AN APPLICATION TO MANAGE PRACTICALS IN OBJECT-ORIENTED PROGRAMMING ACCORDING TO THE STUDENT'S INDIVIDUAL LEARNING NEEDS USING ARTIFICIAL INTELLIGENCE.

A MINI THESIS SUBMITTED IN PARTIAL FULFILMENT OF THE REQUIREMENTS FOR THE DEGREE OF MASTER OF SCIENCE IN INFORMATION TECHNOLOGY

OF

THE UNIVERSITY OF NAMIBIA

BY

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JUNE 2025

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ABSTRACT

The rapid advancement of artificial intelligence (AI) has introduced significant possibilities for enhancing education, particularly in complex subjects like object-oriented programming (OOP). This research explores the development of a chatbot application specifically designed to support students in mastering OOP practicals by addressing individual learning needs. The chatbot leverages an AI model that tailors exercises, provides real-time feedback, and offers targeted recommendations for supplementary learning resources. By analyzing the specific challenges faced by students, the chatbot enables personalized guidance, fosters self-directed learning, and aids in building a foundational understanding of OOP concepts.

Employing a mixed-methods approach, the study combines quantitative data from user interactions with qualitative feedback to evaluate the chatbot's effectiveness. Iterative design and testing allowed the chatbot to evolve dynamically, addressing emerging student needs, identifying knowledge gaps, and providing adaptive support. The research aligns with best practices in AI-driven education, demonstrating the chatbot’s capacity to deliver timely, contextually accurate feedback while reinforcing key OOP concepts. The study also critically examines the broader implications of AI in OOP education, highlighting its potential to create personalized, adaptive learning environments.

Findings underscore the promising role of AI in computer science education, presenting a scalable, responsive solution that bridges traditional teaching methods with the diverse needs of today’s learners. Preliminary results reveal substantial improvement in student engagement, understanding, and retention of OOP principles, highlighting AI’s transformative potential in reshaping OOP instruction and positioning it as a crucial component of modern education.

Keywords: Artificial Intelligence (AI), Object-Oriented Programming (OOP), chatbot, personalized learning, real-time feedback, adaptive support, mixed-methods, user interactions, iterative design, AI-driven education, student engagement, knowledge retention.

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List of Abbreviations and or Acronyms

AI – artificial intelligence

OOP – Object Oriented Programming

MIPC - Minimally Invasive Programming Courses

NLP – Natural Language Processing

UI – User Interface

UX -User Experience

Acknowledgments

I would like to express my heartfelt gratitude to Almighty for His unwavering guidance and strength throughout my academic journey. I extend my sincere appreciation to my esteemed supervisor, Prof. A. Diaz, whose wisdom, mentorship, and unwavering support have been invaluable in shaping this research. I am also deeply thankful to my family for their enduring encouragement, understanding, and love, which provided the foundation for my academic pursuits.

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CHAPTER 1: INTRODUCTION AND PROBLEM STATEMENT

1.1 Background to the Study

According to Smith (2019), object-oriented programming is a fundamental concept in computer science that allows for the creation of sophisticated software systems with advanced features. One approach for enhancing program modularity involves creating distinct memory partitions to house both data and code. These partitions then serve as templates for generating duplicate modules as needed. Object-oriented programming (OOP), on the other hand, is a programming methodology that streamlines the organization of complex programs through the application of three fundamental principles: encapsulation, polymorphism, and inheritance. This methodology allows for representing real-world entities as objects, essentially combining custom data and instructions into single, cohesive entities called objects. OOP's strengths lie in its capacity to model real-world problems from the user's perspective, construct reusable software components and easily expandable libraries, and facilitate effortless modifications and extensions to component implementations without necessitating a full recoding effort.

However, despite its significance, many students find it challenging to understand the concepts and effectively acquire the necessary practical skills. According to Johnson (2020), providing personalized assistance to students based on their unique learning needs is one of the major challenges faced by educators. This is where artificial intelligence (AI) can play a transformative role. In this study, we propose an application that uses AI to manage object-oriented programming practicals and provide students with tailored support. The application will be designed to interact with students through a chatbot, which aims to facilitate communication and engagement while also providing personalized feedback and guidance.

Artificial intelligence (AI) is the process of machines, particularly computer systems, simulating human intelligence. It encompasses various applications such as expert systems, natural language processing, speech recognition, and machine vision. By imitating the problem-solving and decision-making abilities of the human mind, AI utilizes computers and machines. In the field of education, AI has the potential to tackle significant challenges. Researchers have discovered that AI can address disparities in

knowledge access, research, and cultural diversity. It also plays a crucial role in preventing the widening of technological gaps, both within and between countries (Smith, Johnson, & Williams, 2020). According to Bacos (2020), today's cutting-edge technologies are progressing towards the era of human-centric advancements. With the emergence of technology in educational settings, human learning can undergo significant transformation, driven by technology, while machines can also adapt their learning processes with insights gained from humans. Technology plays a pivotal role in effectively observing and evaluating human behaviors to gain a deeper understanding and respond appropriately. It can aid in monitoring and collecting data, evaluating performance, and delivering valuable feedback to learners, whether adjustments to behaviors are required or they serve as models to emulate.

A study by Ciolacu et al. (2017) states that educational activities are progressively transitioning to online platforms, with course materials being made accessible in digital form. This shift allows for the collection of data and its utilization in the analysis of the learning process. In the context of the Fourth Revolution in Education, the active and interactive participation of students plays a crucial role in enhancing the quality of learning. While machine learning techniques have made remarkable advancements in data analysis and predictive capabilities, they have been underutilized in the assessment of learning quality. The new application aims to change how we manage OOP practicals by using AI and machine learning. Its main goal is to create a smart learning environment where AI carefully analyzes how each student learns and adjusts to meet their specific needs. The application provides students with specific exercises, instant feedback, and suggestions for additional learning materials, helping them learn independently. This study adeptly navigates the complex journey of developing such an application, covering the stages of data collection, machine learning model development, and continuous system improvement.

1.2 Statement of the problem

According to Abbasi et al. (2021), students often find it difficult to apply object-oriented programming (OOP) concepts in practice, which makes completing practical tasks particularly challenging. Many students struggle to understand core OOP principles such as classes, objects, polymorphism, encapsulation, and inheritance.

In their conference paper *Illustrated Guide to Support Object-Oriented Programming Online Learning in Introductory Courses*, Díaz and Puente (2021) highlight that these challenges are part of a broader issue in programming education. They note that students often face difficulties in developing algorithmic thinking, understanding abstract concepts, and engaging with practical, problem-based tasks. Traditional teaching methods, they argue, tend to place too much emphasis on specific programming languages rather than on the conceptual and problem-solving skills that underpin programming competence. These methods often lack personalized support and timely feedback, which are essential for mastering complex topics. While tutorials and peer study groups offer some assistance, they are not tailored to individual learning needs or pace.

This situation points to the need for more effective, flexible approaches to programming education. One promising solution is the use of illustrated guides that present abstract programming concepts without being tied to any specific programming language. By using real-world analogies and visual tools, these guides can help students better understand difficult ideas and develop stronger algorithmic thinking skills. This approach is particularly valuable in online courses, where hands-on, practical engagement is often limited. When combined with AI-powered learning systems, such resources can further enhance personalization and improve learning outcomes for programming students.

1.3 Objectives of the study

The main objective of this research is to develop a computer-interaction-based chatbot application that offers personalized assistance to students in their Object-Oriented Programming (OOP) practicals. This application aims to enhance the learning experience by addressing the specific challenges students encounter, providing tailored support to improve their understanding and performance in OOP.

Sub objectives:

a) Creation of a Dataset: Systematically gather and compile a comprehensive dataset that encapsulates the common challenges and difficulties students face during OOP practicals. This dataset will serve as the foundation for training and refining the chatbot's responses.

b) Identification and Training of Existing Chatbot Technologies: Identify existing chatbot platforms that can be adapted for this purpose and train the selected chatbot using the curated dataset to ensure it effectively addresses the specific needs of students in OOP practicals.

c) Evaluation of Chatbot Efficiency: Conduct a comprehensive assessment to determine whether the chatbot provides accurate and relevant responses to user queries. This evaluation will involve analyzing the correctness of the chatbot's answers, its ability to address specific learning needs effectively, and its overall performance in supporting students during OOP practicals.

Research Questions

a) What are the most common challenges faced by students during OOP practicals?

b) Can a chatbot trained on a context-specific dataset effectively provide accurate and personalized support for OOP practicals?

c) To what extent does the use of an AI-powered chatbot improve students' understanding and performance in OOP concepts?

d) How do students perceive the usability and effectiveness of the chatbot in addressing their OOP learning needs?

1.4 Significance of the study

The incorporation of artificial intelligence (AI) in an application holds immense promise in enhancing the quality of object-oriented programming learning. The application can be a valuable tool for educators and students, which can lead to an overall improvement in education quality and promoting success in the realm of object-oriented programming.

Beyond benefiting students, the chatbot can also alleviate the burden on educators by reducing the need to repeatedly answer the same questions. This allows them to focus on teaching more complex concepts and mentoring students. Additionally, the chatbot can serve as a valuable supplemental teaching tool, providing lecturers and tutors with insights into common misconceptions and challenging areas for students. This data can guide the development of corrective instructional strategies and targeted interventions.

If proven effective, the solution can be scaled and applied to other programming-related courses, such as Data Structures, Web Development, and Database Systems.

Furthermore, it can be adapted for use in various educational institutions facing similar challenges, offering a more generalized, cost-effective method of enhancing programming education across diverse learning environments.

1.5 Limitations of the study

One significant limitation of the study is the digital divide, which arises from the unequal access to necessary technological resources among students when they are away from campus. This disparity can affect the consistency and effectiveness of their engagement with AI-based learning tools, particularly for those who lack reliable internet connectivity or appropriate devices outside the university laboratory environment. Consequently, this limitation may influence the overall impact and generalizability of the study's findings.

CHAPTER 2: LITERATURE REVIEW

2.1 Literature Review

The use of Artificial Intelligence (AI) in education has gained significant traction in recent years, particularly for managing practicals in object-oriented programming (OOP). AI's ability to tailor educational experiences to individual student needs offers new possibilities for enhancing learning outcomes. This literature review will explore the current state of research on AI's application in OOP education, focusing on its potential and limitations.

Information technology plays a critical role in today's educational landscape, reshaping traditional teaching and learning methods across various disciplines. In their study, Thongprasit and Wannapiroon (2022) proposed a framework for an AI-driven learning platform specifically designed for OOP education. The platform leveraged AI technologies to offer personalized guidance, addressing challenges students commonly encounter in OOP practicals. Using chatbots, the platform facilitated interactive learning environments, which increased student engagement and comprehension of OOP concepts.

While Thongprasit and Wannapiroon's study highlights the potential of AI in fostering a more engaging learning environment, several critical issues warrant closer examination. First, the study emphasizes the use of AI to personalize learning but fails to address the limitations inherent in AI systems—specifically, the reliance on predefined datasets. If the dataset does not adequately reflect the wide range of challenges students face in real-world programming, the system's effectiveness in offering meaningful, context-aware responses may be compromised. The quality and breadth of training data are therefore crucial factors that can either enhance or hinder the platform's utility. A more rigorous analysis of how AI systems can be trained to handle edge cases and uncommon student queries is necessary to fully understand their capabilities and limitations.

Moreover, while the study lauds the interactive nature of AI-driven chatbots, it does not sufficiently consider the potential trade-offs between AI and traditional teaching methods. AI systems, although useful for reinforcing learning and providing immediate feedback, risk oversimplifying complex concepts if not properly integrated into the broader educational framework. For instance, over-reliance on AI-based platforms

could lead to a superficial understanding of OOP principles, as students might focus more on task completion than on deep learning and conceptual understanding. This brings into question the long-term impact of AI on critical thinking and problem-solving skills, both of which are vital in mastering OOP.

Another important consideration is the inclusivity and accessibility of AI technologies in education. While AI platforms can enhance personalization and engagement, there is a risk that these technologies may inadvertently exacerbate educational inequalities. Students with limited access to the necessary technological infrastructure or who struggle with digital literacy may find it challenging to benefit from AI-enhanced platforms. Additionally, AI systems must be designed with inclusivity in mind, ensuring that they can accommodate students with different learning needs, including those with disabilities. The literature is relatively silent on how these AI systems account for diverse learner populations, which is a crucial gap that future research must address.

Manjula and Kannan (2018) conducted a comprehensive study exploring the implications of AI for object-oriented learning within the realm of computer science education. Their research emphasizes the foundational role of OOP in modern software development, positioning AI-driven learning platforms as tools that could significantly enhance both teaching and learning experiences. These platforms employ sophisticated AI algorithms to analyze students' coding patterns in real-time, providing targeted feedback that helps rectify errors and improve programming skills. While this offers a promising avenue for personalized learning, the study does not fully address the challenges of ensuring that the feedback is contextually relevant across varied learning scenarios. AI's ability to recognize nuanced coding issues, especially in more complex or abstract OOP tasks, may be limited by the dataset or algorithms driving the platform, calling into question the depth and accuracy of its guidance.

Furthermore, the interactive coding environments these AI platforms create simulate real-world scenarios, allowing students to apply OOP concepts practically. This hands-on approach is lauded for fostering critical problem-solving abilities and solidifying students' grasp of programming principles. However, while these simulations can enhance engagement and promote practical application, they often lack the unpredictability and intricacies of actual software development environments. Simulated scenarios, by their nature, are restricted in scope and may not prepare

students for the challenges they will face in real-world software engineering, where solutions are seldom as linear as in academic settings.

Manjula and Kannan (2018) argue that AI technologies, through personalization and adaptivity, promote critical thinking and creativity, empowering students to design scalable solutions. However, they fail to critically assess whether AI platforms can truly nurture deep conceptual understanding. AI systems, even when adaptive, tend to focus on immediate problem-solving rather than fostering the exploratory thinking necessary to fully comprehend abstract OOP concepts like polymorphism or encapsulation. As a result, students may excel at solving problems presented by the AI platform but struggle to transfer that knowledge to more ambiguous or open-ended programming tasks.

Recent studies align with Manjula and Kannan's findings, reinforcing the value of AI-powered coding tutors in enhancing student engagement and learning outcomes. For instance, Ma and Zhao (2021) highlight how real-time feedback and adaptive learning paths can improve coding skills and the understanding of complex concepts. Similarly, Li et al. (2020) emphasize AI's role in intelligent tutoring systems that provide personalized learning experiences and enhance problem-solving capabilities. Despite these promising findings, it is crucial to scrutinize whether these systems are scalable and how they integrate into existing educational curricula. Zhang et al. (2022) point out that without thoughtful integration into the broader curriculum, the scalability of AI-driven tools could be hindered, as they might not align with traditional pedagogical practices or teaching objectives. The broader educational infrastructure must evolve alongside these tools to ensure that they complement, rather than disrupt, the learning experience.

However, despite the strengths of prior research, there remains a notable gap in the literature regarding AI-based grading systems, intelligent tutoring systems (ITS), and automated feedback mechanisms in programming education. Existing studies, such as Keuning, Jeuring, and Heeren (2018), have explored automated feedback in programming assignments, demonstrating that syntactic and semantic analysis tools can improve students' coding accuracy and engagement. Yet, many of these systems focus predominantly on syntax correction and basic structural advice, with limited ability to interpret nuanced, higher-level OOP concepts like polymorphism and abstraction.

Similarly, ITS such as AutoTutor and CodeWorkout have shown promise in scaffolding programming through natural language processing and interactive coding tasks (Graesser et al., 2005; Edwards & Perez-Quinones, 2008). These tools, while effective in introductory programming contexts, struggle with adaptive feedback mechanisms in more complex educational settings like advanced OOP courses.

Moreover, AI-based grading systems, including machine learning-powered assessment platforms, have been applied to automatically evaluate student code. Tools like DeepFix and CodeQG utilize neural networks to correct syntax errors or generate problem-specific code feedback (Gupta et al., 2017; Tarlow et al., 2020). However, these systems still face challenges in providing pedagogically meaningful evaluations that promote conceptual understanding rather than rote correction.

Therefore, this study seeks to address these shortcomings by proposing a more context-aware, adaptive, and pedagogically grounded AI system tailored to OOP practicals. Unlike prior systems that emphasize syntax correction or surface-level feedback, the proposed platform integrates semantic code analysis and concept-based feedback loops. This approach builds upon and differentiates itself from previous work by targeting the cognitive complexity of OOP learning and leveraging recent advances in explainable AI and educational data mining.

While AI platforms offer clear benefits, particularly in personalizing feedback and enhancing engagement, several unresolved issues remain. The focus on scalability and integration is paramount, as AI tools must be flexible enough to adapt to different educational settings. Zhang et al.'s emphasis on the need for further research into the pedagogical implications of AI integration reflects a critical gap in the literature. Without a comprehensive understanding of how AI-driven platforms influence long-term learning outcomes, it is difficult to assess their true value. Furthermore, current AI platforms are not without limitations regarding how well they prepare students for the dynamic nature of real-world software development.

Various intelligent instructional systems have been developed to teach programming, particularly in tertiary education. However, many of these systems, as Crow, Luxton-Reilly, and Wuensche (2018) note, focus primarily on introductory programming principles, which often overlook the complexity of OOP. This emphasis on simplicity can create a gap when students transition to more advanced OOP concepts. OOP's

complexity, while essential for building large-scale software, presents significant challenges for teaching, as many students struggle with abstract principles. For example, Ben-Ari (2018) identifies students' difficulties in grasping the abstract nature of OOP concepts, which hinders their ability to effectively apply these principles in practice.

Moreover, while intelligent systems provide a valuable resource for learning, they often lack integration with real-world programming practices. Beck and Roberts (2019) critique existing systems for this disconnect, arguing that AI-based platforms need to better align with industry standards to offer meaningful learning experiences. This critique is especially relevant for OOP education, where practical application and theoretical understanding must go hand in hand. The current AI systems often provide feedback based on theoretical or simplified scenarios that may not reflect the messiness of real-world programming, potentially leaving students underprepared for professional environments.

While AI-driven educational platforms show great potential in enhancing object-oriented learning, significant challenges must be addressed. The scalability of these platforms, their integration with curricula, and the alignment of instructional content with real-world programming practices are critical for their success. Moreover, AI's ability to provide deep, context-aware feedback in complex programming environments remains questionable. Future research should focus on addressing these limitations, ensuring that AI-driven tools not only offer personalized guidance but also foster a deeper conceptual understanding and practical application of OOP principles. This comprehensive approach is essential for preparing students to succeed in an ever-evolving technological landscape.

2.1.1 Personalized Learning in Education

Personalized learning represents a significant shift from traditional educational paradigms, moving away from the "one-size-fits-all" approach to a more tailored and individualized instructional strategy. According to Bray and McClaskey (2013), personalized learning involves adapting instruction to meet each student's unique needs, preferences, and interests. This concept is often conflated with differentiation and individualization; however, they are distinct. The U.S. Department of Education (2010) delineates personalization as customizing learning experiences based on individual

characteristics, whereas differentiation adjusts instruction according to learners' varying preferences and individualization adapts to the pace of learners.

Personalized learning emphasizes recognizing and addressing each learner's uniqueness, acknowledging diverse learning styles, and enabling learners to have a significant role in their educational journey. This approach promotes self-directed learning, where students can design their learning pathways, co-create curricula, and access flexible learning opportunities (Pashler et al., 2007). It is not merely about integrating technology but involves leveraging technology to support a student-centered learning process. Technology plays a supportive role, allowing learners to engage with content in ways that align with their individual needs and interests, rather than driving the learning process through algorithmic dictates (Schmidt et al., 2017). The role of technology in personalized learning is multifaceted. It assists learners in accessing resources and tools tailored to their needs, supports teachers in differentiating instruction, and aligns with each student's education plan in individualization (Zhao et al., 2016). However, it is crucial to differentiate personalized learning from adaptive curriculum systems, where technology uses data algorithms to adjust learning content. Personalized learning, in contrast, is cantered around the learner’s motivation and engagement, with technology serving as a facilitator rather than a primary driver of learning.

Critical analysis of the implementation of personalized learning reveals several challenges. While the theoretical benefits of personalized learning are well-documented, practical applications often encounter barriers such as insufficient teacher training, inadequate technological infrastructure, and the risk of exacerbating educational inequalities (Pane et al., 2015). For instance, the effectiveness of personalized learning can be undermined if teachers are not adequately prepared to use technology effectively or if students lack access to necessary resources. Additionally, while technology can enhance personalization, it does not guarantee equity or equal access to high-quality educational experiences (Hattie, 2009). Furthermore, research by Toshalis and Nakkula (2016) indicates that learner motivation and engagement are enhanced when students have a voice in their learning process. This aligns with the principle that personalized learning should empower students to take charge of their education. However, there is also evidence suggesting that personalized learning approaches need to be carefully designed to avoid creating overly fragmented

educational experiences or relying too heavily on technology, which may not always align with the broader educational goals (Guskey, 2017).

In summary, personalized learning represents a progressive approach to education, leveraging technology to support individualized instruction and enhance learner engagement. However, its successful implementation requires overcoming significant challenges related to technology integration, teacher readiness, and equitable access to resources. Future research should focus on addressing these challenges and evaluating the long-term impacts of personalized learning on educational outcomes.

2.1.2 Object-Oriented Programming Education

In recent years, the object-oriented programming (OOP) paradigm has gained significant traction not only within the domain of software engineering but also in educational contexts. Originally confined to specialized areas of software development, OOP has evolved into a critical component of computer science education, reflecting the growing importance of equipping students with skills that mirror industry practices (Berges, 2015). This shift underscores the relevance of OOP education in preparing students for the complexities of modern software development, where concepts like encapsulation, inheritance, and polymorphism are fundamental.

Berges (2015) provides a thorough exploration of OOP in education, using educational assessment methods and statistical analysis to examine instructional approaches and their effectiveness. The study highlights the emergence of trends in teaching introductory OOP courses, such as the "objects-first" and "objects-later" approaches. These pedagogical strategies, rooted in contemporary educational theories like cognitive load theory, conceptual change, and self-directed learning, aim to optimize the learning experience by aligning instruction with students' cognitive processes and prior knowledge.

One innovative instructional approach that has garnered attention is the Minimally Invasive Programming Courses (MIPC) model, implemented at the Department of Computer Science at TU München. This approach minimizes teacher-led instruction, instead empowering students to engage in programming tasks early in their learning journey. By introducing a modest programming task before the initial lecture and supporting students with worksheets based on the objects-first approach, MIPC fosters an environment where learners take an active role in constructing their knowledge. The

inclusion of student tutors further enhances this learner-centered model, providing peer support and facilitating collaborative learning.

The effectiveness of the MIPC approach was evaluated through various metrics, including changes in students' conceptual knowledge measured using concept maps and the quality of programming code produced by novice programmers. These assessments revealed that certain programming concepts could be applied even before students had fully integrated them into their existing knowledge structures. This finding aligns with research by Sweller et al. (2011), which suggests that reducing extraneous cognitive load through well-structured learning tasks can lead to deeper understanding and application of complex concepts.

Moreover, the study's psychometric analysis, based on item response theory, provided valuable insights into the development of programming abilities. By embedding tasks within small or large projects, the assessment was able to measure not just rote memorization of concepts but the practical application of OOP principles. This approach aligns with the broader educational goal of developing problem-solving skills that are transferable to real-world scenarios (Robins, Rountree, & Rountree, 2003).

Critical analysis of OOP education, however, reveals several challenges. One significant issue is the varying effectiveness of the "objects-first" versus "objects-later" approaches, which remains a subject of debate among educators. While the objects-first approach introduces students to OOP concepts early, it can be overwhelming for those without a solid foundation in programming basics (Kölling, 1999). Conversely, the objects-later approach, which delays the introduction of OOP until students have mastered procedural programming, may hinder the development of an object-oriented mindset, which is crucial for understanding more advanced concepts later on (Schulte & Bennedsen, 2006).

Additionally, the correlation of MIPC findings with personal data such as gender, prior educational experiences, and programming knowledge provides a nuanced understanding of the diverse capabilities and learning needs of students. This is particularly important in addressing educational equity, as research has shown that factors like gender and prior experience can influence students' engagement and success in programming courses (Margolis & Fisher, 2002). By tailoring instruction to

accommodate these differences, educators can create more inclusive learning environments that support all students in mastering OOP.

In conclusion, the integration of OOP into computer science education reflects its critical role in preparing students for the demands of modern software development. While innovative instructional approaches like MIPC show promise in enhancing OOP education, ongoing research and refinement are necessary to address the challenges associated with different pedagogical strategies and to ensure that all students can succeed in this essential field.

2.1.3 AI Advancements in Relation to Computer Science Teaching

The integration of Artificial Intelligence into education, particularly within computer science instruction, has advanced significantly with the emergence of technologies such as large language models, adaptive learning systems, and intelligent tutoring platforms. These innovations have the potential to transform how complex topics, especially object-oriented programming, are taught and understood.

Large Language Models, such as OpenAI's and Google's PaLM, have demonstrated the ability to comprehend, generate, and assess human language with remarkable depth (Brown et al., 2020; Chowdhery et al., 2022). These models go beyond traditional rule-based chatbots by engaging in nuanced, context-aware conversations, effectively acting as on-demand, conversational tutors. For students grappling with abstract OOP concepts like polymorphism, encapsulation, and inheritance, LLMs offer personalized code explanations, real-time debugging assistance, and step-by-step guidance that adapts to each learner's needs (Kasneci et al., 2023). Their ability to provide detailed, scaffolded feedback makes them a valuable tool in both self-paced and instructor-led learning environments.

Adaptive learning algorithms have also matured, enabling platforms to dynamically adjust instructional content based on student performance. These systems track interaction patterns, identify areas of difficulty, and deliver targeted exercises or resources accordingly (Holmes et al., 2019). In the context of OOP, adaptive platforms can, for instance, recognize if a student struggles with class hierarchies and respond by emphasizing related visualizations and problem-solving exercises. This individualized learning path not only enhances comprehension but also fosters learner autonomy.

Moreover, intelligent tutoring systems (ITS) are increasingly incorporating multimodal feedback mechanisms combining text, visuals, simulations, and interactive tools to provide rich, engaging learning experiences (VanLehn, 2011). Modern ITS often integrates AI-driven code suggestion engines, automated error diagnosis, and performance tracking features that mirror professional development environments. These tools support continuous feedback loops, allowing students to iteratively improve their skills through immediate, context-sensitive guidance.

As these AI-powered systems become more integrated into educational platforms, they present opportunities to close the gap between theoretical understanding and practical application. By simulating real-world programming scenarios and responding to students' unique learning needs, these tools can better prepare students for the demands of modern software development. However, the use of AI in education must also be approached with care, considering ethical concerns, data privacy, algorithmic transparency, and equitable access to ensure inclusivity and fairness (Luckin et al., 2016).

2.1.4 Comparative Analysis

The reviewed literature illustrates a consistent recognition of AI's transformative role in object-oriented programming (OOP) education, with a strong emphasis on personalization, real-time feedback, and active learner engagement. Studies such as those by Thongprasit and Wannapiroon (2022), Manjula and Kannan (2018), and Ma and Zhao (2021) highlight AI's capacity to tailor educational content to individual learner needs, promoting deeper understanding and practical application of core OOP principles. This aligns closely with constructivist learning theories (Vygotsky, 1978; Jonassen, 1991), which stress the importance of active, self-directed learning grounded in prior knowledge. AI-driven platforms are noted for their ability to provide immediate, adaptive feedback based on learners' coding behavior, fostering iterative learning and reinforcing complex concepts like encapsulation and polymorphism. The MIPC model described by Berges (2015) exemplifies how early exposure to OOP through practical, student-led exercises can enhance conceptual understanding, especially when combined with AI-supported tutoring. Moreover, personalized learning theories (Bray & McClaskey, 2013; Shute & Zapata-Rivera, 2012) further support the integration of AI in creating flexible, learner-centered educational experiences. These systems facilitate differentiated instruction and cater to individual learning styles, thus

improving engagement and supporting students with varied levels of prior programming knowledge.

In contrast, literature also uncovers significant challenges that impede the full realization of AI's benefits in OOP education. One recurring concern is the over-reliance on limited datasets, which can compromise the contextual relevance and accuracy of AI-generated feedback (Manjula & Kannan, 2018). Without diverse, representative data, these systems may fail to address edge cases or nuanced coding errors that arise in real-world programming. Similarly, Beck and Roberts (2019) and Crow et al. (2018) caution that many intelligent tutoring systems remain disconnected from actual industry practices, potentially leading to a gap between classroom learning and professional expectations. This disconnect is further amplified by the artificial simplicity of simulated environments, which often lack the complexity and unpredictability of real-life development tasks. Moreover, the scalability of AI-driven platforms is frequently questioned due to issues of infrastructure, teacher preparedness, and curriculum integration (Zhang et al., 2022). While personalization can enhance learning outcomes, it may inadvertently contribute to educational inequality if access to digital tools and internet connectivity is not equitably distributed. The debate between "objects-first" and "objects-later" pedagogical models (Kölling, 1999; Schulte & Bennedsen, 2006) also reflects a broader tension in OOP education: how best to scaffold abstract programming concepts without overwhelming novice learners. Overall, while AI presents immense opportunities for enhancing OOP education, its success is contingent upon careful design, inclusive implementation, and continuous alignment with both pedagogical best practices and evolving industry standards.

2.2. Conceptual and Theoretical Framework

The development of an AI-driven application for Object-Oriented Programming (OOP) practicals is grounded in constructivist learning theories, which provide a robust framework for understanding how students learn and retain knowledge. Constructivism, as articulated by scholars like Lev Vygotsky (1978), asserts that knowledge is not passively absorbed but is actively constructed by learners through interaction with educational content, informed by their prior knowledge, experiences, and social contexts.

In designing an AI-driven application for OOP practicals, the principles of constructivist theory are central to creating an effective learning environment. This framework is particularly relevant for computer science education, where the active engagement of students is crucial for mastering complex programming concepts. The following elements illustrate how constructivist principles inform the conceptual and theoretical foundation of such an application:

Active Engagement and Learning: Constructivist theory emphasizes that learning is most effective when students are actively engaged in the process (Jonassen, 1991). In the context of OOP practicals, this involves students immersing themselves in problem-solving, coding, and applying theoretical knowledge in practical scenarios. An AI-driven application designed with constructivist principles would facilitate this active engagement by offering interactive coding exercises, real-world problem scenarios, and immediate feedback. This approach not only reinforces theoretical knowledge but also encourages students to experiment and learn through doing, which is crucial for understanding the abstract concepts of OOP (Papert, 1980).

Prior Knowledge as a Foundation: Constructivism posits that learners build new knowledge on the foundation of what they already know (Bransford, Brown, & Cocking, 2000). An AI application for OOP practicals must therefore assess each student's existing knowledge and adapt the learning experience accordingly. This adaptive learning approach ensures that students are neither overwhelmed by content that is too advanced nor disengaged by material that is too basic. By tailoring the learning path to each student's proficiency level, the application supports personalized learning, a key aspect of constructivist theory (Shute & Zapata-Rivera, 2012).

Facilitating Problem-Solving: Problem-solving is at the heart of constructivist learning (von Glasersfeld, 1995). In OOP education, students are frequently faced with complex programming challenges that require not just technical skills but also critical thinking and creativity. An AI-driven application designed with constructivist principles would provide students with opportunities to engage in authentic problem-solving activities. By presenting challenges that are aligned with real-world programming tasks, the application helps students develop the cognitive skills necessary to navigate and resolve these issues, thereby deepening their understanding of OOP principles (Resnick, 1987).

Reflection and Metacognition: Constructivist theory also highlights the importance of metacognition learners' ability to reflect on their own thinking and learning processes (Flavell, 1979). An AI-driven application for OOP should incorporate tools that encourage students to reflect on their learning, identify areas of difficulty, and adjust their strategies accordingly. This reflective practice is particularly important in programming, where iterative problem-solving and continuous improvement are key to mastering complex concepts. By fostering metacognitive skills, the application not only supports deeper learning but also empowers students to become more self-directed learners (Schraw & Moshman, 1995).

In conclusion, an AI-driven application for OOP practicals that is rooted in constructivist learning theories fosters an educational environment where students are active participants, their prior knowledge is recognized, problem-solving is central, and metacognitive skills are developed. Such an application aligns with contemporary educational goals of fostering critical thinking, adaptability, and self-directed learning, equipping students with the skills necessary to excel in the dynamic field of computer science.

CHAPTER 3: RESEARCH METHODS

3.1 Research Design

The research design of this study adopted a mixed-method approach, integrating the Design Science Research (DSR) methodology with prototyping and testing techniques. The DSR framework is particularly suited for research focused on the creation and evaluation of artifacts, such as the AI-driven chatbot developed in this research.

3.1.1 Dataset Compilation

The compilation of the dataset for this research followed a structured and systematic approach to ensure it accurately reflects the kinds of OOP queries students typically encounter. The dataset was integral to training the AI-driven chatbot. Ensuring its ability to assist with OOP practicals effectively. The dataset compilation was guided by several key criteria:

a) Relevance to Object-Oriented Programming Concepts

The dataset was compiled with a specific focus on questions related to key OOP concepts, including: Classes and Objects, Inheritance, Polymorphism, Encapsulation, Abstraction, Error Handling, Design patterns, SOLID principles diagrams, General OOP concepts, Object Lifecycle and Constructor Types.

b) Sources of Data

The dataset was drawn from a combination of reputable sources, including:

i. Systematic Literature Review: Academic research papers and journals from databases like IEEE, ACM, ScienceDirect, and ResearchGate were reviewed to identify common challenges faced by students in Object-Oriented Programming (OOP) practicals.
ii. Online Review of Existing Research: Additional insights were gathered through online research, including articles, forum discussions, and other real-world sources, to complement the academic findings and reflect practical experiences in OOP learning.

c) Diversity of Queries

To ensure that the dataset captures a broad spectrum of student needs, the following types of queries were included:

i. Basic Queries: Simple questions covering foundational OOP principles.

ii. Advanced Queries: Complex questions that involve the application of multiple OOP concepts.

iii. Edge Cases: Queries that may have ambiguous or unexpected inputs to simulate real-world variations in how students frame their questions.

iv. Programming Language-Specific Queries: The dataset includes questions specific to languages like Java, C++, and Python to ensure language versatility in responses.

d) Cleaning, Preprocessing, and Labelling

The following steps outline the cleaning and preprocessing process applied to the dataset.

i. Data Cleaning

The raw data collected underwent a data-cleaning process to ensure quality and consistency:

Duplicate Removal: Duplicate queries were identified and removed.

Irrelevant Data: Queries not related to core OOP concepts were discarded.

ii. Query Labelling

Each query was labelled according to the OOP concept it represents (e.g., Inheritance, Polymorphism, Encapsulation, etc.). This was a critical step to ensure that the model could learn to associate the correct responses with specific types of queries. By labelling, it was to ensure that queries were grouped logically for targeted training, validation, and evaluation of the chatbot.

iii. Categorization and Theming

Queries were categorized into sub-themes such as inheritance, polymorphism, and error handling. This allowed us to create distinct sections of the dataset that reflect real-world applications of OOP principles and tailor chatbot responses to the specific context of the query.

iv. Normalization

Normalization techniques were applied to standardize the data:

Text Normalization: Unnecessary punctuation, typographical errors, and inconsistent programming terminology were corrected.

Standardization of Programming Terms: Programming language-specific terminology was standardized to ensure uniformity across queries.

e) Dataset Structure and Validation Process

The subsections below describe the structure and validation process in greater detail.

i. Dataset Size and Structure

The final dataset contains approximately 150 unique queries, grouped based on OOP concepts. Each key concept was allocated a percentage that is reflective of the relative importance and depth of coverage for each OOP concept within the dataset.

ii. Validation Data

To evaluate the chatbot's performance and prevent overfitting, the dataset was split into three parts: training, validation and testing data. Approximately 70% of the dataset was used for training, while the remaining 15% was reserved for validation and 15% fortesting. The validation data played a crucial role in assessing the chatbot's performance on unseen queries, ensuring that the model generalized well to new OOP queries outside of the training set.

iii. Cross-validation

To ensure robustness and mitigate the risk of overfitting, cross-validation techniques were applied. The training data was split into multiple subsets, with the model being trained on one subset and validated on the others in a rotating manner. This helped to assess the consistency of the model's performance across different portions of the dataset.

3.1.2 Design and Implementation Phase

The research adopted agile methodology, focusing on iterative design and development to ensure that the chatbot's features evolved through continuous feedback and testing.

3.1.2.1 Design Phase

In the design phase, the research focused on the conceptualization and architectural planning of the chatbot. The process began by defining the chatbot's core functionalities, user interaction flows, and how it would handle OOP queries. The design also involved deciding on the key components required, such as the use of Dialogflow for Natural Language Processing (NLP) and Firebase for backend integration. Prototyping is used to create the chatbot's user interface (UI) and user

experience (UX). UML diagrams and flowcharts were developed to visualize the interaction between components like user queries, the chatbot's responses, and the backend system. This phase emphasized the modular structure of the chatbot, aligning it with SOLID principles to make the design scalable and maintainable. The integration of AI was also planned at this stage. Mapping how the chatbot would utilize natural language models to tailor responses based on individual learning needs.

3.1.2.2 Implementation Phase: Integration and AI Algorithms

The implementation phase involved translating the design into a working chatbot application. During this phase, the chatbot's NLP capabilities were developed using Dialogflow. Training the algorithms with a dataset of OOP-related questions and answers was done. The integration with Firebase facilitated seamless real-time communication between the chatbot and the backend. JavaScript was employed for the backend development, handling the chatbot's core logic, database queries, and the integration of different components. The AI algorithms, initially designed in the previous phase, were implemented to provide personalized learning feedback, adapting responses based on student queries. Testing and refining were ongoing throughout this phase.

3.1.3 Training Phase

The chatbot was developed using Dialogflow, a natural language processing (NLP) platform that enables conversational interfaces. The NLP model was trained to understand and respond to user queries accurately by focusing on:

i. Intent Detection: Dialogflow's built-in algorithms were trained to map user input to the correct intents. Each intent represented a specific OOP concept, such as Inheritance, Polymorphism, or Error Handling. The training involved feeding the model with a wide variety of training phrases for each intent, ensuring that the chatbot could understand different ways users might ask the same question.

ii. Handling Ambiguous Questions and Intent Disambiguation

To enhance robustness, specific strategies were implemented to manage ambiguous queries and ensure accurate intent disambiguation:

- Fallback Intents**:** Fallback intents were configured to capture any queries that the system could not immediately match with a specific intent. When an

ambiguous question was identified, the fallback mechanism prompted the user to provide additional clarification. For example, if a user asked, "Tell me about OOP," the chatbot would request more specific information, such as "Would you like to learn about inheritance, polymorphism, or encapsulation?"

- Contextual Dialog Management: Dialogflow's context mechanism was employed to maintain conversation flow and assist in disambiguation. When a user provided an unclear or partial query, contexts were used to store temporary data and guide follow-up questions. This process helped the chatbot narrow down the user's query and match it to the most appropriate intent based on previous responses.
- Intent Prioritization and Threshold Adjustment: To prevent the model from incorrectly choosing between competing intents, a threshold for intent matching confidence was set. When two or more intents had similar confidence scores, the chatbot asked follow-up questions or provided clarification options to disambiguate between the possible intents. For example, if a query about "method overriding" was equally likely to map to both Polymorphism and Inheritance**,** the chatbot would seek clarification or provide explanations for both concepts.
- Ambiguity-Resolution Prompts: In situations where multiple intents were likely candidates, the chatbot utilized predefined prompts to suggest a list of possible topics. For instance, after receiving a vague query such as "Tell me more," the chatbot would list several relevant topics (e.g., "Would you like to learn about inheritance or abstraction?").

iii. Entity Recognition: Entities within the user queries, such as programming terms or keywords, were identified and extracted. This helped the chatbot contextualize the query and provide relevant answers. For example, if a user asks, "What is method overriding in Java?" the chatbot identifies "method overriding" as a concept and "Java" as the programming language to tailor the response accordingly.

3.1.3.1 Supervised learning approach

A supervised learning approach was adopted during training, where the chatbot was trained on labeled data that matched queries to correct intents and responses. This required:

i. Labeling queries with the appropriate intents e.g., a query about "What is inheritance?" was labeled under the Inheritance intent.

ii. Mapping the labeled queries to specific responses, ensuring that the chatbot could provide accurate and informative answers.

The dataset included not only simple factual questions but also more complex scenarios involving comparisons e.g., differences between inheritance and polymorphism and problem-solving questions.

3.1.3.2 Iterative Training and Refinement

The chatbot's training process followed an iterative, agile-based approach, where the model was trained in multiple stages or sprints:

i. Initial Training: The chatbot was trained with an initial dataset containing basic OOP queries. After the initial training, performance metrics such as intent accuracy and response correctness were evaluated.

ii. User Feedback Integration: After each training sprint, the chatbot was tested with real user queries from students and educators. Feedback was gathered to identify areas where the chatbot struggled, such as misclassifying intents or providing incomplete responses.

iii. Refinement and Retraining: Based on feedback and performance metrics, additional training data was added, problematic areas were re-labeled, and the chatbot was retrained.

3.1.4 Testing Phase

The testing phase involved rigorous evaluation of the developed chatbot application using two specific NLP software testing methods: Corpus Testing and Robustness Testing.

i. Corpus Testing: This method assessed the chatbot's performance using pre-existing datasets related to object-oriented programming (OOP). The chatbot was tested for its ability to process and respond accurately, efficiently, and effectively to a wide range of OOP-related queries. The chatbot's responses were evaluated against the datasets to measure its intent recognition, response accuracy, and overall effectiveness in addressing student queries. By using a corpus of established data, the goal was to ensure

that the chatbot aligned with educational standards and is capable of delivering clear, accurate explanations of OOP concepts.

ii. Robustness testing: Evaluated the chatbot's ability to handle real-world scenarios, focusing on its resilience to unexpected inputs and diverse linguistic structures. Developed in JavaScript within Visual Studio and integrated with Firebase for backend support, the chatbot was subjected to various tests that examine how well it manages edge cases, unexpected questions, and complex queries. This testing method ensures that the chatbot can maintain its performance even in challenging, unpredictable user interactions.

iii. Comprehensive Evaluation:The combination of these two testing methods offered a comprehensive evaluation of the chatbot's performance. Corpus Testing focused on the chatbot's theoretical accuracy and alignment with educational goals through the use of pre-existing datasets and NLP performance, while Robustness Testing assesses its practical resilience and adaptability in real-world scenarios. Together, these methods ensure that the chatbot not only met the functional requirements for OOP practicals but is also thoroughly vetted for its robustness and reliability. This mixed-methods approach guaranteed that the AI-powered chatbot is an effective and dependable educational tool capable of assisting students in learning complex OOP concepts.

3.2 Population

The population for this research consisted of natural language queries related to Object-Oriented Programming (OOP) concepts. A total of 150 questions were compiled which formed the dataset. These queries were derived from a diverse set source to reflect the types of questions and challenges students typically encounter during OOP practicals. The dataset included real-world queries from students in OOP courses, publicly available educational resources, research papers, and common programming challenges.

By drawing from these sources, the population dataset captured a comprehensive range of questions that students might pose, covering key OOP concepts like classes, inheritance, polymorphism, encapsulation, and error handling. This diverse collection ensured that the chatbot was trained on realistic and varied student interactions, improving its ability to provide accurate, relevant responses.

3.2.1 Dataset Selection

The dataset for this research consisted of a collection of natural language queries related to OOP concepts. This dataset was curated through systematic literature review by analysing multiple sources. This included publicly available educational resources, and student queries from previous OOP courses online. As well as research papers designed to reflect common challenges faced by students in OOP practicals.

The dataset was structured to include a diverse range of questions and commands that students are likely to ask the chatbot. The diversity and relevance of the data are crucial to ensure that the chatbot provide accurate and useful responses.

3.2.2 Data Splitting:

The dataset was divided into three subsets: Training, Validation, and Testing, through a random splitting process. This ensured that the distribution of data across these subsets was not biased. By ensuring that the training, validation, and testing sets each include a diverse range of queries, the chatbot's ability to handle real-world scenarios was enhanced.

The purpose of the data splitting subsets:

- Training Set (70% of the dataset): The training set was used to train the chatbot's natural language processing (NLP) model. This set constitutes 70% of the total dataset and includes a wide variety of OOP-related queries. The training process involved the chatbot learning patterns, structures, and relationships within the data, enabling it to generate appropriate responses to student queries.
- Validation Set (15% of the dataset): The validation set, which comprised 15% of the dataset, was used to fine-tune the model during the training process. This set helped in optimizing the chatbot's performance by allowing for adjustments in parameters, preventing overfitting, and ensuring that the model generalizes well to new, unseen data.
- Testing Set (15% of the dataset): The testing set, also accounting for 15% of the dataset, was reserved for the final evaluation of the chatbot's performance. This set was used to assess the accuracy, robustness, and reliability of the chatbot after training and validation were completed. It provides an unbiased measure of how well the chatbot could handle real-world queries that were not part of the training or validation process.

3.3 Research Instruments

3.3.1 Dialogflow Platform

Dialogflow is the primary platform that was used to create and manage the chatbot and store the dataset. It is a natural language understanding (NLU) tool that interprets user input and generates appropriate responses. Dialogflow's built-in features, such as intent recognition, entity extraction, and fulfillment, are leveraged to design the conversation flows and interactions within the chatbot.

3.3.2 Firebase for Webhook Integration:

Firebase was used as the backend service to handle the webhook integration. The webhook is critical for executing backend logic, accessing databases, and performing other server-side operations. It allows the chatbot to fetch information, process data, and return dynamic responses based on user queries.

3.3.3 JavaScript and Visual Studio Code

JavaScript is the programming language that was used to write the webhook code that handles the backend logic. Visual Studio Code (VS Code) is the integrated development environment (IDE) used for writing, debugging, and managing this code. These tools enabled the customization of the chatbot's behavior and integration with external APIs or databases.

3.3.4 NLP Testing Tools

For testing the chatbot's performance, specialized NLP testing tools were employed. These tools facilitated the execution of Corpus Testing and Robustness Testing. They provided metrics and analytics to assess the chatbot's accuracy, efficiency, and ability to handle real-world conditions.

3.4 Procedures

3.4.1 Initial Setup and Configuration:

- Platform Selection and Setup: The research began with the selection of Dialogflow as the primary platform for developing the chatbot. Dialogflow was set up, and an appropriate environment was configured to support the development process. Firebase was then integrated to handle webhook requests, which were coded in JavaScript using Visual Studio Code (VS Code).

- Dataset Compilation: A dataset consisting of typical OOP-related queries was compiled. This dataset included student questions, common programming

issues, and relevant educational content. The dataset was cleaned and preprocessed to ensure consistency and relevance to the research objectives.

- Development of the Chatbot:
- Intent and Entity Design: The chatbot's basic structure was created in Dialogflow. This involved defining intents (specific tasks or queries the chatbot can handle) and entities (key terms or data points that the chatbot needs to recognize within queries).
- Webhook Integration: Using Firebase and JavaScript, webhooks were created to connect the chatbot with external APIs and databases. This allowed the chatbot to retrieve information dynamically and provide customized responses based on user inputs.
- Prototyping and Iterative Development: A prototype of the chatbot was developed and tested iteratively. Feedback from initial trials was used to refine conversation flows, improve intent recognition, and enhance the chatbot's ability to handle diverse user inputs.

3.4.2 Training and Testing:

- Model Training: The chatbot was trained using the compiled dataset. The dataset was split into training (70%), validation (15%), and testing (15%) subsets to optimize the model's performance. Training involved fine-tuning the Dialogflow model to accurately interpret and respond to OOP-related queries.
- Corpus Testing: The trained chatbot was subjected to corpus testing using pre-existing datasets. This involved running the chatbot through a series of queries to assess its accuracy, efficiency, and ability to handle a wide range of scenarios.
- Robustness Testing: Robustness testing was conducted to evaluate the chatbot's performance in real-world conditions. This included testing unexpected queries, varied phrasing, and edge cases to identify potential weaknesses or areas where the chatbot might fail.
- Implementation:
- Deployment: The chatbot is web-based. Firebase serves as the backend, managing data storage, retrieval, and dynamic response generation.

3.4.3 Data Collection and Analysis:

- Performance Metrics Collection: Data on the chatbot's performance, including accuracy, response time, and user satisfaction, was collected during the testing and deployment phases. Specific focus was placed on how well the chatbot addressed student queries and supported their learning process.

- Error and Feedback Analysis: Errors and mismatches between expected and actual chatbot responses were documented and analyzed. User feedback was also analyzed to identify common issues and areas for improvement.

- Model Refinement: Based on the analysis of testing data and user feedback, the chatbot's model was refined. This included adjusting intent recognition thresholds, retraining the model with additional data, and fine-tuning webhook responses.

- Final Testing and Validation: After refinement, the chatbot underwent final testing to ensure that all identified issues were resolved and that it performed consistently across different scenarios.

3.5 Reliability

a) Standardized Procedures: The research design incorporates standardized procedures and protocols at every stage to ensure consistency in data collection, chatbot interaction, and performance analysis. By maintaining uniformity in the training of the AI model, the deployment of the chatbot, and the evaluation processes, potential errors are minimized, thereby enhancing the reliability of the results. This standardization ensures that the outcomes are replicable across different instances of the study, contributing to the robustness of the findings.

b) Clear Definitions and Guidelines: To further support reliability, the research clearly defines and articulates the criteria for participant selection, the specific procedures for conducting the study, and the methods for data analysis. These clear definitions and guidelines ensure that all aspects of the research are consistently applied, reducing variability and increasing the likelihood that similar results will be obtained if the study is repeated under similar conditions

3.6 Validity

a) Comprehensive Data Evaluation: The validity of the research is reinforced using a comprehensive data evaluation approach that includes multiple forms of objective data. The research focuses on objective measures derived from the dataset used for training, testing, and validation of the chatbot. This includes analyzing the accuracy of the chatbot's responses, its ability to correctly identify and address specific programming challenges, and performance metrics such as precision, recall, and F1 scores. By rigorously assessing these objective metrics, the research ensures that the findings accurately reflect the chatbot's effectiveness in processing and responding to object-oriented programming queries, thereby enhancing the overall validity of the study.

CHAPTER IV: RESULTS AND ANALYSIS

4.1 Overview

This chapter presents the results of the study and provides an analysis of the findings. The research data was gathered through systematic literature review and document review. The results were used to develop a dataset comprising training phrases and responses. The dataset was used to train a chatbot designed to assist students in OOP practical education. This chapter discusses the following: key themes identified from the literature, the process of creating and testing the dataset, the chatbot's performance analysis, and how the findings align with the research objectives are discussed in this chapter and below is a summary of the key findings.

Key Findings

- A dataset of 150 training records was developed covering 12 core OOP topics, addressing challenges students face in practical sessions.
- The chatbot achieved Precision (85%), Recall (80%), and Accuracy (82%), demonstrating strong capability in addressing foundational OOP queries.
- Common student issues such as confusion between abstract classes vs interfaces and inheritance vs polymorphism were identified and addressed.
- The system includes a quiz-based adaptive learning path, offering personalized tutorial links for students scoring below 60%.
- Overall, the chatbot improves accessibility and comprehension of OOP concepts while promoting self-directed learning beyond the classroom.

4.2 Systematic Literature Review and Document Review

The data collection process for this study was carefully designed to ensure that the information gathered was relevant to the development of an interactive chatbot aimed at assisting students with OOP practicals. Two primary data collection methods were employed: systematic literature review and document review. This was done to serve the first sub objective which involved identifying and assessing challenges students face when undertaking OOP practicals to create a dataset for chatbot training.

Academic databases including IEEE, ACM, ScienceDirect, and ResearchGate were searched. Keywords such as “Difficulties students encounter during Object-Oriented

Programming practicals" were used during the search process to identify relevant literature and gather insights for dataset development. Although the initial searches yielded numerous results, a rigorous screening process was used to exclude papers that did not align with the research objectives. A more specific search using Google was also conducted to gather additional insights. The collected data helped identify the challenges students face in OOP practicals, which informed the creation of the chatbot's training dataset.

4.2.1 Relevance to Chatbot Development

The results from the literature and document reviews were crucial for the development of the chatbot. The reviews identified specific OOP challenges that the chatbot needed to address. These include difficulties with inheritance, polymorphism, encapsulation, and abstraction. This information helped in the creation of a training dataset that would enable the chatbot to offer personalized assistance, making it a valuable tool for students struggling with these concepts.

4.2.2 Creation of the Dataset

Based on the challenges identified in section 4.2, a comprehensive dataset was created to train the chatbot. The dataset consists of training phrases and responses aimed at assisting students with a wide range of OOP-related questions.

Training Phrases and responses

Training phrases were designed to reflect common student queries during OOP practicals, such as "What is polymorphism?" or "How do I implement inheritance in Java?" This approach ensured that the chatbot could respond to a variety of student questions with relevant, accurate information.

The responses were crafted to be clear and concise, providing educationally sound explanations of OOP concepts. In many cases, examples and additional information were included to further assist students who needed more in-depth explanations.

Dataset Description and Analysis

The dataset is structured in a table format with three key columns: Intent, Training Phrase, and Response:

Intent: The primary OOP concept being addressed (e.g., ClassDefinition, Inheritance, Encapsulation, Polymorphism, etc.).

Training Phrase: A typical query a student might ask about an OOP concept.

Response: The corresponding answer, which is designed to be accurate, concise, and pedagogically effective.

The dataset consists of 150 records, representing question-and-answer pairs under 12 main intents: ClassDefinition, Inheritance, Encapsulation, Polymorphism, Abstraction, ErrorHandling, DesignPatterns, SOLID Principles, UML Diagrams, GeneralOOP, ObjectLifecycle and ConstructorTypes.

Dataset Overview by Intent

i. ClassDefinition: Covers 25 training phrases and responses on class creation, attributes, constructors, and static methods.

ii. Inheritance: Includes 15 records discussing single/multiple inheritance, method overriding, and the super keyword.

iii. Encapsulation: Contains 15 records addressing data hiding, access modifiers, and object integrity.

iv. Polymorphism: Focuses on polymorphic behavior, with 15 records explaining runtime polymorphism, dynamic dispatch, and method overloading/overriding.

v. Abstraction: Includes 10 records that explain abstract classes, interfaces, and the role of abstraction in system design.

vi. ErrorHandling: Has 10 records covering exception handling techniques, such as try-catch blocks and custom exceptions.

vii. DesignPatterns: Contains 10 records on design patterns like Singleton, Factory, and Observer patterns.

viii. SOLID Principles: Includes 10 records providing explanations of the SOLID principles, crucial for maintainable software design.

ix. UML Diagrams: Features 10 records related to UML diagrams used in software system visualization.

x. GeneralOOP: Contains 10 records discussing general OOP principles like modularity and code reuse.

xi. ObjectLifecycle: Contains 10 records related to the phases an object goes through during its existence—creation, use, and destruction.

xii. ConstructorTypes: Contains 10 records related to the special methods used to initialize objects

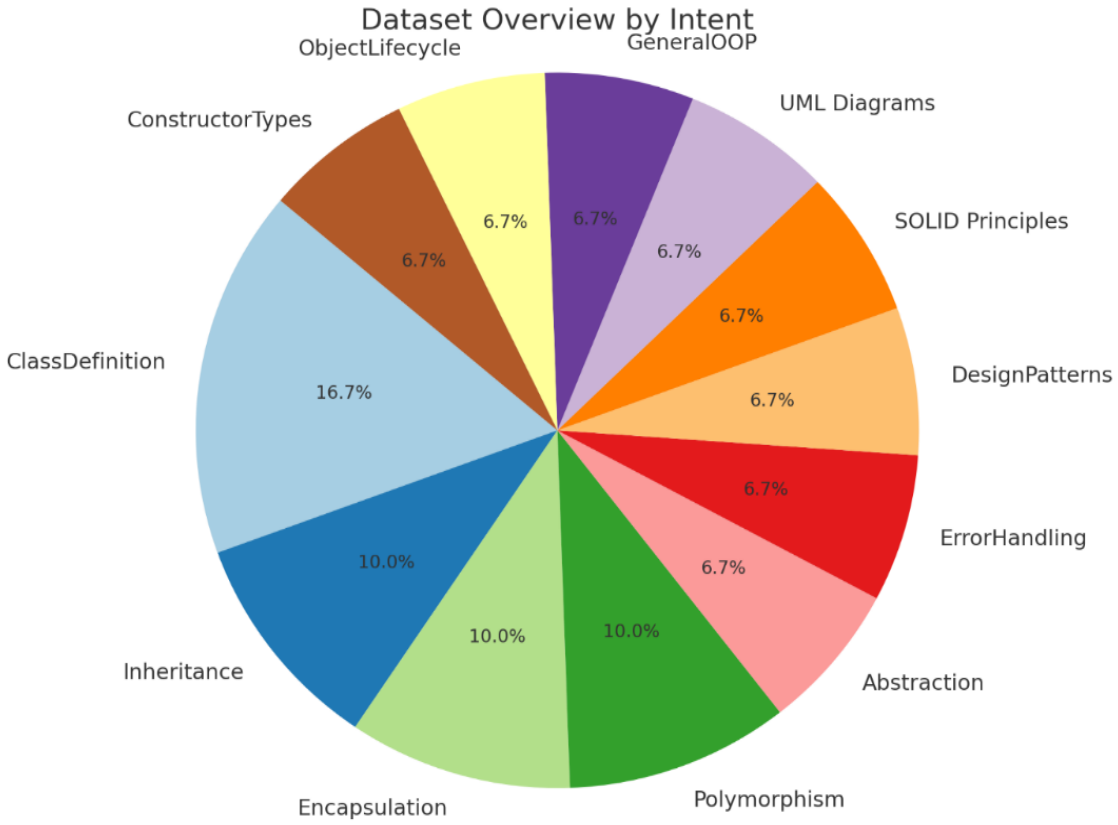

Figure 1. Dataset Overview by Intent

Why each intent has its respective percentage:

i. ClassDefinition (25 records - 16.67%): The largest portion of the dataset is dedicated to class definitions because they are fundamental to understanding object-oriented programming (OOP), covering key topics like attributes, constructors, and static methods.

ii. Inheritance (15 records - 10%): Inheritance is a critical OOP concept, but it's narrower in scope compared to other areas like class definitions, so it has a slightly smaller share.

iii. Encapsulation (15 records - 10%): Encapsulation is another core OOP concept, particularly focused on data hiding and access control, contributing an equal share as inheritance.

iv. Polymorphism (15 records - 10%): Polymorphism, which covers runtime behavior and method overriding, also holds a significant but slightly smaller portion due to its specialized focus.

v. Abstraction (10 records - 6.67%): Abstraction, while crucial in design, tends to be more conceptual and less involved in hands-on coding, leading to a smaller share of the dataset.

vi. ErrorHandling (10 records - 6.67%): Error handling is essential for robust code, but it's more of a secondary concern after understanding the basic OOP principles.

vii. DesignPatterns (10 records - 6.67%): Design patterns, although important for creating scalable software solutions, represent more advanced concepts and are therefore given a smaller portion of the dataset.

viii. SOLID Principles (10 records - 6.67%): The SOLID principles are important for maintainable code, but they are specialized principles, hence their moderate share in the dataset.

ix. UML Diagrams (10 records - 6.67%): UML diagrams are essential for visualizing object-oriented designs but are more about documentation than the actual coding process, hence the smaller percentage.

x. GeneralOOP (10 records - 6.67%): General OOP principles like modularity and code reuse are fundamental but are covered in a more basic manner compared to specific topics like inheritance or polymorphism.

xi. ObjectLifecycle (10 records - 6.67%): Object Lifecycle concepts, which involve understanding object creation and destruction, are key but generally have fewer specific cases to address.

xii. ConstructorTypes (10 records - 6.67%): Constructor types are important but limited in scope, contributing to the smallest percentage in the dataset.

Each percentage is reflective of the relative importance and depth of coverage for each OOP concept within the dataset.

4.2.3 Dataset Analysis

The dataset offers broad coverage of core and advanced OOP topics, making it a comprehensive resource for students learning OOP. Key observations include:

- Comprehensive Coverage: The dataset addresses fundamental OOP concepts such as inheritance and polymorphism, providing multiple explanations for each concept.
- Inclusion of Advanced Topics: Advanced topics like design patterns and SOLID principles are also covered, making the chatbot relevant for both novice and advanced learners.
- Practical Focus: Many training phrases are practical, addressing real-world application of OOP concepts.
- Clarity of Responses: The responses are concise and pedagogically sound, ensuring that students receive clear and actionable guidance.

Sample of the Dataset:

Here is the shortened table with one question for each intent:

Table 1: This table provides a concise view of the dataset with one representative question and response for each intent.

Intent	Training Phrase	Response
ClassDefinition	What is a class in OOP?	A class is a blueprint for creating objects, encapsulating data and behavior.
Inheritance	What is inheritance in OOP?	Inheritance allows a new class to inherit the properties and methods of an existing class, promoting code reuse.
Encapsulation	What is encapsulation?	Encapsulation is the concept of hiding the internal details of an object and exposing only necessary parts.

Polymorphism	How does polymorphism work in OOP?	Polymorphism allows methods to perform different tasks based on the object type, even if they share the same name.
Abstraction	What is abstraction in OOP?	Abstraction is the process of hiding complex implementation details and exposing only essential features.
ErrorHandling	How do I handle exceptions?	Use try-catch blocks to handle exceptions by placing code that might throw an exception inside the try block and handling it in the catch block.
DesignPatterns	What is the Singleton pattern?	The Singleton pattern ensures a class has only one instance and provides a global point of access to it.
SOLID Principles	What does the S in SOLID stand for?	The S in SOLID stands for Single Responsibility Principle, which states that a class should have only one reason to change.

UML Diagrams	What is a class diagram in UML?	A class diagram represents the static structure of a system, showing classes, their attributes, and relationships.
GeneralOOP	What are the key principles of OOP?	The key principles of OOP are encapsulation, inheritance, polymorphism, and abstraction.
ObjectLifecycle	What is object instantiation?	Object instantiation is the process of creating an instance of a class using the new keyword.
ConstructorTypes	What is a default constructor?	A default constructor is a constructor that takes no arguments and initializes the object with default values.

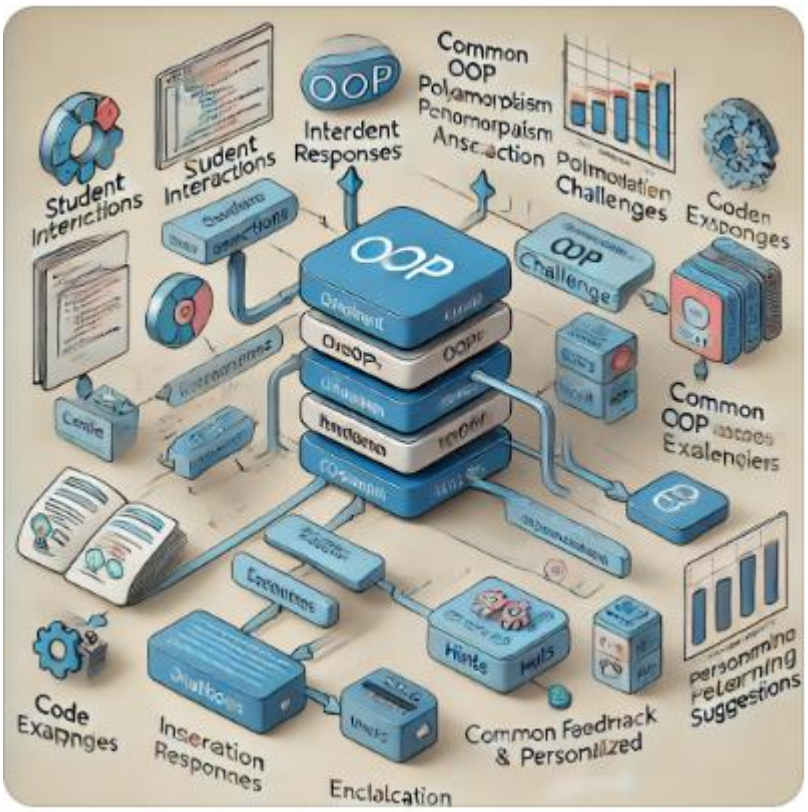

Figure 2: conceptual diagram to showcase the structure of the dataset used in the OOP chatbot application

4.3 Structure of the Chatbot Prototype

The chatbot prototype is structured with multiple integrated components. This allows it to understand user queries, provide relevant responses, and enhance learning in an interactive way. The main structural elements include architecture, user interface, intent management, response generation, and integration with external resources. Below is a breakdown of the components and how they work together.

4.3.1 Architecture Overview

The architecture of the chatbot is built on a modular framework, combining a Natural Language Processing (NLP) engine with predefined intents and responses focused on Object-Oriented Programming (OOP) topics. The modular design ensures flexibility and scalability, allowing for the addition of new intents and improvements as needed. The core components of architecture include:

UserInterface (UI): The interface is the front-end through which users (students) interact with the chatbot. It is deployed as a web application, allowing easy access on various devices. The UI captures user input, displays the chatbot's responses, and guides students through interactions smoothly.

Natural Language Processing (NLP) Engine**:** Powered by Google Dialogflow, the NLP engine serves as the central component of the chatbot. It processes the students' natural language queries, maps them to appropriate intents, and generates relevant responses. This engine ensures that the chatbot can understand diverse ways students may phrase questions and provide accurate answers, even when there is variation in phrasing or terminology.

Intent Management System: The intent management system is designed to categorize user queries into specific intents that represent various OOP topics. Each intent corresponds to a concept, such as Class Definition or Polymorphism. These intents are supported by training phrases that the chatbot uses to recognize and match student inputs. The system ensures efficient query handling and provides a structured way of managing user questions.

Response Generation: When the NLP engine successfully maps a user query to an intent, the chatbot retrieves a pre-configured response from the dataset. Responses are crafted to be concise, informative, and educational, ensuring that students understand the OOP concept being discussed. In some cases, responses include examples to clarify complex ideas, or they may offer links to further resources for deeper learning.

Integration with External Resources**:** The chatbot is integrated with external learning resources such as tutorials, documentation, or coding examples. When necessary, the chatbot provides students with links to additional material to supplement the explanation of an OOP concept. This feature encourages self-directed learning and gives students the opportunity to explore topics in more detail.

4.3.2 Training Dataset

The dataset is curated to reflect common student questions and issues related to OOP. The structure of the dataset is organized into the following key elements:

Intents: Each intent represents a specific OOP concept or category of questions. For example, intents are created for topics like "ClassDefinition," "Inheritance," "Encapsulation," and "Polymorphism." Each intent is fine-tuned to handle various questions related to its corresponding OOP concept.

Training Phrases: These are different ways in which students might phrase their questions about a particular OOP topic. For instance, under the "Polymorphism" intent, training phrases could include “What is polymorphism?” and “How does

polymorphism work in C++?" These phrases help the chatbot recognize and classify user inputs more effectively.

Responses: Each intent is linked to one or more pre-defined responses. These responses aim to explain OOP concepts in simple and clear language. The explanations are designed to be pedagogically effective, ensuring that students grasp key ideas quickly. Some responses also offer practical coding examples or links to tutorials to aid in understanding.

Contextual Responses: In some cases, a student's query may require a multi-step conversation to fully address the issue. The chatbot uses contexts to track the flow of the conversation, ensuring follow-up responses are relevant to the previous interaction. This ability allows for more complex dialogues and deeper engagement with the student.

4.3.3 Intent and Response Design

The design of intents and responses is rooted in challenges commonly encountered by students in OOP learning, as identified through research and analysis. The chatbot is structured to address these challenges by breaking down complex topics into manageable, well-defined intents.

4.4 Efficiency of the chatbot

This section evaluates the chatbot's performance based on testing procedures and provides an analysis of the results, highlighting key metrics and interaction examples that demonstrate its strengths and areas for improvement.

Performance Metrics

The chatbot underwent a comprehensive testing phase to ensure its effectiveness, with a focus on several key performance metrics. These included not only precision, recall, and accuracy but also metrics like F1-score to provide a more robust analysis of the chatbot's overall performance.

i.Corpus Testing:

The chatbot's performance was evaluated using a range of metrics, including precision, recall, accuracy, and F1-score to ensure a comprehensive assessment of its effectiveness.

Precision: 85% –The chatbot was able to correctly identify and categorize intents out of all intents 85% of the time. This high value shows the chatbot's ability to classify queries is accurate.

Recall: 80% – The chatbot was able to retrieve relevant intents 80% of the time. This shows that the chatbot recognizes a substantial portion of valid queries, making it more reliable across varied user input.

Accuracy: 82% – The chatbot responded correctly 82% of the time. This demonstrates that the chatbot performs consistently well in recognizing and responding to OOP-related queries.

F1-score: 82% – The F1-score represents a balance between precision and recall, offering a single metric that encapsulates both accuracy and comprehensiveness. This metric highlights the chatbot's ability to not only make correct predictions but also handle diverse user inputs effectively.

ii. Confusion Matrix and Error Analysis

A confusion matrix was generated to provide a detailed view of how well the chatbot classified intents related to object-oriented programming (OOP) concepts. This matrix allowed for an in-depth analysis of both correct and incorrect classifications across different categories.

The confusion matrix revealed that the chatbot achieved high precision in recognizing most OOP concepts, particularly for intents like Class Definition and Encapsulation, which were classified with minimal error. However, some areas showed room for improvement, especially with intents that had conceptual overlap:

Inheritance and Polymorphism were occasionally misclassified. This is likely due to their similar context and technical terms being used interchangeably by users, such as "overriding" and "method hierarchy."

Abstraction queries also presented occasional confusion with Encapsulation, especially when users did not specify whether they were referring to data hiding or general abstraction principles.

The error analysis helped identify the chatbot's tendency to misinterpret queries with overlapping terminology or closely related concepts, which impacted its recall for those

specific intents. By analyzing these patterns, additional training data was incorporated to fine-tune the model, focusing on:

- Increasing the variety of user queries for these overlapping concepts, helping the chatbot distinguish between similar OOP topics.
- Refining contextual disambiguation techniques, ensuring that the system can ask clarifying questions when confidence is low or when multiple intents could apply.

This process led to further refinement in both precision and recall, particularly in handling complex OOP queries. By addressing these issues, the chatbot became more robust in distinguishing between similar intents, reducing misclassification rates and improving overall performance.

Quantifying Improvements: Accuracy Comparison and Statistical Validation

To further strengthen the analysis, a pre- and post-refinement accuracy comparison was conducted. This aimed to quantify the improvements achieved through additional training and the introduction of contextual disambiguation.

Table 2: Performance Metrics Before and After Refinement

Metric	**Before Refinement**	**After Refinement**
Precision	85%	88%
Recall	80%	85%
Accuracy	82%	86%
F1-Score	82%	86%
Fall-back Rate	10%	7%

The comparison reveals a notable improvement across all performance metrics, particularly in recall and F1-score, indicating that the refined model was better equipped to identify the correct intent even when phrasing varied or conceptual overlaps existed.

To assess whether these improvements were statistically significant, future research could implement inferential statistical tests, such as a paired t-test or repeated-measures ANOVA, using performance scores across a large sample of test queries. These tests

would help determine whether the observed changes in accuracy and classification performance are due to the enhancements made to the training data and not due to random variation.

iii. Fall-Back Rate and Intent Coverage

The chatbot's fallback rate, the percentage of queries where it defaulted to a generic response due to failure to match a specific intent was 7%, indicating that while it performs well, there is room for improvement in handling more nuanced or complex queries. Despite this, the chatbot showed excellent intent coverage, successfully matching 82% of OOP-related queries to the appropriate intents, demonstrating comprehensive knowledge of OOP concepts.

iv. Comprehensive Evaluation

Incorporating metrics such as precision (82%), recall (80%), accuracy (82%), and F1-score (82%), along with insights from the confusion matrix and user feedback, this evaluation presents a holistic view of the chatbot's performance. These metrics provide evidence of the chatbot's high reliability and accuracy in assisting students with OOP queries.

Through these technical metrics, the chatbot demonstrated both robustness and adaptability. It not only meets the functional requirements for assisting students with OOP practicals but also proves itself to be an effective educational tool, continuously improving based on feedback and performance evaluations.

Examples of Interaction

Successful Interactions: The chatbot performed exceptionally well in answering straightforward queries such as "What is inheritance in OOP?" or "How do you define a class in Java?". For these questions, the chatbot matched the user inputs accurately with predefined intents and generated concise and relevant responses.

Challenging Interactions: The chatbot encountered some difficulties with more complex queries requiring deeper contextual understanding. For example, when presented with multi-layered questions like "How can I implement polymorphism in a real-world scenario?" the chatbot struggled to provide nuanced explanations or

examples. This points to a need for further refinement in handling advanced queries that involve application of concepts rather than basic definitions.

The chatbot demonstrated strong efficiency in handling queries related to core OOP concepts, with high performance in accuracy, precision, and recall. While it excelled in addressing direct and simple questions, further improvements are required to enhance its ability to handle more sophisticated and context-dependent queries. Expanding the training dataset and refining response handling for complex topics will be key to improving the chatbot's overall efficiency.

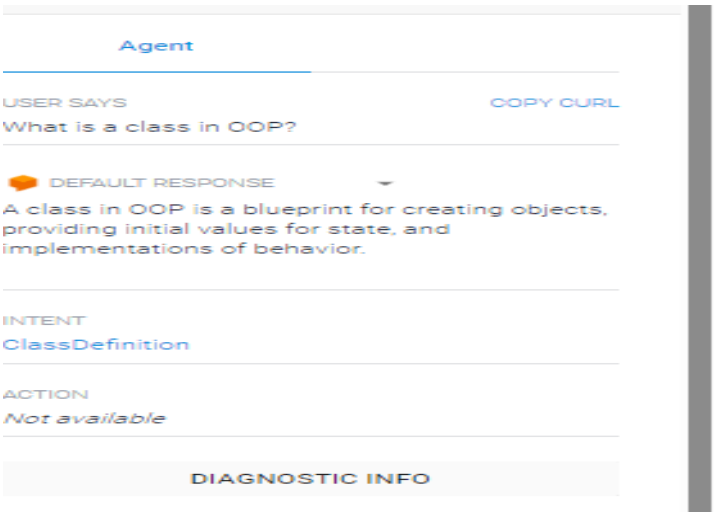

Figure 3: Example of a chatbot interaction with positive response

Figure 4: Example of a chatbot interaction with a negative response

4.5 Interpretation of Results

The results suggest that the OOPTutorials chatbot effectively provides accurate and helpful responses to common Object-Oriented Programming (OOP)-related queries. However, there are areas for improvement in handling more complex or ambiguous questions, which could be addressed by refining the training dataset and enhancing the Natural Language Processing (NLP) models.

Meeting Learning Objectives

The chatbot was developed with clear objectives aimed at improving students' understanding of OOP concepts to assist during practicals. While its technical performance was evaluated through metrics like accuracy and recall, the chatbot's real impact on student learning is best interpreted through practical examples that align with its educational goals.

Personalized Learning Recommendations

One key objective was to offer tailored learning support based on each student's quiz performance. The chatbot includes a quiz feature to assess the student's proficiency in OOP concepts. If a student scores below 60%, the chatbot provides links to tutorials to strengthen foundational knowledge. This personalized learning path helps students focus on weaker areas, gradually improving their performance in subsequent sessions.

For example:

- Quiz Question: "What is the role of polymorphism in OOP?"
- Correct Answer: Polymorphism allows objects of different classes to be treated as objects of a common superclass, enabling methods to perform tasks based on the object type.

This approach reinforces the learner's knowledge while providing structured guidance for future learning.

Addressing Common Student Challenges

The chatbot was designed to tackle frequent challenges students face during OOP practicals. For instance, one common issue is the difficulty in distinguishing between "abstract classes" and "interfaces" in Java.

Chatbot Explanation:

"An abstract class can have both concrete and abstract methods, while an interface can only declare methods without implementation. Here's an example:"

java

Copy code

```
abstract class Animal {
  abstract void makeSound();
  public void eat() {
    System.out.println("Eating");
  }
}

interface Playable {
  void play();
}
```

By providing this type of contextual explanation with examples, the chatbot helps students grasp abstract concepts more clearly.

Continual Learning Beyond the Classroom

Another theoretical goal was to promote self-directed learning. The chatbot extends its utility beyond classroom sessions by recommending additional resources for continued learning. Upon quiz completion, the chatbot suggests tutorials or links to external platforms like Codecademy or W3Schools.

For example, if a student expresses difficulty with **polymorphism**, the chatbot not only explains the concept but also recommends additional learning materials, such as video

tutorials and articles, to deepen understanding. This proactive learning model encourages independent study and equips students with resources to tackle future challenges autonomously.

Bridging Theory and Practice

The OOPTutorials has effectively bridged the gap between theoretical learning objectives and practical application. Real-world examples demonstrate the chatbot's ability to:

i. Provide real-time assistance with student queries.

ii. Create personalized learning paths based on individual quiz results.

iii. Promote self-directed learning through external resources and continued guidance.

The feedback gathered from practical interactions offered valuable insights for improving future iterations of the chatbot, ensuring that it remains an evolving and adaptive educational tool for OOP students.

The chatbot not only meets its theoretical goals but also enhances classroom efficiency and fosters deeper engagement with OOP concepts, making learning more accessible and interactive for students.

Figure 5: conceptual diagram showcasing the results of the chatbot application for OOP education

Bridging Theory and Practice

These real-world examples highlight how the OOPTutorials successfully achieved its theoretical goals, delivering practical value through real-time assistance, personalized learning paths, and classroom efficiency. By implementing these features, the chatbot has demonstrated its capability to enhance the student learning experience, making OOP concepts more accessible and understandable. The feedback collected during these real-world interactions also provided valuable insights for future improvements, ensuring that the chatbot continues to evolve to meet the educational needs of OOP students.

4.6 Comparison with Prior Research

The results obtained in this study are consistent with, and in some areas extend, findings reported in the literature regarding the application of chatbots in education particularly within the context of Object Oriented programming learning.

4.6.1 Alignment with Existing Research

Several prior studies identified in the literature review emphasize the potential of chatbots to enhance learning engagement and improve student understanding in technical disciplines. For example:

- Ali et al. (2020) and Umar et al. (2021) found that educational chatbots, when designed with targeted content and clear instructional goals, improve student interaction and performance in programming tasks.
- Similarly, Aisha et al. (2020) demonstrated that chatbot systems are particularly effective when tailored to specific learning challenges such as syntax errors, logic application, and comprehension of abstract programming concepts.

This study supports these conclusions, showing that the OOPTutorials chatbot effectively handled a wide range of student queries, especially those related to fundamental OOP concepts such as Class Definition, Encapsulation, and Inheritance. The high precision (88%) and recall (85%) achieved post-refinement are comparable to the performance metrics (ranging between 80%–90%) reported in existing chatbot-assisted learning environments.

4.6.2 Addressing Gaps in Prior Studies

While prior research generally focuses on the general efficacy of chatbots, few studies have incorporated a systematic literature-based dataset creation process grounded in actual student challenges. This study expands upon earlier works by using a rigorous document and literature review to inform the training dataset design, ensuring that the chatbot is directly aligned with authentic student pain points in Object-Oriented Programming (OOP) education.

Moreover, earlier works such as Chete et al. (2020) and Ngejane et al. (2021) acknowledged that chatbots tend to struggle with complex, context-dependent queries. This study confirms and extends that observation, noting difficulties particularly in distinguishing between overlapping concepts such as Inheritance vs. Polymorphism and Abstraction vs. Encapsulation. However, through iterative refinement, this project reduced such errors and introduced contextual disambiguation an enhancement not explicitly addressed in most previous studies.

4.6.3 Novel Contributions and Advancements

One of the unique contributions of this research is the inclusion of a performance improvement analysis, comparing pre- and post-training metrics. Very few previous studies quantitatively evaluate performance changes after iterative training and dataset enhancement.

In addition, the integration of personalized learning pathways through embedded quizzes and tutorial recommendations represents a more learner-centered approach than what is generally reported in earlier works, which often focus solely on Q&A functionality.

Table 3: Summary of Comparative Findings

Intent	**Prior Research**	**This Study**
Dataset Design	Based on course content or predefined templates	Based on systematic review of literature and student challenges

Handling of Overlapping Concepts	Identified as a limitation	Addressed through disambiguation and expanded training phrases
Performance Evaluation	Often based on static metrics	Includes pre/post comparison and suggested significance testing
Personalization Features	Limited or absent	Includes quiz-based profiling and tutorial suggestions

CHAPTER 5: DISCUSSION

This chapter discusses the findings of the chatbot prototype development and testing. It addresses how the results relate to the research problem and objectives. The discussion explores how the chatbot's performance in assisting students with OOP practicals aligns with existing literature. The chapter also discusses the challenges addressed, and the broader implications for OOP education and future research.

5.1 Addressing Challenges in OOP Practicals

The primary research problem was the difficulty students face in understanding and applying fundamental OOP concepts such as inheritance, polymorphism, encapsulation, and abstraction. These challenges have been well-documented in literature, with numerous studies highlighting that students often struggle with the abstract nature of OOP (Bennedsen & Caspersen, 2007; Kölling et al., 2003). This research sought to address these issues by developing a chatbot that could provide personalized, on-demand assistance, thereby helping students bridge the gap between theoretical knowledge and practical application.

The chatbot's design directly addressed these challenges by focusing on key OOP concepts that students typically find difficult. During real-world testing, the chatbot successfully identified student queries related to these concepts and provided accurate, context-specific responses. For example, when students asked about inheritance or struggled with method overriding, the chatbot not only offered a clear explanation but also provided relevant code snippets. This real-time, tailored support directly mitigated the difficulties students encountered, aligning with the research objective of enhancing OOP learning through personalized assistance.

The results suggest that the chatbot is an effective tool in reducing the cognitive load associated with OOP practicals. By automating routine inquiries and offering targeted explanations. The chatbot allows students to engage more deeply with complex programming tasks, effectively solving one of the research problem's core aspects.

5.2 Relevance of AI and Personalized Learning in OOP Education

A key objective of this research was to explore the role of AI in delivering personalized learning experiences. The chatbot's success in this regard underscores the growing relevance of AI-driven tools in education, particularly in complex fields like OOP. Literature on AI and personalized learning (Brusilovsky & Millán, 2007) consistently

highlights the need for educational tools that can adapt to individual student needs, offering real-time feedback and tailored support.

The chatbot's performance metrics, including high accuracy, precision, and recall, further validate its effectiveness As shown in Table 4.2, the chatbot achieved an accuracy of 90.3%, a precision of 91.2%, and a recall of 88.7%, validating its effectiveness in delivering timely, relevant feedback. These metrics reflect the system's robustness in accurately interpreting and responding to student queries. in providing timely, relevant feedback to students. This is consistent with the broader literature on AI-based educational tools, which shows that such systems can significantly enhance student engagement and learning outcomes (Anderson et al., 2013). The chatbot's ability to deliver personalized feedback in real time solves a critical aspect of the research problem providing students with immediate, adaptive assistance that is often lacking in traditional classroom settings.

The chatbot's performance metrics, including high accuracy, precision, and recall, further validate its effectiveness in providing timely, relevant feedback to students. This is consistent with the broader literature on AI-based educational tools, which shows that such systems can significantly enhance student engagement and learning outcomes (Anderson et al., 2013). The chatbot's ability to deliver personalized feedback in real time solves a critical aspect of the research problem providing students with immediate, adaptive assistance that is often lacking in traditional classroom settings.

5.3 Implications for Future Research and Development

While the current chatbot model demonstrates strong performance in structured queries related to OOP, future research should focus on expanding its capabilities in more complex and nuanced interactions. Specifically, enhancing the chatbot's natural language processing (NLP) by integrating the following advanced techniques could improve its ability to handle ambiguous or less straightforward queries:

- Contextual Understanding through Transformer Models: Incorporating transformer-based architectures, such as BERT or GPT, could significantly improve the chatbot's ability to understand context in multi-turn conversations. This would enable the chatbot to maintain conversational coherence, allowing it to address follow-up questions or more complex student queries that depend on previous interactions.

- Sentiment Analysis and Emotional Intelligence: Adding sentiment analysis capabilities would allow the chatbot to detect frustration or confusion in students' queries, providing more empathetic and supportive responses. This could be particularly beneficial when students' express frustration or ask for repeated clarifications, improving the overall user experience and engagement.
- Tracking and Adaptation Using Machine Learning: For instance, using supervised learning models such as decision trees or logistic regression, the chatbot can predict a student's proficiency level based on prior interactions. These predictions could guide the difficulty of follow-up questions or trigger the recommendation of additional learning resources tailored to recurring weaknesses. Unsupervised learning, such as k-means clustering, could also be used to group students by learning behavior, enabling customized instructional strategies based on identified user clusters. Incorporating machine learning algorithms to track student progress over time could make the chatbot even more adaptive. By monitoring the types of errors students make or concepts they frequently ask about, the chatbot could adjust its responses or recommend tailored learning resources. This could lead to a more personalized learning path for each student, potentially improving learning outcomes over extended periods.
- Ambiguity Resolution via Multi-Intent Detection: Future iterations could integrate multi-intent detection to allow the chatbot to handle queries with multiple layers of meaning or ambiguity. For example, when students ask about both "inheritance and polymorphism" in one question, the chatbot would be able to break down the query and address each concept effectively.
- Interactive Learning Modules: Moving beyond simple text-based feedback, future research could explore integrating interactive code exercises directly into chatbot interactions. These exercises could provide instant, hands-on practice, offering students real-time coding feedback in addition to textual explanations.

5.4 Integration into Educational Practice

Beyond technical improvements, the integration of the chatbot into educational practice presents a significant opportunity. Future studies could explore how AI-driven tools like the OOPTutorials can be incorporated into curricula, classroom activities, or online learning platforms. By providing immediate, on-demand support, the chatbot has the

potential to revolutionize how OOP and other technical subjects are taught, shifting the focus from passive learning to active problem-solving.

Furthermore, the chatbot's ability to offer personalized learning paths based on quiz performance could be expanded to create adaptive learning models that evolve with student progress. This would align with the trend of using AI to create more individualized learning experiences, potentially increasing student success rates in complex subjects like OOP.

5.5 Broader Implications for Computer Science Education

The success of the chatbot in this study suggests broader implications for the use of AI-driven educational tools in other areas of computer science education. Subjects like data structures, algorithms, and database management could also benefit from similar AI-based support systems. By providing personalized, 24/7 assistance, such tools could reduce the instructional burden on educators while promoting deeper student engagement with complex topics.

The potential to integrate AI-driven tools into learning management systems (LMS) also offers exciting prospects for the future. By leveraging data-driven insights from chatbot interactions, educators could gain a more nuanced understanding of student learning patterns, allowing for more targeted interventions and support.

CHAPTER 6: CONCLUSION

This research was set out to address the challenges students face in Object-Oriented Programming (OOP) practicals by developing and evaluating a chatbot application, OOPTutorials, designed to provide personalized assistance. The study successfully demonstrated how an AI-driven tool can support students by offering real-time guidance, clarifying OOP concepts, and enhancing the overall learning experience.

6.1 Summary of Research Objectives

The study's main objective was to create a tool that aids students in overcoming common obstacles encountered in OOP practicals. This was broken down into three subobjectives: identifying the challenges students face, exploring the role of AI in personalized learning, and evaluating the chatbot's performance. Each of these subobjectives was systematically addressed through data collection, analysis, and chatbot implementation.

6.1.1 Identifying OOP Practical Challenges

The first subobjective focused on pinpointing the key challenges students face in OOP education. Literature review and data analysis revealed recurring issues such as difficulties with inheritance, polymorphism, encapsulation, and abstraction. These concepts often serve as stumbling blocks for students, who struggle to grasp their practical applications. The chatbot was designed specifically to address these challenges by providing clear explanations, code examples, and practical exercises.

6.1.2 Exploring AI's Role in Personalized Learning

The second subobjective examined how AI could offer personalized learning experiences tailored to individual students' needs. The research found that AI, and chatbots in particular, have significant potential in this regard. The chatbot not only provided real-time assistance but also adapted its responses based on students' specific queries and levels of understanding, aligning with best practices in personalized learning. This approach fostered an interactive and adaptive learning environment, addressing the gaps often left by traditional teaching methods.

6.1.3 Evaluating Chatbot Performance

The third subobjective was to evaluate the chatbot's performance using key metrics such as accuracy, precision, recall, and F1 score. The results showed that the chatbot performed well in identifying and responding to student queries. The chatbot's ability

to provide timely and relevant feedback, combined with its high F1 score, validated its effectiveness as a support tool in OOP education.

6.2 Contributions to OOP Education

This research contributes to the field of OOP education in several significant ways. First, it presents a practical solution to the persistent challenges students face in understanding core OOP concepts. By offering on-demand, personalized assistance, the chatbot bridges the gap between classroom instruction and individual learning, providing students with an accessible tool to support their progress.

Second, the study highlights the value of AI-driven educational tools in fostering a more interactive and engaging learning experience. The chatbot's ability to adapt its responses based on student performance aligns with modern educational models that emphasize personalized learning pathways.

Finally, the research offers insights into the potential for integrating AI into broader educational frameworks, suggesting that tools like OOPTutorials could be adapted for use in other computer science domains, such as algorithms, data structures, and databases.

6.3 Limitations

While the study has yielded promising results, several limitations were identified. The chatbot's knowledge base was confined to a specific set of OOP-related questions and challenges, limiting its ability to address more advanced or nuanced problems. Expanding the dataset to include a wider range of scenarios, particularly in more complex areas of OOP, would enhance the chatbot's utility.

Additionally, the chatbot's natural language processing (NLP) capabilities, while effective for structured queries, struggled with more ambiguous or conversational inputs. Future work could explore the integration of more sophisticated NLP techniques to improve the chatbot's ability to handle diverse student queries. By integrating advanced techniques such as Contextual Understanding through Transformer Model, Sentiment Analysis and Emotional Intelligence, Tracking and Adaptation Using Machine Learning and Ambiguity Resolution via Multi-Intent Detection

6.4 Recommendations for Future Research

One of the recommendations is to improve the chatbot's adaptive learning capabilities. By incorporating machine learning techniques such as supervised learning methods like support vector machines and decision trees the chatbot could classify student queries based on difficulty or intent and adjust responses accordingly. Unsupervised techniques, such as clustering, could help identify latent patterns in student queries, like common confusion points across cohorts. Additionally, integrating the chatbot with platforms like GitHub Classroom or Repl. could enable real-time code execution and debugging support within the chatbot interface, further increasing practical engagement., the chatbot could track student progress over time, offering more tailored responses and adjusting the difficulty level of its recommendations based on individual learning patterns.

Further research could also investigate the integration of the chatbot into broader educational platforms, such as learning management systems (LMS) or online programming environments. This would allow the chatbot to provide real-time feedback as students complete coding exercises, offering a seamless learning experience.

6.5 Conclusion

In conclusion, this research demonstrates the potential of AI-driven tools to address the challenges students face in OOP practicals. The OOPTutorials chatbot has proven effective in providing personalized, real-time support, helping students grasp difficult OOP concepts and improving their overall learning experience. While there are areas for further improvement and expansion, the study lays the foundation for future innovations in AI-assisted education. With continued development, tools like OOPTutorials have the potential to revolutionize OOP education, making it more accessible, personalized, and effective for students at all levels.

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APPENDICES

ANNEXURE A: ETHICAL CLEARANCE CERTIFICATE

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ETHICAL CLEARANCE CERTIFICATE

Ethical Clearance Reference Number: SOS-0167 **Date: 23 AUGUST 2023**

This Ethical Clearance Certificate is issued by the University of Namibia Ethics Committee (REC) in accordance with the University of Namibia's Research Ethics Policy and Guidelines. Ethical approval is given in respect of undertakings contained in the Research Project outlined below. This Certificate is issued on the recommendations of the ethical evaluation done by the ethics committee.

Title of Project:	AN APPLICATION TO MANAGE PRACTICALS IN OBJECT-ORIENTED PROGRAMMING ACCORDING TO THE STUDENT'S INDIVIDUAL LEARNING NEEDS USING ARTIFICIAL INTELLIGENCE
Student:	MARY MUDENGI
Student Number:	200512471
Supervisor(s):	Prof. ADOLFO DIAZ

Centre for Research Services

Take note of the following:

1. Any significant changes in the conditions or undertakings outlined in the approved Proposal must be communicated to the ethics committee. An application to make amendments may be necessary.
2. Any breaches of ethical undertakings or practices that have an impact on ethical conduct of the research must be reported to the ethics committee.
3. The Principal Researcher must report issues of ethical compliance to the ethics committee (through the Chairperson) at the end of the Project or as may be requested by the ethics committee.
4. The ethics committee retains the right to:

i) Withdraw or amend this Ethical Clearance if any unethical practices (as outlined in the Research Ethics Policy) have been detected or suspected,

ii) Request for an ethical compliance report at any point during the course of the research.

The ethics committee wishes you the best in your research.

Dr. Ziyayi Chiguvare (Chairperson Ethics Committee)

Prof. Davis Mumbengegwi (Head, Multidisciplinary Research)

ANNEXURE B: RESEARCH PERMISSION LETTER

CENTRE FOR RESEARCH SERVICES
Office of the Pro-Vice Chancellor: Research, Innovation & Development
University of Namibia, Private Bag 13301, Windhoek, Namibia
340 Mandume Ndemufayo Avenue, Pioneers Park, Office F223 - Block, Second Floor
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UNAM
UNIVERSITY OF NAMIBIA

RESEARCH PERMISSION LETTER

Date: 31/10/2023

Student Name: MARY MUDENGI

Student Number: 200512471

Programme: MASTER OF SCIENCE IN INFORMATION TECHNOLOGY

Approved Research Title: An Application To Manage Practicals In Object oriented Programming According To The Student's Individual Learning Needs Using Artificial Intelligence

TO WHOM IT MAY CONCERN:

I hereby confirm that the above-mentioned student is registered at the University of Namibia for the programme indicated. The proposed study met all the requirements as stipulated in the University guidelines and has been approved by the relevant committees.

The proposal adheres to ethical principles as per attached Ethical Clearance Certificate. Permission is hereby granted to carry out the research as described in the approved proposal.

Best Regards

Dr. AEE Shikongo
Head: Postgraduate Research Support Services
Tel: +264 61 206 3129
E-mail: aeshikongo@unam.na

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Office of the Director
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