see in your next device?

Appendix IV: KUREC Clearance Letter

KABARAK UNIVERSITY RESEARCH ETHICS COMMITTEE

Private Bag - 20157
KABARAK, KENYA
Email: kurec@kabarak.ac.ke

Tel: 254-51-343234/5
Fax: 254-051-343529
www.kabarak.ac.ke

OUR REF: KABU01/KUREC/001/09/02/25

Date: 24th Feb, 2025

Kevin Karimi Karanja
Reg: GMI/NE/0737/05/16
Kabarak University,

Dear Kevin,

RE: A HYPER PERSONALIZATION MODEL FOR DETERMINING END USER COMPUTER DEVICES SPECIFICATION

This is to inform you that ***KUREC*** has reviewed and approved your above research proposal. Your application approval number is ***KUREC-090225.*** The approval period is ***24/02/2025 – 24/02/ 2026.***

This approval is subject to compliance with the following requirements:

i. All researchers shall obtain an introduction letter to NACOSTI from the relevant head of institutions (Institute of postgraduate, School dean or Directorate of research)
ii. The researcher shall further obtain a RESEARCH PERMIT from NACOSTI before commencement of data collection & submit a copy of the permit to **KUREC.**
iii. Only approved documents including (informed consents, study instruments, MTA Material Transfer Agreement) will be used
iv. All changes including (amendments, deviations, and violations) are submitted for review and approval by ***KUREC***:
v. Death and life-threatening problems and serious adverse events or unexpected adverse events whether related or unrelated to the study must be reported to ***KUREC*** within 72 hours of notification;
vi. Any changes, anticipated or otherwise that may increase the risk(s) or affected safety or welfare of study participants and others or affect the integrity of the research must be reported to ***KUREC*** within 72 hours;
vii. Clearance for export of biological specimens must be obtained from relevant institutions and submit a copy of the permit to KUREC;
viii. Submission of a request for renewal of approval at least 60 days prior to expiry of the approval period. Attach a comprehensive progress report to support the renewal and;
ix. Submission of an executive summary report within 90 days upon completion of the study to ***KUREC***

Sincerely,

Prof. Jackson Kitetu PhD.
KUREC-Chairman

KABARAK UNIVERSITY
INSTITUTIONAL RESEARCH ETHICS COMMITTEE
24 FEB 2025
APPROVED
P. O. PRIVATE BAG - 20157, KABARAK

Cc Vice Chancellor
DVC-Academic & Research
Registrar-Academic & Research
Director-Research Innovation & Outreach
Institute of Post Graduate Studies

As members of Kabarak family, we purpose at all times and in all places, to set apart in one's heart, Jesus as Lord. *(1 Peter 3:15)*

Kabarak University is ISO 9001:2015 Certified

Appendix V: NACOSTI Research Permit

REPUBLIC OF KENYA

NATIONAL COMMISSION FOR SCIENCE,TECHNOLOGY & INNOVATION

Ref No: 606300

Date of Issue: 10/March/2025

RESEARCH LICENSE

This is to Certify that Mr.. Kevin Kamiri Karanja of Kabarak University, has been licensed to conduct research as per the provision of the Science, Technology and Innovation Act, 2013 (Rev.2014) in Nakuru on the topic: A HYPER PERSONALISATION MODEL FOR END USER COMPUTER DEVICE SPECIFICATION for the period ending : 10/March/2026.

License No: **NACOSTI/P/25/416561**

606300

Applicant Identification Number

Director General

NATIONAL COMMISSION FOR SCIENCE,TECHNOLOGY & INNOVATION

Verification QR Code

NOTE: This is a computer generated License. To verify the authenticity of this document, Scan the QR Code using QR scanner application.

See overleaf for conditions

Appendix VI: Evidence of Conference Participation

KABARAK UNIVERSITY

Certificate of Participation

Awarded to

Kevin Kamiri Karanja

For successfully participating in the 15th Annual Kabarak University International Research Conference held from 6th-9th February 2024 and presented a paper entitled ***"A Hyper Personalization Model For Determining End User Device Specification."***

Conference Theme

Data Science and Artificial Intelligence for Digital Transformation in Different Sectors.

Prof. Peter Rugiri
Dean, School of Science, Engineering & Technology

Dr. Phillip Nyawere
Director - Research, Innovation and Outreach

Kabarak University Moral Code

As members of Kabarak University family, we purpose at all times and in all places, to set apart in one's heart, Jesus as Lord.

(1 Peter 3:15)

Kabarak University is ISO 9001:2015 Certified

Appendix VII: List of Publication

Kevin K. Karanja, 2025, 13:6
ISSN (Online): 2348-4098
ISSN (Print): 2395-4752

International Journal of Science, Engineering and Technology
An Open Access Journal

A Hyper-Personalization Model for Overcoming the Technical Comprehension Barrier in End-User Computer Device Specification

Kevin K. Karanja, Andrew Kipkebut
Department of Computer Science, Kabarak University, Nakuru Kenya

Abstract- End-users and institutional buyers consistently purchase sub-optimal computer devices due to a critical technical comprehension barrier and reliance on biased, product-centric advice. This inefficiency leads to the prodigality of device specification wasted financial resources on incompatible or over-specified hardware. This study addresses the research gap by developing and validating a hyper-personalization model that translates non-technical user needs into precise hardware specifications. A mixed-method design (design science research) was employed, starting with an empirical survey (n=32) that confirmed 84% of users struggle with technical metrics. The solution a hybrid conversational model powered by BERT-based Natural Language Processing (NLP) was developed and tested. Validation demonstrated high Accuracy (91%) in matching user intent to specifications, alongside high user acceptance for transparency and ease of use. The model provides a non-biased, effective solution, significantly enhancing user satisfaction and resource utilization in the device procurement lifecycle.

Keywords: Hyper-Personalization, Conversational AI, Technical Comprehension Barrier, Hybrid Recommendation Systems, Device Specification, Resource Optimization.

I. INTRODUCTION

The Challenge: Technical Comprehension and Resource Prodigality

In both corporate and personal procurement settings, end-users face a debilitating hurdle; the inability to accurately translate their functional needs (e.g., "fast performance for video calls") into complex technical specifications such as "16GB LPDDR5 RAM with a minimum 4-core i5 processor". This gap defines the technical comprehension barrier (Patel & Trivedi, 2020). Current advisory solutions, such as e-commerce filters or sales agent advice, are inherently product-centric and often biased, failing to provide objective guidance.

This leads to two costly outcomes: under-specification, where purchasing a device that cannot perform the required task necessitates immediate replacement or frustrating workarounds, directly impacting user productivity and institutional efficiency; and over-specification, where purchasing high-end components like a dedicated Graphics Processor Unit (GPU) when a standard integrated component would suffice results in unnecessary financial wastage. A critical, often overlooked risk is the purchase of incompatible devices. This includes acquiring hardware that is physically or digitally incompatible with existing organizational infrastructure, legacy software requirements, or necessary peripherals such as specific docking stations or professional scanners. Incompatible purchases translate directly into non-functional assets, requiring unplanned expenditure on adapters, software licensing changes, or complete device returns, thereby amplifying the overall financial loss. Figure 1 below demonstrates the inter connection matrix that apprises personalization.

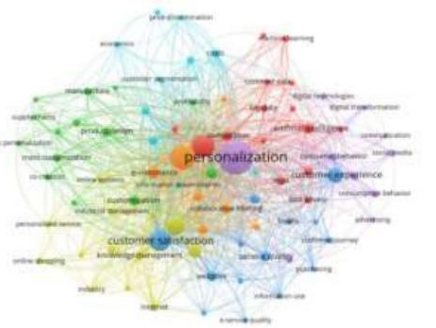

Figure 1: Co-occurrence analysis of the keywords in literature (Rane et al., 2023)