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A Framework for Evaluating the Reliability of Health Monitoring Technologies Based on Ambient Intelligence



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A **Thesis** submitted in **Fulfilment** of the **Requirements** for the **Degree of Doctor of
Philosophy** in **Computer Science** in the **Faculty of Science and Agriculture** at the
University of Fort Hare

Supervisor: Prof N.R. Jere

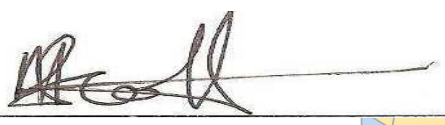
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I, **Mfundo Shakes Scott, Student Number, 200340441**, hereby declare that I am fully aware of the University of Fort Hare's policy on research ethics and I have taken every precaution to comply with the regulations. I have adhered to the requirements of the ethical standards throughout the studies, even though this study did not involve any humans or data from disadvantaged communities. The first Registration for this study was before 2019. The research started in April 2019. The study did not involve humans, animals, or plants and did not degrade the environment. An ethical clearance certificate was not required as the study commenced before the current Ethics Policy was approved in November 2019 at the University of Fort Hare; however, I have maintained the required ethical research standards.



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I, **Mfundo Shakes Scott**, hereby take this opportunity to thank the **Lord Almighty** for affording me an opportunity to have a life and a breathing soul, when most people have passed on. Indeed, all things are bright and beautiful, all creatures are great and small, the **Lord God** made them all (**by D. F. Alexander**), and so as this moment, which has only been made possible by him. Thank you, my true **Lord**, to **God be the Glory**. My journey has been tough, full of challenges, speed humps, potholes, and corrugations. However, **God** provided me with guardrails to protect me from rolling off on this road to success.

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As an employed person, I would like to close by thanking my workmates and the University *of Fort Hare* for approving my study leave in order to complete my research.



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Publications

The list of publications outlined herein below were related and contributed to the origin and this study direction. The study initially started in 2014 with the main focus on Zero Effort Technologies; however, it evolves with time to the current topic.

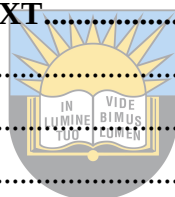
1. Shadreck K. Mudziwepasi, Mfundo S. Scott and Khulumani Sibanda. *Development of a Wireless Sensor Network for Zero Effort Technologies: A Child Monitoring Test Case*. SATNAC (Southern Africa Telecommunication Networks and Applications Conference), in Port Elizabeth, Eastern Cape Province of South Africa, 30 August – 1 September 2014
2. Mphenduli Ntsizi, Mfundo Shakes Scott and Khulumani Sibanda. *Development of a Location Based Service for Zero Effort Technologies: A Children Monitoring Test Approach*. SATNAC (Southern Africa Telecommunication Networks and Applications Conference), in Port Elizabeth, Eastern Cape Province of South Africa, 30 August – 1 September 2014
3. Shadreck K. Mudziwepasi and Mfundo S. Scott. *Assessment of a Wireless Sensor Network Based Monitoring Tool for Zero Effort Technologies: A Cattle-Health and Movement Monitoring Test Case*. IEEE ICAST, 6th International Conference on Adaptive Science and Technology, Canaan Land, Covenant University, Ota, Nigeria, 29 - 31 October 2014
4. Xolani Delman, Zelalem Shibeshi and Mfundo Shakes Scott. *Development of a Location Based Service for Technician Allocation*. IST-Africa 2016 International Conference. 11th Annual Series of Ministerial Level Technology Research Conferences, Lilongwe, Malawi, 11 – 13 May 2016
5. Ntini Beki and Mfundo Shakes Scott. *A Zero Effort Technology-enabled Automated Teller Machine for the Blind*. IST-Africa 2017 International Conference. 12th Annual Series of Ministerial Level Technology Research Conferences, Windhoek, Namibia, 10 – 12 May 2017

Authors' Contribution

In each of the papers, the author of this thesis contributed differently. For example, in Paper 1, the author guided the setting up of the network environment and the running of the experimentations. For Paper 2, the author worked on the methodologies and the required technologies appropriate for child monitoring. In Paper 3, the author provided the literature review and the discussion section respectively. Paper 4 enabled the author to set up the location-based technologies and environment that enabled the different devices to be installed. The final paper enabled the author to engage the disadvantaged users and the challenges faced in using specific devices relevant to blind people.

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Abstract

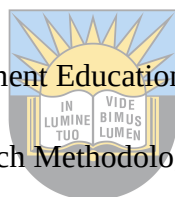
The advancement of health monitoring technologies rooted in Ambient Intelligence (AmI) has created innovative solutions for improving healthcare delivery and supporting independent living. However, a critical challenge persists because of the absence of a standardised, integrated framework to evaluate the reliability of these systems. This gap is particularly significant in resource-constrained environments, where operational uncertainties and infrastructure limitations exacerbate reliability issues. To address this problem, this study proposes a comprehensive framework for evaluating the reliability of AmI-based health monitoring technologies. The framework encompasses key dimensions, including data accuracy, system robustness, reliability and context or environment considerations. It was developed using a combination of simulation-based modelling, reliability block diagrams, and Monte Carlo Markov Chain (MCMC) techniques to systematically quantify and analyse reliability metrics. These methods were applied to case studies such as continuous glucose monitoring and heart rate monitoring in elderly care to validate the framework's practical relevance.

Results from these applications demonstrate the framework's efficacy in identifying and addressing reliability challenges. The findings highlight its ability to facilitate systematic evaluation, enhance fault tolerance, and ensure adaptability across diverse operational contexts. The presented framework contributes significantly to various stakeholders as it offers researchers a structured methodology for reliability assessment, provides healthcare practitioners with tools to ensure dependable patient monitoring, and guides policymakers in the adoption of reliable health technologies. By bridging the gap between technological innovation and practical application, this research advances the field of AmI-based health monitoring, fostering improved healthcare outcomes and greater trust in intelligent systems. Software developers, researchers, Health Monitoring devices manufacturers, Internet of Things (IOT) experts and patients on chronic medication who require regular monitoring, and the health sector are the targeted beneficiaries of the framework. Using two case studies which are Continuous Glucose Monitoring and Heart Rate Monitoring in elderly care the main limitations was the effectiveness of reliability in addressing these issues. This lays the groundwork for further refinement and application of the framework in broader contexts. Thus, future research ought to focus on addressing operational challenges, improving explainability in AI models, and discovering innovative applications of AI in healthcare monitoring systems.

Keywords: Health Monitoring Systems, Reliability, Assistive Technologies, Ambient Intelligence, Healthcare Services, Elderly, Healthcare Agents, Practitioners and Caregivers

List of Abbreviations

AJIA	Adaptive Joint Protocol
ATs	Assistive Technologies
AmI	Ambient Intelligence
AEs	Assistive Environments
AAL	Ambient Assisted Living
Apps	Mobile Applications
CGM	Continuous Glucose Monitoring
CTMC	Continuous Time Markov Chains
CV	Computer Vision
DSME	Diabetes Self-management Education
DSRM	Design Science Research Methodology
DTMC	Discrete Time Markov Chains
FTA	Fault Tree Analysis
GDPR	General Data Protection Regulation
GSPN	Generalized Stochastic Petri Net
HIS	Health Information Systems
HIV	Human Immunodeficiency Virus
ICT	Information Communication Technology
IoT	Internet of Things
IEs	Intelligent Environments



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LQI	Link Quality Indicator
LBS	Location-Based Services
ISP	Internet Service Provider
OS	Operating Systems
MCSs	Minimal Cut Sets
mQoS	Microservices' Quality of Service Management
MTTR	Mean Time to Repair
MTTF	Mean Time to Failure
ML	Machine Learning
MDG	Millennium Development Goals
NLP	Natural Language Processing
NOS	Networked Smart Objects
PRISMA	Preferred Reporting Items for Systematic reviews and Meta-Analyses
QoS	Quality of Service
RPM	Remote Patient Monitoring
RBD	Reliability Block Diagrams
ROPT	reliability over a period
RUL	Remaining Useful Life
SAN	Storage Area Networks
SMS	Short Message Service
SVM	Support Vector Machine



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TTR	Time To Repair
UN	United Nations
UTAUT	Unified Theory of Acceptance and Use of technological
WHO	World Health Organization
MCMC	Monte Carlo Markov Chains



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Chapter 1 : Research Context

This chapter introduces the foundation of the study, encompassing the background, problem statement, and objectives. It highlights the research motivation and contributions, focusing on the challenges of evaluating the reliability of AmI-AT systems. A review of preliminary literature explores developments in monitoring systems, reliability challenges, and improvement techniques, concluding with an overview of the thesis structure.

Chapter 1: Research Context

Chapter 2: Understanding AmI-ATs' Development and Challenges in Developing Countries

Chapter 3: Reliability Designs and Considerations for AmI-ATs

Chapter 4: Research Methodology

Chapter 5: Development of the Proposed Conceptual Framework for Reliability Engineering in AmI-ATs

Chapter 6: Experimental and Numeric Analysis of the Conceptual Framework

Chapter 7: Implications of the Conceptual Framework

Chapter 8: Research Conclusion



1.1 Introduction and Background

The integration of technology into healthcare has revolutionised how health monitoring is conducted, providing innovative tools to improve patient care and outcomes. Health monitoring technologies, including wearable devices, remote patient monitoring (RPM), and smart home systems, enable continuous tracking of vital signs and health conditions, facilitating early diagnosis and intervention (Baucas, Spachos, & Gregori, 2021). These advancements are particularly critical in addressing the challenges posed by aging populations, chronic diseases, and the increasing demand for personalised healthcare services (McTavish et al., 2012). However, despite their potential, the adoption of these technologies faces several barriers, including technical limitations and user acceptance (Coeckelbergh, 2010). In resource-constrained environments, these challenges are magnified by

infrastructural deficiencies and socio-economic disparities, emphasising the need for robust and reliable health monitoring systems.

Ambient Intelligence (AmI) represents a paradigm shift in intelligent computing, where environments are equipped with sensors, processors, and adaptive systems to seamlessly support user activities (De Ruyter et al., 2024). AmI technologies integrate artificial intelligence, ubiquitous computing, and sensor networks to create intelligent spaces that respond to users' needs in real-time. These environments are characterised by their non-intrusiveness, context awareness, personalisation, adaptability, and anticipatory capabilities (Stephanidis, Antona, & Ntoa, 2021). In healthcare, AmI has enabled the development of advanced assistive technologies (ATs) that offer personalised support for individuals with disabilities, chronic conditions, or age-related challenges. By leveraging the principles of AmI, these technologies promise enhanced autonomy, safety, and quality of life for users while reducing the burden on caregivers and healthcare systems (Cicirelli et al., 2021).

While health monitoring technologies and AmI-based systems offer significant benefits, their effectiveness hinges on their reliability. Reliability, defined as the ability of a system to perform consistently under varying conditions, is a critical factor in ensuring user trust and system efficacy (Rodrigues et al., 2005). Unreliable systems can lead to inaccurate diagnoses, delayed interventions, and compromised patient safety, undermining the intended benefits of these technologies. In resource-constrained settings, where infrastructure and technical expertise are limited, ensuring reliability becomes even more challenging (Xing, 2020). Despite these challenges, there is a notable lack of standardised frameworks to evaluate the reliability of AmI-based health monitoring systems. Addressing this gap is essential to advancing the field and ensuring the successful adoption of these technologies in diverse and demanding environments.

This study aims to develop a comprehensive framework for evaluating the reliability of Ambient Intelligence-based health monitoring technologies. By focusing on key dimensions such as data accuracy, system robustness and user acceptance this research seeks to address the identified gap and provide practical tools for assessing and enhancing the reliability of these systems. The framework is designed to support diverse stakeholders, including researchers, healthcare practitioners, and policymakers, in optimising the deployment and adoption of reliable health monitoring technologies, particularly with the experiences from the resource-constrained environments.

This chapter provides a background of Assistive Technologies based on Ambient Intelligence and links them to assess the problem domain targeted by this study. Additionally, the chapter delineates and conveys the research questions and their associated objectives pointedly and significantly. As a final point, this preliminary chapter concludes by providing a summarized overview of the remaining chapters of this thesis.

1.2 Problem Statement

Evaluating the reliability of health monitoring technologies remains a persistent challenge due to the complexity and variability of operational environments. Factors such as infrastructural deficiencies, heterogeneous devices, inconsistent data accuracy, and the lack of an integrated framework complicate the assessment of these systems. These challenges are further exacerbated by the dynamic nature of health monitoring environments, where system components must operate seamlessly in real-time while adapting to evolving user needs and environmental conditions (Yusif, Soar, & Hafeez-Baig, 2016). Moreover, ensuring interoperability among diverse devices and platforms presents significant obstacles, often resulting in fragmented systems that lack coherence and reliability (Kumar, Renuka, Rose, & Wartana, 2022). This challenge is particularly pronounced in resource-constrained settings, where technical limitations exacerbate reliability concerns (Xing, 2020).

In the context of Ambient Intelligence (AmI), specific issues arise regarding system reliability. AmI-based health monitoring technologies depend on seamless integration of sensors, data processing, and adaptive algorithms to function effectively. Failures in any of these components can compromise system performance, user trust, and overall effectiveness. Despite these critical requirements, recent studies highlight the absence of standardised methods to quantify and address reliability issues in AmI-based systems (Yazdi, 2024).

This study seeks to address these challenges by developing a comprehensive framework for evaluating the reliability of AmI-based health monitoring technologies. By incorporating key dimensions such as data accuracy, system robustness and user acceptance the framework aims to provide practical solutions for stakeholders. This approach will facilitate systematic reliability assessments, ensuring these technologies meet the demands of diverse and resource-constrained environments.

This study seeks to address these deficiencies by developing a framework that evaluates and enhances the reliability of AmI-ATs in diverse and resource-constrained environments. The study intends to develop user-friendly devices that people can use locally because most of these devices were designed from outside, even though people may have a variety of devices that they can use for different diseases at home (Merugu, Kumar & Ghinea, 2022). However, they may not be able to recognise when these devices start to pick up incorrect readings. Therefore, it is essential to develop gadgets that members of the local community can use, read, and record faults.

1.3 Research Aim and Objectives

The following research objectives are for the study:

1.3.1 Research Aim

The aim of this research study is to formulate a framework for assessing the reliability of AmI-ATs used in healthcare monitoring and elderly living monitoring in developing countries. To pursue this aim, the study used as a guide, the following research questions and objectives:

1.3.2 Research Objectives

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The primary aim of this study is to develop a comprehensive framework for evaluating the reliability of AmI-based health monitoring technologies. This framework will provide a structured approach to assess technical reliability using controlled environments and simulation-based methodologies.

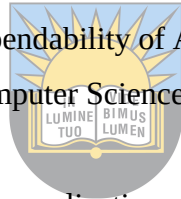
The specific objectives of this research are:

1. To identify the key framework components for AmI-based health monitoring technologies, focusing on dimensions such as fault tolerance, adaptability, and consistency.
2. To apply different algorithms and mathematical models that enable a simulation-based framework for evaluating the components in controlled environments, ensuring comprehensive reliability assessments.
3. To create an integrated framework for evaluating the reliability of AmI-based health monitoring technologies based on the formulated components.

4. To validate the framework using selected case studies of AmI-based health monitoring technologies towards drawing up key strengths, weaknesses and recommendations before full implementation.

1.4 Research Contribution

This thesis makes significant contributions to the fields of Computer Science, Statistical Modelling, and Healthcare Monitoring Systems, specifically in the domain of Ambient Intelligence Assistive Technologies (AmI-ATs). The primary contribution lies in the development of a comprehensive reliability evaluation framework that integrates advanced computational models and probabilistic methods to address critical challenges in the design and assessment of AmI-ATs. By employing methodologies such as Markov Chain Monte Carlo (MCMC) simulations and Reliability Block Diagrams (RBDs), the study bridges the gap between theoretical reliability assessments and practical applications in resource-constrained environments. This framework provides a novel, systematic approach to evaluate and enhance the dependability of AmI-ATs, contributing to the broader field of system reliability engineering within Computer Science.



Furthermore, the study demonstrates the application of statistical models to complex, real-world problems, showcasing their adaptability in evaluating dynamic and interdependent systems like healthcare monitoring technologies. The framework is validated through secondary data analysis and practical case studies, including Continuous Glucose Monitoring (CGM) and Heart Rate Monitoring (HRM) for elderly care, emphasising its utility in healthcare contexts. By addressing the unique challenges of reliability in developing countries, the research offers a replicable model for enhancing healthcare monitoring systems, ensuring scalability and robustness.

Additionally, this work contributes to Human-Computer Interaction (HCI) by providing insights into designing user-centric interfaces that are intuitive and reliable, particularly for vulnerable populations. Device manufacturers can leverage the framework to optimise the design and functionality of assistive technologies, ensuring higher reliability and user satisfaction. These contributions not only advance the state of knowledge in health informatics but also provide actionable insights for developers, healthcare practitioners, and policymakers aiming to deploy reliable assistive technologies globally.

At the time of writing, to the best of the researcher's knowledge, this work represents the first work to review and summarize the practice of quantifying and measuring reliability in AmI-ATs in developing countries, specifically in South Africa. This indicates that, in general, the area of AmI-AT reliability quantification is nascent and yet under-researched. This study led to the following contributions:

1.5 Thesis Structure

Including the current chapter, the work presented in this thesis is subdivided into seven chapters. Chapter 1 focuses on the background of the study, objectives, problem statement, research questions, preliminary literature as well as motivation and contribution of the study. Chapter 2 discusses the state of art in AmI-AT reliability and associated concepts. Chapter 3 presents the reliability designs and considerations for AMI-ATs. Chapter 4 provides the methodology and techniques in the study. Chapter 5 delves in the development of the conceptual framework for reliability in AmI-AT's. Chapter 6 discusses the experimental implementation of the framework and its validation as well as a discussion of the main themes that emerged from the literature. Finally, Chapter 7 concludes the study by summarizing the key issues, outcomes and consequences, and future recommendations.

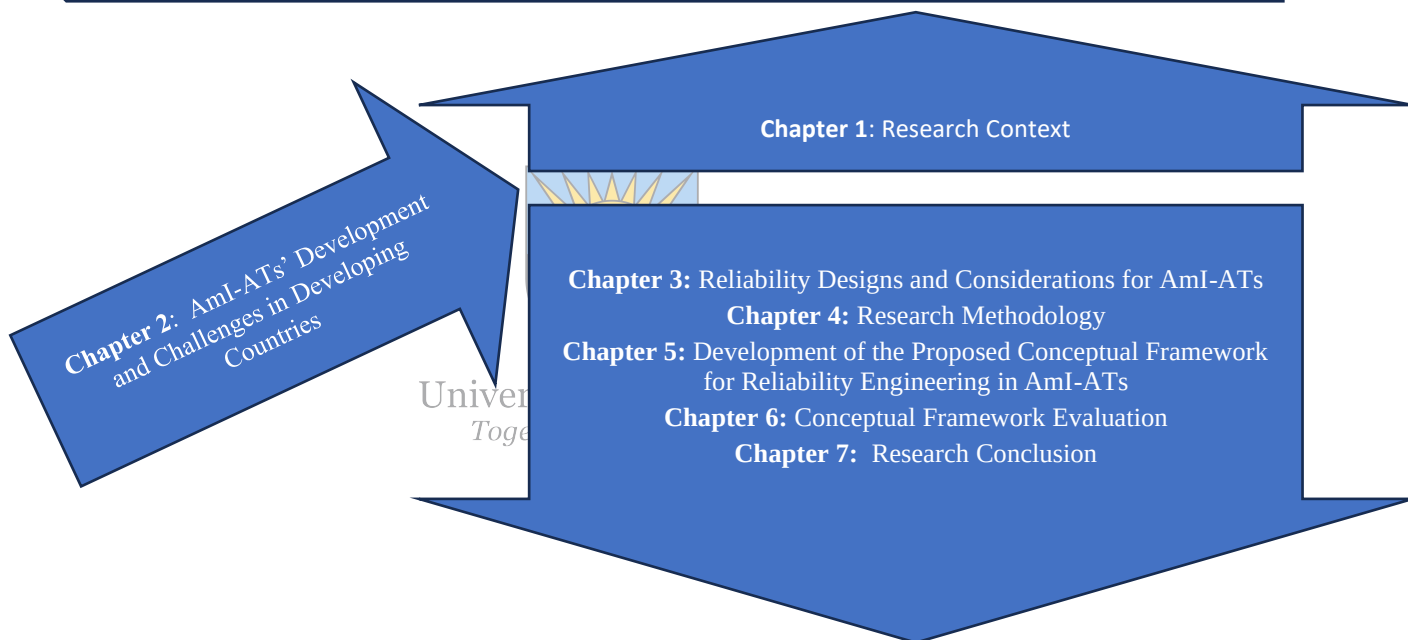
1.6 Chapter Summary

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This chapter introduced the context for the research study by discussing the background and research problem, research objectives and contributions. Hence the next chapter focuses on defining Reliability, components of Reliability, health Monitoring Technologies and Ambient Intelligence, overview of Ambient Intelligence, examples of Health Monitoring Technologies, Reliability in Health Monitoring Systems. It also provides an overview of the theoretical framework and gaps in literature.

Chapter 2 : AmI- Factors in Health and Challenges

This chapter focuses on Definitions of Reliability, Components of Reliabilityhealth Monitoring Technologies and Ambient Intelligence, Overview of Ambient Intelligence, Examples of Health Monitoring Technologies, Reliability in Health Monitoring Systems. The discussion extends to Existing Evaluation Frameworks, Assessment of Current Frameworks and Gaps in Literature.



2.1 Introduction

This chapter provides an overview of AmI-ATs with a specific emphasis on introducing the concept AmI-ATs and its background as one of the emerging fields of a broader umbrella on ICTs and its numerous ubiquitous benefits. The chapter provides an overview of health status, specifically in South Africa. ICT monitoring systems, developments that have been done and challenges experienced in such a field of technology. The chapter explores existing monitoring systems, approaches, and requirements. The chapter also outlines the technologies and techniques that form the core of designing AmI-ATs. Additionally, it is important that a comprehensible explanation of

the tools and key design elements for AmI-ATs be clearly set out to provide an understanding of the building blocks of AmI-ATs. The chapter also stipulates common AATs devices used for Diabetes, Heart diseases, and glucose monitoring and then concludes with the chapter summary.

2.2 Defining AmI-AT Reliability

Technological assurance serves as a guarantee of product quality, promising reliability under stipulated operating conditions. However, the reality of Ambient Intelligent Technologies (AmI) is that operating conditions are not always constant. Failures can and do occur, emphasizing the critical need for reliability engineering. Reliability engineering focuses on mitigating failures and faults arising from inconsistencies in hardware, software systems, and environmental conditions (Xing, 2020). Mirzaei et al, (2023) indicated that reliability engineering encompasses the techniques, processes, and models used to ensure the development and maintenance of high-quality systems, and its role is indispensable for the efficient operation of AmI systems.

When it comes to AmI technologies, dependability is crucial. For AmI-AT systems to perform as intended, precise data sensing, processing, and transmission are essential (Breneman, Sahay & Lewis, 2022). False monitoring reports, protracted delays, or even data loss may arise from unreliable operations in any of these areas. Such flaws might undermine public confidence in IoT-based systems, a fundamental component of AmI, in addition to jeopardising the efficacy of AmI-AT devices. As far as we know at the time of writing, there isn't a single, widely recognised definition of dependability in the AmI-AT domain, despite the fact that reliability is crucial for AmI-AT.

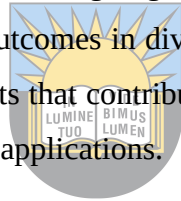
According to Modarres and Groth (2023), the capacity to carry out a necessary function under specified conditions for a predetermined amount of time is the definition of dependability in AmI-AT for the purposes of this study. The accepted description offers a framework to assess the presentation of the system and may be represented quantitatively as a probability. The definition, as per Modarres et al, (2023), emphasises the following key considerations:

- Ability to Perform Required Functions
- Ability to Perform Without Error
- Ability to Perform Without Failure
- Ability to Perform Under Specified Conditions

This study adopts these considerations as the foundation for evaluating reliability in AmI technologies. Grounding the research in these principles aims to ensure that AmI systems are not only functional but also robust, dependable, and capable of supporting the critical needs of healthcare and elderly living monitoring. This approach seeks to bridge the current gaps in reliability definitions within AmI and establish a comprehensive framework for assessing and improving system reliability.

2.2.1 Key AmI-AT Reliability Factors

Reliability is a critical aspect of AmI-AT systems, particularly in healthcare and elderly living environments, where device failures can have significant consequences. The reliability of AmI systems depends on a range of interrelated factors that influence their ability to perform consistently under varying conditions. Key factors include the robustness of hardware and sensors, the accuracy of data processing algorithms, fault tolerance, and the ability to adapt to environmental changes. Understanding these factors is essential for designing systems that can maintain their functionality, ensure user safety, and deliver reliable outcomes in diverse and often unpredictable scenarios. This section explores the fundamental elements that contribute to the reliability of AmI-AT systems and highlights their importance in real-world applications.



2.2.2 Hardware Factors

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Rahman et al, (2023) specified that hardware reliability depends on other things, such as power and environmental variables, such as temperature. Zhu et al, (2023) indicated that because hardware components work with constant failure rates (ρ_{ps}). The operational phase by utilizing the exponential reliability framework to assess the hardware reliability can be modelled as:

- Sensors
- Actuators
- Power (battery)
- Processing power
- Maintenance and Lifecycle management “useful”

- Communication services
- Applications

Furthermore, Moore et al, (2020) a probabilistic framework for measuring reliability in connected IoT devices, positing that the failure of IoT devices adheres to a certain probability distribution. Moore et al, (2020) outlined reliability measure $R(t)$ as the probability that the device is operating correctly at a time interval $[0, t]$. This probabilistic function permits estimation of the expected time to failure, accessibility and reliability for a given IoT device.

Mavrogiorgou et al, (2018), focused on Mean Time to Repair (MTTR), MTTF, MTBF, and availability metrics which projected a mechanism for capturing the reliability of heterogeneous IoT devices. This mechanism reflected both known and unknown device types and sought to distinguish between which devices were reliable, and which were not, with the goal of collecting data from reliable ones and discarding data from undependable devices. The mechanism by Moore et al, (2020) entails several stages, specifically, device recognition, specifications classification, reliability estimation and reliability validation. In addition, Kim (2016) a weighted framework for quantifying reliability in the IoT which consisted of four quality criteria: functionality, reliability, efficiency and portability. These classical metrics provide a useful starting point in the quantification of IoT reliability but have not yet matured in capability and cannot attest to reliability across all levels of the IoT architecture.

Furthermore, Ashouri, Davidsson and Spalazzese (2021) presented a framework to evaluate trust factors and reliability over a period (ROPT) for IoT systems. Due to the notion that identical IoT sensors might be deployed in drastically different environments (like exposed to varying levels of humidity, temperature, wind) these identical IoT sensors might exhibit different expected lifetimes. Ashouri et al, (2021) anticipated that ROPT is calculated for every individual device and gateway in the IoT system to gain a full understanding of how reliable the system is and a trust factor rating scale on how some IoT applications require higher levels of trust.

This study used one metric to regulate the reliability of the system and cannot represent the entire picture of reliability in the IoT. Li et al, (2012) also three nonstandard reliability metric definitions to observe real-time quality of data collected from devices in IoT environments. A more complete

framework for managing quality and reliability is by Sicari et al, (2016), which was designed to quantify the security and quality of individual devices in IoT applications. The framework used NOS (Networked Smart Objects) to extract metadata from IoT nodes in a network (Sicari et al, 2021). The framework was tested using Raspberry Pi and sensors from a meteorological station, and it was successfully able to calculate the specified parameters (Sicari et al, 2021). This relates to data quality characteristics of IoT nodes through the quality metadata, which is not appropriate in describing the holistic reliability of an IoT system.

2.2.3 Connectivity Factors

According to Sai et al, (2022) mobility is one of the crucial expectations of an IoT network whereby users of the network can vigorously move between applications while the device onboarding and identification happen flawlessly in the background. Though, there is a trouble in IoT given that manufacturers do not co-ordinate to offer unique identifiers for all IoT devices. This means that the duty of conveying unique identification resides within the IoT network itself (Guillemín et al, 2022). IoT devices are expected to be mobile, and this creates a problem given that the device ID might differ across different networks; thus, the traceability of the device can be lost.

This then introduces a reliability concern when it comes to tracking or auditing the device as it moves through different IoT applications de Barros Filho et al, (2021) indicated that due to the scarce resources and intermittent communication, the network is liable to drop readings or produce unreliable readings. This notion that readings can be dropped due to the inherent nature of IoT networks is an area for concern, especially given that IoT infrastructure is often responsible for managing mission-critical applications (Farooq & Zhu, 2021).

- Network connectivity protocols
- Mobility and network migration
- Intermittent communication

Moreover, there is also a need to attest to the reliability of the network infrastructure that forms the backbone of IoT communication. A novel IoT network QoS metric was planned by Ilyas et al, (2020),

which designed a lightweight and energy-efficient routing protocol to improve and measure reliability in IoT applications, specifically emergency applications. Singh et al, (2024) a mechanism called AJIA (Adaptive Joint Protocol based on Implicit ACK) for packet loss and route quality evaluation. Mugerwa et al, (2023) specified that the nearby nodes could, therefore, “overhear” the message being sent, and this overhearing function is used rather than traditional ACK messages to ensure reliability of the message being sent. The links between nodes are then estimated with a metric called Link Quality Indicator (LQI), which uses the history of packet loss in the link to regulate the reliability of that path. Other QoS metrics, such as delay throughput and packet loss, were quantified by (Boucetta, Nour, Cusin & Moun gla, 2021).

Boucetta et al, (2021) designated an approach of reliability modelling using generalized Stochastic Petri Net (GSPN), which theorized mathematical models at edge nodes to offer statistics on the performance of IoT devices. The metrics calculated were time consumption, response time, failure rate and repair times. These metrics only express the performance of the device-to-edge layer and offer a very limited view of network performance, which does not present a holistic view of IoT reliability (Moore et al, 2020).



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2.2.4 Software Factors

Software reliability is not a direct function of time since software has no ageing property/does not deteriorate with time. Moore et al, (2020) quantified that reliability is vital for efficient IoT communication, because undependable sensing, processing, and transmission can cause false monitoring data reports, long delays, and even data loss, which would reduce people’s interest in IoT communication. Therefore, the rapid growth of IoT communication stresses high reliability.

2.2.5 System Factors

Approximately research has been conducted to evaluate IoT reliability at a system level (Moore et al, 2020). These methods are at a high level, and do not capture the individual details for reliability, like which devices are responsible for failures, or which parts of the network are responsible for traffic problems. According to Eroshkin, Vojtech and Neruda, (2021) a method of modelling reliability in a service-oriented IoT. Eroshkin et al, (2021) that reliability could be measured by modelling the

availability of the program to run the service, the availability of input required for the service to run, and the service reliability of subsystems associated with the system.

However, to present a true reflection of reliability, it is required to have a mechanism that can alert the user to failures in the system before critical actuations are made. Kharchenko et al, (2022) the use of a Markov framework to predict the reliability requirements of an IoT system. The probabilistic nature of the Markov framework enables the prediction that the system will move from one state to the next and can begin the probability of a failure at a given point in time. This framework only reflects the states specified in the design of the framework and is not accomplished of reacting to new situations that were not catered for in the design of the framework.

2.2.6 Human User Factors

Human factor can be involved in the IoT system; therefore, a human action can influence the reliability of the IoT. Human reliability can mean preventing accidents and minimizing the consequences of accidents that do occur (Moore et al, 2020). The decisions made by people to act or not to act have consequences for the technological systems they operate. Major system failures are frequently a sequence of events where one or more people have decided or taken some action while operating, maintaining or repairing some technological system.

Potential consequences are significant, such as catastrophic loss of equipment, long-term damage to the environment, or loss of life, then reliability engineers working collaboratively with others can have an important impact (Pokorni, 2016). Procedures, rules, codes, standards and laws cannot entirely prevent system failures but rather they can reduce system failures.

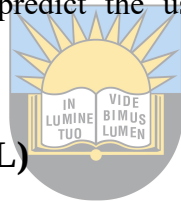
2.3 Ambient Intelligence (AmI)

Ambient Intelligence builds on the concept of IEs and adds ubiquitous computing to create spaces that are not only smart but pervasive (De Ruyter, Wegener, Cassens & Aarts, 2024). Mark Weiser first introduced this idea in 1991, envisioning a future where computers were embedded seamlessly into surroundings and currently, his vision is a reality (Rocher, Tigli, Lavirotte & Thanh, 2020). Many everyday objects now include sensors, processors, and wireless communication modules, allowing them to receive, process, and transmit information effortlessly. These spaces evolve into AmI

environments, equipped with sensing, processing, and networking systems that provide various services.

An AmI environment is designed to support users' activities in a seamless, non-intrusive manner (De Ruyter et al, 2024). It adapts to individual needs, unlike older technologies that require users to adjust to the system. The environment becomes responsive and sensitive to the presence and activities of individuals. Stephanidis, Antona and Ntoa, (2021) highlighted that AmI systems should have the following features:

- Non-obtrusive: Embedded and invisible devices that do not disrupt daily life.
- Context aware: Systems that can anticipate and respond to the user's evolving context.
- Personalized: The ability to customize according to different users and environments.
- Adaptive: Systems that adjust to user needs and can evolve with new functionalities.
- Anticipatory: The ability to predict the user's desires and the environment's state, responding proactively.



2.4 Ambient Assisted Living (AAL)

Assistive Technologies (AT) encompass tools, systems, or services designed to help individuals with disabilities improve their quality of life. According to Stephanidis, Antona and Ntoa, (2021), these technologies are vital for the elderly, who may struggle with activities like opening doors or bathing. Environments equipped with these technologies, known as Assistive Environments (AEs), offer accessible services that cater to users' needs.

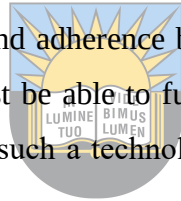
Cicirelli, Marani, Petitti, Milella and D'Orazio, (2021) stated that AAL focuses on using AmI solutions to assist elderly individuals in living independently by helping them with their daily activities (ADLs). It covers a wide range of technologies, from smart homes to personalized healthcare, enhancing the independence of older adults in their homes and communities. Additionally, AAL technologies improve healthcare delivery and rehabilitation.

Furthermore, one of the related concepts is Telecare, which remotely monitors elderly or dependent individuals, alerting caregivers when necessary. While AAL supports patients in maintaining their independence, Telecare focuses on keeping caregivers informed and responsive to patient needs

(Johannessen, Storm & Holm, 2019). According to Kumar et al., (2025) AI methods have become dominant in the healthcare sector for patient risk assessment, medication detection as well as disease diagnosis. An extensive range of health data sources are required for accurately diagnosing illnesses using AI techniques such as genetics, computed tomography tests, ultrasound, electromagnetic resonance imaging, mammograms (Kumar et al., 2025). Hence, this study focuses on using smart home technologies to develop AAL systems for individuals with cognitive decline. The next section will explore AmI-AT-specific contexts.

2.5 AmI-ATs Background

The introduction of ICTs to the knowledge society has made it possible to minimize the barriers of having to manually conduct operations. The existence of technologies such as mobile phones, desktop computers, hand-held devices, emails and the use of the Internet has become a central part of the culture and society, and they play a vital role in one's day-to-day operations (Mosco, 2017). These ICTs require two-way communication and adherence between the actual technology and the users involved. This means that the users must be able to fully understand the concerned technology in order to be able to operate it fully, and such a technology must be able to comprehend the users' inputs to produce relevant outputs.



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For example, a user is expected to be able to understand how to operate a mobile phone in order to make a call or send an SMS notification. Most user technologies require a user's input for operation; however, humans get tired or bored, lose concentration, and generally become fed-up if they have to repeat the same task over-and-over again (Masood, Hoda, Blincoe & Damian, 2022; Hamamra & Qabaha, 2024). This presents more challenges for humans with physical challenges or disabilities who have limited or no means of interacting with such ICTs.

The introduction of AmI-ATs comes in as a prospective method to minimize the operational day-to-day challenges faced by physically impaired people. This is due to the fact that AmI-ATs have an incredible latent to provide support to people with chronic health conditions with little or no effort on the part of the primary user or the related caregivers or clinicians (Czarnuch & Mihailidis, 2011; Marcello et al, 2019). Such help is made possible because AmI-ATs employ advanced techniques such as AI, undistruptive or risk-free sensors or SF, decision-making and planning, and machine

learning to support the autonomous collection, analysis and application of data about users and their context (Marcello et al, 2019). AmI-ATs make use of such techniques and tools for context-aware situations for the physically handicapped communities as well.

Furthermore, AmI-ATs are using concepts applied in the development and implementation of pervasive or widespread intelligent computing technologies and settings for health and rehabilitation, and design principles that this approach entails (Czarnuch & Mihailidis, 2011; & Marcello et al, 2019). For AmI-ATs to accomplish their main objective, which is to bridge the technology divide between the privileged and the physically handicapped people, they must apply design principles with the goal of ensuring that the safety and well-being of the people who depend on them are not compromised (Haux et al, 2016). In such a process, the AmI-ATs, as monitoring systems, should also have a way of assuring their reliability, which guarantees or speaks to the safety requirements of the concerned users.

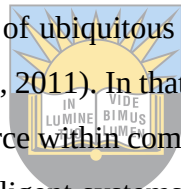
In order to implement many of the ideas of AmI-ATs, various upcoming areas of computer science and technology are required. Such areas are meant to help provide the missing or necessary intelligence, flexibility and comprehensiveness needed by this emerging class of technologies (Kbar et al, 2015). One of the main advantages of having AmI-ATs is to provide effortless monitoring to audiences who are unable to monitor themselves efficiently. Therefore, this research study makes use of such an advantage to come up with a framework to use for evaluating the reliability of such AmI-ATs as monitoring systems.

In addition, the formulated framework is meant to assist and guide the designs and developments of AmI-ATs' tools for monitoring systems that are created to supervise daily operations of the health and wellness of human beings. The infrastructure, functionality, operational behaviour, and maintenance of such AmI-ATs' tools are also guided by the formulated reliability framework. Throughout this research study, the standard of AmI-ATs, which is to provide monitoring systems at minimal or no effort to the intended users, has been preserved and adhered to during the framework formulation.

2.6 Ambient Intelligence (AmI) from an ICT Perspective

The inception and ideology of the existence of ICTs were to obliterate the challenges of manual labour from various human operations the world maybe undertaking. The numerous benefits of ICTs, which are kept on being developed and upgraded timeously, have made it easy for different kinds of humans to have tools, systems, gadgets and platforms that can assist them. ICTs, as an umbrella field, consist of a combination of various specialty-contexts, which are used individually in some cases and amalgamated in others to achieve specific tasks. Some popular and new fields under this umbrella of ICTs are ubiquitous computing and AmI, which are characterized by intelligent, persistent, and unobtrusive computer systems embedded into human environments, personalized to the individual's context-aware needs (Bimpas, Violos, Leivadeas & Varlamis, 2024).

As a result, from that combination, AmI has been regarded as a future vision of the information society stemming from the convergence of ubiquitous computing, ubiquitous communications and intelligent, user-friendly interfaces (Sadri, 2011). In that understanding, AmI, therefore, consolidates its role as a new paradigm and driving force within computer science as a field and ICTs at large that exploits the opportunities to deploy intelligent systems supported by new technology (Miano et al, 2015).



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According to (Miano et al, 2015), most developments related to AmI thus far are concentrated either in the healthcare sector, such as Smart Homes for the Elderly or monitoring of people with physical challenges, or in the automotive industry, such as smart cars, as examples respectively. (Gams et al, 2019) labels AmI as being intrinsically and thoroughly connected with AI, of which in the process, AI owes its success to the phenomenal developments of ICTs. As a result, Gams et al, (2019) further argue that the cost functions for optimizing the AmI solutions are usually related to improving the subjectivity of human experience, which is only indirectly measurable. This means that if an AmI is a component or an element of ICTs with various technological applications that can be developed from it, it should be human-centric in nature.

In addition, the existence of AmIs is centered around the safety and ease of convenience for human-beings, in an environmental-centric perspective. Therefore, in that regard, its ATs' applications

become deducible for the development of assisting with solving and mitigating of people's challenges, more especially for the under-catered areas of the human-spheres. However, AmI-ATs focus on helping with the monitoring of humans does not say much about its reliability as an umbrella field of ICTs (Ortiz, Hussein, Park, Han & Crespi, 2014). This, therefore, has opened a space for this research study to identify variables, characteristics and parameters that can be used to address the missing reliability component, which is not a very clear and straightforward feature. The thesis achieved this through the formulation of a framework, which was used as an evaluation tool or platform to ascertain if a particular AmI-AT is reliable and trustworthy enough for the human-sphere concerned.

2.7 Health Monitoring Technologies and Ambient Intelligence

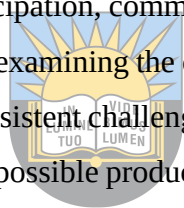
ATs are relatively novel tools used for research and daily care in various facilities, such as long-term care based, that are faced with the burgeoning of older population, physical disabilities and impairments, and dwindling staffing resources (Dorsten et al, 2009; Borg et al, 2022). Such tools are generally used in inspecting, testing, and signifying technologies that have the potential to improve the quality of life for target populations, such as individuals with physical and mental disabilities, adults aged 65 and older, who may require AT devices to aid in maintaining or improving their quality of life (Borg et al, 2022). Central to the role of ATs to support and improve the quality of life is the development of non-obtrusive technologies for the targeted audiences, populations, guardians and caregivers, individually (Courtney et al, 2019). This analogy sets parenthesis for ATs, to adhere to for current and future designs and developmental considerations for monitoring systems of such designated populations. Ideally, the core of the existence of ATs has monitoring involved and embedded in it, as one of the key fundamental features of its operational functionalities.

According to Desmond et al, (2018) it is arguable that all technology is assistive in some way, and thus the use of ATs has become universal. With various technologies around humans and their use to perform multiple tasks in everyday lives, there is a high expectation that ATs will support people to accomplish ADL. Such an expectation dictates that, from a designer's perspective, certain requirements need to be considered when dealing with humans versus Ats3 for mutual inclusivity. In

that regard, (Desmond et al, 2018) further argue that culturally sensitive and competent ATs provisioning is essential for consideration, and this means that ATs designs and developments must be sensitive to, but not limited to:

- A person's personal goals and desired outcomes (Desmond et al, 2018).
- The way the AT portrays and depicts the human variation which a person is experiencing (Desmond et al, 2018).
- Whether the locus of intervention with AT products is the person themselves, or the environment, in order to close any capability gap (Desmond et al, 2018).

There are various benefits of ATs for the human-sphere, as far as monitoring is concerned, and the work of ATs enabled or combined with AmI as umbrella fields if ICTs, are increasingly notable in the living surroundings. Such benefits make it appropriate for the user and the user's environment to increase independence and improve participation, communication and mobility through the existence of ATs. The WHO (2024) in its work for examining the challenges for children with disabilities, with ATs as a remedy field to help mitigate persistent challenges and possible divides in such a population, came up with a category list of ATs with possible product example tools (World Health Organization UNICEF, 2015).



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Table 2.1 provides the outline categories, which are not only standard with children's challenges, but also common to adults or elderly living with physical disabilities or impairments. This, therefore, means that, the product example list, can be deduced for use by the elderly or ageing community, facing the same physical disability challenges as the children outlined by the WHO's (2024) study.

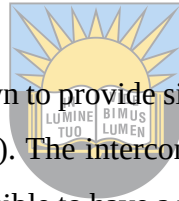
Table 2.1 Examples of ATs Categories and Products' Tools (World Health Organization UNICEF, 2015)

Category	Product examples
Mobility	Walking stick, crutch, walking frame, manual and powered wheelchair, tricycle Artificial leg or hand, leg or hand splint, clubfoot brace Corner chair, supportive seat, standing frame Adapted cutlery and cooking utensils, dressing stick, shower seat, toilet seat, toilet frame, feeding robot
Vision	Eyeglasses, magnifier, magnifying software for computer White cane, GPS-based navigation device Braille systems for reading and writing, screen reader for computer, talking book player, audio recorder and player Braille chess, balls that emit sound
Hearing	Headphone, hearing aid Amplified telephone, hearing loop
Communication	Communication cards with texts, communication board with letters, symbols or pictures Electronic communication device with recorded or synthetic speech
Cognition	Task lists, picture schedule and calendar, picture based instructions Timer, manual or automatic reminder, smartphone with adapted task lists, schedules, calendars and audio recorder Adapted toys and games

Consequently, ATs as well, provides various enormous endless possibilities of technology services and tools to assist the humans with life improvement opportunities and monitoring capabilities, more especially the elderly or aging people and physically challenges populations, respectively. However, emphasis about their reliability and how it becomes perceived and evaluated by the users is not really addressed. It is also on these grounds that this research study articulates such a loophole to formulate a framework to be used to evaluate their reliability, as a missing known characteristic feature.

2.7.1 Monitoring of Health Services

In this case ICTs have been used as a monitoring tool in which platforms such as e-Health portals, as fondly known in the health sector, came into existence, which was initially mostly used as tools for supporting health system functions such as data collection for surveillance (Leon & Schneider, 2012). Furthermore, Thilakarathne, Kagita, Gadekallu and Maddikunta, (2020) pinpoints that the e-Health systems need to be further improved in order to promote greater flexibility in use, more functionality in terms of services provided and ubiquitous access, as such, a consequence of those initiatives resulted into m-Health applications being introduced. This saw hand-held electronic devices such as PDAs, e-Pens, handheld scanners and mobile phones as well as the interaction of these devices with web-based information systems was actively used daily (Leon & Schneider, 2012). The existence of such devices and associated ICTs lead to the introduction of healthcare tracking systems, databases for healthcare information storing and information systems for data retrieval and knowledge dissemination.



As such, ICTs and EMRs have been shown to provide significant benefits in developed countries due to this development (Clifford et al, 2008). The interconnection and interlinked benefit of having e-Health and m-Health systems made it possible to have a variety of services and applications that serve the purpose of monitoring systems. However, the most important aspect of having such a harmonization of interlinked systems is that they have to be easily accessible via the web and allow flexibility in searching in a variety of localized languages (Clifford et al, 2008).

Accordingly, having m-Health embedded into the process translates to ubiquitous access and real-time monitoring (Leon et al, 2012). Thus, with all such benefits of embedding ICTs into health services as a means of providing real-time monitoring systems approach, there could be plenty of ways to put ICTs in good use to bridge the monitoring difficulties persistent in health services. A practical example of using ICTs as a health monitoring system is that ICTs can be used for mobile patient monitoring. In this example, a mobile patient monitoring system makes use of mobile computing and wireless communication technologies for continuous or periodic measurement and analysis of the bio-signals of a mobile patient (Pawar et al, 2012). In this way, ICTs have been used as a patient monitoring system that is able to provide mobile and remote patient monitoring. Such an

ICT monitoring system approach, in several trials, verified their user-friendliness, convenience and efficacy for both patients and healthcare professionals (Pawar et al, 2012).

Furthermore, another practical example of reaping the ICTs in health services as a monitoring approach is that ICTs can be used by doctors and hospitals to remotely monitor their patients for supporting the appropriate provision and application of medicine (Awad, Trenfield, Pollard, Ong, Elbadawi, McCoubrey & Basit, 2021). In this case, with the use of ICTs, the doctor can provide directions to hospital personnel on how the patients should be administered with medication. Patients can be monitored over the network through the existence and installation of RFID tags at their disposal. Thus, through ICTs, the patient can be monitored to verify if it's the correct person to be medically administered, the type and amount of medicine given, and in all such cases, the system is able to raise alarms through RFIDs in the event of malpractice or errors.

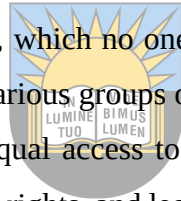
According to Chatterjee et al, (2023), the most important lesson about the monitoring systems provided by ICTs to the patients under surveillance is that there is no effort required from them to fiddle with any system that monitors them. That is, the monitoring systems provide adequate monitoring with no expectation of being tempered by the patient, and therefore, the little effort needed from the patients' side is their presence for the system to have something to monitor, and therefore, this constitutes them as Aml-ATs in this regard. Generally, because research allows for interconnection and interdependency of some degree between e-Health and m-Health systems, (Leon et al, 2012) outlined different applications of m-Health for community-based healthcare settings.

Such applications are generally for data collection, management, clinical service delivery, health promotion activities, education and training. Consequently, Labrique et al, (2020) concurred with the same outline and analogy by providing a pointedly similar but extended set of common m-Health and ICT applications (Labrique et al, 2020). The outlined common m-Health and ICT applications portray the fundamental and significant role ICTs play as monitoring systems in the context of healthcare services. Therefore, in this regard, ICTs are used as strengthening tools in the endeavour of improving healthcare service delivery and monitoring of wellness of the human-sphere, respectively.

2.7.2 Monitoring of Physical Disabilities

The human population across the globe is unevenly created, with various identical abilities, intellectuality, similarities, differences, disabilities and impairments. These are unique differentiators that are perceivably misused by certain humans to wrongly identify or label other humans across living environments, which normally makes the affected groups feel isolated and divided by their lack of ability to function properly like other people. Martins et al, (2020) specified that there are various reasons that result in people being physically disabled or impairment, however there is no person who has control over how it arises or when it will happen, or to prevent it from occurring. As a result, people suffer from various disabilities or impairments such as hearing, visual, mobility, and learning, which are generally associated with the proper use of sensory organs such as eyes and ears as examples (Jagannathan et al, 2020).

In addition, this may be caused by various life incidences such as accidents at birth or during the growing period, or ageing of human life, which no one has control over. In this regard, ICTs have opened up many new opportunities for various groups of populations, and it became imperative that people with disabilities are entitled to equal access to education and employment, equal rights to parenthood, property ownership, political rights, and legal representation (Hossain, 2010; Majinge & Stilwell, 2014).



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Through such advantages, the ICTs deliver, computers, adaptive technology and the Internet can help disabled people to take advantage of education, employment and normal life benefits, leading to sustainable long-term empowerment opportunities (Hossain, 2010). Practically, from day-to-day living, without the use of ICT tools and systems to monitor the physically challenged populations, the reliance becomes a burden-dependence on a second person, guardian or caregiver to provide the required monitoring. However, technology as an umbrella field for ICTs provides the potential to free people from dependence on others by enabling them to participate more fully in society and to take an active and creative role in their own embodiment (Kleine, 2013).

According to (Gould et al, 2022), promoting and achieving equal accessibility to ICTs requires promoting and supporting ATs for people with disabilities. However, without proper support resources, the deployment of ATs and their effective adoption by people with disabilities can only

fail, and critical to the proper deployment of ATs are training and support of users and the maintenance of their technology (Gould et al, 2022). As a result, Fuentes, Moreno and Díez (2022) specified that technical familiarity and competence stimulate confidence in the ability to manipulate and control the environment and enhance self-esteem, which, in essence, can minimize the possibility or culture of under-utilizing or abandoning technology by people with disabilities.

Furthermore, apart from such foreseeable possible failures, experts also perceived the highest impact of ICT for people with disabilities to be on independent living, employment, education, and access to government services (Gould et al, 2022). Such endeavours would see digital technologies enable people with disabilities to receive information and content in the format they can perceive and prefer, even from a monitoring and care-giving perspective (Fuentes et al, 2022).

Generally, the topic and initiatives of ICTs for monitoring people with physical disabilities and impairments set the ground for mitigating and obliteration of the digital divide and thereby drive digital inclusion using ATs, for the under-catered for populations (Thompson, 2018). The various ICT tools or systems used for monitoring people with physical disabilities and impairments, also known as ATs, have their intelligence reliant on Aml for effective and efficient functionality. Hence, this research study terms them as AmI-ATs due to such an amalgamated reliance. However, this research study, observed that their focus is purely on assisting the selected population or targeted audience through the use of technology, and does not dwell much on the reliability of the tools or systems it produces or a particular framework to use to evaluate them.

2.7.3 Monitoring of Elderly or Aging In-Home Living

Old age is part of a human journey that no one can modify nor change, across the globe. In many background living environments, communities and cultures, ageing is seen, perceived, and accepted as a blessing that bears the fountain and wealth of knowledge and experience that comes with old age. However, the elderly age comes with its own challenges, such as memory loss, loss of energy and power to execute certain tasks, poor eye vision, and reduced hearing ability, just to mention a few.

Moreover, these challenges become excessively severe if the affected elderly person happens to live alone in his/her home without any present guardians and/or caregivers to monitor him/her. Such a

dire situation requires a third-party intervention to assist with monitoring services for the safety of elderly or ageing people, living in-home alone. Xie et al, (2021) indicated that ICTs come in handy in this regard, with the embedding of its applications, such as AmI-ATs, in the living environment of the elderly or ageing people, to conduct daily monitoring of them, thereby guarding their safety, in the absence of a physical caregiver. However, Sen, Prybutok and Prybutok, (2022) stated that ageing population trends, rising healthcare costs, social, physical and digital inclusions, access to technology, and lack of training for existing systems are some of the factors associated with the challenges faced by older adults interfacing with technology.

Now, the existence of ICTs offers the opportunity to mitigate and bridge these challenges through its enormous benefits, such as the introduction of AmI as part of ICT ATs (Xie et al, 2021). Leonidis et al, (2019) further argue that people can use the living room not only as a traditional social and individual space where many activities take place, but also as a smart ecosystem that permits the following welfares: Enhances leisure activities by providing a rich suite of entertainment applications; Implements a home control middleware; Acts as an intervention host that is able to display appropriate content when users need help or support; Behaves as an intelligent agent that communicates with users in a natural manner and Becomes an intermediary communications centre for the family. Consequently, ICT-based artefacts and computers would fade into the background, while people would be surrounded by intelligent and intuitive interfaces embedded in all kinds of items

In these opportunities, the elderly or ageing in-home living have the advantage of being afforded endless possibilities of technocratic systems that can monitor them around the clock and ubiquitously. For example, Oniga (2016) defines a set of assistive and social robots that can be used to support various challenges faced by this kind of population, which are personal assistance, rehabilitation, wheelchairs, companions, manipulators for physically disabled, educational, and some kind of interaction robots, respectively. Generally, the users of these robots could be elderly or ageing adults, physically impaired persons, people with cognitive disorders, and students (Oniga, 2016). According to Oniga (2016), the tasks that can be achieved by personal assistive robots are everyday life support, functional capacity evaluation, exercise function development, communication support, and education.

It is very important to note that the active functionality of the assistance provided, such as robots and ICT monitoring tools thereof and their intelligence, is made possible by the availability and embedding of AmI on them. In all these endeavours, associated with recent developments and breakthroughs in portable and intelligent communication technology and computer systems, ICTs have been given a central pivotal role to play in the advancement of active ageing for the elderly (Gabner & Conrad, 2010; Chakrabarti et al, 2015). The issue of ICTs' tools, systems, ATs and AmI with the elderly or ageing in mind, has its core focus on safety, health and wellness, emergencies and activity monitoring and reporting as its objective.

Furthermore, the reliability of the actual AmI-AT as an element or component of ICTs monitoring tools or systems is not formally addressed, to accurately tell whether the system is reliable, trustworthy or not, from a users' and caregivers' sides (Sen, Prybutok & Prybutok, 2022). This is a challenge that is further evident in research by the lack of a platform that can be used to evaluate how reliable an individual AmI-AT is, from the point of monitoring the elderly or ageing individual, to the point of being reliable to the remotely located caregiver. This is a key feature required, which AmI-ATs should deliver as well, for users and caregivers respectively, so this framework is meant to address such nonexistence by providing a guiding platform to evaluate its reliability at any given moment as a standard practice.



2.8 Challenges of Developing Monitoring Systems

The introduction and development of ICT monitoring systems that are regarded to be zero or minimal effort or that operate independently of being manipulated by the monitored species is slowly penetrating various sectors of the human-regime, especially audiences who are unable to effectively monitor themselves or areas that require a third-party for helpful monitoring. This analogy can be attested by the penetration of ICTs in healthcare and well-being services, children, livestock, physical disabilities or impairments, elderly or ageing in-home living monitoring, as discussed in this chapter, respectively (Baniyasadi et al, 2018). However, embedding ICTs in such areas, as a means of providing effective and ubiquitous monitoring systems, has its own challenges in as far as the development of ICT monitoring systems is concerned and their reliability thereof. The selected targeted areas, for the purpose of this research study, are regarded as entities that cannot monitor themselves, and therefore, in this case, the existence of ICTs and their numerous benefits has been taken advantage.

Moreover, using ICTs as tools to monitor such areas is an effective measure to guarantee zero or minimal effort monitoring at little or no effort required from each supervised entity, area or species. However, the main challenge observed with this method, is the development and reliability of such ICT tools, which are suitable for the provision of the required AmI-ATs monitoring, effortlessly. Sittig and Singh, (2015) specified that such a challenge is largely caused by the fact that many various technologies, methods and procedures are used as standalone in the development and implementation of ICT monitoring tools, and their reliability varies depending on individual complexities. Furthermore, according to Abdulrahman et al, (2020), the challenges of developing ICT monitoring tools are mainly fueled by the lack of proper guiding platforms, such as frameworks to also evaluate their reliability, which is why this research study focused on formulating a framework for evaluating AmI-ATs' reliability.

Although the focus of the framework is mainly on addressing guidelines to evaluate AmI-ATs reliability for ICT tools for monitoring healthcare and well-being services, elderly or ageing in-home living, the general challenges for their design and development are equivalently common across many various ICT monitoring tools (Sittig and Singh, 2015). For example, by introducing ICTs in healthcare monitoring, the common development challenges that should be addressed must be able to cater to the mapping, monitoring, and surveillance of the most neglected diseases (Baker et al, 2017). In the context of reliability, the users and caregivers become faced with challenges of not knowing which AmI-ATs are reliable, accurate, and trustworthy, due to the lack of a mechanism to evaluate them, from a reliability perspective. So, the responsible standardized developmental and reliability framework should, since it exists to provide integration of different technologies into one tool, guarantee effective emergency messaging approaches wirelessly, to guarantee pervasive and ubiquitous monitoring (Varshney, 2008).

Generally, the associated developmental challenges, to enable ubiquitous monitoring, should always strive to introduce effective monitoring models and decision protocols to utilize when developing monitoring tools, which should thereby seek to address embedded opportunities and challenges (Sneha & Varshney, 2009). This is because mobile computing, which is of major importance in healthcare, offers the potential to improve the quality and safety of patient care by decreasing the errors and inefficiencies currently caused by inadequate, and sometimes inaccessible, patient documentation at the point and time of care (Kumari, Tanwar, Tyagi & Kumar, 2018). Not only does

the issue of mobility in design require addressing, but the associated technology devices and sensor networks need fewer complications in their development. However, as outlined by Damaševičius, Bacanin and Misra (2023), the responsiveness of the monitoring tools is very vital, especially for emergency-response purposes whose demands are fast and effective action, especially for life-threatening situations.

2.9 Benefits of Embedding Aml's in Monitoring Systems

To summarize the discussions, Aml's perspective of ICT usage in monitoring systems and subsequent special focus was dedicated to ATs from a monitoring perception. Thereafter, a further discussion was provided for ICT usage in monitoring systems, followed by a series of monitoring categories such as health services, physical disabilities, and elderly ageing in-home living. The importance and significance of all these cases was on the emphasis of showing how ICTs are used for monitoring, with little or no effort required from the intended users, which is the ideology that forms the originating basis of Aml-ATs. In such discussions, the fundamental basis of embedding ICTs into monitoring systems can be categorized into three broad interlinked benefits, which are context awareness, behaviour evaluation and improved performance.

The rationale behind their interlinked functionality is that there can be no improved performance if there is no context-awareness and behavioural evaluation of the monitored species. The challenges of developing ICT monitoring systems also require a centralized approach or framework as a technique remedy to assist with such developmental challenges.

To add more, basic components of the benefits of embedding ICTs into monitoring systems of which they all feed directly to the three broad interlinked benefits. An efficient and effective ICT monitoring system has to guarantee assessment and awareness of the species it is monitoring, and thereby be able to provide accurate alerting to a responsible caregiver (Abidi, Umer, Mia & Al-Ahmari, 2023). Furthermore, the monitoring system should provide observation and conditioning of the species monitored, which should subsequently enable proper inspection and improved security.

Subsequently, in all these components, the ICT monitoring system should have an efficient, effective, and reliable capability to record and report on the status of the monitored species. According to Mihailidis, Boger, Hoey and Jiancaro, (2022), the ICT monitoring system should provide zero-effort

monitoring with little, or no effort required from the monitored species, and thereby allowing ubiquitous remote access care for relevant caregivers. Therefore, combining all these components into a single ICT monitoring system, context-awareness and behavioural evaluation of the monitored species is simplified and accurate.

In essence, if the monitored species can be properly evaluated in terms of behaviour and context, that would mean the components of the benefits of embedding ICTs into monitoring systems are performing their duties diligently when all applied into one system (Mihailidis et al, 2022). Therefore, this means that improved performance is guaranteed in terms of the capability and functionality of the ICT system that would be providing monitoring of a certain species on a zero to minimal effort basis.

In contextualization, all the components must be tiered and considered for inclusion into the design of the framework for evaluating the reliability of AmI-ATs to guarantee smooth and simplified developments of their monitoring systems and their required reliability. The emphasis made by the outlined components of embedding ICTs into monitoring systems, with a view and perspective of AmI-ATs core functionality, is to equally and effectively combine such benefits to achieve maximum efficiency and to guarantee the reliability of the tool or system that conducts monitoring (Abidi, Umer, Mia & Al-Ahmari, 2023). Reliability, therefore, becomes a key characteristic on users base their analysis of selection and choice of the tool or system, with an eye on trustworthiness being supported by the assurance of reliability as a key feature of the AmI-AT that sets it out as the best monitoring platform that users can confidently rely on.

2.10 Classical Challenges in Designing AmI-ATs

There are various precautionary measures and challenges to consider when designing AmI-ATs, simply because there are diverse technologies to incorporate together to come up with one unified system. Furthermore, the targeted audience and its problem domain must be considered as well in order to have a mutual understanding between the two respects, especially from the technology point of view, whose main job is to provide the actual monitoring functionality (Demiral, 2023). So, the formulation of the required framework's main objective is to also incorporate reliability when

addressing the challenges faced when designing such tools and come up with possible remedies that form a standard for building AmI-ATs.

In addition, this is largely because of the independent intelligence that is expected to be contained and exist in such systems. Subsequently, such technological intellect and astuteness require different computer science fields and expertise such as LBS, GPS, WSN, AI, HCI, mobile apps and so forth to have a synergized communication channel of understanding to produce the independent intelligence needed from AmI-ATs' monitoring tools or systems (Lakshmanan, Kaluri, Gundluru, Alzamil, Rajput, Khan & Alhussen, 2022).

Thus, the first major challenge of designing AmI-ATs is based on the technologies used because the existence of technology has been largely based on interactive approaches between itself and its users (Lakshmanan et al, 2022). The second major challenge is the targeted audiences that the AmI-ATs are built for because of their limitations and capabilities of using technology at large, for instance, the physically impaired and elderly in-home living people, respectively. Therefore, these are the barriers that AmI-ATs are trying to overcome, such that even the under-addressed areas of the human sphere are well accommodated as far as technology-reach is concerned. So, in that sense, this analogy generally brings the focus to the key design principles that must be followed and addressed when dealing with the challenges of designing AmI-ATs, and according to Czarnuch and Mihailidis (2011) and Burgstahler (2015), there are seven such principles, which are outlined and discussed as follows:

Principle One – Equitable Use: Principle One states that a design should be useful and marketable to people with diverse abilities (Czarnuch & Mihailidis, 2011; Burgstahler, 2015). So, this, in essence, means that a particular AmI-ATs design must be helpful, functional, valuable, positive, and viable for the targeted audience that it is built for. Thus, in specific terms, such a design is required to provide the same means of use for all users, by means of being identical whenever possible and equivalent when not (Czarnuch & Mihailidis, 2011; Burgstahler, 2015). So, for example, it is therefore expected that an AmI-ATs tool or system for monitoring children against disappearances and trafficking can absolutely follow the same procedure for monitoring livestock against rustling or raiding, hypothetically. Lastly and generally, the equitable use principle stipulates that any design should be appealing to all users with respect to aesthetics, materials, installations, ease of use, understanding, and so on (Czarnuch & Mihailidis, 2011; Burgstahler, 2015).

Principle Two – Flexibility in Use: Principle Two's objective is aimed at ensuring that a design accommodates a wide range of individual preferences and abilities (Czarnuch & Mihailidis, 2011; Burgstahler, 2015). Taking an example of a ZET tool designed for low-resourced communities, it might be suitable to design a system that allows ease of use even for the lowest technology-literate people or maybe that has an option for language localization preferences to suit various home languages for the targeted users and caregivers. So, this flexibility must provide a choice of how a user can interact with a product or environment and adapt to various learning styles and paces (Czarnuch & Mihailidis, 2011; Burgstahler, 2015).

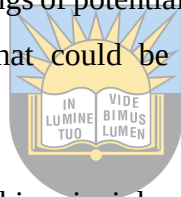
Principle Three – Simple and Intuitive Use: Principle three's utter objective stipulates that a technology, tool or system must be easy to understand and use, irrespective of the user's experience, knowledge skills, language proficiency, or cognitive abilities (Czarnuch & Mihailidis, 2011; Burgstahler, 2015). This is a very valid and fundamental statement for an Am-ATs tool that is meant for monitoring systems for a variety of resource areas, but with the notion of proving its reliability as a key feature. This is because the types of AmI-ATs' monitoring systems to develop for such an audience must be very user-friendly, robust, ease of use and understanding, but most importantly, eradicate the digital divide at various user levels, with reliability at the core.

However, this must not diminish the issue of pervasive computing in AmI-ATs, which is to reduce or eliminate the learning that is required to use a new technology, tool or system (Czarnuch & Mihailidis, 2011; Burgstahler, 2015). Therefore, principle three's main objective suggests that, simple and intuitive use is accomplished through the reduction and elimination of unnecessary complexities, being consistent with user expectations and intuition, accommodation of a wide range of literacy and language skills or proficiency, and thereafter providing effective prompting and necessary feedback during and after certain tasks are completed (Czarnuch & Mihailidis, 2011; Burgstahler, 2015).

Principle Four – Perceptible Information: This principle builds upon the concept of providing effective prompting and necessary feedback to a user by ensuring that the design communicates necessary information effectively to the user, irrespective of ambient conditions or the user's sensory and cognitive abilities (Czarnuch & Mihailidis, 2011; Burgstahler, 2015). This is a very valuable aspect of AmI-ATs in this research study as well, since monitoring should have a way of providing

prompting and feedback with no conditional restrictions to both the user and the caregiver. Perceptible information is specifically referenced to the feedback measure and mechanisms, whereby the design or system should use different feedback modalities and provide compatibility with a variety of techniques or devices that a person may already be using, such as an AT (Burgstahler, 2015). In this case, concepts of reporting via mobile applications become relevant, and more especially with supporting technologies such as GPS, LBS and WSN.

Principle Five – Tolerance for Error: Principle five dictates that a design is desired to minimize hazards and potential adverse outcomes that may result from accidental or unintended actions (Czarnuch & Mihailidis, 2011; Burgstahler, 2015). This means that extra precautionary safety and security procedures must be considered when addressing system designs. The significance of the tolerance for error principle is that, the design of any particular AmI-ATs tool or system should arrange elements (for example, buttons, controls, handles, and stairs) in a way that minimizes hazards and potential errors, provides clear warnings of potential hazards or errors, provides fail-safe features, and discourages unconscious actions that could be hazardous (Czarnuch & Mihailidis, 2011; Burgstahler, 2015).



Principle Six – Low Physical Effort: This principle states that the design must be able to be used efficiently and comfortably with a minimum amount of fatigue (Burgstahler, 2015). This simply means that any design must not expose the targeted users to exhaustion, weaknesses, weariness and low energy. Therefore, principle six can be extended to include low cognitive effort in order to accommodate those users with cognitive or intellectual disabilities (Burgstahler, 2015). As such, the principle of low physical effort is at the heart of many AmI-ATs, as these technologies, tools, systems and devices are specifically designed to make everyday tasks easier for people, both with and without disabilities and who require monitoring (Burgstahler, 2015).

Principle Seven – Size and Space for Approach: This focuses on the environment within which a person may be completing a task, such as operating a technology and space is provided for approach, reach, manipulation, and use regardless of the user's body size, posture, or mobility (Burgstahler, 2015). This comprises of offering users with a clear line of sight to vital elements and ensuring that acceptable space is provided for users who have assistive technologies like wheelchairs or personal assistance, for example, a caregiver (Burgstahler, 2015). This is very relevant and applicable for

monitoring systems used in confined spaces such as houses, hospital rooms, and aftercare quarters. So, reporting and feedback in such cases, are done remotely through the provisioning of the existence of mobile applications, which must be interlinked to a particular AmI-ATs tool or system responsible for the actual monitoring.

Moreover, heterogeneity is an important feature of the target systems, and it also applies to the reliability area, both in design and operation. For example, some devices have software established through demanding software development practices and in programming languages that are safe by design, while some others may have agile software development in unsafe programming languages (Wang, Yan, Wang, Li & Pedrycz, 2022). Additionally, because of runtime instantiation, the ability of various devices to tolerate faults varies; if certain components may transmit mistakes, others may be able to hide them.

Also, the fact that the operation is executed in real-time suggests that reliability measures cannot significantly alter the timing. Xing, (2020) stated that while there is a mature design and development of reliability for hard real-time systems, the target systems pose new challenges because they are developed much faster and they operate in more diverse and uncertain environments. According to Bagchi et al, (2020) related to the issue of reliability is the notion of predictable behaviour from the system, despite the presence of multiple unpredictable factors in the IoT platform, in interactions among the platforms, and in interactions between the system and the human users.

In addition, user-in-the-loop or human-on-the-loop systems are common in IoT systems; the former require human participation in the decision-making process, while the latter allow it to be optional. Humans differ in their level of aversion to uncertainty, which emphasizes the necessity of this component of IoT system operation. Bagchi et al, (2020) highlighted that there are extensive themes in the relevant research disputes that face reliability of IoT systems, as shown below.

Handling Correlated Failures which involves dealing with failures that are correlated in space and time. Spatial correlation occurs because multiple devices may face similar physical or cyber environments, such as wireless congestion or high temperature fluctuation (Xing, 2020). A physical phenomenon that spreads over time and affects equipment serially, for example, high moisture

content leading to device failures or the coordinated movement of an immense number of individuals creating an excessive number of immediate temporal correlations.

Handling Unpredictable Failures, as stated by Bagchi et al, (2020) are a large fraction of failures are unpredictable in any system. In IoT systems, this effect is amplified for a few reasons. First, the energy resources are depleted in an unpredictable way, such as when a rechargeable solar battery is subjected to environmental conditions or when an unexpected load causes a high level of communication activity. Second, there is a little safety factor built into the implementation of an IoT system, meaning that it has little headroom when it is implemented (Bagchi et al, 2020). Therefore, even somewhat abnormal circumstances, such as little increases in load, can send the system into a tailspin and result in failures. In contrast to server-class systems, these systems' failure mechanisms are not as well modelled.

Debugging Failures is important to enable automated debugging of failures in IoT systems, with the stress on automation since the systems are made of a large number of heterogeneous devices, which would stress human cognition for debugging (Bagchi et al, 2020). The inability to log all execution data at the devices and the inability to transfer all logged data to a back-end for debugging make automated debugging difficult (Moore et al, 2020). Distributed debugging, which combines traces from several devices, is also frequently required.

Human Considerations: As per Bagchi et al, (2020), this reliability challenge arises due to the human-in-the-loop (or on-the-loop) in many of these IoT systems. In certain applications, and even in various deployments for the same application, this might signify different things. For instance, some human users could find it extremely difficult to tolerate false alarm rates, while others might find it unpleasant to view alarms on devices with small form factor displays (Moore et al, 2020). Distracted human users engaging with the systems are a common example of human-centric unreliability. Therefore, this subject is closely linked to the maintainability issue, which is that these systems should be able to be maintained (updated, re-flashed, reconfigured and so forth) with little professional assistance and little to no human intervention.

Nevertheless, Kouroupis et al, (2024) specified that heterogeneity poses a substantial challenge in diverse medical conditions, like Chronic Obstructive Pulmonary Disease, critical illness

consequences, ventilator-associated pneumonia, sepsis, as well as lung cancer. This is due to the fact that heterogeneity of these conditions grants complications in understanding pathophysiology, diagnosis, treatment, and calculating outcomes. For instance, Chronic Obstructive Pulmonary Disease heterogeneity complicates the identification of effective treatment strategies (Xu, Sheng, Luo, Xu & Zhang, 2023), whereas the pathobiological heterogeneity of ventilator-associated pneumonia contributes to diagnostic challenges (Gouda et al, 2024).

Furthermore, Kouroupis et al, (2024) indicated that heterogeneity in sepsis patients concerns the benefit derived from earlier time-to-antibiotics while the heterogeneity of lung cancer, both in primary and metastatic disease, presents challenges in diagnosis and treatment (Belizário, Garay-Malpartida & Faintuch, 2023). According to Levy-Jurgenson, Tekpli, Kristensen and Yakhini, (2020), tumor heterogeneity is a major challenge when predicting mutations by means of whole slide images. This emphasizes the complexity of addressing heterogeneity in several medical conditions and the need for individualized methods to patient care (Shields et al, 2024). Thus, addressing heterogeneity entails a personalized technique for patient care and a deeper understanding of the original pathophysiology of the diseases.



2.11 Common AATs in South Africa Mainly for Diabetes and Heart Diseases, Monitoring

Diabetes among older South Africans is associated with increased impairment and a poor quality of life (Werfalli Kassanje, Kalula, Kowal, Phaswana-Mafuya & Levitt, 2018). Progressing health systems' ability to assist patients' advancing requirements demands attention. To help women in resource-poor settings in South Africa manage their diabetes, Rotheram-Borus et al. (2012) tested the acceptability and practicality of a peer support intervention based on a mobile phone. They came to the assumption that sharing health messages and receiving peer support via mobile phone is a minimal and reliable approach.

Furthermore, diabetes self-management education (DSME) in South Africa is constrained in content and stability, specifically in the public services (Dube, Van den Broucke, Dhoore, Kalweit & Housiaux 2015). According to Dube et al, (2015), diabetes education programs and resources must

be initiated and modified to the target audiences' socioeconomic situation, culture as well as reading proficiency.

The incidence of diabetes is rising in South Africa, according to Zwane et al, (2023), and most diabetic individuals go to public primary healthcare institutions with uncontrolled glucose. Thus, possibly innovative methods are required to advance the efficacy of diabetes. It is valuable to consider how information technology might be used to maintain diabetes, and meeting each patient's appeal for self-care will also need to be taken into consideration.

On the contrary, chronic co-morbidities with HIV are a main public health problem since they are linked with higher rates of death, lower general quality of life and increased use, which requires health services (Godongwana, De Wet-Billings & Milovanovic, 2021). The South African primary care system still has complications in providing high-quality treatment, in spite of the fact that integrated healthcare methods are employed in primary care settings, which can intensely lower hospital admissions and mortality rates among patients.

Moreover, continuous glucose monitoring (CGM), insulin pumps and closed-loop techniques have been shown to be useful in lowering hypo- and hyperglycemia, as well as glucose adaptability, in adults with diabetes; however, less is known for those who are in their 70s and 80s (Huang et al, 2023). According to Huang et al, (2023), data presently available on insulin administration technology is restricted to people who are cognitively and functionally intact. For instance, there is less data on the use of diabetes-related technology, multi-morbid, functionally impaired older adults and people from distinct social backgrounds. Older people are believed to use technology at a low rate.

The KDIGO (2012) stresses how essential it is to focus on cardiovascular disease in diabetic people. Lawler and Naby (2020) underscores that patients with elevated blood glucose levels demand glucose monitoring. Morris-Paxton, Rheeder, Ewing, and Ewing (2018) stated that non-communicable diseases account for almost 63% of all fatalities that occur worldwide each year. These illnesses particularly comprise cancer, diabetes, cardiovascular disease, and chronic respiratory disorders. According to Morris-Paxton et al, (2018), diabetes is now the third most predominant cause of mortality, while hypertensive heart disease is the second most common cause.

Morris-Paxton et al, (2018) conveyed that there was a significant improvement in blood pressure and glucose control for 1702 individuals who were known to be hypertensive, 183 who were reflected at-risk or had high normal systolic blood pressure readings, 341 who had diabetes, and 34 who were at risk to develop the disease. Furthermore, according to Nxedlana, Douglas and Emmanuel (2023), diabetes mellitus is South Africa's second greatest common cause of death, accounting for about 90,000 deaths from diabetes. Therefore, since nurses are basically responsible for managing and supporting patients with diabetes in primary health care settings, Landu (2022) revealed that nurses need training and supportive chronic care systems for them to be able to provide self-management support.

2.12 Theoretical Models and Frameworks for Assessing Reliability in Aml

In order to address system reliability challenges, various theoretical models and frameworks have been developed, each providing unique methodologies for assessing and enhancing reliability. In this section, the study explores key models and frameworks applicable to reliability assessment in Aml.

To improve the quality of care for the elderly, intelligent systems and Ambient Assisted Living technologies have been employed progressively in the framework of digital healthcare delivery, according to Ahmad et al, (2022). Ambient supported living, assistive technology, healthy ageing, and technology adoption are some of the elements that affect the adoption of ageing at-home technologies (Jaschinski et al, 2021). Moreover, there is an increasing demand for trustworthy AIAT devices to assist senior citizens as artificial intelligence continues to advance in healthcare applications (Ahmad et al, 2022). Ovi et al, (2024) claimed that maintaining the accuracy and reliability of AIAT devices' outputs is one of the main issues in evaluating them.

A strong theoretical foundation is also necessary for the creation and assessment of technology-enabled solutions for family carers (Madake et al, 2023). The way artificial intelligence is being used to change healthcare procedures, like Google Health's efforts, shows how AIAT may empower carers and enhance the health of patients (Mwogosi & Kibusi, 2024). Hoque and Sorwar (2017) noted that frameworks like the Unified Theory of Acceptance and Use of technological (UTAUT) are being used in assessing the uptake of assistive technologies, including AIAT, for older people in the context of accessibility and technological acceptance. According to Liu, Li, and Han (2022), a range of

theoretical frameworks and models have an impact on factors influencing older people's use of digital assistive technology. Likewise, integrated approaches that take into account a variety of factors and decision-making techniques might help patients' technology adoption choices (Ahmad et al, 2022).

Fault tolerance models are foundational in reliability assessments, as they address the need to maintain functionality even in the presence of system faults (Jaschinski et al, 2021). Redundancy models, for instance, incorporate duplicate components to ensure that a system remains operational when one part fails. In elderly monitoring systems, redundant sensors can maintain data integrity despite hardware malfunctions. Similarly, error detection and correction models use algorithms to identify and autonomously rectify system anomalies (Ahmad et al, 2022). Continuous glucose monitoring (CGM) systems often leverage these algorithms to validate real-time data, ensuring accurate readings essential for patient care.

Probabilistic and stochastic models provide a quantitative approach to reliability assessment by evaluating the likelihood of system success or failure. Monte Carlo simulations, for example, use random sampling and statistical techniques to predict system performance under varying environmental and operational conditions (Liu, Li & Han, 2022). These simulations are particularly valuable for assessing the reliability of heart rate monitoring systems in rural environments, where power supply and connectivity may be intermittent. Another probabilistic tool, Markov chains, models system states and transitions to capture dynamic behaviours over time. This approach is ideal for understanding sensor reliability in elderly living environments, where activity levels and environmental factors fluctuate unpredictably.

Reliability frameworks extend the concept of reliability to include attributes such as availability, safety, and maintainability (Jaschinski et al, 2021). The Dependability Tree Framework, for example, deconstructs system dependability into these attributes, enabling a comprehensive evaluation of AmI-ATs (Ovi et al, 2024). In healthcare scenarios, this framework is useful for assessing systems such as wearable devices that need to function seamlessly during emergencies. Similarly, the RAMS (Reliability, Availability, Maintainability, and Safety) framework provides an integrated perspective, making it particularly relevant for evaluating elderly care technologies that require frequent maintenance and high availability.

Nevertheless, reliability frameworks also encounter several shortcomings and challenges as illustrated by Moore et al., (2020) that a primary shortcoming in reliability prediction approaches consists of the lack of sustenance for modeling and evaluating concurrency in a scalable way. According to Liu and Xiao (2021) there is a need for new probabilistic reliability principles to overcome inadequacies in threat-based failure rates. In the same vein, Roth et. al., (2016) emphasized the need for an integrated eco-human decision-making framework when they critically review frameworks used for evaluating the reliability and relevance of (eco)toxicity data. This clearly underlines the importance of addressing the shortcomings of current reliability frameworks to improve their usefulness and applicability in several spheres.

Human-centric reliability models address the unique challenges posed by user interaction in AmI-ATs, particularly when these technologies are used by non-technical individuals such as the elderly (Ovi et al, 2024). The user-inclusive design framework emphasises the importance of considering user behaviour, feedback, and cognitive limitations during the design phase. For example, smart home systems designed for elderly individuals must simplify user interfaces to ensure reliability in daily use. Resilience engineering models further enhance this approach by focusing on the system's ability to adapt and maintain functionality in the face of unexpected challenges (Jaschinski et al, 2021). Fall detection systems, for instance, benefit from adaptive reliability models that account for individual behavioural patterns, ensuring accuracy across diverse user profiles.

Hybrid approaches combine multiple models and frameworks to address the multifaceted nature of reliability assessment in AmI-ATs (Jaschinski et al, 2021). Integrated reliability models merge fault tolerance, probabilistic analysis, and human-centric design to leverage the strengths of each approach. For example, CGM systems can utilize redundancy and stochastic modelling while incorporating user feedback to refine reliability metrics (Ovi et al, 2024). Another hybrid approach, the system-of-systems framework, examines the interdependence of multiple AmI-ATs operating in a shared environment. This framework is particularly relevant for evaluating interactions between wearable health devices and smart home systems, ensuring a cohesive and reliable ecosystem.

Thus, assessing the reliability of AmI-ATs is a multidimensional challenge requiring a combination of theoretical models and practical frameworks. Fault tolerance models, probabilistic and stochastic methods, dependability frameworks, human-centric designs, and hybrid approaches each offer

valuable insights and methodologies for reliability assessment (Jaschinski et al, 2021). For applications in healthcare and elderly living monitoring, integrating these models into a unified framework can ensure robust and trustworthy systems. Such an approach is particularly critical in resource-constrained environments of developing countries, where the consistent performance of AmI-ATs can significantly impact quality of life and well-being.

2.13 Reliability Theory

Reliability Theory serves as a fundamental framework in the evaluation of systems, particularly in assessing the likelihood that they will perform their intended functions under detailed conditions for a given period. In assessing AmI-ATs, Reliability theory plays a decisive role in ensuring that AmI-AT systems meet the rigorous standards required in such sensitive environments. At its core, Reliability Theory provides a quantitative basis for understanding the probability of failure or success within a system composed of numerous interconnected components (Briesch, Swaminathan, Welsh & Chafouleas, 2014). It enables researchers to analyse and predict system behaviour over time, considering the complexities and dependencies among individual parts. The theory encompasses several foundational principles, including system decomposition, lifetime distribution models, and fault tolerance. These principles are particularly relevant for studying AmI-ATs, as they offer insights into both component-level performance and overall system functionality.

Gavrilov et al, (2005) specified that the application of Reliability Theory to AmI-ATs highlights its critical role in ensuring dependable performance. These technologies rely on various components such as sensors, communication modules, and software algorithms, all of which must operate seamlessly to deliver accurate and timely healthcare data. Reliability Theory aids in identifying potential vulnerabilities within these components and provides tools to mitigate risks (Modarres & Growth, 2023). For example, lifetime distribution models like the Exponential, Weibull, or Lognormal distributions are instrumental in predicting the time-to-failure for AmI devices, ensuring that critical healthcare applications are supported by robust and durable systems.

Reliability theory's capacity to study system behaviour across time is another important feature (Briesch et al, 2014). It is critical to comprehend the long-term stability of systems in healthcare monitoring because ongoing data collecting is crucial. In the ever-changing world of senior

healthcare, where proactive measures depend on real-time monitoring and predictive analytics, this is especially pertinent. The necessity for thorough dependability evaluations that are specific to developing nations is further highlighted by the particular environmental difficulties they confront, such as unreliable power supply, poor network access, and extreme temperatures.

Quantitative methods such as Monte Carlo simulations, Failure Modes and Effects Analysis (FMEA), and Reliability Block Diagrams (RBDs) are indispensable tools within this theoretical framework. Monte Carlo simulations, for instance, allow researchers to model and evaluate the performance of AmI-ATs under varying conditions, providing a probabilistic understanding of system reliability (Moore et al, 2020). Similarly, FMEA offers a systematic approach to identifying and addressing potential failure points, while RBDs provide a visual representation of how individual components contribute to overall system reliability.

These methods enable a comprehensive analysis of AmI-AT systems, ensuring they are equipped to handle the complexities of real-world healthcare scenarios (Mavrogiorgou et al, 2018). Additionally, integrating machine learning with reliability assessment presents an exciting opportunity to enhance predictive capabilities. By leveraging historical data, machine learning algorithms can anticipate failures and recommend pre-emptive measures, improving overall system reliability. Moreover, exploring adaptive systems that utilize real-time data to dynamically adjust and optimize performance could revolutionize the field of reliability in healthcare technologies.

The importance of Reliability Theory is further underscored in its application to case studies presented in this study. The case studies demonstrate the practical implementation of reliability principles in critical AmI-AT contexts. Lifetime distribution models can assess device reliability in capturing continuous physiological data. Liu et al, (2014) indicated that Monte Carlo simulations can assess the performance of sensor networks in varying environmental conditions. Ehiagwina et al, (2022) stated that Fault tree analysis can identify and address potential failure pathways, ensuring robust and dependable healthcare solutions.

2.14 Literature Gaps - Critical Analysis

Countless shortcomings and inconsistencies are found in studies on machine learning, health issues, device makers, and human-computer user interfaces. Whereas the development of AI has long been

a computer industry aim, little attention has been devoted to the unique challenges that device makers confront when integrating AI technologies into practice (Valavanidis, 2023). Furthermore, studies currently do not sufficiently explore the potential threats to health connected to the broad use of AI, especially in healthcare applications, as reported by (Nadella et al, 2023). AI may also be used to combat challenging problems and enhance human intelligence along the connection of machine learning and human-computer interaction (Fui-Hoon Nah, Zheng, Cai, Siau & Chen, 2023; Zhan et al, 2024).

Health is a major subject that has been widely scrutinized in different approaches. Kimokoti et al, (2016) assess the link between nutrition, health and growing older, stressing its significance for overall health. Similarly, Ataguba et al,'s work (2015) explores socio-economic-associated health inequality in South Africa, such as income-based and discovered that there is a connection between those with high and low income when it comes to access to health. Furthermore, a study conducted by Diaz-Serrano et al, (2016) on the impact of leadership and regime transitions on health expenditure indicates that in the case of Sub-Saharan Africa, political factors have an influence on health outcomes. However, various technological devices are designed to address various health issues and to increase independence and quality of life for people including those with disabilities or other health concerns known as assistive technologies. However, even though assistive technologies have the potential to be beneficial to health conditions, concerns in terms of ethical issues, and privacy may arise (Coeckelbergh, 2010). Thus, to address the demands of health conditions and maintain their dignity and autonomy in healthcare settings, Garçon et al, (2016) made it clear that assistive technology is vital.

According to Learning Disabilities Online (2017) and WHO (2024), these technologies can be visible like walkers, canes, hearing aids, wheelchairs, and prosthetic limbs. For instance, for those who might have a speech or hearing impairment, medical practitioners can help them speak by using assistive technologies, such as assistive listening devices (NIH, 2019). Enabling patients and to reduce the strain on healthcare systems worldwide using assistive technologies in healthcare is key (Balasubramanian, Beaney & Chambers, 2021), even though the adoption and discontinuation of assistive devices can also have some difficulties. Although these devices may possibly enhance health and well-being, people may stop using them for a range of reasons, such as a lack of assistance or training (Mettler, Daurer, Bächle & Judt, 2023).

In addition, remote patient monitoring (RPM) is a form of remote telehealth service that employs medical devices to monitor and treat patients regardless of distance (Baucas, Spachos & Gregori, 2021), and it reduces the need for patients to travel for sickness diagnosis because both can be done via a wireless network.

Wearable devices, according to Baucas, Spachos, and Gregori (2021), are the majority basic types of assistive technology, and their main purpose is to gather the identified data for which they are designed. For example, an IoT network can monitor various patients at once with a wearable ECG sensor (Baucas, Spachos & Gregori, 2021) since it has a long battery life due to its low power consumption. This functionality increases the system's overall reliability and quality of service. However, by offering proactive support, assisting devices afford the patient more engaging real-time treatment and can map each patient's movements using a support vector machine (SVM) classifier (Baucas, Spachos & Gregori, 2021).

According to Sehume and Markus (2020), insufficient healthcare systems, low patient-to-doctor ratios, and lack of educational systems have a negative impact on medical diagnosis of patients in most developing nations, mostly in rural areas. According to Godongwana, De Wet-Billings, and Milovanovic (2021), there are still challenges to healthcare access in South Africa, specifically for patients living in rural areas where the distance between their home and the health institution frequently involves travelling expenses. According to Sehume and Markus (2020), these intelligence systems incorporate wireless monitoring systems, sensor networks, medical equipment, wireless communication, middleware software, and software applications that support the progress of healthcare improvements.

In bringing innovation and sustainable health solutions, it is critical to understand what is happening within the health sector. As an example, the World Health Organization (WHO, 2021) estimates that about 15% of the world lives with some form of disability, of whom 2-4% experience significant difficulties. People with disabilities have remained conspicuously absent from policies and technological advancements aimed at individual development and wellbeing, especially in the global South, which constitutes most of the World's developing countries (Dandona et al, 2019). In South Africa, for instance, the national disability prevalence rate is 7,5%, increasing with age and higher amongst females (Bornman et al, 2016). Haldorai, Murugan and Ramu (2021) indicated that the

progressive evolution of ICTs has constantly witnessed the introduction of ICT technologies that are not designed to cater for users with physical challenges and impairments. As far as ICTs are concerned, this oversight creates a digital divide between humans with no physical challenges and those with unfortunate conditions of being physically impaired (Kaihlanen, Virtanen, Buchert, Safarov, Valkonen, Hietapakka & Heponiemi, 2022).

By allowing systems to interact with their surroundings in a seamless manner and proactively adapt to user demands, the incorporation of Ambient Intelligence (AmI) into assistive technologies has become an important advancement (Guillemin et al, 2022; Heta et al, 2022; Demiral, 2023). AmI-based assistive devices use artificial intelligence, sensor networks, and ubiquitous computing to offer people, specifically those with disabilities or specific needs, personalized and adaptive assistance (Rocher, Tigli, Lavirotte & Thanh, 2020; Shahbudin & Jamil, 2024). These technologies are necessary for enhancing users' safety, autonomy, and quality of life.

Advanced Technology Services provides industrial contract maintenance services that use technology to boost uptime and fill skills shortages, according to Behrendt et al, (2021). Gebrehiwet (2023) asserts that companies such as Astronics offer cutting-edge technological solutions that support improvements in monitoring systems. It is crucial to carefully consider the implications of creating AI systems and technologies, especially in monitoring applications (Devagiri et al, 2022; Rashid & Kausik, 2024).

Nevertheless, there are significant obstacles to the use of these technologies, especially when it comes to securing their reliability. According to Yazdi (2024), reliability includes a system's capacity to function effectively across a range of operational situations and contexts. According to Sahoo et al. (2021), AmI-based assistive technologies depend on reliability as a key component for gaining support over users and facilitating broad adoption, not only as a technical need.

In addition, an AmI system is particularly identified by several characteristics such as context awareness, adaptiveness, ubiquity and transparency (Stephanidis, Antona & Ntoa, 2021). By drawing from advances in artificial intelligence (AI), AmI systems can be even more sensitive, responsive, adaptive, and ubiquitous (Jovanovic, Mitrov, Zdravevski, Lameski, Colantonio, Kampel & Florez-Revuelta, 2022). Ghosh, Mehta, Kumar, Mishra, Panda and Parvathaneni, (2023) indicated that the

AmI concept also refers to intelligent interfaces that recognize human presence and preferences and adjust smart environments to suit their immediate needs and requirements. Therefore, ATs embedded with AmI, for the context of this research, are termed as AmI-ATs. However, computer systems can fail, mainly due to system error that results from the constituent component's failure. Despite continuous improvements in IoT technology, ensuring reliability in IoT systems and their related services remains a significant challenge.

Furthermore, given that the IoT has a tendency of widespread exploitation (Moore, Nugent, Zhang & Cleland, 2020; Xing, 2020) argues that reliability requirements in an IoT related system could be satisfied in an IoT architecture framework targeting a specific use case, for example, childcare or elderly. The user component in systems reliability is often omitted, presenting the misinformed assumption that computer systems are isolated from human users (Maciel, 2023). The omission of the user from reliability considerations results in a distorted representation of reliability estimates, especially for user-based systems, which can prove to be fatal when considering healthcare systems (Ghosh et al, 2023).

According to Vaccaro et al, (2024), little has been discovered about the datasets that are now accessible to support this human-machine collaboration. The necessity for human interpretation of outcomes because of the grey zone is another issue raised by the healthcare sector's use of big datasets for AI predictions (Zicari et al, 2021). With the goal to solve these issues and the potential negative effects of AI technology, additional research is necessary to determine how humans and AI can coexist and develop. In order to address the shortcomings and gaps in knowledge on the implications of AI in different industries and the role of human-computer interaction in influencing the future of AI, Xu et al, (2023) and Fadhel et al, (2024) concurred that more detailed research is necessary. Hence, the aim of this study is to cover some of these aforementioned gaps.

2.15 Chapter Summary

The provided reliability framework redressed with a mutual platform to guide the developmental process and evaluation of reliability. The next chapter provides an overview on the core reliability issues and design considerations for AmI-ATs. It examines application contexts, target users, and environmental and technological challenges. Techniques for improving reliability and fault tolerance

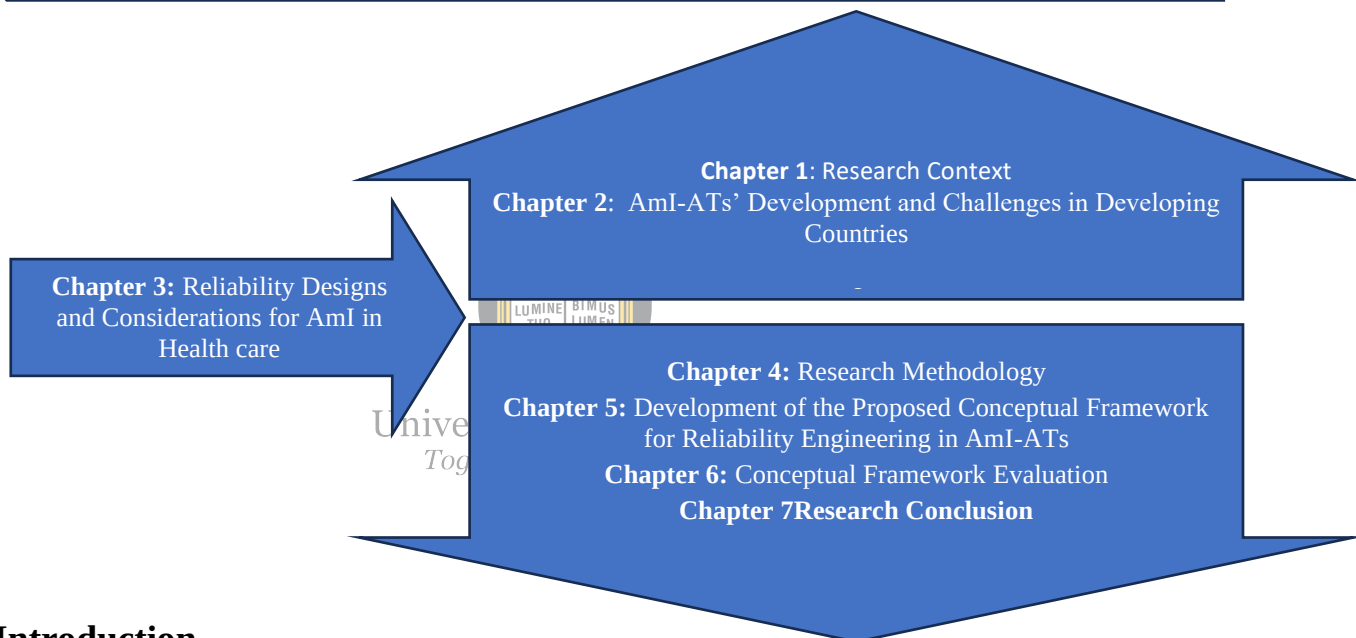
are discussed alongside security considerations and gaps in device manufacturing and human-computer interaction.



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Chapter 3 : Reliability Designs and Considerations for AmI in Health Care

This chapter delves into the core reliability issues and design considerations for AmI-ATs. It examines application contexts, target users, and environmental and technological challenges. Techniques for improving reliability and fault tolerance are discussed alongside security considerations and gaps in device manufacturing and human-computer interaction.



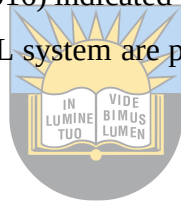
3.1 Introduction

The process of designing a technology framework is enormous and complex. As such, various considerations must be examined, and proper plans must be put in place. This is a necessary groundwork approach that determines the various characteristics of the framework and several components that are the building blocks of the framework. So, all such basics have to be covered before an attempt to design a framework is made because that will give the necessary guiding design approach for the success of the framework. Thus, the design considerations must cover all the necessary requirements for formulation and analysis beforehand to recognize the present state of AmI-ATs and trends thereon. This also outlines the factors affecting AmI-ATs designs in the market, the successes of existing AmI-ATs designs and unforeseen or loopholes or missing gaps in such

designs. Considering all of these requirements gathering and analysis, this research study also explored various design factors for the success of the framework in question. As such, the following sub-sections dig deeper into the AmI-ATs design considerations that were undertaken in this work.

3.2 Application Context

The design and development of an AAL system involves different aspects that can be summarized in three principal words: who, where, and what (Collins, Joseph & Bielaczyc, 2016). Target people are individuals with a range of talents and competencies that the system must keep an eye on (who). Although the application contexts change between indoor and outdoor settings, new solutions are needed from a technological and methodological standpoint (where). Finally, Cicirelli et al, (2021) indicated that an Ambient Assisted Living (AAL) system implies a wide range of functionalities that span from simple alerts when dangerous events happen, to more complex behavioural analysis (what). Collins, Joseph and Bielaczyc (2016) indicated that the main characteristics to be considered in the design and development of an AAL system are possible users (who), environments (where?), and functionalities (what?).



3.3 Target Users

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AL systems are primarily designed for older individuals with the goal of providing ongoing assistance and extending their independent lives in a healthy and active manner. Medical studies have categorized elderly people into three different classes, depending on their age: those between the ages of 65 and 74 years are classified as youngest-old, those between 75 and 84 years old as middle-old, and those aged over 85 years as oldest-old (Heta, Robo, Ostreni, Haxhiu, Resuli, Rumano & Kapaj, 2022). In recent years, several applications for diabetes control, depression treatment, hypertension control, medication adherence, and psychological support have been developed to allow people to live alone while having the possibility of daily control over their health status (Zhao, Zhao & Song, 2022). Applications for alarm alerting can save lives when they identify dangerous situations like falls, extended periods of inactivity, or environmental threats.

Before a significant decline in the fundamental tasks of everyday life occurs, behavioural alterations must be identified early. People's levels of activity drastically decline when they retire; hence, early

identification of the risk factors of functional decline can be prevented in a large portion of the elderly population at the time of retirement by targeting timely interventions and reducing the risks (Haque, Alam, Gow, Neville & Keramat, 2024). Also, applications of behavioural transformation include tracking harmful attitudes like smoking, calorie consumption for nutrition and exercise, and levels of physical activity.

3.4 Environments

The integration of Ambient Assisted Living (AAL) systems into healthcare monitoring has demonstrated remarkable potential in both indoor and outdoor environments. The integration of artificial intelligence (AI) in healthcare monitoring systems has shown significant advancements in recent years for instance Özkurt's (2024) pinpoints the pivotal role of explainable artificial intelligence in disease diagnosis methodologies like tuberculosis. Additionally, Gangothri et. al., (2023) recommend a sensor-based ambient healthcare architecture using blockchain and IoT, signifying the integration of ambient intelligence in healthcare platforms. Likewise, Mazumdar et. al., (2025) present an innovative approach for automated polyp segmentation in colonoscopy images using AI techniques and the Internet of Medical Things, stressing the progress of smart healthcare systems. These systems leverage advanced sensor technologies and data analytics to deliver continuous, real-time monitoring and support for elderly individuals. By addressing unique challenges associated with each environment, AAL systems contribute to enhancing the quality of life, promoting independence, and ensuring safety.

3.4.1 Indoor Environments

Much of the research focuses on Ambient Assisted Living (AAL) systems designed for indoor environments (Al-Shaqi, Mourshed & Rezgui, 2016; Rupasinghe & Maduranga, 2022). Devices that provide healthcare services via mobile communication make these systems especially pertinent to medical and public health procedures. Many tools and techniques have been created to provide treatments, track results, and continuously monitor biological, behavioural, and environmental data. Queirós and da Rocha, (2018) indicated that these systems gather data from heterogeneous sensors, along with self-reported data, to provide insights into physiological, psychological, emotional, and environmental states.

Indoor spaces can be further divided into retirement communities and individual dwellings. People may reside in residences alone or with a small number of family members. The bigger groups that dwell in retirement homes, on the other hand, share common areas and engage in both individual and group activities, such as supervised physical activities (Al-Shaqi, Mourshed & Rezgui, 2016). It is possible to evaluate health by tracking food consumption, evaluating rest intervals, identifying behaviours, and examining movements. By identifying deviations from predicted patterns in behaviour, behavioural analysis is carried out. It is also possible to keep an eye on social interactions, both inside groups and with friends or family. Data on a resident's whereabouts, interactions with things, and health is collected via sensors placed throughout residences.

For instance, in a retirement home, heterogeneous sensors collect data that support caregivers, while also providing information on the indoor localization of residents and caregivers (Robinson, Park, Lane, Skubic & Rantz, 2020). Moreover, Robinson et al, (2020) indicated that systems can detect incidents like falls, alerting caregivers using devices such as Wi-Fi-enabled bracelets as well as robots to assist bedridden residents in requesting help.



3.4.2 Outdoor Environments

Elderly individuals often spend several hours outside their home environments, engaging in outdoor activities that benefit them physically, spiritually, and socially. Activities such as walking, shopping, and socializing contribute to the prevention of functional decline (Tak, Kuiper, Chorus & Hopman-Rock, 2013). However, outdoor environments pose new safety concerns, including risks like falls, extreme weather conditions, and for those with early dementia, wandering or becoming lost.

AAL systems play a vital role in supporting elderly individuals in outdoor environments by checking routes, recognizing abnormal behaviours, and evaluating motion activities. Recently, Cicirelli et al, (2021) focused on expanding AAL systems from indoor to outdoor spaces, aiming to provide services that enhance well-being. By safely collecting and evaluating observational data, these systems can provide action plans for either general or monitoring situations. These technologies can also assist older people in decreasing the rate of cognitive and behavioural deterioration by providing them with individualized instruction.

3.5 Technology

A wide range of technologies is utilized in the development of AAL systems, from simple IoT devices to complex sensor networks involving environmental sensors, intelligent devices, and video cameras (Cicirelli et al, 2021). Data that varies in size, heterogeneity, and sample frequency is significantly more complicated because of this variety. Communication protocols, security restrictions, energy usage, failure detection, and compatibility amongst devices from various suppliers are some of the difficulties that come with managing this data. According to Nissenbaum (2020), privacy and data protection are essential as sensitive data collection, storage, and transmission may result in legal duties.

Besides, the quick development of ICT technologies has made it possible to find and use multipurpose devices, which improves the efficiency of AAL systems by combining ICT and sensor technologies. According to Mukherjee, Suleman, Pilloton, Narang, and Rani (2022), many types of devices, including wearables, smartwatches, smart objects, connected sensors, and smartphones, have non-invasive sensors like cameras or infrared sensors built in, allowing for monitoring in both indoor and outdoor environments. The following sections examine key categories of technologies as per Alsadoon, Al-Naymat and Jerew (2024):

- Wearable sensors, which require user acceptance but are easy to use
- Smart objects, which are less intrusive yet require equipment or other structural elements.
- Environmental sensors, and
- Socially assistive technologies.

These technologies aim to be non-invasive, easily accepted by users, and integrated effortlessly into daily life, remarkably for individuals with special needs.

3.5.1 Devices and Infrastructure

The field of AmI-ATs is made up of a variety of combinations of devices and technocratic infrastructures, ranging from hardware, software and the network, from a high-level point-of-view (Möllers, 2021). In each of these entities, there are sub-small technology tools, systems, portals, gadgets, apparatus, and/or devices, which can be seen working perfectly well as standalones and as

part of a combination of one another. In this research study, a combination of all the necessary devices and their subsequent infrastructures, which formed part of the developed framework for monitoring purposes, were explored and highlighted based on the selected targeted audience. This was necessary to put all the devices and infrastructure required for developing AmI-AT monitoring systems into perspective and category before reliability was assessed and evaluated. This was particularly important because the framework was properly structured to provide the users with a clear guiding approach, irrespective of which audience is targeted.

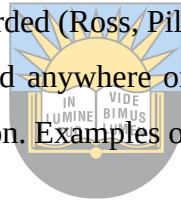
Moreover, the technique of device and infrastructure considerations is further necessitated by the overlaps of some of the devices used for monitoring and the unstandardized methods used for their development. Building devices as standalones, but which can further be used as a combination of other devices, further creates inconsistencies and lack of standardization when developing monitoring systems, let alone evaluating their reliability (Mshali, Lemlouna, Moloney & Magoni, 2018). Thus, users turn to use what is immediately available for them and what will quickly solve their monitoring challenges, without looking at a holistic reliability standardized approach that is backed-up and benchmarked through the use of an existing evaluation framework. So, for providing standardization, this research study started by categorizing all possible devices and infrastructures that can be used to develop AmI-ATs monitoring systems, which thereby fits into the basic building blocks of the developed framework. These are divided into three categories and have been grouped into clusters as follows:

3.5.2 Hardware Cluster

The AmI-ATs hardware cluster is sub-divided into broad categories, which are interconnected and interdependent in terms of functionality and use (Ortíz-Barrios et al, 2022). Such categories are listed as follows, with a brief description, use, and examples, in line with this research study:

- **Mobile Clients:** are the devices that roam around with users and/or caregivers Foong et al, (2020). They are used to access services associated with monitoring and alerts, ubiquitously as provided by the AmI-AT. This is an invention that works best for synchronous monitoring that is not limited to geographic settings. Examples of them are PDA, Mobile Phones, and Digital Cameras.

- **Monitoring Agents:** are devices that have a fixed location but can be transferred to any location when the need arises. They are used as the containers of AmI-ATs to monitor clients or to guard or surveil targeted audiences, species or entities selected by using a software client located or installed onto them (Cyphers & Gebhart, 2019). Examples of them are Desktop Computers, Laptops, Servers (Lima, Rosa, Cruz & Simões, 2020).
- **Network Access:** according to Oughton et al, (2021), are the devices that form the network and can either have a fixed location and/or scattered around wirelessly. Access to them can either be via a LAN connection or a Wi-Fi depending on the set-up the user and/or caregiver is using (Oughton et al, 2021). This makes the AmI-AT accessible ubiquitously via a varied list of devices. Ghani et al, (2020) specified that the examples of network access comprise Routers, Switches, Wi-Fi APs.
- **Storage Facilities:** are the facilities that are used to store information associated with AmI-ATs monitoring alerts, reports, and personal files for the audiences, species, clients and entities being monitored or guarded (Ross, Pillitteri, Dempsey, Riddle & Guissanie, 2019). These facilities can be accessed anywhere on the network, if there are approved access rights and verified authentication. Examples of them are Servers, Databases, Cloud (Ghani et al, 2020).



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3.5.3 Software Cluster

The AmI-ATs software cluster can encompass any selection of software for development, with the choice depending largely on the developers and the specific type of monitoring required, as well as the client being monitored (Paščinski, Trnkoczy, Stankovski, Cigale & Gec, 2018). There are no strict limitations on the software that can be used. However, for this research study, eight broad software categories have been selected to provide a clear overview of available market choices for developing AmI-ATs at the software level. This selection highlights software requirements that can be combined to create a comprehensive AmI-AT monitoring system. When developing an AmI-AT, components from each of these eight categories may be integrated to produce a cohesive tool. These categories are designed to interconnect and functionally complement each other. Below is an outline of the categories, with a brief description, usage, and examples, aligned with the focus of this study:

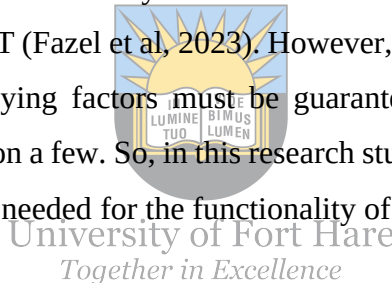
- **Operating Systems (OS):** are fundamental for devices hosting the AmI-AT monitoring client, which is used to receive, observe, and analyse alerts generated by the monitoring tool (De Giorgi, 2023). Devices that require an OPS include desktop PCs, laptops, digital cameras, mobile phones, and PDAs. Examples of OPSs for these devices are Unix, Linux, Microsoft Windows, iOS, and Mac-OS.
- **Programming Platforms:** according to Babun, (2021), relate to software-level AmI-AT development, various platforms that are available for developers, depending on the tool's intended functionality or monitoring capabilities. Kurbel (2008) stated that they enable prototyping, testing, and simulation. Examples include LAMP, WAMP, Visual Studio, JDK, and JDE.
- **Programming Languages:** AmI-AT prototypes developed on programming platforms rely on a variety of programming languages. Developers have the freedom to choose any language that suits their needs, the type of tool, and its expected functionality (Wooldridge & Ashurst, 2024). Common languages include Java, C-family languages (C++, C#), PHP, and Python (Alomari, Halimi, Sivaprasad & Pandit, 2015).
- **Location-Based Services (LBS):** LBS is a critical component for tracking and locating the entities being monitored, a key aspect of AmI-ATs. Huang et al, (2018) indicated that its functionality can be managed at the software level; for example, LBS includes tracking and location services, mapping, and information services.
- **Storage Area Networks (SAN):** Just as in the hardware cluster, storing information about monitored entities is vital for AmI-AT functionality. Data generated by the system must be stored for both synchronous and asynchronous use (Nagothu, 2013). This storage is managed at the software level, for instance, Google Drive, virtualization, and network drives (Sadri, 2011).
- **Mobile Applications (Apps):** These are software applications installed on mobile devices and accessed through their respective OPSs. Kulshrestha and Verma, (2019) indicated that mobile apps serve as monitoring clients, connecting the AmI-AT system at the monitored site with the caregiver or guardian. They act as receivers and conveyors of alerts and information across the network, such as Play Store apps, native apps, and hybrid apps.
- **Computer Vision (CV):** according to Debnath et al, (2022), the key functionality of an AmI-AT is vision-based intelligence, enabling sensory capabilities during monitoring. This

intelligence is accomplished at the software level and stored in memory for each monitored entity. Ekanem et al, (2024) specified that CV software is essential for acquiring, processing, analyzing, and understanding visual data. It includes image acquisition, analysis, and interpretation systems.

- **Artificial Intelligence (AI):** A fully developed AmI-AT integrates AI capabilities, making it possible for the system to perform intelligent monitoring autonomously and reliably (Ghosh, Kesharwani & Khatri, 2024). Coding and simulation are used to integrate these AI features into the system. Key AI components include speech recognition, machine learning, vision, and natural language processing (NLP), according to Rane et al, (2024).

3.5.4 Network Cluster

The hardware and software clusters, combined functionalities, embedded within an AmI-AT monitoring tool, depend on the availability of the network for effective communication of the components making up a AmI-AT (Fazel et al, 2023). However, the availability of the network is not enough alone, and some underlying factors must be guaranteed, such as reliability, bandwidth, security and scalability, to mention a few. So, in this research study, the network cluster incorporated the various network components needed for the functionality of AmI-ATs



Network Devices: The AmI-AT network must have basic infrastructure devices for connectivity, security and availability, such as routers, switches, servers, firewalls and Aps (Hussain et al, 2024).

- **Access Devices:** These are PCs and Mobile Phones used as monitoring agents for which the AmI-AT sends alerts into, and which caregivers or guardians use to monitor clients (Doyle-Delgado & Chamberlain, 2020).
- **Network Technology:** as per Subedi and Pyun (2020), is the wireless links, generational signals, and RFID wirelessly transmitting information between the base stations and the user devices via the AmI-AT reporting capabilities.

3.5.5 Services and Applications

After considering and consolidating the devices and infrastructure needed to develop AmI-ATs monitoring systems, the research study had to focus on services and applications that can be end-

products of AmI-ATs based on the devices and infrastructure. There are a number of services and applications the human mind can think of and can design and develop, based on the variety of devices and infrastructure, and some of them already exist in the market. However, the purpose of this section is to further outline possible research initiatives that would result in AmI-ATs services and applications.

Since this study's targeted audiences have been outlined as two-fold, Healthcare-based services for physical disabilities/impairment and elderly/ageing in-home living, some additional hypothetical possible services and applications that can be resultant AmI-ATs products are tabled as further extensions to the selected audiences, to promote investigations and research. These examples are not limited to services and applications that can be designed based on the provided cluster information and the developed framework but are an indication of the scarcity of AmI-ATs systems within and around the chosen targeted audiences of this research study.

3.6 Designers Classification



AmI-AT monitoring systems cannot be designed by a single person due to their nature of being an amalgamation of various technologies that are operating at software, hardware, and network levels, respectively. For a successful AmI-AT monitoring system to be delivered as a product ready for the market, a team of different technology and non-technology expertise is required to contribute individual pieces of information and knowledge to the invention being designed (Szmeja, 2023). Thus, for any AmI-AT tool that requires to be developed, there should be a classification of designers, which are individually chosen on their skill set and based on what the tool shall monitor, and additionally on the set functional requirements of such as systems (Symmons, 2021). This classification is also particularly important or a valuable requirement for the development of the framework, because the framework itself is made to simplify designers' work and thereby ensure the reliability of the end product. So, from a high-level point-of-view, the designers must be factored-in as one of the components and classifications of the framework. Subsequently, this research study outlines and categorizes the AmI-ATs monitoring systems designers' classification as follows:

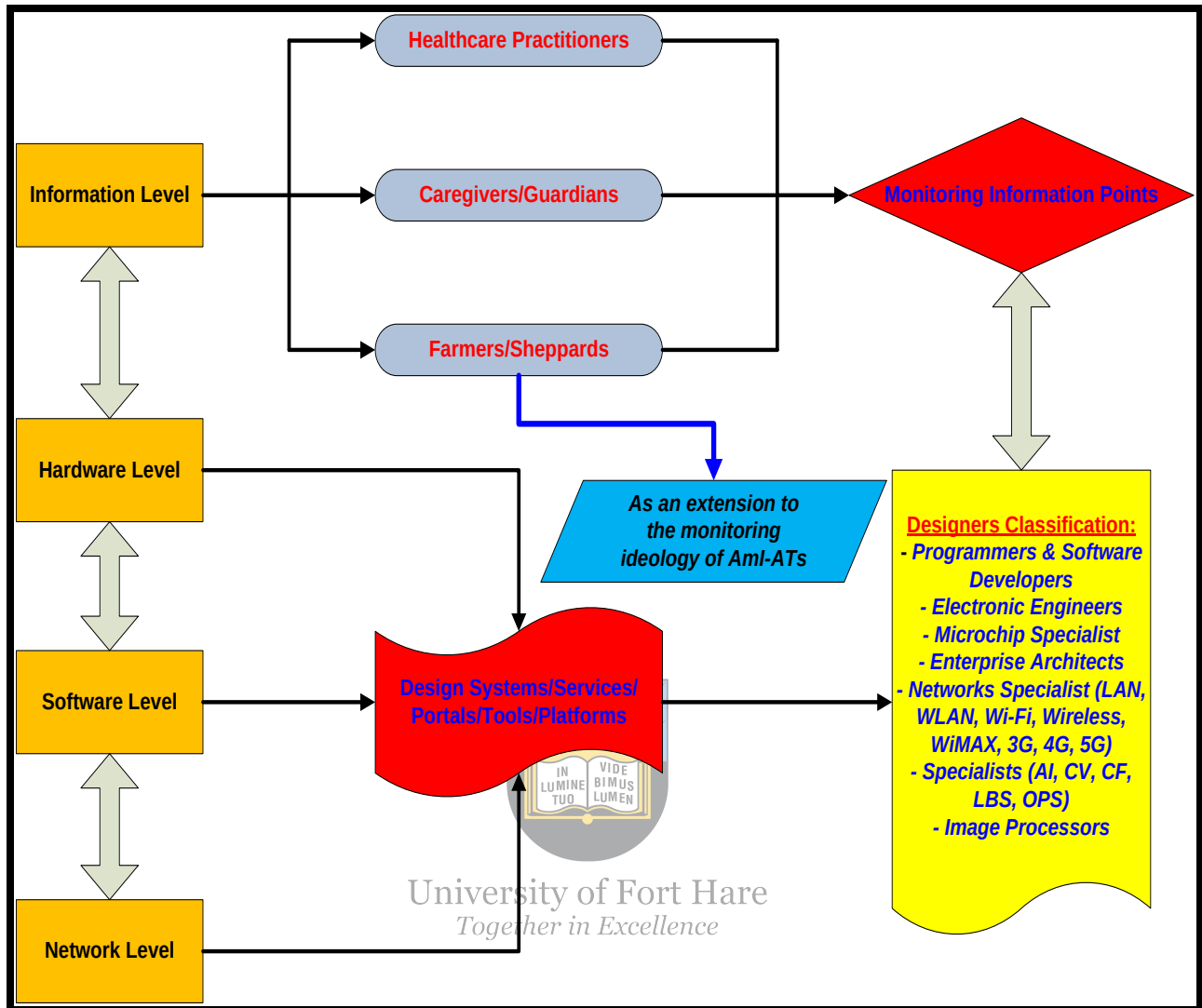


Figure 3.1: AmI-ATs Designers Classification

It has been deduced that the functionality of AmI-ATs is not only limited to the selected audience of this research study, but rather to any field that requires it, such as in children and farming capacities (Reyes-Cruz, Fischer & Reeves, 2022). Thus, Figure 3.1 also portrays such an extension and consideration, inclusively.

3.7 Security Considerations

AmI-ATs monitoring systems' designs are complex due to the many different technologies that are used to develop them and to produce a single autonomous system. Also, another complexity they

possess is the fact that they are mainly designed to cater to the human sphere and entities that cannot monitor themselves (Qorbani, 2020). Thus, this articulates that the security of AmI-ATS monitoring systems is critical and requires serious and important consideration. Rane et al, (2024) stipulated that the considerations to be made, in general, also requires the acuteness of handling issues of privacy versus security, which is a big dilemma, especially because implementing security programs may additionally raise ethical issues. Therefore, for AmI-ATs monitoring systems based on the design reflections of this study, a set of security considerations has been and standardized for all developmental determinants of the reliability of such systems.

3.8 Reliability Challenges in AmI-AT Systems

The need to provide stable results in the face of extensive and inaccurate information technology is emphasized by studies on reliability issues in assistive technologies. The design of smart houses that use modular discrete controller synthesis has been addressed by Guillet et al, (2014) in relation to assistive technologies for people with disabilities. In their study, Soekadar et al, (2019) confront the problem of embedding brain/neural assistive technology into daily life settings, paying special attention to the reliability of brain control when brain signals are captured safely.

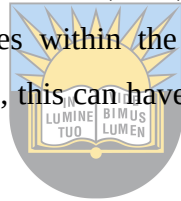
Mohammed (2021) highlights the need to use simplicity to manage complexity in software systems to increase its durability and reliability. Nonetheless, there are still difficulties that people and organizations face when attempting to use sensitive and elaborate systems to provide reliable results. Abbassi, Mammar, and Graiet (2021) emphasized the transactional patterns that assure the reliability of composite services that are designed to meet the unique requirements of designers. Sahoo, Ranjbar, and Kumar (2021) offer a technique used to assess multi-core systems' reliability that takes aggressive power management's effect and persistent errors into account.

All things considered, this clearly illustrates the necessity of consistent performance in useful systems, whether in the creation of software, online services, multi-core systems, or brain/neural assistive technologies. Therefore, it is essential to recognize and overcome reliability difficulties to protect the efficacy and usefulness of assistive technologies for health issues.

3.8.1 The Reliability of IoT Sub-Systems

Al Sadawi, Hassan and Ndiaye, (2021) detailed that ensuring the reliability of IoT systems presents considerable challenges, primarily because of the diversity of devices, ranging from small, low-power gadgets to high-performance systems. The key issue arises in implementing robust multilayer security across these heterogeneous networks, which are inherently more vulnerable to security attacks and the transmission of faulty data (Islam et al, 2024). As a result, any IoT system must incorporate standardized mechanisms to detect and mitigate redundancy, particularly during malfunctions or in response to security breaches.

Furthermore, Islam et al, (2024) indicated that in a heterogeneous IoT system with a multilayered infrastructure, achieving reliable data transmission is a complex task. The inconsistencies in device performance can result in the generation of erroneous data, which may compromise the accuracy of predictions, such as the Remaining Useful Life (RUL) of components or systems (Kang, Catal & Tekinerdogan, 2021). The vulnerabilities within the system often lead to the transmission of anomalous data, and in critical situations, this can have severe consequences, potentially impacting human lives.



3.9 Challenges in Anomaly Detection

Zahran, Elkadi and Helmy, (2022) signaled that IoT systems working on heterogeneous platforms generate huge amounts of data, necessitating large computational resources. Handling such vast data requires anomaly detection to identify misbehaving data within normal datasets.

3.9.1 Challenges on Equipment Reliability

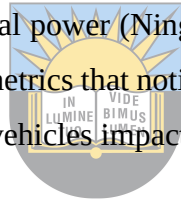
The reliability of equipment ensures that it meets the expectations set by manufacturers and maintenance personnel. However, optimizing IoT devices and equipment during large data management presents challenges (Zahran, Elkadi & Helmy, 2022). Data-driven mathematical and computational models mostly depend on equipment efficiency. Any compromise in equipment reliability affects data quality, leading to false predictions about the remaining useful life of components.

3.9.2 Challenges in IoT Architecture

IoT systems operate on multilayered architectures, and it is essential that they produce reliable outputs throughout their mission cycles. The major layers in common IoT architectures, like service, support, communication, and perception that, pose unique challenges. Failures in these layers lead to unreliable outputs and false predictions (Swamy & Kota, 2020). For instance, smart sensors in the service layer measure engine parameters like exhaust gas temperature, while the communication layer faces issues such as wireless communication failures, noisy data, and signal attenuation (Adam et al, 2024). Failures in the perception layer, such as sensor node malfunctions, further complicate reliable data monitoring.

3.9.3 Performance Challenges

The heterogeneity of IoT systems introduces complexity and constraints on both hardware and software, requiring massive computational power (Ning et al, 2020). Throughput, latency, and data correctness are among the performance metrics that noticeably suffer consequently. For instance, the need for high accuracy in unmanned air vehicles impacts system latency.



3.10 Challenges in Network Reliability of Fort Hare

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Maintaining network reliability in IoT systems is crucial, with continuous assessment and quantification of Quality of Service (QoS) being necessary (Chakour, Mhammedi, Daoui & Baslam, 2024). To ensure sufficient network reliability, quantification of metrics such as delay, and throughput must be performed. Xing, (2020) indicated that QoS profiles, linked to various components in a multilayered system, help assess factors like latency and bandwidth. Redundancy models and statistical approaches aid in evaluating repair times and ensuring reliability.

3.10.1 System Security Challenges

Various security threats have been identified by some scholars (Alhanahnah, Stevens & Bagheri, 2020; Vulpe et al, 2021; Habbal, Hamouda, Alnajim, Khan & Alrifaie, 2024). Multilayered IoT systems are vulnerable to security attacks. To mitigate these risks, IoT system designs must consider factors like physical security, communication, scalability, and privacy.

3.10.2 IoT Reliability Issues

Reliability in communication between devices is a critical factor for IoT adoption. IoT reliability is measured by device hardware, software, network capabilities, and power supply. Cheruvu et al, (2020) specified that connectivity methods like RFID, Wi-Fi, and ZigBee introduce varying levels of reliability issues. Organizations aiming for IoT adoption must recognize the potential for reliability issues, and ensure systems are available and perform efficiently when needed.

3.10.3 The Need for a Reliability Strategy

According to Mukherjee et al, (2024), reliability may not be a primary focus for organizations adopting IoT, but it is essential for realizing the benefits of the technology. A comprehensive reliability strategy should include redundancy to eliminate single points of failure and ensure high availability. For instance, Xing (2020) indicated that while a single IoT device may create a single point of failure, redundancy in middleware servers can prevent data loss. Network performance is also vital for reliability; reducing network complexity improves processing efficiency and limits potential latency issues.



3.10.4 IoT Reliability Policy

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There is a need to develop a reliability policy before adopting IoT, which should address availability and performance expectations based on the organization's specific needs Xing (2020). For example, while the retail industry may prioritize consumer behaviour prediction, the healthcare sector requires higher reliability for continuous patient monitoring. Although guaranteeing a minimum level of reliability is challenging, setting performance and availability benchmarks can help manage expectations.

3.10.5 IoT Reliability in Healthcare

Qadri, Nauman, Zikria, Vasilakos and Kim, (2020) specified that the healthcare industry faces unique reliability challenges with IoT, where system failures can lead to severe consequences, including patient harm. High reliability is critical, and healthcare organizations can achieve this by fostering a culture of continuous improvement, reporting small issues before they escalate, and following strict

policies, processes, and procedures (World Health Organization, 2021). By doing so, healthcare organizations can make significant strides toward achieving high reliability in their IoT systems.

3.11 Gaps on Device Manufacturers, Health Challenges, Machine Learning and Human-Computer Interaction and Available Data Sets

According to Valavanidis (2023), Principles for comprehending AI's potential carry transformative influence similar to that of the Internet, mobile phones, and personal computers (Valavanidis, 2023). AI tools like machine learning have been used in the healthcare industry to evaluate patient data and improve clinical decision-making procedures, according to Qiu et al, (2023). The availability of deep learning data sets is one of the difficulties in this field, nevertheless, and it could impact the extent to which AI applications can evolve (Bohr & Memarzadeh, 2020). In healthcare environments, where natural language processing (NLP) is essential for promoting interpersonal relationships between computers and people, human-machine interaction is essential, as asserted by Alowais and Huang (2024).

Although AI has the potential to completely transform healthcare, Khan et al, (2023) pointed out that there are problems with its application as well, like privacy and data gathering issues. In order to address these problems and control how AI technologies and data protection interact, the General Data Protection Regulation (GDPR) was established (Bharti & Aryal, 2023). According to Anderson and Rainie (2018), human-AI interaction is anticipated to expand significantly as AI advances and is being encompassed into healthcare systems. An area of artificial intelligence called machine learning makes it possible for computers to learn without explicit programming, bringing novel opportunities for data analysis and decision-making (Belle & Papantonis, 2021).

As stated by Pelc (2024), executive directives and other regulatory measures have been put in place to regulate the use of AI, machine learning, and data science in the healthcare sector in order to safeguard the safe and reliable development of these technologies. Therefore, so as to fully fulfil AI's promise in healthcare, issues with data availability, human-computer interaction, and data privacy must be resolved, even if AI offers numerous chances to improve healthcare outcomes. Dwivedi et al, (2023) emphasized that in order to close the gaps and strengthen the present systems, cooperation between healthcare professionals, device makers, and AI specialists is vital.

3.12 Analysis of Reliability Modelling Techniques

Figure 3-2 illustrates the reliability modelling techniques approaches to measuring reliability. These are critical in Chapter 5 when the framework is presented.

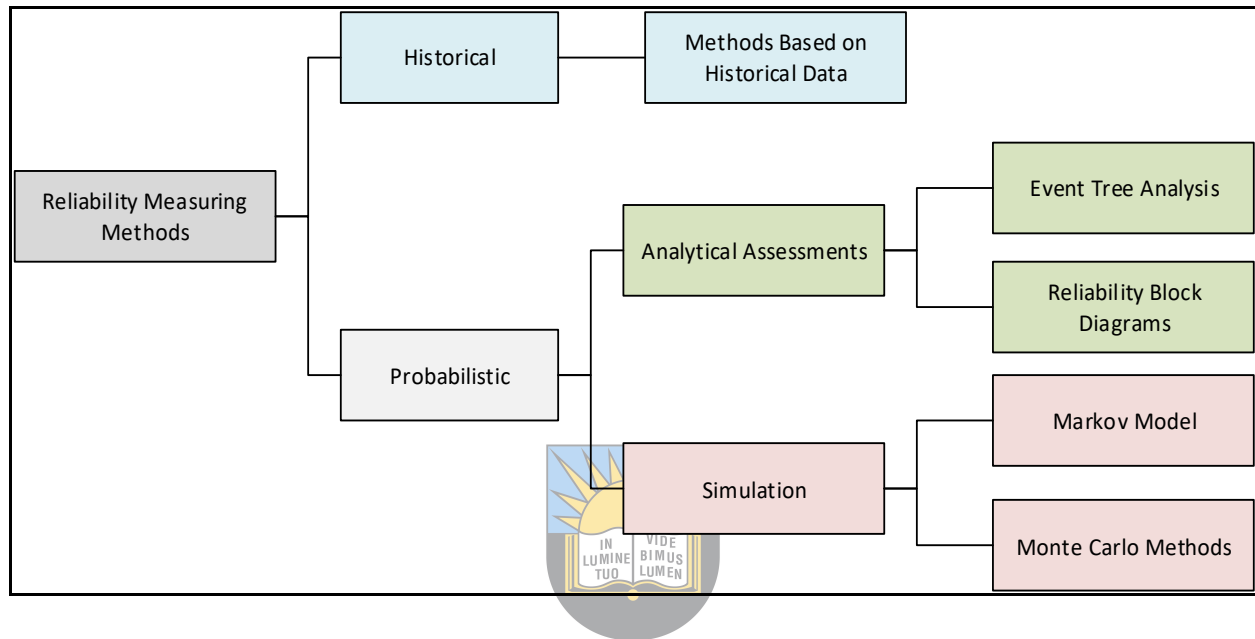


Figure 3.1: Reliability Measuring Methods
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Series-parallel block diagrams and Markov chains are generally used to assess system reliability. However, they have limitations when modelling simultaneous component failures or analyzing complexly interconnected systems. Ambient Intelligent (AmI) Technologies, particularly within the domain of healthcare and elderly living monitoring, exemplify such complex systems. AmI's rely on a synergy of IoT-enabled subsystems that operate collectively, enhancing the reliability and utility of the overall system. This aligns with the principle of systems theory: "The whole system is always better than the addition of its parts."

This research examines AmI systems as integrated units rather than isolated components. By doing so, it addresses unique reliability challenges arising from the interconnectedness and interdependence of subsystems. AmI-s supports a stack of devices and applications that require stringent safety measures to mitigate unpredictable behaviours, ensuring enhanced system reliability, which is a critical property for successful systems.

The heterogeneity inherent in AmI systems, stemming from their IoT-based nature, introduces significant reliability challenges. The interactions between hardware, software, and communication interface demand precise normalization and robust implementation. Unpredictable failures in physical systems, often the foundation of IoT devices, pose serious risks. Traditional reliability theory, which provides tools like failure distributions and reliability functions, offers a foundation, but its application to the end-to-end reliability of IoT systems, particularly AmI-s, remains underexplored. In this study, we adopt a hybrid approach, leveraging Reliability Block Diagrams (RBDs) for structural reliability analysis and incorporating Markov Chain Monte Carlo (MCMC) techniques for modelling dynamic and stochastic failure processes. While RBDs are well-suited for static structural analysis, MCMC allows for probabilistic modelling of time-dependent and interconnected failures.

3.12.1 Reliability Block Diagrams

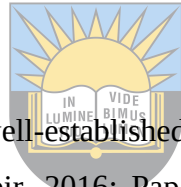
A system's reliability structure may be shown visually via Reliability Block Diagrams (RBD). Blocks in an RBD stand in for parts, subsystems, or processes, and the connections between them show how these components cooperate to provide the overall functioning of the system. If there is a functioning path from the beginning to the finish of the diagram, the system is deemed operational in an RBD. Moore (2020) indicated that reliability of systems with several parts or subsystems is frequently examined using RBDs, and the connections between blocks can represent different configurations such as series, parallel, or combinations thereof:

- **Series Configuration:** For the system to work in this configuration, every part has to work. Any component failure results in system failure.
- **Parallel Configuration:** When at least one component is functioning, the system operates in parallel. By using redundancy, this configuration is frequently utilised to improve system dependability.
- **Combination Configuration:** To get the required dependability levels, more complicated systems may combine parallel and series connections.

Thus, analysts may determine essential components and compute crucial reliability measures like mean time to failure and system reliability by using RBDs. When developing systems to fulfil specified dependability objectives, this method is very helpful.

3.12.2 Fault Tree Analysis

A graphical method called Fault Tree Analysis (FTA) is used to examine the circumstances and contributing elements of an undesirable top event, or critical event, which has the potential to bring down the entire system when it occurs (Häring & Häring, 2021). A tree with the top event at its root represents these reasons for system failure. A fault tree's preceding nodes are represented by gates, which are used to connect two or more cause events that result in a single fault in a certain way (Ehiagwina et al, 2022). When one defect is sufficient to enforce the fault, for instance, an OR FT gate may be employed. In this case, Häring and Häring (2021) specified that a qualitative analysis makes it possible to identify any arrangement of fundamental failure events, or "cut sets," that might result in the top event.



The FTA is also recognized as another well-established and well-understood technique widely used to determine system dependability (Kabir, 2016; Papadopoulos, 2012). The logical relationships between deficiencies and their causes are graphically shown in fault trees. FTA is deductive in nature, which means that in order to identify the root cause, the analysis begins with a top event (a system failure) and proceeds backwards from the top (Papadopoulos et al, 2011; Aizpurua & Muxika, 2013). The analysis's findings demonstrate how several component failures or specific environmental factors might work together to result in a system breakdown. The qualitative analysis is performed by reducing fault trees to minimal cut sets (MCSs), which are a disjoint sum, consisting of the smallest combinations of basic events that are necessary and sufficient to cause the top event (Kabir 2018, Gudemann & Ortmeier, 2010).

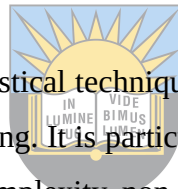
In order to connect two or more events that result in a single fault in a certain way, gates are employed to symbolize the preceding nodes of the fault tree. When one defect is sufficient to enforce the fault, for instance, an OR FT gate may be employed. When all of the cause events are necessary to enforce the fault, however, the AND FT gate is employed.

3.12.3 Markov Chain

According to Gagniuc (2017), a Markov chain is a stochastic framework that describes a series of potential events where the probability of each event only depends on the state reached in the preceding event, which is used to indicate the transition from one state to another. The starting state and the likelihood of a transition from one state to another are denoted by the initial state and the probability, respectively. Starting from an initial state, the process moves from one state to the next based on transition probabilities, which are solely dependent on the current state according to the memoryless or Markov property. In addition, discrete Time Markov Chains (DTMC) and Continuous Time Markov Chains (CTMC) are the two groups into which Markov chains are often divided (Wu & Cui, 2021). For reliability analysis, Markovian models are commonly used in situations where failure or repair events might happen at any moment (Wu & Cui, 2021).

3.12.4 Monte Carlo

Monte Carlo Simulation (MCS) is a statistical technique used to estimate the reliability of complex systems through repeated random sampling. It is particularly effective in scenarios where analytical methods are impractical due to system complexity, non-linear dependencies, or uncertain parameters.



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The MCS process involves the following steps in line with Chakour, Mhammedi, Daoui and Baslam, (2024):

1. **System Model Definition:** A probabilistic model of the system is developed, incorporating failure and repair rates, redundancies, and interdependencies of components.
2. **Random Sampling:** Random values are generated for the uncertain parameters of the system based on their probability distributions. For example, time-to-failure for components might be sampled from an exponential distribution if the failure process is memoryless.
3. **System Behaviour Simulation:** The system's performance is simulated over a predefined time horizon. For each iteration, component states (working or failed) are determined, and the system's operational status is evaluated.

4. **Repetition:** The simulation is repeated thousands or millions of times to account for variability and provide a statistically significant result.
5. **Reliability Metrics Calculation:** Based on the results, reliability metrics such as system reliability, availability, downtime, and mean time to failure are estimated.

Monte Carlo Simulation offers several advantages, such as flexibility in handling complex system configurations and the ability to model dynamic interactions between components. It is widely applied in reliability assessment, particularly for systems with high variability, interdependencies, or non-standard configurations. However, the technique can be computationally intensive, especially for large-scale systems with numerous components.

3.13 Critical Analysis – Reliability

Health issues continue to be a challenge in most communities which requires various sectors and systems to address such challenges. Even with the development of assistive and AmI technologies, assessing reliability of the systems is still extremely challenging (Xing, 2020; Wu & Cui, 2021; Yazdi, 2024). In order to determine the effectiveness and acceptability of these technologies, existing assessments tend to rely on user studies. According to Wu and Cui (2021), Wang, Xie, and Shiyuan (2022), and Singh et al. (2024), user interaction offers useful insights regarding usability and real-world application, but it also introduces difficulties that may hide technological problems and inconsistencies.

A significant research gap is highlighted by the lack of a user-independent, standardised methodology for assessing the reliability of assistive technologies based on AmI (Jordan, 2022; Maciel, 2023; Zagirov, Chebotareva, Osokin, Li & Magid, 2024). During the design and pre-deployment stages, developers possess challenges in verifying the adaptability of their systems in the absence of a framework (Lima et al, 2020; Zhou, Wang & Li, 2022). Thus, the framework for this study presents technical and the reliability of these systems. By offering a framework that emphasises technical reliability actions, this study fills this gap and device manufacturers to find and fix weaknesses in the system before integrating users into practical applications.

The key feature that needs to be addressed on AmI-ATs is their reliableness from a user's perspective, which thereby entrenches and guarantees its trust as a reliable and dependable monitoring tool (Dodson, Hajduk, Ged, Krumholz, Murphy, Tsang & Chaudhry, 2020). It is, therefore, imperative that any AmI-AT, that is selected based on conducting monitoring, undergoes evaluation and concedes the requirements, based on the set measurement properties, for it to be regarded as reliable. The core of the existence of AmI-ATs is to provide the human-sphere with monitoring systems that require minimal effort from the users (Dodson et al, 2020). AmI-ATs are a suitable technology remedy for ubiquitous monitoring situations due to their ability to function independently.

Furthermore, reviewed literature shows a lack of models that can be used to evaluate the reliability of selected AmI-ATs to accurately and surely be conversant of the reliability of the chosen AmI-AT (Yusif, Soar & Hafeez-Baig, 2016; Howard, Fisher, Kemp, Lindsay, Tasker & Tree, 2022; Kumar, Renuka, Rose & Wartana, 2022). To that effect, this study seeks to develop a framework to address the deficiencies posed by the reviewed sources and provide an effective means for assessing AmI-AT reliability to meet the challenges presented in developing countries' operating environments. The reliability of Ambient Intelligent Technologies (AmI) is a research problem that involves the assessment of the performance, dependability, and consistency of these systems in various contexts. Kumar, Renuka, Rose and Wartana, (2022) specified that AmI technologies are designed to provide users with seamless and intelligent interactions with their environment, using sensors, data processing, and machine learning algorithms. According to Howard et al, (2022), the reliability of AmI technologies is a critical issue that needs to be addressed to ensure their successful adoption and deployment.

3.14 Chapter Summary

The identification of these components will assist the developers in having a clear direction about which developmental technical and, awareness and reliability considerations to make. Thereafter, the necessary or required hypothetical AmI-AT monitoring system or tool, can be developed with these considerations accommodated. Subsequently, this research followed the same developmental considerations approach to formulate the required framework for evaluating the reliability of AmI-AT monitoring systems. Such a framework as well has also been developed to make provisions for the targeted audiences, markets, caregivers, guardians, and technical and awareness considerations.

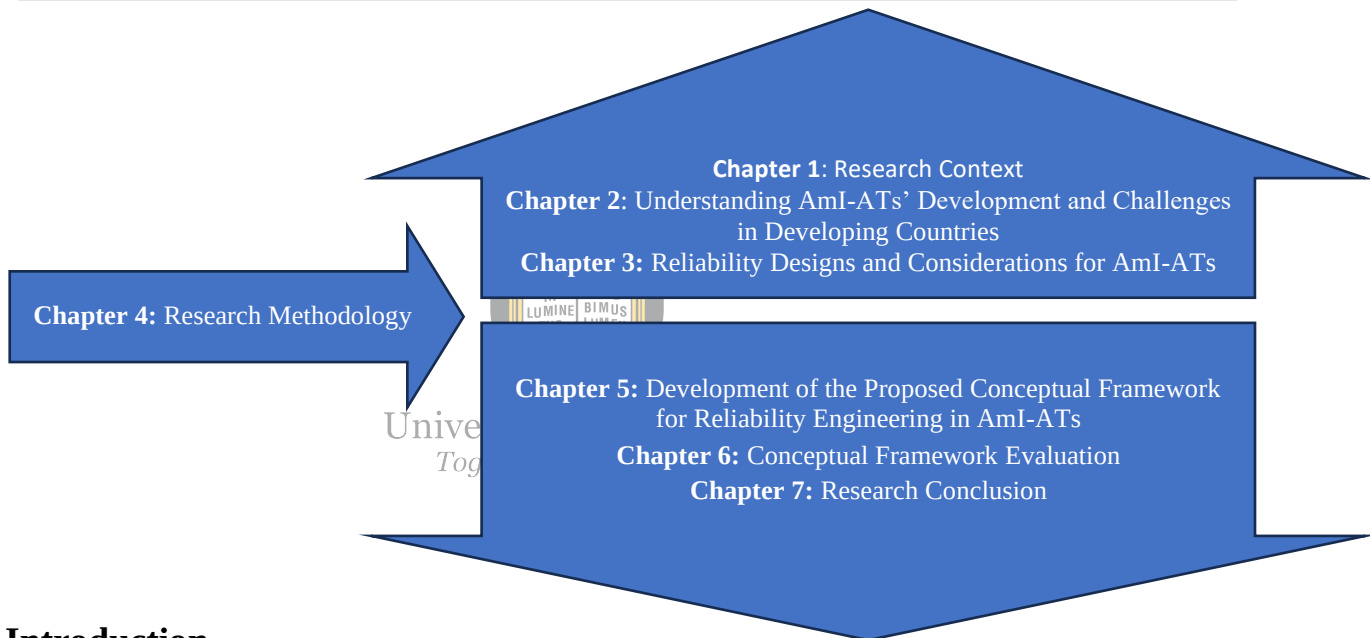
Thus, the next chapter presents the methodology, outlines the design, approach, and reliability quantification techniques used in the study. It provides the inclusion criteria, reliability assessment tools, and presents case study analyses, focusing on Continuous Glucose Monitoring and Heart Rate Monitoring in healthcare contexts.



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Chapter 4 : Research Methodology

The methodology chapter outlines the design, approach, and reliability quantification techniques used in the study. It describes the inclusion criteria, reliability assessment tools, and simulation methods. The chapter also presents detailed case study analyses, focusing on Continuous Glucose Monitoring and Heart Rate Monitoring in rural healthcare contexts.



4.1 Introduction

In order to achieve the goal of this research study, which is to create a framework for evaluating the reliability of AmI-ATs, this chapter provides the rationale for the research procedures that were employed. The main research goals outlined in Chapter 1 are addressed by the components that make up this chapter. The research design paradigm's backdrop and the chosen general technique for the investigation are covered in the previous chapter.

4.2 Research Design and Approach

The study applied a mixed approach. Both quantitative and qualitative approaches were considered. The study used an experiment method and documentary review, was based on case studies for individuals with different ailments. This secondary data helped in coming up with the experiments and case studies used in the study. The qualities aspects were mainly on the drawing up of themes and interpretation of findings from case studies. All ethical considerations such as acknowledging the reviewed author's work since the study did not directly engage with human beings were adhered to during the study to enhance validity, trustworthy and reliability. For secondary data, Google Scholar, Scopus and Paper Digest were used to search for various articles and documents in correspondence with the PRISMA 2020 conditions by Haddaway, Page, Pritchard and McGuinness, (2022), as shown below.

4.2.1 Inclusion Criteria

The objectives of the study were used as keywords for searching articles. This includes the following

- Reliability in AmI-AT systems
- Characteristics and the functional requirements of existing AmI-AT systems
- Failures in the components of an AmI-AT systems
- A reliability assessment framework for AmI-AT systems
- IoT Reliability



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The design paradigm is a framework containing all the commonly accepted views and conventions, the directions a particular study should follow, and how the research should be undertaken (Shuttleworth & Wilson, 2017). In general, paradigms contain all the distinct, established patterns, theories, common methods and standards that enable researchers to recognize an experimental result as belonging to a particular field or not (Shuttleworth & Wilson, 2017). The Design Science Research Methodology (DSRM) design paradigm was used in this study, which looked at the design paradigm approach and its goals. In essence, design science is a paradigm for problem-solving that aims to produce innovations that characterize concepts, procedures, and technological capabilities (vom

Brocke et al, 2017). Effective and efficient analysis, design, implementation, management, and information systems are made possible by design science.

The DSRM modification selected and used for this investigation is depicted in Figure 1. The solution was obtained by applying the DSRM cycle technique shown in Figure 1, which gave the required information and comprehension of the study challenge. The adopted DSRM approach guided the study from the conceptualization, design, development and evaluation of the reliability framework. The DSRM assisted in the reliability framework development. This was explained in Chapter 5.

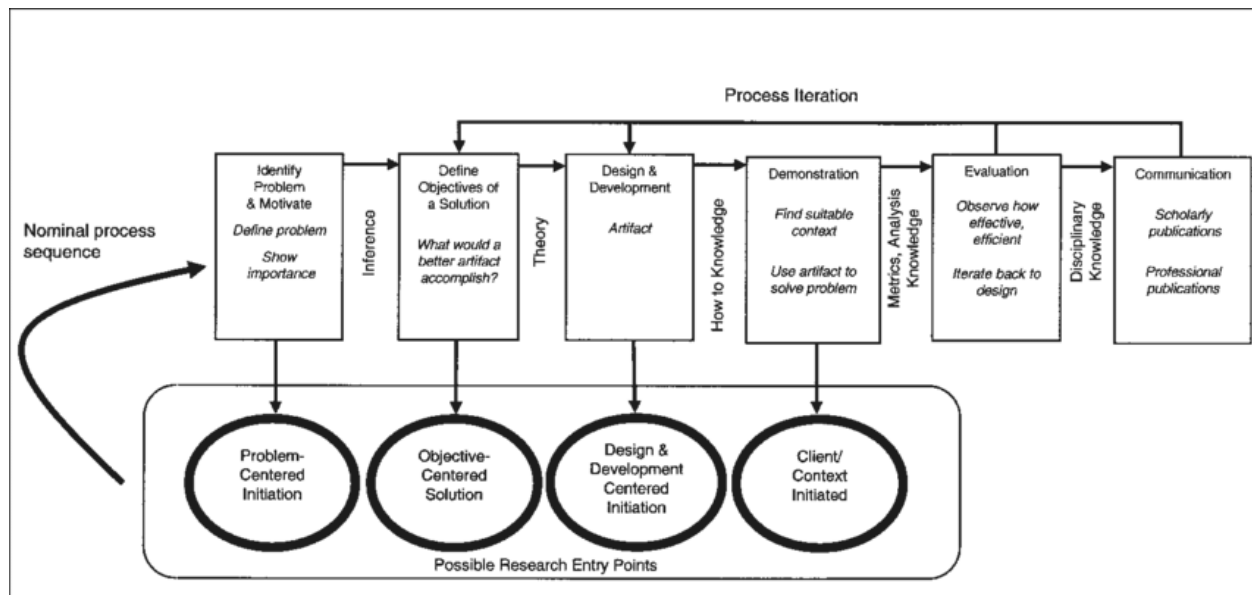


Figure 4.1: Design Science Research Cycles adopted from (vom Brocke et al, 2017)

4.3 Reliability Quantification: Selection of Appropriate Reliability Assessment Methods and Tools

Predicting the reliability of an IoT-related system can be mandatory, especially when the devices concerned are associated with healthcare. Predicting reliability helps in system design to establish optimal operational parameters. The reliability of AmI-AT is paramount to its successful operation, and this can be reflected in its energy efficiency and timely data transmission (Azghiou, Mouhib, Koulali & Benali, 2020). In AmI-ATs, sensors cooperatively sense, collect and process information in the monitoring environment, typically on the human body. Therefore, there is a need for real-time

acquisition and timely processing of data to aid in administering corrective medical procedures and improving the comfort of the AmI-AT user.

Moore (2020) indicated that improving the reliability of AmI-AT can undoubtedly enhance the user experience and encourage the adoption of AmI-ATs. However, there is a need to represent reliability in ways that users can easily understand. Hiari, Mesleh and Aljanini (2021) specified that to this end, reliability should be described as a quantitative measure that broadly represents an AmI-AT system's ability to perform its intended function. The two methods adopted for this study are Reliability Block Diagrams (RBD) for framework design and Markov Chains for framework implementation and simulation.

4.3.1 Reliability Block Diagrams

Reliability Block Diagrams (RBD) are graphical and mathematical models of the elements of a system that permit the calculation of system reliability, given the reliability of the components Hiari et al, (2021). The framework reflects the reliability performance structure, including series, parallel, standby, and other arrangements of system elements, which are graphical structures consisting of blocks and connector lines. Each block in the diagram represents a function of a component. If the function is available, the block can facilitate a connection through the block, and if the function fails, there is no connection through the block. Thus, understanding the block state can then be used to identify the suitable RBD configuration to regulate the complete reliability of the given AmI-AT system ref.

In this study, RBDs are adopted to framework the AmI-AT system structure transitions through a predictive diagnostics approach for assessing the reliability of AmI-ATs as a complex system. The study used diagnostics data to estimate the reliability of AmI-AT components, leveraging the usage of a hierarchical reliability framework to assess the reliability curve of the system under analysis. While a reliability block diagram is a snapshot of the AmI-AT system when it is constructed, the assets present, how the system operates, and the constraints present, the use of a tuned reliability curve, enables the predictive computation of the system failure probability in each future time interval.

4.4 Non-Users' Involvement in the AmI-AT Framework Development

The decision to exclude users at this stage is well-justified for focusing on the technical reliability of assistive technologies. It ensures the development of a robust and scalable framework, which can later be extended or validated through user engagement in subsequent studies. This phased approach aligns with a systematic and ethical research methodology in computer science. The following are some of the reasons that were considered:

4.4.1 Technical Focus

- The study emphasises the *technical reliability* of AmI-AT-based systems, focusing on the system's ability to perform as intended under varying conditions without considering user behaviour or preferences.
- Reliability testing includes metrics such as fault tolerance, consistency, latency, response accuracy, and adaptability—factors that can be objectively measured in controlled environments without requiring direct user interaction.

4.4.2 Standardization and Benchmarking

- Developing a framework that evaluates assistive technologies in a controlled, user-independent manner helps create standardised benchmarking protocols.
- This approach ensures consistent and repeatable assessments, allowing technologies to be compared objectively without introducing variability due to individual user differences.

4.4.3 Initial Development Phase

- The framework is designed for the early stages of technology development, where the primary focus is on validating system performance, functionality, and reliability before deployment in real-world scenarios.
- User engagement is more appropriate in later stages (for instance, usability testing or field trials) after ensuring the technology's foundational reliability.

4.4.4 Simulation and Testbed Capabilities

- Advances in simulation environments and testbeds enable realistic testing of AmI-AT systems by mimicking real-world scenarios, including sensor interactions and contextual variability, without involving actual users.
- These tools provide a controlled and repeatable environment for assessing reliability.

4.4.5 Minimizing Ethical and Practical Challenges

- Direct user involvement often involves ethical considerations, particularly when working with vulnerable populations who rely on assistive technologies, which could have been a challenge.
- Avoiding user engagement in the initial phase reduces ethical complexities, such as obtaining informed consent and ensuring participant safety, while allowing researchers to focus on system performance.

4.4.6 Focus on Systemic Reliability



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- User engagement often evaluates usability, user experience, or social acceptance, which are distinct from systemic reliability.
- By excluding users, the framework concentrates entirely on factors such as system integrity, fault recovery, sensor accuracy, and contextual adaptability.

4.4.7 Relevance to Ambient Intelligence

- Ambient Intelligence systems rely on autonomous and adaptive interactions with their environment. The reliability of such systems depends on their ability to perceive, interpret, and respond accurately to environmental changes.
- Since these interactions are machine-centric, they can often be assessed without involving users.

4.4.8 Cost and Efficiency

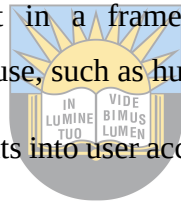
- User studies are resource-intensive, requiring participant recruitment, logistics, and ethical approvals.
- Focusing on technical evaluations reduces costs and accelerates the research timeline, particularly when the goal is to develop a foundational framework.

4.5 Potential Limitations and Mitigation Strategies

There were limitations that the study pointed mainly on non-user involvement in the framework development. This is also explained in Chapter 5 and 6.

4.5.1 Limitations

- Excluding users might result in a framework that overlooks practical challenges encountered during real-world use, such as human error or diverse interaction patterns.
- The framework may lack insights into user acceptance or the real-world applicability of the assistive technologies.



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4.5.2 Ethical Clearance

The data utilized are publicly available or have been obtained with prior permission from relevant authorities, ensuring compliance with all applicable data protection and ethical guidelines. No direct interaction with human participants is involved, and the study adheres to the ethical principles of confidentiality, integrity, and respect for data privacy. Ethical clearance considerations have been adhered to and all data sources have been appropriately cited and acknowledged.

4.5.3 Mitigation Strategies

- Incorporate user-centric considerations indirectly, such as using data from prior user studies or established benchmarks for user behaviour in AmI-AT environments, such as the considered cases in this study.

The study acknowledges that engaging users shall enhance and assist in the applicability of the developed framework. However, this exercise is beyond the scope of this study.

4.5.4 Theoretical Basis

Monte Carlo methods provide a powerful tool for understanding the effects of failures on system performance (Chakour et al, 2024). This enables more accurate predictions and supports the development of informed maintenance strategies. Monte Carlo methods use probabilistic modelling to simulate sensor behaviours under varying conditions and estimate the likelihood of system failures over time. By incorporating real-time anomaly detection data into these simulations, the framework can evaluate how sensor malfunctions impact overall system reliability and predict potential failures. This probabilistic approach enables a deeper understanding of failure dynamics and their propagation within the system, allowing for more accurate predictions and better-informed maintenance strategies. For example, by combining sensor criticality rankings with Monte Carlo simulations Chakour et al, (2024), the framework can simulate the effects of prioritizing repairs for high-criticality sensors, assessing the long-term impact on system reliability.

Additionally, the use of Markov Chains through the case studies further enhances the conceptual framework. Markov Chains provide a structured way to model the states of sensors, such as normal operation, degraded performance, and failure, and analyse the transitions between these states over time. By leveraging historical data and outputs from real-time anomaly detection, Markov Chains predicts not only when a sensor might fail but also the cascading effects of such failures on the broader system. This proactive insight is invaluable for guiding manufacturers and maintenance teams in addressing issues before they escalate. The dynamic integration of anomaly detection methods ensures that Markov Chain models remain accurate and relevant, as they continuously update probabilities based on current sensor behaviour.

According to Wang, Xie and Shiyuan, (2022), incorporating Markov Chains into the conceptual framework for AmI system reliability bridges the gap between theoretical modelling and practical application (Wang, Xie & Shiyuan, 2022). By enabling system-wide failure modelling, these probabilistic tools provide insights into how individual sensor failures propagate across the network, impacting overall performance. This capability facilitates the prioritization of interventions by quantifying the impact of failures, especially for high-criticality devices and sensors, which are

essential in resource-limited environments. Moreover, the use of Markov Chains supports the development of robust maintenance and response strategies tailored to the unique operational challenges of AmI systems in these environments. This study adopts a novel integration of probabilistic modelling techniques, combining Markov Chains and Monte Carlo methods to aid in formulating the conceptual reliability framework presented in this study.

The Markov chains Monte Carlo (MCMC) approach combines two key principles: Markov chains and Monte Carlo sampling and the combination of Markov Chain and Monte Carlo simulation is used to model the probabilistic behaviour of these systems (Chakraborty et al, 2020). Markov chains excel at modelling systems with complex states, allowing transitions between these states based on defined probabilities. Monte Carlo simulations complement this by emulating the real-life behaviour of systems through randomized sampling, generating performance statistics for deducing reliability measures. Together, these methods create a robust framework for estimating the reliability of high-dimensional systems while considering probabilistic dependencies. This allows the algorithms to narrow in on the quantity being approximated from the distribution, even with a large number of random variables. Combining Markov Chain and Monte Carlo allows random sampling of high-dimensional probability distributions that honours the probabilistic dependence between samples by constructing a Markov Chain that comprises Monte Carlo samples.

4.6. Justification of Markov Chain Monte Carlo Reliability Analysis

The high-availability requirements of IoT-related systems mean that they are more at risk of unintended, non-malicious downtime. When designing AmI-ATs, it is necessary to provide a close to real-life estimation of the system's hardware and software components reliability, including the user's effect on the system. The failure of AmI-AT systems is posited to be rare. However, from the practical failure rates of its constituents, it is possible to estimate the failure statistics of an AmI-AT system and thereby determine its reliability.

Wang, Xie and Shiyuan (2022) suggest several approaches with the most effective use of Markov chains and Monte Carlo simulation models. Chakraborty, Goyal, Mahapatra, and Soh (2020) highlighted that Markov chains allow for the modelling of a complex system's state, factoring in other possible states. At the same time, Monte Carlo simulation models empower the designer to

emulate the real-life behaviour of a complex system, thereby obtaining its performance statistics and deducing reliability measures.

Chakraborty, Goyal, Mahapatra and Soh, (2020) indicated that Markov Chain Monte Carlo sampling provides a class of algorithms for systematic random sampling from high-dimensional probability distributions. Unlike Monte Carlo sampling methods that can draw independent samples from the distribution, Markov Chain Monte Carlo methods draw samples where the following sample is dependent on the existing sample, called a Markov Chain (Chakraborty, Goyal, Mahapatra & Soh, 2020). This allows the algorithms to narrow in on the quantity being approximated from the distribution, even with a large number of random variables. Wang, Xie and Shiyuan (2022) specified that combining these two methods, Markov Chain and Monte Carlo allow random sampling of high-dimensional probability distributions that honours the probabilistic dependence between samples by constructing a Markov Chain that comprises the Monte Carlo sample.

Since AmI-ATs operate in dynamic, uncertain environments characterized by sensor degradation, environmental noise, and user interaction's conventional reliability assessment methods become inadequate. This approach is tailored to address the novel challenges associated with AmI-AT systems in Health Monitoring Technologies, focusing on:

- Dynamic reliability assessment under real-life conditions such as sensor degradation, environmental noise, and user interventions.
- Complex state transitions that characterize AmI-AT operations, modelled using Markov chains.
- Probabilistic sampling to emulate system performance under varying conditions, facilitated by Monte Carlo methods.

Markov Chain Monte Carlo systems have been broadly used in statistical modelling for numerous applications since it allows to compute accurate approximations in organised additive regression models. Wang et al., (2024) confirmed the efficiency of high-dimensional application distributions in MCMC methods by using sequential Monte Carlo methods. MCMC methods have demonstrated to be valuable in innumerable statistical models by offering robust inference and accurate estimates such as in DNA sequence segmentation, spatial GLMMs, Markov logic, latent Gaussian models,

signifying its adaptability and effectiveness in statistical modelling. Hence, it was preferred over other statistical methods in this study.

4.7 Use Case Analysis

The use case analysis technique is used to achieve the AmI-AT reliability assessment framework's effectiveness, identify the reliability requirements, and define the processes in an existing AmI-AT application to ensure it will ultimately fulfil the deployment purpose. This process begins with identifying a typical AmI-AT application used for modelling. In this study, two cases were employed to instantiate the reliability framework and provide analysis to reflect the actual characteristics of a real-life system. The overall goal of this step is to provide sufficient details to understand the effectiveness of the reliability assessment framework. Use case analysis considers standardized parameters for the algorithms in order to investigate the robustness, accuracy and efficiency of the implementation of the framework. Healthcare and Elderly In-Home Living monitoring has been selected as a basis and case study for this development to allow other cases to be catered deducible and suitable for being evaluated using the same framework. The two selected use cases are presented in this section.



4.8 Case Study Description

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As Ambient Intelligent (AmI) systems continue to evolve, their application in healthcare monitoring has shown significant potential, particularly in rural areas where access to medical infrastructure and personnel is often limited. To explore these applications, this chapter presents two case studies focusing on Continuous Glucose Monitoring (CGM) and Heart Rate (HR) monitoring devices (Huang et al, 2023). These studies demonstrate the use of advanced anomaly detection and probabilistic modelling techniques to address reliability concerns, ensuring these critical devices perform effectively in resource-constrained settings.

The AmI-AT reliability assessment framework was developed to cater for a wide and varied set of audiences and use case scenarios. The core motivation was to create a framework that would provide a standard to evaluate AmI-ATs, requiring the assessment of users' reliability based on the system or entity under its monitoring. A typical healthcare monitoring system comprises several health

indicator sensors that connect to a central gateway that provides communication with the external infrastructure (Abdulmalek et al, 2022).

In addition, the setup allows for the constant monitoring of the patient in real time. AmI-ATs system in this use case consists of the data acquisition part, referred to as the sensing layer, and the data transmission part. The application layer comprises software components that allow the caregiver and healthcare practitioners to check the patients' health indicators (Philip, Rodrigues, Wang, Fong & Chen, 2021). The sensing layer is composed of sensor nodes placed on and or in the patient's body to monitor the patients' health indicators. Philip et al, (2021) indicated that the sensing component is part of the hardware component of the AmI-ATs, and hardware also constitutes other components, such as the power and connectivity modules.

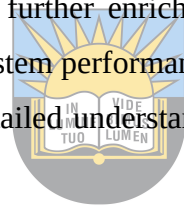
4.8.1 Continuous Glucose Monitoring (CGM)

The CGM monitoring case study examines the use of CGM devices, which play a crucial role in monitoring glucose levels for patients with diabetes. In rural environments, where regular clinical visits may not be feasible, CGM devices offer a lifeline by providing continuous data on glucose trends and enabling timely interventions. However, the reliability of these devices is critical, as failures can lead to delayed responses or incorrect treatments. To address this, real-world CGM data is analyzed to identify typical patterns and anomalies, such as sudden glucose spikes or drops, calibration errors, and data transmission issues (Huang et al, 2023).

Markov Chain Monte Carlo (MCMC) methods are employed to model the state transitions of the CGM devices, capturing states such as normal operation, degraded performance, and failure (Huang et al, 2023). Using MCMC, the transition probabilities between these states are estimated based on historical and real-time data. This probabilistic approach not only predicts the likelihood and timing of sensor failures but also allows for uncertainty quantification, enabling more robust reliability assessments of CGM devices. The simulations estimate overall system reliability by modelling how environmental factors, device usage, and maintenance schedules influence failure rates. This combination of techniques enables a comprehensive assessment of CGM device reliability, offering insights into how quickly anomalies can be detected, how failures affect patient outcomes, and what strategies can mitigate these risks.

4.8.2 Heart Rate Monitoring in Rural Healthcare

The second case study focuses on HR monitoring devices, which are essential for tracking cardiac health and detecting early signs of cardiovascular issues. In rural areas, these devices empower healthcare providers to monitor patients remotely, reducing the need for frequent clinic visits. However, as with CGM devices, the reliability of HR monitors is paramount to ensuring their effectiveness. For this case study, real-world HR data is analyzed, capturing variations during normal activities and stress conditions. Historical failure data, such as sensor disconnections, battery depletion, and inaccurate readings, is also analyzed. Anomaly detection methods, including Random Forests and SVM, are applied to identify abnormal HR patterns, such as erratic spikes, sudden dips, or signal loss. Markov Chains are then used to model the states of HR monitors, tracking transitions between normal, degraded, and failed states (Mirzaei et al, 2023). This probabilistic approach provides predictions on sensor reliability over time and identifies patterns that may precede device malfunctions. Monte Carlo simulations further enrich the analysis by simulating various failure scenarios. These simulations evaluate system performance under different patient activity levels and environmental conditions, offering a detailed understanding of how HR monitors perform in real-world rural settings.



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Through this analysis, the study examines the accuracy and reliability of HR data, the effectiveness of anomaly detection methods in identifying health-critical events, and long-term reliability predictions. These insights inform preventive maintenance strategies and highlight the importance of robust monitoring systems in rural healthcare.

4.9 Datasets and Preparation for CGM and HR Use Cases

The datasets utilized in this study include data from Continuous Glucose Monitoring (CGM) devices and Heart Rate (HR) sensors, both pivotal for evaluating the reliability of Ambient Intelligent Technologies (AmI-ATs) in healthcare. These datasets consist of real-world and synthetic data representing diverse operational conditions, ensuring comprehensive coverage of potential scenarios. The CGM dataset focuses on glucose level trends and anomalies, while the HR dataset captures variations in heart rate during different activities and states of rest. The data used contained multiple parameters, and the study only extracted parameters applicable to the research context.

Table 4.1: Dataset Selection and Preparation

Case Study	CGM Data	HR Data
Source	Data from publicly available repositories, clinical studies, and device manufacturers' testing environments.	Datasets from fitness trackers, medical-grade monitors, and controlled studies.
Pre-processing	- Identify and handle anomalies such as abrupt spikes, missing data, and calibration errors. - Normalise glucose readings to align with international standards for comparability across devices. - Apply time-series decomposition to extract trends, seasonal variations, and irregularities. - Examine battery levels data	- Remove noise caused by motion artefacts or device placement issues using signal processing techniques. - Identify and flag abnormal Data patterns - Segment the data into meaningful intervals for focused analysis. - Examine battery levels data
URL Links	https://github.com/IrinaStatsLab/Awesome-CGM? http://smarthealth.cs.ohio.edu/OhioT1DM-dataset.html .	https://physionet.org/content/activity/1.0.0/ https://physionet.org/content/mimic-iv-ed
Permissions and attributions	Attribution ShareAlike 4.0 International license: https://creativecommons.org/licenses/by-sa/4.0/legalcode https://www.mit.edu/~amini/LICENSE.md	Goldberger, A., Amaral, L., Glass, L., Hausdorff, J., Ivanov, P. C., Mark, R., ... & Stanley, H. E. (2000). PhysioBank, PhysioToolkit, and PhysioNet: Components of a new research resource for complex physiologic signals. Circulation [Online]. 101 (23), pp. e215–e220.

4.10 RBD Modelling of Use Cases

Reliability Block Diagram (RBD) modelling provides a structured method to analyse system reliability in the use cases by representing components and their interconnections. This section outlines the process of RBD modelling of the use cases.

4.10.1 Breakdown of the Use Case AmI-AT into the Key Components:

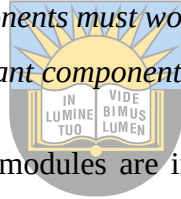
- Sensor reliability (R_{sensor}): Continuous glucose sensor
- Data processing unit reliability ($R_{process}$): Processing algorithms
- Communication module reliability (R_{comm}): Wireless communication
- Power supply reliability (R_{power}): Battery or power management
- Human Factor (R_{human})

4.10.2 Define the System Configuration

Determine whether the system components are in a series or parallel configuration. The system configuration has a bearing on whether a system goes into a faulty state or functions in a degraded state:

- **Series Configuration:** *All components must work for the system to function.*
- **Parallel Configuration:** *Redundant components ensure reliability.*

Typically: Sensors and communication modules are in series because failure in any will lead to system failure. Power supplies may have parallel redundancy.



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4.10.3 Calculate Reliability

The reliability of series and parallel systems can be calculated using the following formulas:

Formula 1:

- **Series System Reliability:**

$$R_{series} = R_1 \times R_2 \times R_3 \times \dots \times R_n$$

- **Parallel System Reliability:**

$$R_{parallel} = 1 - \prod_{i=1}^n (1 - R_i)$$

Where R_i is the reliability of the i -th component.

4.10.4 Use Simulation for Estimation

Since component reliabilities might involve variability, MCMC simulations can be used to estimate system reliability under uncertainty.

4.11 Data Analysis Techniques

Figure 2 outlines the procedures used to assess the AmI-AT reliability framework. The first step in the evaluation process is to think about the use case scenario that will be used in the simulation environment. Next, the use case is simulated using MCMC techniques. The simulation settings serve as guidance for the framework's execution within the simulation environment. The simulation results are then displayed, along with a summary of the conclusions.

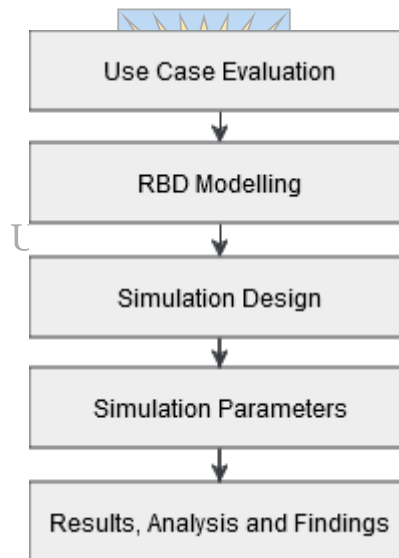


Figure 4.2: AmI-AT Reliability Framework Assessment

Given that the AmI-AT is made up of multiple components, the reliability of each component must be determined to come up with the overall reliability estimate for the AmI-AT system. Model checking enables the rigorous verification of a system's temporal features and the description of its behaviour in the form of a state machine. Verification of probabilistic qualities is made possible by probabilistic framework checking, which expands on the concepts of standard framework checking

for the study of MCMC. The study employs the probabilistic model-checking approach for modelling, simulating, and analysis of MCMC as applied to the study.

4.12 Chapter Summary

The previous discussion outlined the approach used to develop the conceptual framework for the reliability of Ambient Intelligent Technologies (AmI-ATs). These methods ensure that the framework is both robust and adaptable, meeting the reliability demands of AmI-ATs operating in real-world settings. The strategies employed are rooted in a comprehensive understanding of reliability concepts, as explored in the literature review from the previous chapter. To understand the nature of system design in AmI-ATs, a case analysis method was employed.

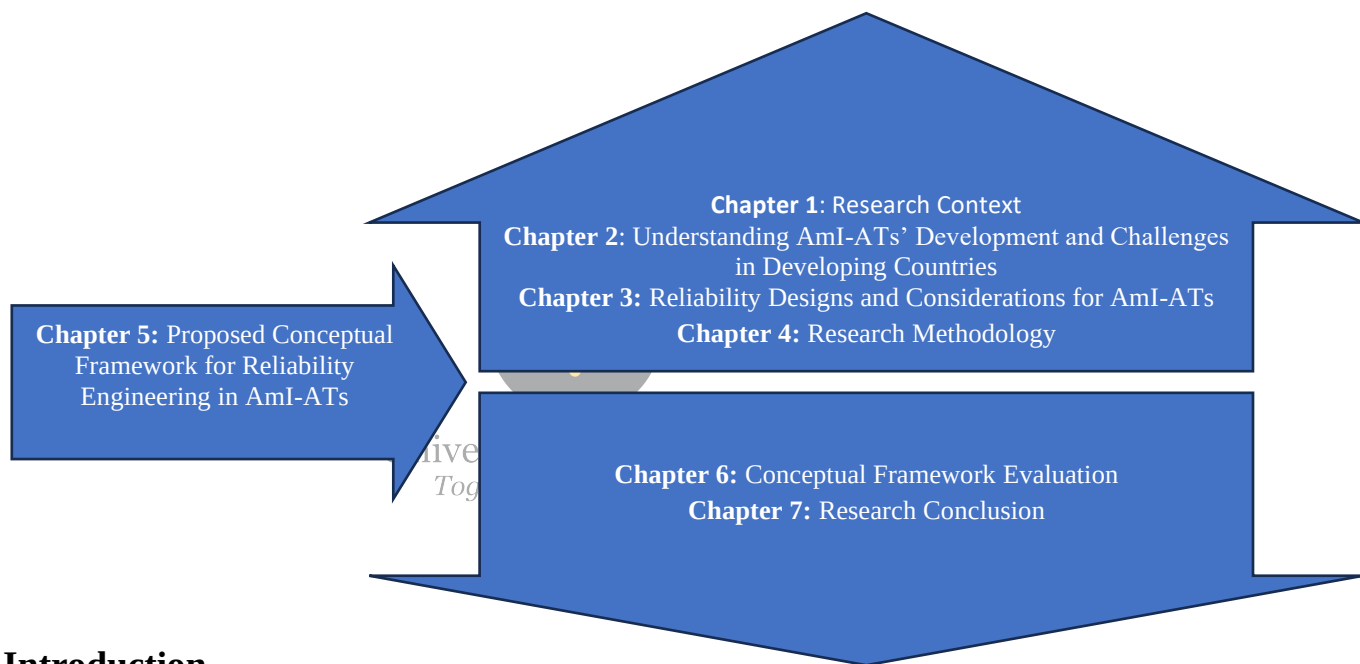
Hence the next chapter presents the development of a conceptual framework for evaluating AmI-AT reliability. It offers the justification for design choices, potential limitations, and mitigation strategies as well as synthesises insights from literature and proposes reliability metrics and models tailored to resource-constrained environments.



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Chapter 5 : Conceptual Framework for Reliability in AmI-ATs

This chapter presents the development of a conceptual framework for evaluating AmI-AT reliability. It includes justification for design choices, potential limitations, and mitigation strategies. The chapter synthesises insights from literature and proposes reliability metrics and models tailored to resource-constrained environments.



5.1 Introduction

The approach used to develop the suggested conceptual framework is described in the preceding chapter. In this chapter, the development of the suggested conceptual framework is covered. In order to motivate the construction of the framework, the chapter begins with a discussion of the key discoveries in literature framework development considerations are then discussed, followed by a discussion on the AmI-AT framework. A discussion of mathematical modelling follows. After that, the chapter discusses the framework implementation. The chapter concludes with a chapter summary in the section.

5.2 Theoretical Underpinnings of the Framework

This introduces the foundational theories supporting the formulated conceptual framework for evaluating the reliability of Ambient Intelligence Assistive Technologies (AmI-ATs) as a component of Health Monitoring Technologies. This section emphasizes the integration of mathematical modelling techniques, such as Reliability Block Diagrams (RBDs) and Markov Chain Monte Carlo (MCMC) simulations, to address the complex, dynamic behaviours of multi-component systems. The theories presented focused on understanding system interactions, redundancy, fault tolerance, and user-centric reliability factors. These theoretical insights provide a robust basis for analysing and enhancing AmI-AT reliability in diverse and resource-constrained environments. These guiding theories are presented in this section to recall the description which has been given in literature and present how the MCMC was applied.

5.2.1 Mathematical Modelling of the AMI-AT Reliability Framework

The conceptual reliability framework for Ambient Intelligent Technologies is grounded in the principles of Reliability Block Diagrams. RBDs provide a systematic and visual method to model the reliability of complex systems by representing them as interconnected components or subsystems. This approach enables the identification of critical failure points, and the evaluation of system-level reliability based on the reliability characteristics of individual components.

Furthermore, mathematical modelling leverages the RBD methodology to analyse and simulate the performance of AmI-AT systems under varying operational conditions. The framework integrates key parameters, including sensor accuracy, data transmission efficiency, environmental influences, and device interoperability, to construct a comprehensive reliability profile. Probabilistic Markov chain Monte Carlo (MCMC) techniques are incorporated to predict the likelihood of system failures and to assess their impact on overall system reliability.

5.2.2 MCMC State Simulation for a n-Component AmI-AT System

As discussed in the literature, the state-space technique for reliability modelling utilizes a collection of states, each representing a distinct operational condition of the AmI-AT system. In the context of an n -component AmI-AT system, these states may include operational, degraded, recovery or faulty.

The conceptual framework caters to the likelihood of the system entering each state over time with the possibility of successful recovery in case of a degraded or faulty state. Given that at any point, the AmI-AT system may either remain in its current state or transition to another, with the total probabilities across all states summing to unity. As time progresses, the state probabilities stabilize into limiting or time-independent values, which are critical for long-term reliability assessment.

To model the reliability of an n -component AmI-AT system, this study a probabilistic state-space stochastic approach, specifically a Markov chain Monte Carlo (MCMC) technique discussed in the methodology chapter. This approach is particularly suitable for AmI-AT systems due to its ability to capture complex inter-component interactions, such as load balancing and standby redundancy, that significantly influence system reliability. Unlike traditional reliability modelling techniques, the MCMC approach can effectively model the dynamic interdependencies and degradation processes within a multi-component system.

In the MCMC approach, each component of the n -component AmI-AT system is represented as a state within the system's state space. The transition matrix, derived from the state diagram and state space categorization, defines the probabilities of transitions between states. This transition matrix is central to the MCMC simulation, as it enables the representation of complex time-dependent behaviours and inter-component dependencies.

Benefits of MCMC for reliability simulation in an n -component system include:

- **Mathematical Generality:** MCMC can accommodate a wide range of transition probability distributions, making it versatile for diverse system architectures.
- **Traceability:** The MCMC framework provides a clear representation of the evolution of state probabilities over time, facilitating the analysis of reliability trends.
- **Component Degradation Modelling:** The approach captures the degradation processes of individual components more effectively than standard Markov processes, allowing for better analysis of long-term reliability.
- **Scalability:** The MCMC method is computationally efficient for large, multi-component systems, ensuring that the model remains manageable without sacrificing detail.

The transition matrix in the MCMC simulation ensures that all possible states and transitions of the n -component system are accounted for, providing a comprehensive and detailed reliability analysis. This makes MCMC a method of choice in dealing with AmI-AT, particularly in restricted environments with complex requirements, such as healthcare and elderly living monitoring applications.

5.2.3 Reliability Formulation

Reliability formulation for an AmI-AT system at a time t is represented as:

Formula 2:

$$R(t) = \int_0^t f(t-x)dx$$

The considered key components that contribute to AmI-AT reliability framework for this study are given as:

- Hardware
- Software
- Connectivity
- Human user



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$$Rel_{system}(t) = \sum_t Rel_{hardware}(t).Rel_{software}(\alpha).Rel_{connectivity}(t).Rel_{user}(t)$$

For a given AmI-AT system, S composed of n components, denoted by i where $i \in \{1,2,34, \dots\}$.

The state variable of the component i is given as follows:

$$X_i(t) = \begin{cases} 1 & \text{if the component is in a functioning at time } t \\ 0 & \text{if the component is in a failed state at time } t \end{cases}$$

Given that $X_i(t)$ is a random operational feature of the component i .

The state vector $X_i(t)$ at time t if formed by $n - \text{uplets}$ of state variables, represented as follows:

$$\mathbf{X}(t) = (X_1(t), X_2(t), \dots, X_n(t))$$

The overall state of the AmI-AT system can be described as a binary function:

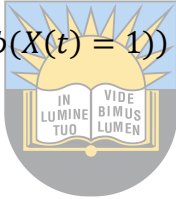
$$\phi(\mathbf{X}(t)) = (X_1(t), X_2(t), \dots, X_n(t))$$

Where $\phi(\mathbf{X}(t))$ is the structure-function of the AmI-AT system presented as:

$$\phi(\mathbf{X}(t)) = \begin{cases} 1 & \text{if the system is in a functioning at time } t \\ 0 & \text{if the system is in a failed state at time } t \end{cases}$$

Since reliability is described as a probability for each component i , the reliability of an AmI-AT at a given time t is described as:

$$\Pr(X_i(t) = 1) = p_i(t) \text{ for } i = 1, 2, \dots, n$$

$$\Pr(\phi(\mathbf{X}(t)) = 1) = p_s(t)$$


5.2.3.1 Series Structure

For a given AmI-AT, a single device was considered as a system made up of a series of components. This is consistent with the fact that the failure of an internal component, for example, a lack of battery, causes the entire AmI-AT device to fail, therefore affecting the device's reliability. As such, the state of the AmI-AT can be described stochastically as independent variables.

Formula 3:

$$p_i(t) = R_i(t) \text{ for } i = 1, 2, \dots, n$$

The whole system can be described as:

$$p_s(t) = R_s(t)$$

An AmI-AT can be described as a stochastic series structure in a reliability block diagram.

$$\phi(X(t)) = \prod_{i=1}^n X_i(t)$$

Where $\mathbf{i}$ is a component of the modelled system and $\mathbf{X}(t)$ is its state vector. The following equation presents the serial structure reliability.

$$R_s(t) = E\phi(X(t)) = E\left(\prod_{i=1}^n X_i(t)\right) = \prod_{i=1}^n E(X_i(t)) = \prod_{i=1}^n R_i(t)$$

5.2.3.2 Parallel Structure

A parallel structure organizes components such that the overall system failure happens only if all components fail.

The parallel structure can be modelled as follows:

Formula 4:



$$\phi(X(t)) = 1 - \prod_{i=1}^n (1 - X_i(t))$$

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The reliability of a parallel structure is given as follows;

$$\begin{aligned} R_s(t) &= E(\phi(X(t))) = E\left(1 - \prod_{i=1}^n (1 - X_i(t))\right) = 1 - \prod_{i=1}^n E((1 - X_i(t))) \\ &= 1 - \prod_{i=1}^n (1 - R_i(t)) \end{aligned}$$

5.2.3.3 Factoring Redundant Subsystems

If an AmI-AT is such that **k-out of-n** structures are required for the system to be functional, the corresponding structure function of a **k-out of-n** system is as follows:

Formula 5:

$$\phi(X(t)) = \begin{cases} 1 & \text{if } \sum_{i=1}^n X_i(t) \geq k \\ 0 & \text{if } \sum_{i=1}^n X_i(t) < k \end{cases}$$

Where $\mathbf{i}$ is a component of a system, and $\mathbf{X}(t)$ is the state vector of the system. Given the above, the study assumes that reliability of all components is the same. As such,

$$R_s(t) = \sum_{y=k}^n \binom{n}{y} R(t)^y \times (1 - R(t))^{n-y}$$

5.2.3.4 Interpretation and Formulae Meaning to the Framework

Mapping Framework Components to Chapter 4 Formulae

Based on the framework development and the mathematical underpinnings outlined in Chapter 4 and the ones presented in this chapter, here is how specific formulae are integrated into the framework components, showing their relevance and application:

1. Reliability Block Diagram (RBD) for System Components

Equation:

Equation 1: For series systems: $R_{sys} = \prod_{i=1}^n R_i$
For parallel systems: $R_{sys} = 1 - \prod_{i=1}^n (1 - R_i)$

Application in Framework:

- **Framework Component:** System Components Layer.
- **Use:** The RBD method models the AmI-AT system's internal structure by organising components (for instance, sensors and communication modules) in series or parallel configurations. For instance, a failure in a series system like glucose monitoring leads to total system failure, emphasising critical points for intervention.

- **Impact:** This formula allows evaluation of the overall system reliability by considering individual component reliabilities. It provides insights into whether adding redundancy or reconfiguring components can enhance reliability.

2. Markov Chain Monte Carlo (MCMC) for Probabilistic State Modelling

Equation:

Equation 2: State probability transition: $P(t) = P(0) \cdot e^{Qt}$, where Q is the transition matrix.

Application in Framework:

- **Framework Component:** AmI-AT Management Layer.
- **Use:** The MCMC approach is applied to simulate the dynamic behaviour of the system under varying operational conditions, such as sensor degradation or environmental impacts. Transition probabilities model how the system shifts between operational, degraded, or failed states.
- **Impact:** MCMC provides detailed insights into time-dependent reliability and long-term performance trends. It highlights failure probabilities over time, guiding targeted maintenance.



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3. Reliability Metrics Integration:

Equation: For a k -out-of- n system:

Equation 3:

$$R_{\text{sys}} = \sum_{j=k}^n \binom{n}{j} R^j (1-R)^{n-j}$$

Application in Framework:

- **Framework Component:** Reliability Metrics and Contextual Layer.
- **Use:** This formula evaluates configurations where partial system functionality suffices (e.g., redundant power supplies). It quantifies the reliability of systems with overlapping dependencies or subsystems.

- **Impact:** It ensures adaptability by assessing reliability for varying operational thresholds, especially in resource-constrained setups.

4. Simulation-Based Reliability Assessment:

Method: Python simulation environment to implement RBD and MCMC.

Application in Framework:

- **Framework Component:** Assessment Layer.
- **Use:** Simulation validates theoretical reliability models, analysing real-time performance under stress conditions. It helps refine the framework by incorporating experimental data, such as device failure rates and environmental stressors.
- **Impact:** Provides empirical validation of the framework's assumptions and recommendations for improving component design.



Each formula contributes to the framework's robustness by modelling, assessing, and improving different aspects of system reliability, ensuring its adaptability to real-world applications. To provide an analysis of the formulae in this chapter and their relationship to the framework components, the study identifies and explains each formula, map it to the relevant components of the reliability framework, and describe how it assisted in the framework development.

The formulae in this chapter relate to the framework's reliability modelling components. The following section is an explanation of each formula and its role in developing and connecting to the framework's components.

1. Series System Reliability:

Formula 4: $R_s = R_1 \times R_2 \times \dots \times R_n$ $R_s = R_1 \times R_2 \times \dots \times R_n$

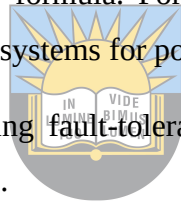
- **Meaning:** This formula calculates the overall reliability of components connected in a series. The reliability of the entire system decreases as more components are added in a series, reflecting the dependency on each component functioning correctly.

- **Framework Component:** This applies to sub-systems like sensors and connectivity modules in the framework. For example, if one sensor in a continuous glucose monitoring system fails, the whole monitoring system's reliability is compromised.
- **Contribution:** This formula helps identify critical weak points in the system by showing how failures propagate through serially connected components.

2. Parallel System Reliability:

Formula 5: $R_p = 1 - [(1 - R_1)(1 - R_2) \dots (1 - R_n)]$ $R_p = 1 - [(1 - R_1)(1 - R_2) \dots (1 - R_n)]$

- **Meaning:** This formula evaluates the reliability of systems with redundant components. It assumes the system remains operational if at least one component functions.
- **Framework Component:** Redundancy strategies, such as having multiple sensors or power sources, are modelled using this formula. For example, in ambient intelligence assistive technologies (AmI-ATs), backup systems for power or data transmission enhance reliability.
- **Contribution:** It aids in designing fault-tolerant architectures by showing the reliability benefits of parallel configurations.



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3. MCMC State Simulation:

- **Role:** Used to simulate the probabilistic behaviour of system states over time, including operational, degraded, and failed states.
- **Framework Component:** This technique is central to modelling the dynamic reliability of the AmI-AT system, capturing interdependencies among components like sensors, actuators, and connectivity modules.
- **Contribution:** The MCMC approach enables comprehensive reliability predictions, accommodating complex interactions and degradation over time.

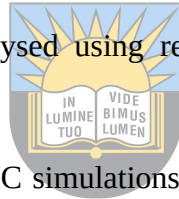
4. Reliability Estimation for n-Component Systems:

Formula 6: $R(t) = e^{-\lambda t}$ $R(t) = e^{-\lambda t}$ (exponential reliability model)

- **Meaning:** Calculates the probability that a system will function without failure over time assuming a constant failure rate λ .
- **Framework Component:** Applied to estimate reliability over time for critical system components like batteries or communication modules.
- **Contribution:** Provides a temporal view of reliability, aiding in maintenance scheduling and resource allocation.

Application to Framework Components

- **Sensors and Actuators:** Modelled using series and parallel reliability to assess their individual and collective contributions to the overall system.
- **Power and Connectivity:** Analysed using redundancy-based parallel models to ensure uninterrupted operation.
- **System-Level Reliability:** MCMC simulations integrate component reliabilities, offering a holistic view of system dependability under real-world conditions.



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Recommendations for Enhancing the Framework

- **Linkage Clarity:** Explicitly number and reference all formulas in the thesis.
- **Mapping Examples:** Inclusion of concrete examples linking formulas to specific components, such as glucose monitoring or heart rate sensors.
- **Validation:** Use case studies (Continuous Glucose Monitoring) to validate the theoretical models against practical outcomes.

These steps ensure the framework's robustness and highlight its contributions to AmI-AT reliability.

5.2.3.5 The Human Factor

While the reliability of a device can be estimated without considering the impact of the user, AmI-ATs require the factoring of the human user since most of the devices are in direct contact or in some cases, installed within the human body (Singh et al, 2023). Variations in user knowledge, mood and choices can affect the overall performance of an AmI-AT and subsequently affect its reliability. The human factor is denoted as a variable in the estimation of reliability. This further concerted the novel approach in reliability estimation in this study.

5.3 Guiding Literature Towards Framework Design

This section presents critical findings from secondary data that enabled the formulation of the framework components. It was evident that AmI-AT systems are prone to failure due to the inherent large-scale and heterogeneity of their underlying IoT design and infrastructure. The scale of the IoT presents maintainability challenges (Cortés et al, 2022). AmI-ATs devices, such as electronic or mechanical systems, are prone to failure due to aging and degradation of electronic circuits, battery manufacturing defects and other components. Eventually, AmI-AT devices will require repair, replacement, or decommissioning. As such, in managing the device lifecycle it is crucial to estimate the reliability of the device and predict its behaviour over its lifespan (de Barros Filho et al, 2021).

Despite being a major concern, scant research work has been done towards the reliability of AmI-AT with regards to device ageing and degradation. Modarres and Groth, (2023) specified that the reliability of AmI-ATs can be improved if an understanding of reliability variables is presented since reliability is affected by numerous factors. Furthermore, Eroshkin et al, 2021) indicated that the reliability of a component could degrade over time due to continued use.

In system reliability analysis, it is commonly assumed that deterioration and failures are statistically independent of each other (Breneman, Sahay, and Lewis, 2022). However, the intricate connections among components of Ambient Intelligent Technologies (AmI-ATs) challenge this assumption. Degradation in one component can propagate through interconnected systems, amplifying its impact on overall reliability. To accurately model and understand these dependencies, MCMC methods can be utilised. MCMC enables the simulation of complex, high-dimensional probability distributions, capturing how degradation in one component influences the likelihood of failures in others. For

example, when degradation rates increase due to factors such as environmental stressors or component ageing, MCMC simulations can quantify the cascading effects on system reliability.

The results illustrated Figure 5-1 demonstrate that higher degradation rates result in a sharper decline in the system's reliability curve, indicating not only a reduced probability of recovery but also an accelerated timeline to system failure. This aligns with empirical observations, where degraded components in AmI-ATs such as sensors or communication modules introduce errors that compromise system-wide performance. Furthermore, increased degradation impacts the redundancy mechanisms of AmI-ATs, leading to a reduced ability to adapt to failures dynamically. By integrating degradation impacts into reliability analysis through MCMC simulations, more robust predictive models can be developed, enabling better design and maintenance strategies for AmI-AT systems, particularly in critical applications like healthcare and elderly monitoring.

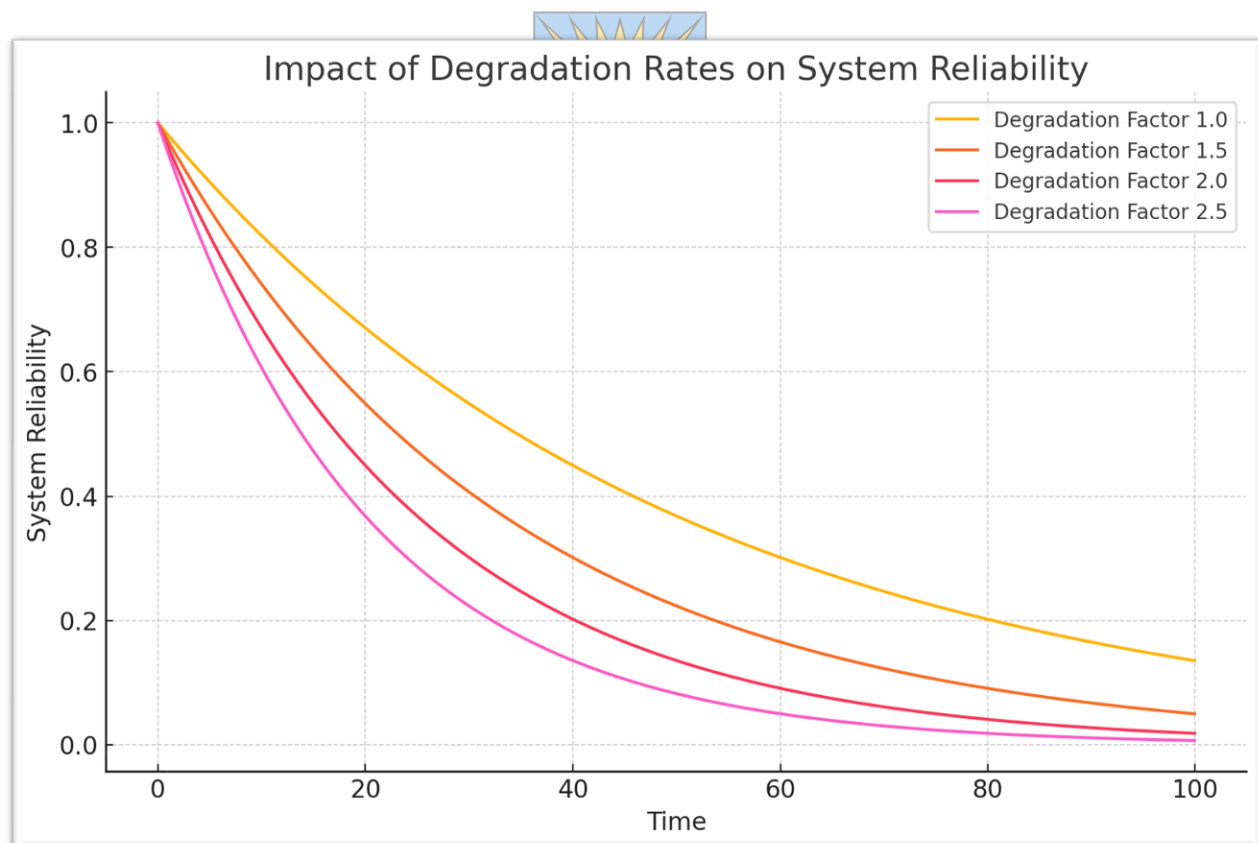


Figure 5.1: Impact of Degradation on AmI-AT Reliability

The system reliability naturally decreases over time due to normal wear and tear. The baseline reliability is denoted by a degradation factor of 1.0. As the degradation factor increases, the reliability drops, illustrating that the deterioration of an AmI-AT system can quickly lead to a non-recoverable state, prompting for the repair or replacement, as shown in Figure 5-1. Although AmI-ATs are said to have a long lifespan, the need for upgrades, maintenance, repairs, or replacements can affect overall system reliability (Bao et al, 2021).

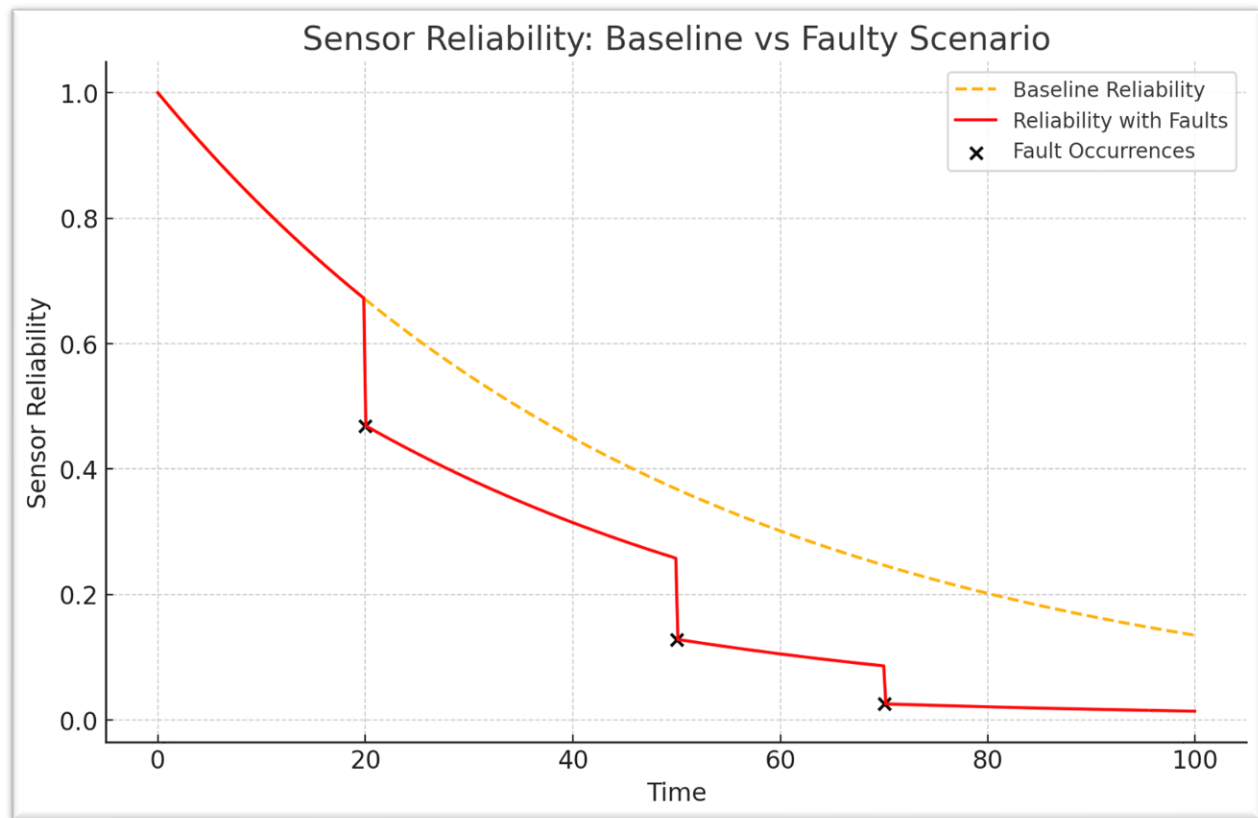


Figure 5.2: Baseline vs Faulty Components

Since AmI-ATs are made up of multiple components, the failure of a component can result in transition from one state to another, or in a degraded performance, once a component goes bad, it can be flagged for repair, or maintenance. Ideally, each cycle of upgrades or maintenance should restore the AmI-AT system to a good as new state. However, not all maintenance routines yield perfect results, and the overall system reliability can be illustrated in a graph. Chiacchio et al, (2020)

indicated that if the maintenance is executed properly and within the expected time frame, the reliability decline for each renewal cycle remains consistent, as each cycle effectively restores -the system to an equivalent condition. Figure 5-2 shows the simulated impact of component failure on overall reliability as benchmarked against the baseline reliability.

Figure 5-2 shows an optimized energy efficiency for the same system. Energy efficiency and reliability are intrinsically linked in systems reliant on sensor technologies, particularly in Ambient Intelligent Technologies (AmI-AT). The interplay between these factors becomes more apparent when considering how energy optimization strategies can mitigate the degradation of sensor performance over time. By leveraging Monte Carlo Markov Chain (MCMC) modelling, we can analyse and predict the impact of these strategies on system reliability, providing a structured approach to addressing the challenges of sensor longevity and performance.

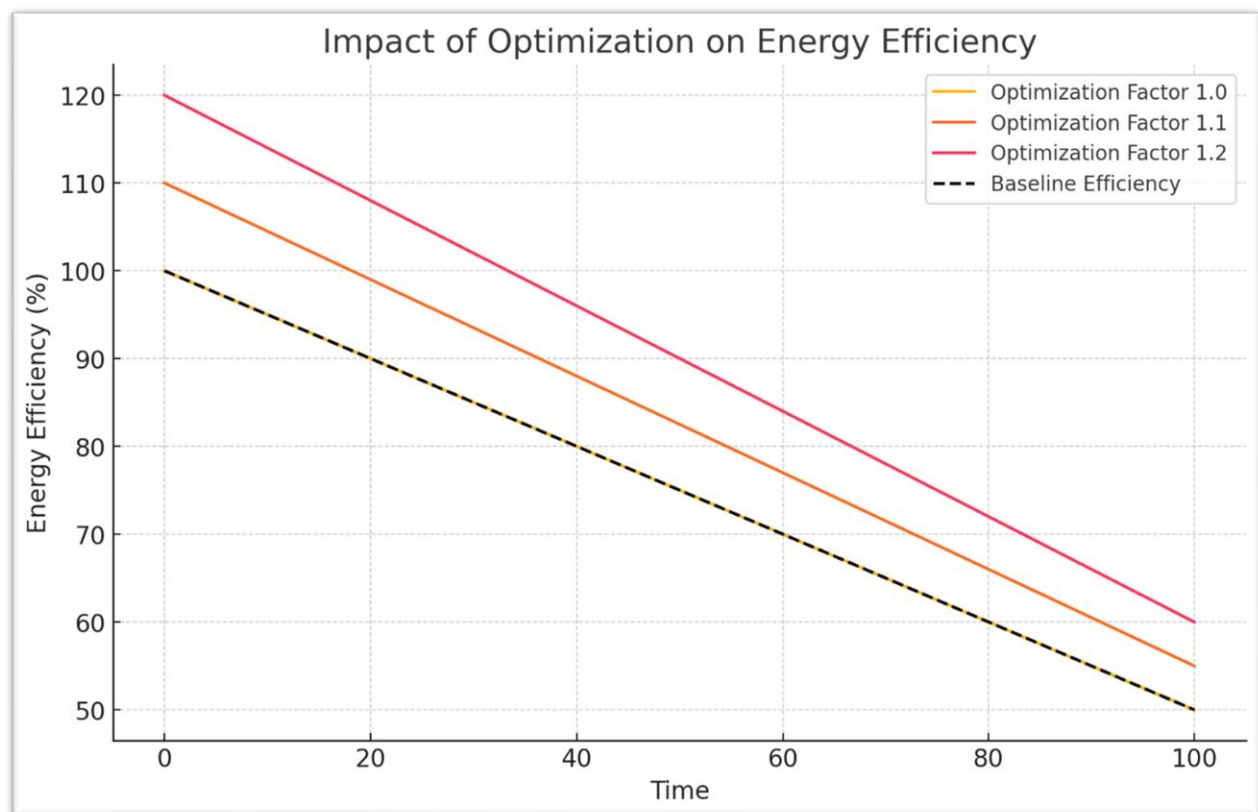


Figure 5.3: Energy Efficiency Optimization

Monte Carlo Markov Chain (MCMC) simulations provide a robust framework for analyzing how energy efficiency impacts system reliability. In the baseline scenario, where no optimizations are applied, MCMC models depict a steady decay in reliability over time. This decay corresponds to increasing degradation rates, driven by energy depletion and other environmental factors. When energy optimization strategies are introduced, the reliability trajectories modelled by MCMC shift significantly.

For instance, optimization factors of 1.1 and 1.2, representing incremental improvements in energy efficiency, can slow the rate of reliability decay. This effect is modelled in MCMC by adjusting the transition probabilities between reliability states. In optimized scenarios, the likelihood of transitioning to lower-reliability states is reduced, effectively extending the system's high-reliability phase. The MCMC reliability chains for optimized systems illustrate this prolonged stability. With higher optimization factors, the chains stabilize at higher reliability values, demonstrating a reduced impact of degradation rates on the system. This insight underscores the importance of energy optimization in maintaining system performance over extended periods.

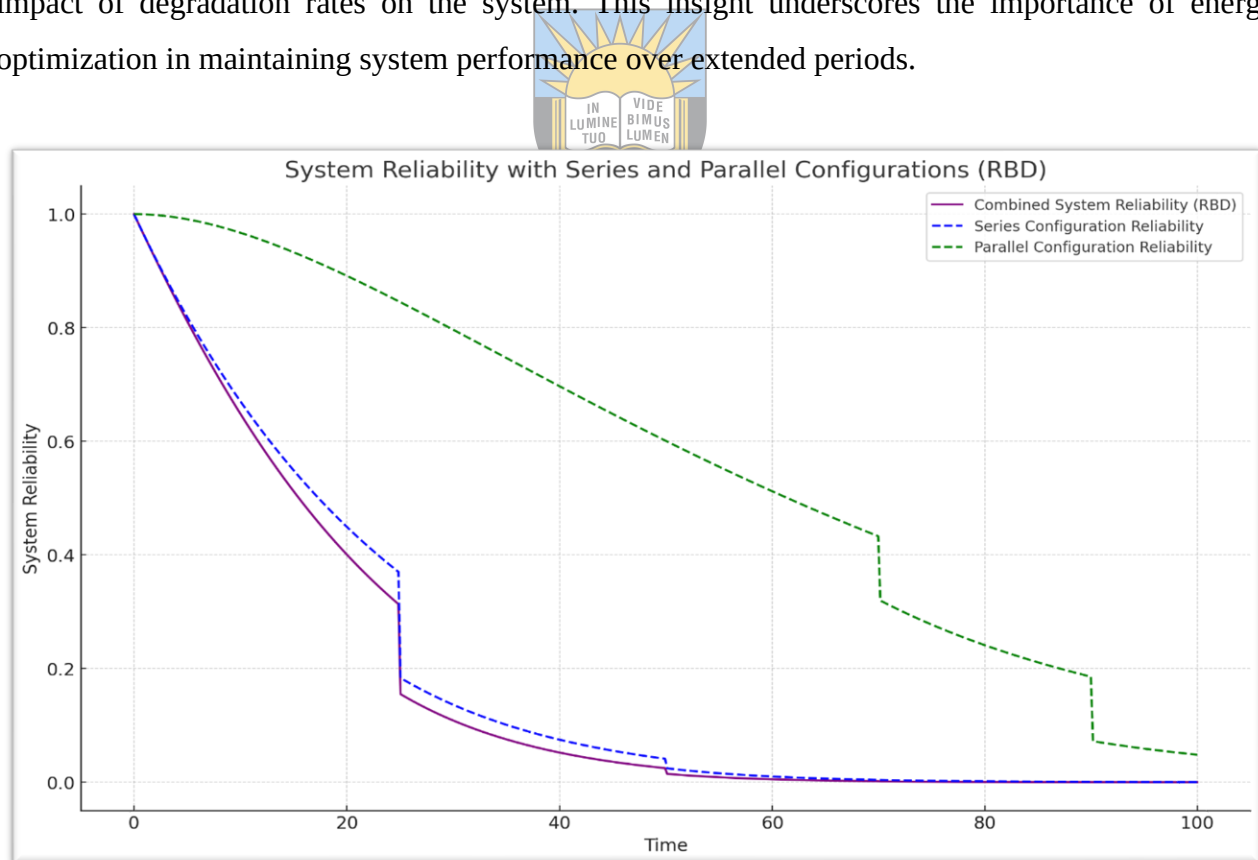


Figure 5.4: System Reliability with Series and Parallel Components

In a series configuration, all components must function correctly for the system to operate. This makes such configurations highly sensitive to individual component failures. In the context of the AmI-AT system. Typically, faults in critical components immediately degrade the AmI-AT system into a failed state. For instance, critical component failures such as power outages and network failures are modelled as critical dependencies. If either of these fails, the system experiences a total reliability drop. This scenario reflects real-world AmI-AT systems where power and network infrastructure are foundational to system performance, and even more critical in rural settings where electricity supply and connectivity are erratic. Series configurations exhibit rapid reliability decay because the system's overall reliability is the product of the reliabilities of its components. As observed, the series configuration reliability declines steeply, emphasizing the vulnerability of critical, sequential dependencies.



In a parallel configuration, only one component in the setup needs to function for the system to remain operational. This provides a buffer against failures and enhances resilience. Using the AmI-AT framework, components such as sensor fault and environmental stress are modelled as parallel components. Disruptions in these parallel systems represent scenarios where redundancy or alternative pathways can mitigate the impact of individual failures. The reliability of the parallel configuration decays more slowly compared to the series configuration, as shown in Figure 5-4. This demonstrates the robustness provided by redundancy, as the system can compensate for individual failures through alternative functioning components.

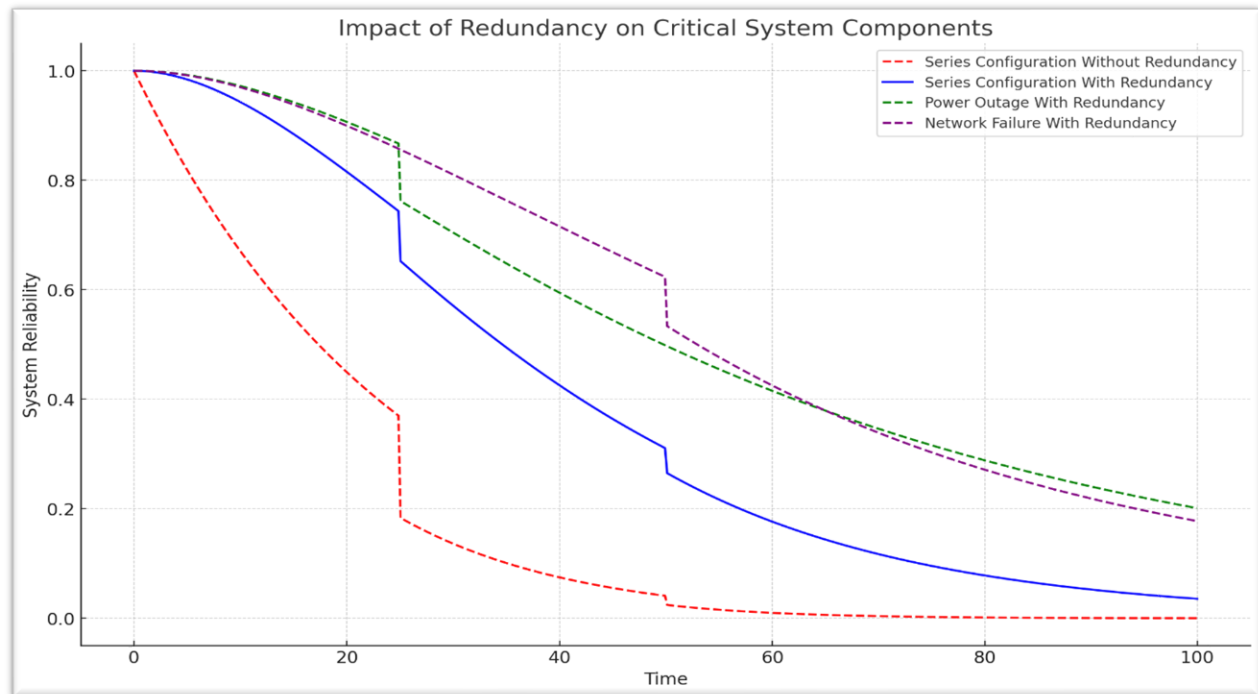


Figure 5.5: Redundancy in Critical Components



Critical system components often determine the overall reliability of a system, particularly when they are arranged in a series configuration. In such setups, the failure of a single component can result in a complete system failure. To address this vulnerability, redundancy can be introduced, allowing backup systems to support primary components and enhance system resilience. This analysis examines the impact of redundancy on two critical components: "Power Outage" and "Network Failure," modelled in a series configuration. In the absence of redundancy, the series configuration of power outage and network failure shows rapid reliability decay. As each component in a series must function for the system to operate, the overall system reliability is the product of the reliabilities of its components.

Consequently, even a moderate reliability declines in either component results in significant system vulnerability. This highlights the critical nature of these dependencies and the need for robust fault mitigation strategies. Redundancy involves introducing backup systems that can take over when primary components fail, effectively creating a parallel configuration at the component level. This significantly improves system reliability by providing alternative pathways to sustain operations.

However, introducing redundancy can adversely affect the cost of acquiring and maintaining the Ami-AT system. The development of Ami-AT monitoring systems or tools must put various considerations in place for it to satisfy its core objective of providing effortless, intelligent, and reliable monitoring. Such considerations must accommodate a range of characteristics that the system or tool is designed to monitor.

According to Schweitzer, (2024), before any Ami-AT monitoring system is developed, it is crucial to identify the targeted audience(s) and market(s) for which the tool is meant, together with a list of possible caregivers and/or guardians who are responsible for the entities being monitored by the tool. The concept of Ami-ATs is relatively new in the technology market, and very little research has been conducted thus far. This is particularly notable because of ideology of the term AmI, which makes it the centre of attraction that articulates the direction to which built Ami-AT systems should adhere, follow or concentrate on for its functional design. The framework developed in this research study is also an addition to this field of Ami-ATs, which has not existed prior. Thus, based on that analogy, one of the major building blocks and requirements of the Ami-ATs reliability framework for monitoring systems, was to outline clear technical considerations and awareness for developmental purposes. This approach assisted with paving a clear understanding of the technocratic infrastructure, that is hardware, software, network, telecommunication and services, that are suitable for the framework implementation.

5.4 Reliability Factors for Ami-AT

Ami-ATs are part of the IoT system, and the IoT is a very complex system. As such, it is difficult to determine the analytical solution for a complex system's reliability. This section describes how this study attempts to solve the challenge of evaluating reliability in Ami-ATs. Different reliability metrics exist to measure and evaluate the reliability of systems, which are important for monitoring reliability growth, performing risk analysis, and decreasing warranty costs. In this context, reliability metrics assess the degree to which an AmI product consistently performs its intended function without failure, meaning it assesses the probability of AmI device or system failure or the rate at which data errors will occur.

Hence, reliability metrics are imperative for estimating reliability since they provide quantitative indicators for reliability management, evaluation and validation, trade-off among cost, schedule, and reliability, monitoring testing process as well as interpretation of reliability behaviour. In order to estimate reliability, its metrics may derive either from the failure occurrence expressions or from the expected outcome metrics. This study proposes eight metrics as expected outcomes for reliability in AmI's based on studies conducted by other researchers. The metrics are defined as follows and shown in Figure 5-6:

- **Accuracy:** The AmI-AT should ensure the provision of the quality and state of being correct or precise with the monitoring information feedback given to the users and/or caregivers.
- **Authenticity:** The AmI-AT should guarantee that the information provided to the users and/or caregivers is genuinely authentic and realistic, for them to take actions and informed decisions pertaining to alerts.
- **Consistency:** The AmI-AT should maintain a consistent monitoring and reporting behaviour, that is logical with no contradiction, in an easily understandable alerting format. Consistency is denoted based on the context of observation.
- **Integrity:** Similarly, to consistency, the AmI-AT should make provision of the quality and fidelity of being a faithful and dependable monitoring platform, unfailingly reliable.
- **Dependable:** The AmI-AT should be trustworthy and ubiquitously available, in real-time, asynchronously and synchronously, and detail-oriented towards the monitoring services and reporting it is meant to provide. A dependable system will have high reliance and, subsequently high reliability.
- **Predictable:** The AmI-AT should behave in a manner in which the correct predictions and conclusions can be made, and it should always behave or occur in an expected way when functionality is put to the test.
- **Responsible:** The AmI-AT should have an obligation to undertake accountable control over the monitoring and alerting being conducted, in order to provide a sense of care for someone or something.
- **Trustworthy:** The AmI-AT functionality should be able to be relied on and be regarded as an honest and truthful monitoring tool, system, or platform based on the results it provides.

- **Validity:** The AmI-AT should have the capability of being logically and factually sound by providing valid, trustable, and usable information deduced from the monitoring alerts generated.
- **Maintainability:** The AmI-AT system must facilitate easy decoupling and seamless fixing and modification without causing obstructions in the AmI-AT system. The AmI-AT must allow for the replacement of hardware and upgrading of software components without loss of service. Typically, AmI-AT component should have less maintainability demands, thereby making the system highly maintainable.
- **Availability:** Availability defines the probability that a system and or its components maintain an operational state, fulfilling its purpose at a specific point in time. Availability is critical in AmI-ATs, both at system level and component level.

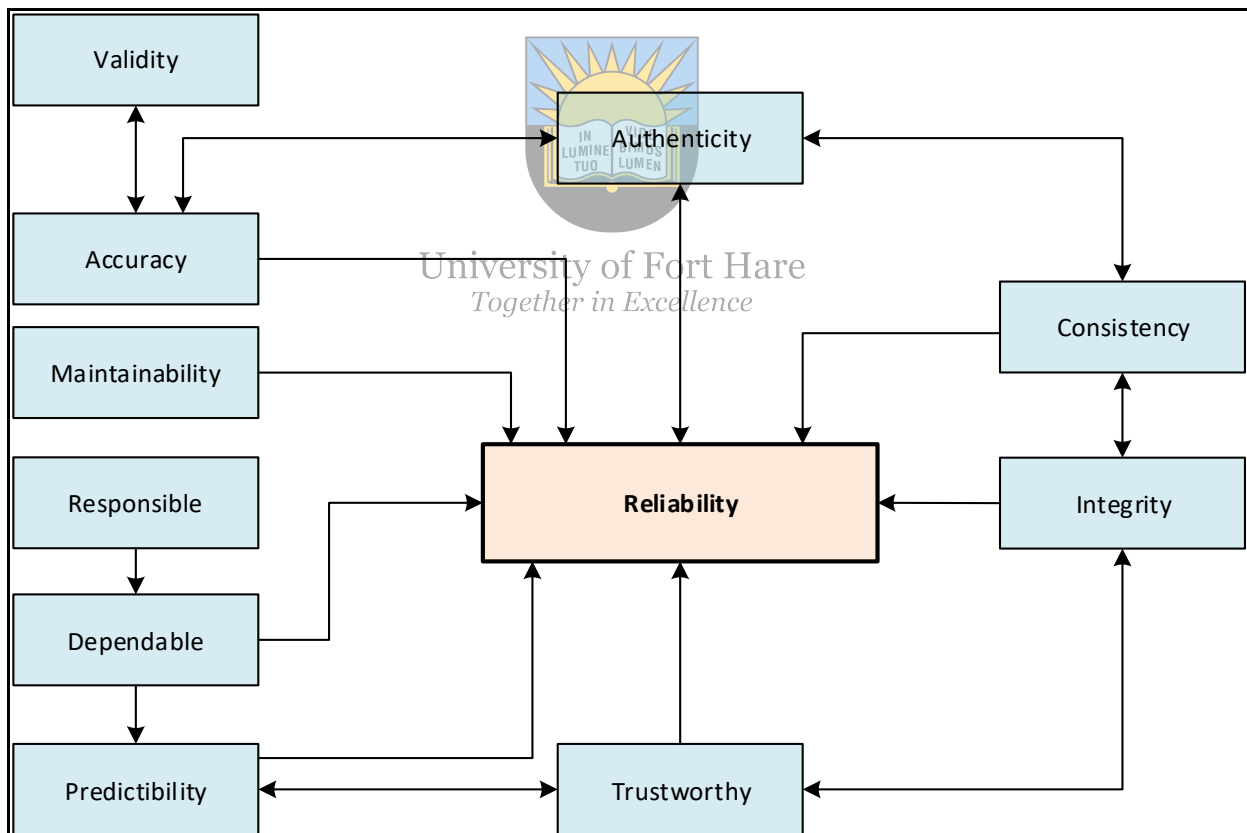


Figure 5.6: Reliability Metrics

These measurement properties are used as the overarching requirements that an AmI-AT should follow and adhere to in order for reliability to be confirmed. This, therefore, means that, they become the standard parameters that the framework employs when evaluation is conducted, for any AmI-AT, especially from a users' perspective. This is also a fundamental basis for consideration and a blueprint for designers and developers of AmI-ATs, from conceptual to production. The outlined set of measurement properties are established for use as a standard operational criterion for determining the reliability of AmI-ATs for evaluation purposes. This is meant to instill reliability-trust especially associated with tool selection by users and caregivers, and on the side of designers and developers for consideration when building AmI-ATs for monitoring purposes.

In addition, these measurement properties, outlined in the matrix, are individually summatively explained in terms of their respective responsibilities, as far as the AmI-ATs are concerned. Such explanations are constituted as reliability requirements, which an AmI-AT must conform to, for it to be considered reliable. Furthermore, it is also important to note as well that, as these measurement properties are labelled as overall and overarching requirements, they also have sub-interdependency characteristics, which further elaborate each of them individually based on their attributes.

5.5 Rationale of Selected of Case Studies

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This section presented the rationale of selected case studies towards the framework formulation. Two case studies were considered to enable the framework development as presented in this study.

Case Study 1: Continuous Glucose Monitoring (CGM):

Rationale for Selection

The Continuous Glucose Monitoring (CGM) system was selected as a case study due to its critical role in healthcare, particularly for diabetes management. In rural settings, where access to medical facilities is limited, CGM systems offer real-time glucose level tracking and enable timely interventions. However, the reliability of these systems is paramount since sensor failures or anomalies can lead to inaccurate readings, delayed responses, or incorrect treatments. This aligns with the study's objective to evaluate reliability in Ambient Intelligence Assistive Technologies (AmI-ATs), especially in resource-constrained environments.

Case Study Setup

The CGM case study integrates the following framework components:

1. **Sensing Layer:** Continuous glucose sensors monitor blood glucose levels and transmit data to processing units.
2. **Data Transmission Layer:** Wireless communication modules transfer sensor data to central processing systems.
3. **Processing Layer:** Algorithms process glucose readings, detect anomalies, and ensure data consistency.
4. **Application Layer:** Provides healthcare practitioners and caregivers with actionable insights via a user-friendly interface.

Real-world and synthetic datasets were used, containing glucose readings and failure data. The analysis focused on anomaly detection, state transitions, and reliability modelling under various operational conditions.



State Transition Heatmap

The state transition Heatmap visualises probabilities of transitions between system states:

- **Normal State:** Stable glucose readings within the ideal range (70–180 mg/dL).
- **Degraded State:** Indicating readings nearing critical thresholds.
- **Recovered State:** Successful return to normal operation after intervention.
- **Failed State:** Absorbing state, highlighting unrecoverable system failures.

Framework Component Evaluation via Heatmap

1. **Recovery Mechanisms:** Demonstrates system resilience and effectiveness of recalibration or manual intervention in transitioning back to normal.
2. **Anomaly Detection:** Highlights patterns and critical thresholds requiring prompt action.

3. **Reliability Assessment:** Tracks transitions to and from the failed state, aiding in identifying areas needing design improvements.

Framework Components and Results

1. **Sensing Layer:** The sensors were evaluated for failure rates and response times. The heatmap indicated that frequent transitions to degraded states necessitate enhanced sensor accuracy.
2. **Data Transmission Layer:** Reliability was assessed based on successful data transfers. Wireless module failures impacted overall reliability, suggesting redundancy strategies.
3. **Processing Layer:** Algorithmic anomalies and data calibration issues were identified as key reliability challenges.
4. **Application Layer:** User interaction data highlighted the importance of intuitive interfaces for rapid anomaly resolution.



Key Findings and Implications

1. **Dominant State Transitions:** High normal-to-normal transition probabilities indicated system stability.
2. **Recovery Rates:** Approximately 24.33% of degraded states transitioned to recovery, showcasing system resilience. However, failed states had low recovery rates (5.31%), emphasising the need for robust failure prevention strategies.
3. **Cumulative Failure Analysis:** Periods with steeper failure rates correlated with environmental factors or user interactions.
4. **Probabilistic Reliability Assessment:** The Markov Chain Monte Carlo (MCMC) approach effectively modelled dynamic state transitions, supporting reliability predictions.

This case study demonstrates the framework's capacity to evaluate CGM systems' reliability comprehensively, emphasising critical areas for improvement and providing actionable insights for deployment in rural healthcare settings where this study's experience is drawn from.

Case Study 2: Heart Monitoring in Elderly Care:

Rationale for Heart Monitoring in Elderly Care

The inclusion of **Heart Monitoring in Elderly Care** as the second case study is strongly justified within the context of the thesis, as it addresses critical gaps in healthcare for aging populations, particularly in resource-constrained environments like rural areas of developing countries. The rationale aligns with the thesis's goals of assessing the reliability of Ambient Intelligence Assistive Technologies (AmI-ATs) in healthcare monitoring systems. Some of the key reasons are as follows:

Alignment with Thesis Objectives

1. Healthcare Monitoring Focus:

- The thesis aims to evaluate AmI-AT reliability in healthcare applications. Heart monitoring is a vital use case because it directly impacts the safety and well-being of elderly individuals, a demographic often vulnerable to cardiac conditions. This is very common in the context and environment where this study is undertaken from.

2. Elderly Care Challenges:

- Elderly individuals often face challenges such as limited mobility, reduced access to healthcare services, and increased risk of cardiac issues. Reliable heart monitoring systems can bridge the gap by enabling continuous, non-invasive, and real-time health tracking, thus aligning with the thesis's focus on providing dependable monitoring systems.

3. Critical Need for Reliability:

- For elderly care, the consequences of system failures are significant, as missed or inaccurate data can lead to delayed interventions during cardiac emergencies. This reinforces the need for a robust framework to assess and ensure system reliability.

Relevance to Developing Countries:

1. Resource Constraints:

- Many elderly care facilities in developing countries lack advanced monitoring systems. Heart monitoring technologies, such as wearable ECG devices, can fill this gap, provided their reliability is validated.

2. Impact on Public Health:

- Heart diseases are among the leading causes of death globally, with developing countries disproportionately affected. Reliable heart monitoring can help reduce mortality rates by enabling early detection and intervention.

3. Use Case Variety:

- Including heart monitoring as a second case study provides a broader perspective on the framework's applicability across diverse healthcare technologies, enhancing its generalisability and relevance.

Integration with the Framework:

The heart monitoring case study evaluates all framework components:

1. **Sensing Layer:** Continuous monitoring of heart rate and rhythm using wearable ECG devices.
2. **Data Transmission Layer:** Assessment of data integrity and latency during wireless communication to processing systems.
3. **Processing Layer:** Evaluation of algorithms for anomaly detection (e.g., arrhythmias or bradycardia) and reliability under dynamic conditions.
4. **Application Layer:** Insights into how caregivers and healthcare providers interact with the monitoring system to respond to alerts and trends.

Research and Practical Implications:

1. **Reliability Challenges:**



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- The study identifies specific challenges, such as sensor degradation, wireless connectivity interruptions, and data calibration errors, within the context of elderly care.

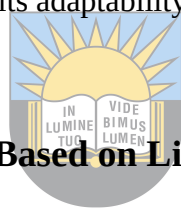
2. Design Improvements:

- Findings can guide the development of fault-tolerant heart monitoring systems, including redundancy strategies and enhanced algorithms.

3. Broader Impact:

- The study emphasises the need for scalable, reliable AmI-ATs tailored to aging populations, aligning with global trends in healthcare technology adoption.

This second case study complements the thesis by diversifying the application contexts of the reliability framework and demonstrating its adaptability to critical healthcare technologies.



5.6 Development Considerations Based on Literature

To enhance equipment reliability and lessen the effect of failures, reliability modelling is essential for determining data needs and information sources in the context of particular applications, such as surface mining equipment (Yazdi, 2024). Validation and sensitivity analysis are crucial methods for assessing the accuracy and reliability of models in a variety of domains, including biomechanical modelling, according to Viceconti et al, (2021). Furthermore, a generic framework for modelling reliability has been created that combines time-driven simulation with discrete-event simulation to offer a thorough method of modelling reliability (Chiacchio et al, 2020).

The development of the framework for evaluating the reliability of AmI-ATs as monitoring tools, systems or platforms for the selected target audiences in line with the targeted markets, followed a process of tabulating a set of requirements that were needed as the basic requirements for the framework. Such considerations were set as a necessity for the initial building blocks for the framework, because the AmI-AT's existence is based on solving monitoring challenges associated

with the amalgamated considerations outlined. This is because, before the reliability framework can be evaluated, an AmI-AT has an initial and core responsibility of monitoring a selected species or entity and thereby producing reporting alerts to the concerned guardians and/or caregivers.

Based on this standard responsibility, the AmI-AT can then be evaluated using the developed framework, then, results and conclusions can be drawn on whether it is reliable or not, from the way it handles monitoring and its subsequent reporting, and thereby guaranteeing the safety of the species or entity under surveillance. The design and developmental considerations integrated herein, in summary, form the basic building blocks and requirements formulation of the developed framework, as characteristics and components. Inclusively, then, they become the foundational AmI-ATs framework considerations. Figure 5.7 illustrates the design considerations, with the evaluation of the reliability of AmI-ATs as a key action measure.

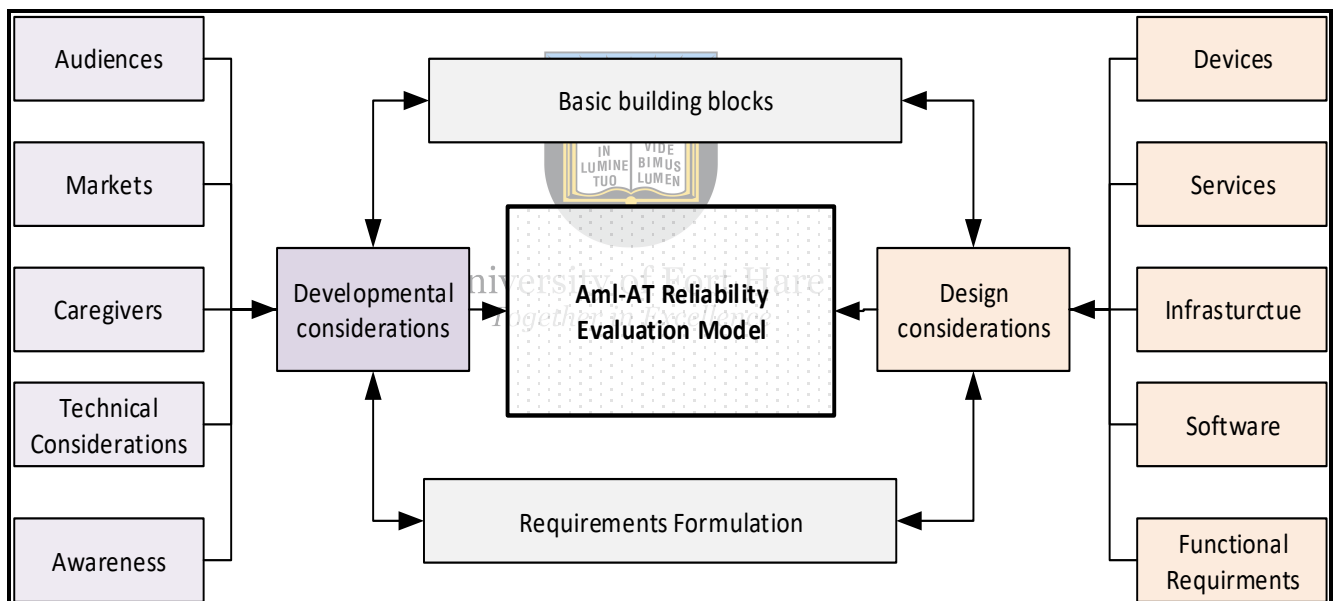


Figure 5.7: AmI-ATs Foundational Framework Considerations

To the best of knowledge, at the time of writing, the framework developed in this study is a novel knowledge addition to the field of AmI-ATs. As such, one of the major building blocks and requirements of the AmI-ATs reliability framework, was to outline technical considerations and awareness for developmental purposes. This approach assisted with paving a clear understanding of the technocratic infrastructure, that is, hardware, software, network, telecommunication, and services, that are suitable for the framework implementation.

5.7 The AmI-AT Reliability Architecture

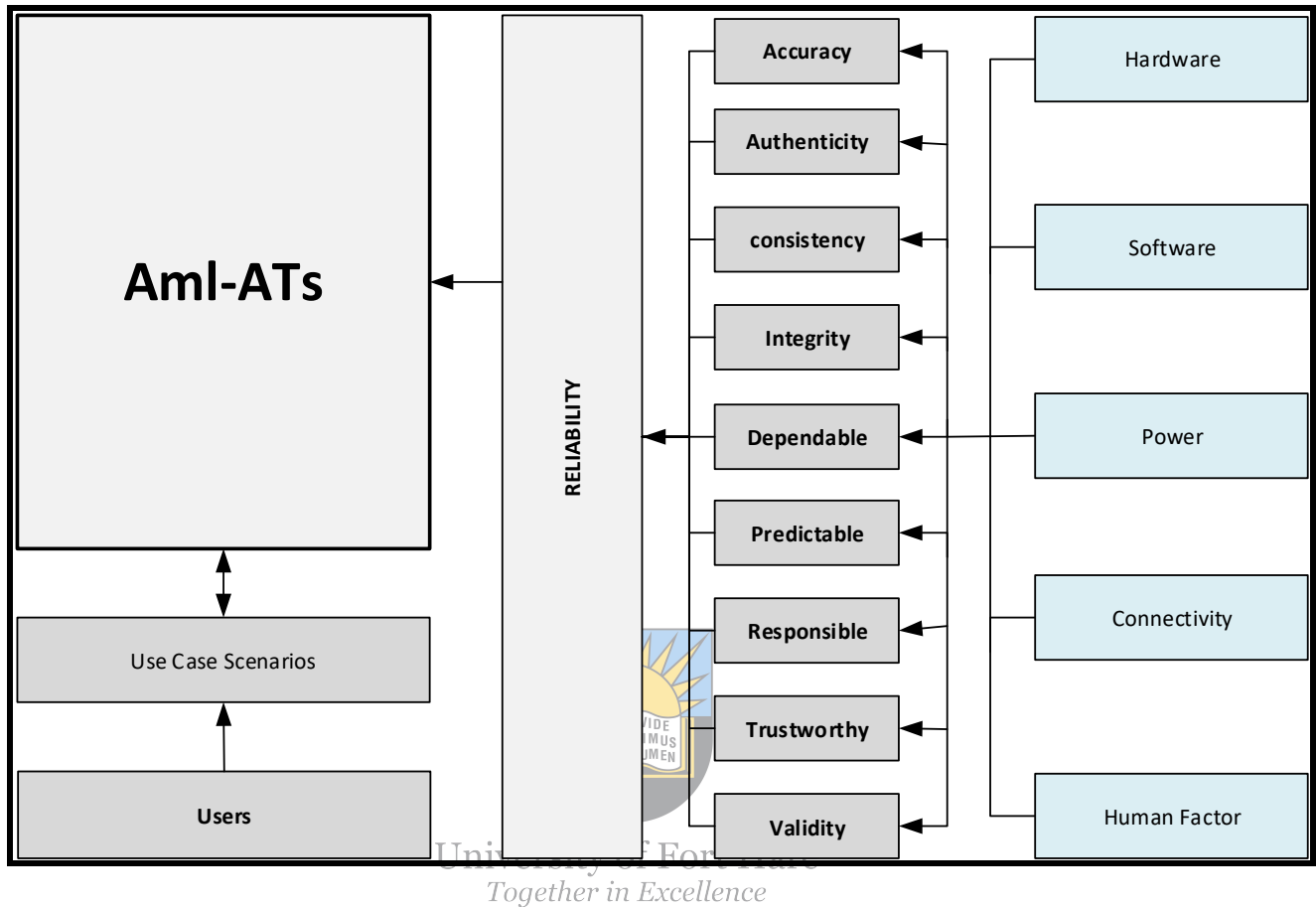


Figure 5.8: The AmI-AT Reliability Architecture

The objective of this framework is to provide practical methods for assessing the dependability of IoT components. Dependability parameters encompass characteristics, requirements, and measurable factors that define the dependability of an IoT application (Moore et al, 2020; Minani, Sabir, Moha & Guéhéneuc, 2024). Evaluating these components lays the groundwork for selecting the right elements to avoid critical failures during application operation. It is essential to test the validity of these components using the dependability assessment framework.

5.8 Conceptual Reliability Framework Process

Having considered all the available and related secondary data and the feedback from the case studies, the framework development then followed a key process. The following logical reasoning and

deductive analysis of the reliability requirements of an AmI-AT system, the roadmap for implementing the AmI-AT reliability framework on a target AmI-AT system is depicted in the figure 5-9. The framework implementation makes it possible to analyse and estimate dependability using the suggested Markov approaches. The framework uses a bottom-up methodology to evaluate the entire system's reliability. Figure 5-9 shows how the bottom-up method is used in the suggested framework to guarantee scalability.

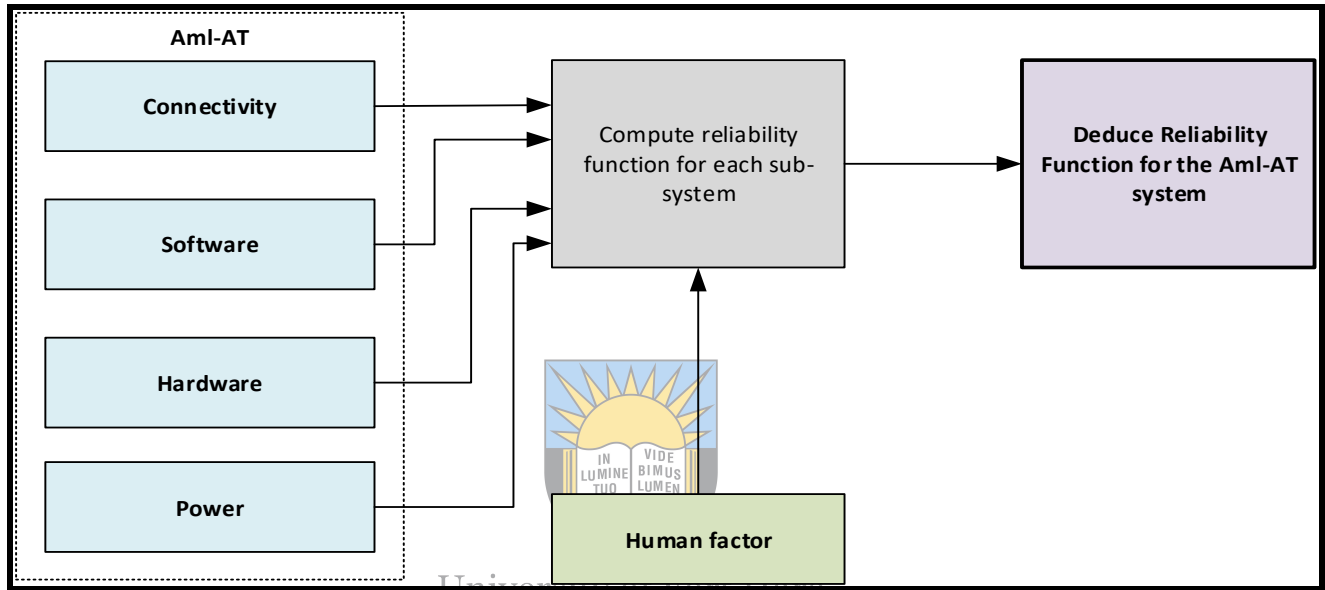


Figure 5.9: Framework Implementation

The availability of certain core parts and features of an AmI-AT, such as power and software services, and connectivity greatly influence its reliability. These core components can function in series or parallel configuration, and their individual operational state as sub-systems, determine the overall reliability of an AmI-AT system.

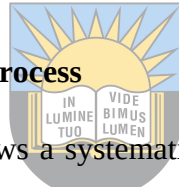
The framework emphasizes a bottom-up approach to reliability evaluation, structured into distinct layers as shown in Figure 5-9. At the foundational level are the subsystems, which include critical individual components such as sensors, actuators, power sources, and connectivity modules. These elements form the building blocks of the AmI-AT system. Moving upwards, the next layer involves intermediate integration, where the reliability of various subsystems is combined to assess the performance of larger functional modules. At the highest level, the system-wide reliability is derived

from the collective evaluations of all modules, providing a holistic view of the AmI-AT's dependability.

In addition to component layering, the framework application process highlights the core component dependencies, focusing on the interplay between power services, software services, and connectivity. These components are pivotal in ensuring the seamless operation of AmI-AT systems. The framework implementation also includes the reliability computation component which incorporates the MCMC models to analyse the probabilistic and dynamic nature of AmI-AT systems allowing for a comprehensive reliability estimation based on real-world usage scenarios. The implementation process is prescribed as guide since different AmI-ATs might have differing configurations, it is crucial to refer to the conceptual framework for modelling seemingly complex assistive devices and systems.

The overall framework development process is presented as follows:

Reliability Framework Development Process



The formulation of the framework follows a systematic process based on the methods outlined in Chapter 4. The process was guided by the DSR. This section provides is a step-by-step outline of how the framework was developed, incorporating key elements from the research methodology and integrating reliability assessment simulation tools.

1. Identifying Framework Objectives:

- **Objective:** To develop a comprehensive framework for evaluating the reliability of AmI-based health monitoring technologies
- **Approach:** Insights from the literature review highlighted gaps in current reliability assessments for AmI-ATs, especially in constrained environments like rural healthcare. The need for a standardised, adaptable, and practical reliability framework was established.

2. Literature-Driven Design:

- **Review of Existing Techniques:**

- Reliability Block Diagrams (RBDs) and Fault Tree Analysis (FTA) were evaluated for their ability to model component interactions and failure mode.
- Markov Chain Monte Carlo (MCMC) methods were identified as ideal for capturing dynamic, probabilistic behaviour in multi-component systems.
- **Key Design Principles:**
 - Incorporate hardware, software, and human factors.
 - Ensure flexibility for diverse AmI-AT configurations.
 - Address environmental and operational constraints

3. Layered Framework Architecture:

- **Components:**

- **System Components Layer:** Hardware (e.g., sensors), software, and communication systems form the core reliability computation units.
- **Input Layer:** Data sources, scenario modelling and simulation parameters.
- **Contextual Layer:** Environmental and operational constraints, including human factors.
- **Management Layer:** Reliability metrics, probabilistic modelling, and assessment components.

4. Mathematical Modelling:

- **MCMC Simulations:**

- Used to simulate state transitions (like operational, degraded, failed) in multi-component systems.
- Transition matrices captured the probabilities of moving between states over time.

- **RBD Integration:**

- Modelled system reliability in series and parallel configurations to evaluate the impact of redundancy and critical failures.

5. Framework Implementation:

- **Bottom-Up Approach:**

- Begin with subsystem evaluations (e.g., individual sensor reliability).
- Integrate results into higher-level modules to derive system-wide reliability.
- Probabilistic methods were applied to capture dynamic and interdependent behaviours.

6. Evaluation and Validation:

- **Use Cases:**

- Continuous Glucose Monitoring (CGM) and Heart Rate Monitoring in Elderly Care were used to validate the framework.
- These cases demonstrated the framework's ability to model reliability under real-world constraints.



- **Results:**

- Generated state transition Heatmap and reliability curves to visualise performance over time.
- Identified failure probabilities and the effectiveness of redundancy strategies.

7. Reliability Framework Process:

The framework process integrates the above steps into a cohesive workflow:

1. **Define Objectives:** Identify system goals and reliability requirements.
2. **Component Analysis:** Evaluate individual hardware, software, and environmental factors.
3. **Simulation Setup:** Model system behaviours using MCMC and RBD techniques.

4. **Data Collection:** Use real-world or synthetic datasets from two case studies for framework components formulation and validation.
5. **Evaluation:** Analyse results to assess system reliability and identify critical weaknesses.
6. **Iterate:** Refine framework components based on findings to enhance robustness.

This structured process ensures the framework is both theoretically grounded and practically applicable, addressing the unique challenges of AmI-ATs in constrained environments.

5.9 Conceptual Reliability Framework

Discussions from the literature survey and methodological studies informed the formulation of the conceptual framework. This section presents the framework and provides the description of the framework and its application.

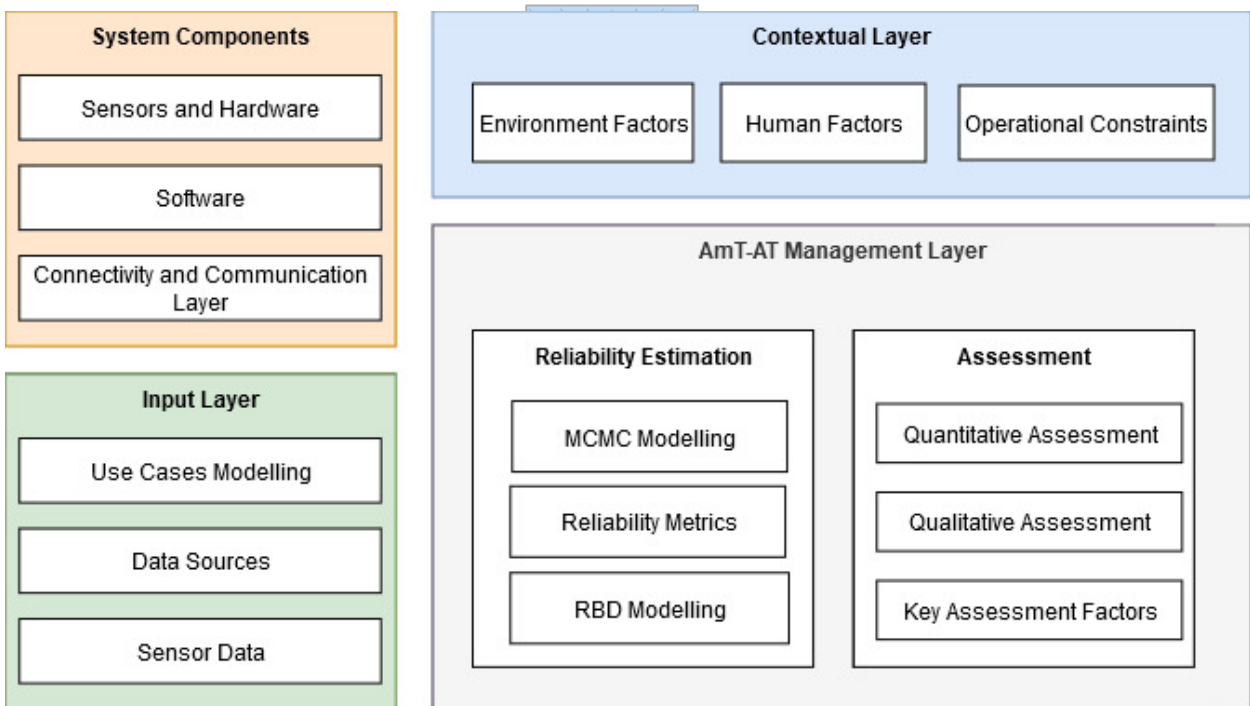


Figure 5.10: AmI-AT Reliability Framework

The conceptual framework comprises of system components, input layer, contextual layer and the AmI-AT management layer. The system components layer describes the internal components that

make up the AmI-AT devices. These components include but are not limited to, hardware, software and communication systems. These components make up the core reliability computation components. The input layer deals with data sources and scenario modelling. It should be noted that in AmI-AT setups, just like in any IoT setup, data does not only emanate directly from sensors and devices, but data is also deduced indirectly via observations and activity modelling. The contextual layer examines environmental factors that contribute to the functioning of the AmI-AT. It also includes human factors and operational constraints.

In addition, the human factor allows for the quantification and estimation of the impact of the human user on the reliability of the AmI-AT in use. Operation constraints help model the impact of unforeseen operation issues that can impact reliability of the AmI-AT. Lastly, the framework includes the AmI-AT management layer. This layer forms the core of the reliability estimation approach. The AmI-AT management layer consists of probabilistic modelling methods for state and reliability modelling and estimation. It also houses the reliability metrics and the RBD modelling approach. The Assessment component of the AmI-AT management layer allows for the assessment of the observations derived from the reliability estimation component. The assessment can be qualitative or quantitative depending on the keys assessment factors under observation. The construction of the framework allows for greater flexibility in implementation as illustrated in the following sections, particularly section 5.14 of this study.

5.10 Framework Discussion

The following sections provide the description, strengths and comparison of the framework with existing literature and other findings. The Ambient Intelligent Technologies Reliability Framework in this study was designed to address the multifaceted reliability challenges inherent in deploying AmI-AT systems for healthcare and elderly monitoring, especially in developing countries. Its strengths are evident in several key areas:

5.10.1 Comprehensive Data Acquisition and Preprocessing

The framework's data acquisition layer integrates various health-related sensors, such as Continuous Glucose Monitors (CGM) and heart rate monitors, ensuring a holistic collection of patient data. This comprehensive approach is crucial for accurate health monitoring and timely interventions. The

preprocessing layer enhances data quality by implementing noise reduction, standardization, and imputation techniques, which are essential for reliable analysis.

5.10.2 Advanced Reliability Modeling with MCMC Techniques

Incorporating Markov Chain Monte Carlo (MCMC) methods allows the framework to model complex, dynamic behaviours of AmI systems under uncertainty. MCMC techniques are particularly effective in healthcare monitoring applications, enabling robust predictions of system performance and reliability. For instance, Monte Carlo and Markov Chains methods have been applied to project cancer incidence and mortality, demonstrating their utility in health-related predictive modelling.

5.10.3 Context-Aware System Characterization

The framework identifies and maps critical functions of AmI devices to specific reliability requirements, considering environmental constraints and user needs. This context-aware approach ensures that the system is tailored to the unique challenges of developing countries, such as limited infrastructure and varying environmental conditions.

5.10.4 Quantitative and Qualitative Reliability Assessment

By combining quantitative metrics (for instance, failure rates, and response times) with qualitative insights (for instance, user feedback, and environmental challenges), the framework provides a comprehensive assessment of system reliability. This dual approach facilitates a deeper understanding of both technical performance and user experience, which is critical for successful implementation.

5.10.5 Adaptive Intervention Strategies

The framework offers actionable recommendations for improving reliability, including hardware enhancements, software optimizations, and user training. This adaptability ensures that the system can evolve in response to emerging challenges and user requirements, promoting long-term sustainability.

5.10.6 Scalability and Integration

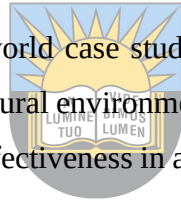
Designed for seamless integration into various healthcare ecosystems, the framework accommodates diverse devices and technologies, supporting scalability for larger networks. This flexibility is vital for expanding healthcare services in developing regions, where scalability can significantly impact service delivery.

5.10.7 Real-Time Reliability Reporting and Visualization

The inclusion of real-time dashboards and tailored reports enables stakeholders to monitor system performance continuously. This transparency fosters trust and facilitates proactive maintenance, which is essential for sustaining system reliability.

5.10.8 Validation Through Real-World Case Studies

The framework's validation using real-world case studies as presented in Chapter 6, such as heart monitoring and diabetes management in rural environments, ensures its practical applicability. These case studies highlight the framework's effectiveness in addressing specific challenges encountered in developing countries.



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5.10.9 Addressing Challenges in Developing Countries

The framework is particularly adept at tackling challenges prevalent in developing countries, such as limited resources, environmental variability, and technology adoption barriers. By leveraging advanced modelling techniques and user-centric designs, it provides solutions that are both effective and contextually appropriate.

5.10.10 Alignment with Current Research and Trends

The framework aligns with current research emphasizing the integration of AI and cyber-physical systems to achieve ambient intelligence. This alignment ensures that the framework remains relevant and incorporates the latest technological advancements. The study introduced a novel approach to addressing the multifaceted challenges of reliability in AmI-ATs by incorporating MCMC in probabilistic modelling of AmI-ATs' reliability. The study acknowledges the existence of some

approaches to solving similar problems. This section provides a comparative analysis of the conceptual framework with existing approaches, highlighting its distinct advantages, innovative features, and alignment with the unique demands of AmI-AT implementation in developing countries.

Table 5.1: Comparative Analysis

Feature	Existing Approaches	Proposed Framework
Probabilistic Modelling	Often, they rely on Monte Carlo methods or static models, which may not account for dependencies and long-term trends effectively.	Uses MCMC for dynamic modelling, enabling the analysis of complex interactions and contextual uncertainties.
Environmental Context	Designed primarily for urban settings with stable infrastructure.	Tailored for rural and resource-constrained environments in developing countries.
Reliability Metrics	Focuses on general metrics like Mean Time Between Failures (MTBF) or uptime without granular contextualisation.	Provides contextual reliability metrics based on environmental and usage-specific scenarios.
Case Study Integration	Limited application to real-world cases, often focused on hypothetical or idealised use cases.	Incorporates real-world case studies such as CGM and HR monitoring in rural healthcare environments.
Simulation Tools	Use single simulation techniques without addressing AmI-specific challenges.	Combines Monte Carlo simulations and MCMC to address AmI-specific reliability challenges.
Adaptability and Scalability	Limited scalability for diverse contexts or large-scale implementation.	Designed for scalability, allowing deployment across small-scale and large-scale healthcare systems.
Ease of Use for Stakeholders	Focuses on technical accuracy but lacks user-friendly tools for healthcare providers and policymakers.	Includes intuitive dashboards and visual reporting tools tailored to stakeholder needs.

5.11 Relevance of Findings to Broader AmI and IoT Fields

The findings from this study are greatly applicable and relevant to the broader fields of Ambient Intelligence (AmI) and the Internet of Things (IoT), as they address critical challenges in reliability, adaptability, and scalability. With the rapid expansion and adoption of AmI-AT systems across various domains, including healthcare, smart cities, and industrial automation, understanding reliability plays a pivotal role in ensuring the effectiveness and adoption of such technologies. The findings of the study can, by extrapolation, be applied to AmI-ATs and IoT environments. This section explores the implications of the framework's findings for the broader AmI and IoT landscapes.

5.11.1 Advancing Reliability Assessment in AmI and IoT

Reliability is a foundational attribute for any IoT or AmI system, especially in mission-critical applications like healthcare and elderly monitoring. The AmI-AT Reliability Framework addresses this gap by integrating probabilistic modelling techniques such as Monte Carlo and Markov Chain Monte Carlo (MCMC) simulations, which enable detailed predictions of system performance and failure probabilities. The framework's findings highlight the importance of context-aware reliability assessment, which considers environmental variability, resource constraints, and user-specific needs. These insights are broadly applicable to AmI and IoT systems, particularly in domains where systems operate in dynamic and unpredictable environments, such as agriculture, disaster response, and remote monitoring.

5.11.2 Enhancing Data Integrity and Preprocessing

In the broader IoT landscape, the reliability of data is a recurring challenge due to noise, missing values, and inconsistencies in sensor readings. The AmI-AT framework's robust preprocessing mechanisms, including noise reduction, data imputation, and standardization, set a precedent for data handling in AmI and IoT applications. By ensuring that decision-making processes are based on accurate and reliable data, these techniques can significantly enhance the quality of services provided by IoT systems across industries. For instance, in smart city applications, where data from heterogeneous sensors is aggregated for traffic management or environmental monitoring, adopting similar preprocessing strategies could improve the reliability and usability of real-time analytics.

5.11.3 Scalability and Modular Design for IoT Systems

Scalability is a critical consideration for IoT systems as they grow to encompass larger networks of devices and sensors. The modular architecture of the AmI-AT Reliability Framework, which allows for the seamless addition of new devices and adaptability to different contexts, provides a model for designing scalable IoT solutions. This design approach is particularly relevant for smart cities, industrial IoT, and large-scale environmental monitoring systems, where the ability to scale without compromising system reliability is essential. Furthermore, the framework's focus on hybrid data architectures that accommodate intermittent connectivity offers a solution to scalability challenges in remote or underserved regions.

5.11.4 Promoting Context-Aware and User-Centric Design

One of the key contributions of the AmI-AT Reliability Framework is its emphasis on context-aware and user-centric design. By tailoring system functionalities to specific user needs and environmental conditions, the framework ensures greater acceptance and usability of AmI systems. This approach has significant implications for IoT applications in domains like smart homes, wearables, and personalized healthcare, where user experience and contextual adaptation are critical to system success. For example, in personalized health monitoring systems, incorporating user feedback and adapting device functionality to individual health profiles could significantly enhance the adoption and effectiveness of such technologies. This study presents non- user involvement as one of the weaknesses of the framework. However, the inclusion of secondary data which contains key personal data even though without exact specific and identifiable features was sufficient to assist in understanding personal information.

5.11.5 Real-Time Reliability Monitoring and Predictive Maintenance

The framework's real-time reliability monitoring capabilities, supported by predictive alerts, have broad applicability in IoT domains requiring continuous system availability. Predictive maintenance, enabled by MCMC-based alerts, is particularly relevant for industrial IoT (IIoT) applications, where equipment downtime can lead to substantial operational losses. By proactively identifying potential failures, this approach can improve efficiency and reduce costs in industries such as manufacturing, logistics, and energy.

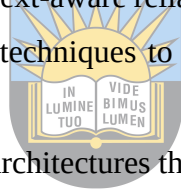
5.11.6 Addressing Challenges in Resource-Constrained Environments

The AmI-AT framework's focus on addressing challenges specific to developing countries, such as limited connectivity, energy constraints, and infrastructural limitations, aligns closely with the broader goal of democratizing IoT and AmI technologies. Solutions designed for such contexts have potential applications in global development initiatives, including rural healthcare, education, and agriculture. These insights can drive the creation of IoT systems that are not only reliable but also accessible and affordable for underserved populations.

5.11.7 Implications for Research and Development

The findings from the AmI-AT framework provide a strong foundation for advancing research in the AmI and IoT fields. They emphasize the need for:

- Developing probabilistic and context-aware reliability models for emerging IoT applications.
- Investing in data pre-processing techniques to enhance the accuracy and reliability of IoT analytics.
- Designing modular and scalable architectures that can adapt to evolving needs.



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These directions are critical for driving innovation and ensuring that IoT and AmI systems remain relevant and effective in diverse applications. The relevance of the AmI-AT Reliability Framework extends beyond healthcare and elderly monitoring to influence the broader AmI and IoT fields. By addressing critical challenges in reliability, scalability, and adaptability, the framework provides a blueprint for developing robust IoT and AmI systems capable of operating effectively in diverse environments. Its emphasis on probabilistic modelling, data integrity, and user-centric design has the potential to shape the future of IoT applications, ensuring that these technologies deliver on their promise of transforming industries and improving lives.

5.12 Chapter Summary

Following the methodological approach undertaken as a technique to formulate the required charter, focus was made on the design and development of the framework for evaluating the reliability of

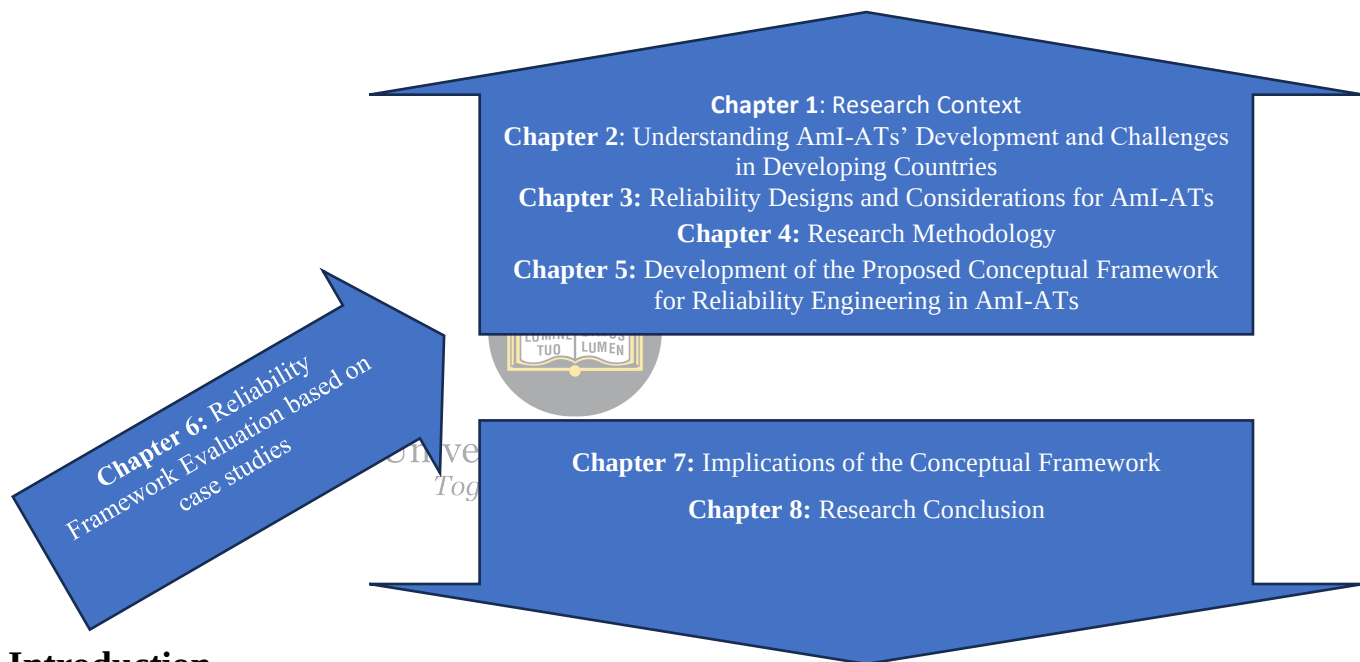
AmI-ATs as the fundamental key echelon of the research study. Such a focus had to put a number of considerations into perspective and amalgamate them into one, as a means of shaping the required framework. This was achieved by putting together the basic and necessary design considerations, such as devices, infrastructure, services, applications, functional requirements and designers' classifications. All of these were particularly important to consider because they are the foundational and most basic building blocks of AmI-ATs and thus are a required consideration for the framework as such.

As part of the bigger umbrella of AmI-ATs existence and, most importantly, in line with the developed framework, it was important to discuss security issues pertaining to the platforms in line with the audience and the defined set of users. This was an important matter to consider and address due to the sensitivity of connecting users, which are humans, and technology as the product, and reliability would be evaluated via the framework. This led to the establishment of a reliability matrix, which has its own set of measurement properties and requirements. The amalgamation of all such considerations resulted in the formulation of the framework in question, which took two modules into account and thereby labelling them as selected audiences as test cases due to the similarities they possess from a monitoring requirement perspective. The framework considerations made in this regard stemmed from a framework for evaluation of the reliability of AmI-ATs, which was subsequently followed by a summative classification and description of the end product. The procedures outlined in the framework are crucial elements needed to evaluate an IoT application's dependability in order to create a reliable application.

Hence the next chapter validates the framework through experimental and numerical analysis. Using case studies on glucose and heart rate monitoring, it evaluates system reliability, anomaly detection, and performance challenges as well as providing insights into the practical application of the framework. The chapter also presents the main themes that emerged from the literature.

Chapter 6 : Reliability Framework Evaluation based on Case Studies

This chapter validates the proposed framework through experimental and numerical analysis. Using case studies on glucose and heart rate monitoring, it evaluates system reliability, anomaly detection, and performance challenges. The results are discussed in detail, providing insights into the practical application of the framework. The chapter also presents the Main themes that emerges from the literature



6.1 Introduction

One of the main objectives of this study was to validate the framework using selected case studies of AmI-based health monitoring technologies towards drawing up the framework. In Chapter 4 the methodology was presented to determine the factors influencing reliability of AmI-AT devices, subsequently leading to the development of the conceptual reliability framework. Discussions of the literature pointed out further knowledge gaps that make it difficult to determine if AmI-AT devices are reliable or functioning properly, especially when it comes to binary state change sensors. This chapter presents case studies applied to ascertain the anomalous behaviour of AmI-AT devices, which could lead to a degradation in reliability. Hence this chapter aims to address the last objective by validating the framework using the case studies of AmI.

6.2 Case Studies Context

The literature survey presented in Chapter 3 highlights how Ambient Intelligent (AmI) systems can transform healthcare and expand the quality of life for elderly and physically challenged individuals, especially in rural areas where access to medical facilities and trained personnel is limited. By incorporating advanced devices such as Continuous Glucose Monitoring (CGM) systems and Heart Rate (HR) monitors into everyday environments, AmI systems enable real-time health tracking and personalized care. These technologies address critical gaps in healthcare delivery, providing timely interventions that reduce the need for frequent and often burdensome travel to medical centres. However, the success of these systems depends heavily on their reliability; sensor failures not only pose risks to patient safety but also undermine confidence in the technology. As a result, ensuring robust mechanisms for reliability assessment and anomaly detection is essential for the effective deployment of AmI systems in rural healthcare.

This chapter focuses on case studies that display the practical application of the AmI-AT reliability framework in healthcare, particularly in rural settings where resources are limited. The reliability of AmI-AT systems is a critical concern, as sensor failures can compromise patient safety and disrupt healthcare delivery. The case studies presented use probabilistic simulation approaches to evaluate sensor behaviours under diverse conditions, estimating the likelihood of failures and their potential impact over time. The methods used are presented in the methodology chapter of the study.

6.3 Case Study 1: Analysis of Continuous Glucose Monitoring

This case study was selected as it is aligned to the common challenges facing many citizens across the globe.

6.3.1 State Transition Heatmap

The state transition Heatmap visualizes the probabilities of transitioning between states across all device instances. It provides an aggregated view of how often the system moves from one state to another based on observed CGM readings. By examining these probabilities, we can better understand the dynamics of system behaviours under varying conditions. The state transition heatmap shows dominant device state transitions, indicating system stability under normal and mildly

degraded conditions. Transitions to and from the Recovered state suggest the effectiveness of recovery mechanisms, whether through intervention or natural stabilization. Zhao et al, (2019) indicated that the nature of the intervention needs to be factored in the Monte Carlo Simulation as this could represent human input or device calibration by trained service providers.

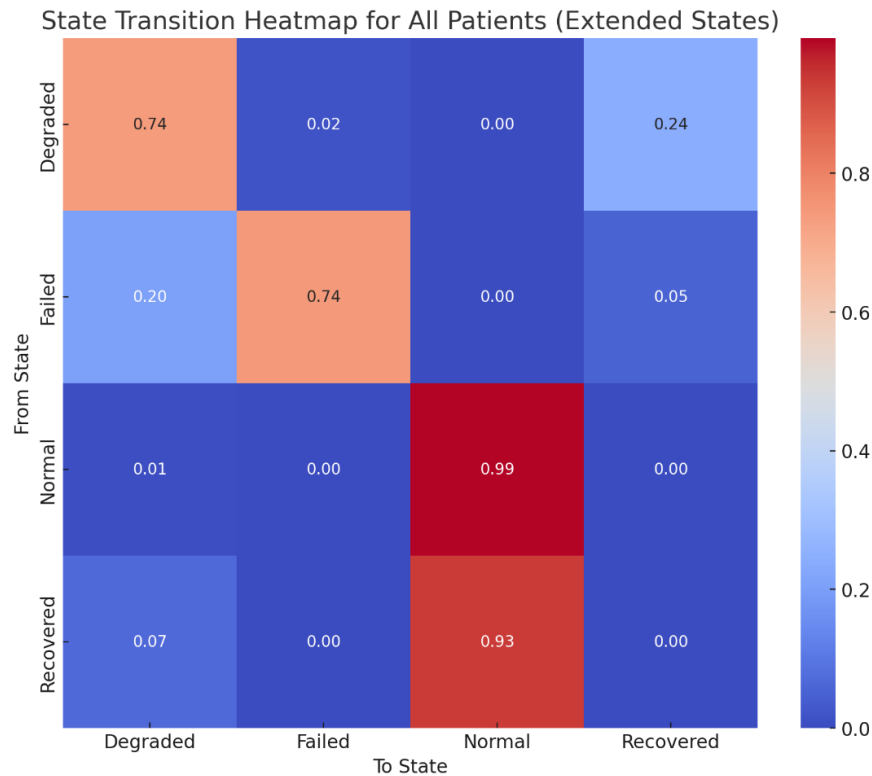


Figure 6.1: Transition Matrix Generated from Training Data

In Figure 6.1 the depth of shade represents transition likelihood, with the darker shade representing a higher likelihood. The state transition Heatmap shows a high normal-to-normal state transition probability reflecting the stability of the system when the glucose levels remain within the ideal range (70–180 mg/dL). The degraded state transition indicates conditions where glucose levels are approaching critical thresholds but has not yet resulted in system failure. The recovered state highlights instances where the system successfully returns to normal operation after being degraded or failed. This state can be achieved via external intervention. The failed state represents the absorbing state, meaning transitions out of this state are rare or non-existent, emphasising the

criticality of avoiding this condition. This condition represents a non-recoverable state, which would warrant a component replacement on the device.

6.3.2 Problematic States Analysis

The analysis of anomaly recovery rates by state provides crucial insights into the behaviour of the CGM system under varying conditions. The Degraded state exhibits a recovery rate of approximately 24.33%, indicating that about one-fourth of the transitions from this state lead to recovery, either back to a Normal state or a Recovered state. This highlights the potential for intervention during the Degraded state to restore system stability before conditions worsen. On the other hand, the Failed state demonstrates a significantly lower recovery rate of approximately 5.31%, emphasizing the criticality of avoiding this state altogether. The rarity of transitions back to stability from the Failed state underscores its near-absorbing nature and the challenges associated with recovery once the system has reached this critical condition.

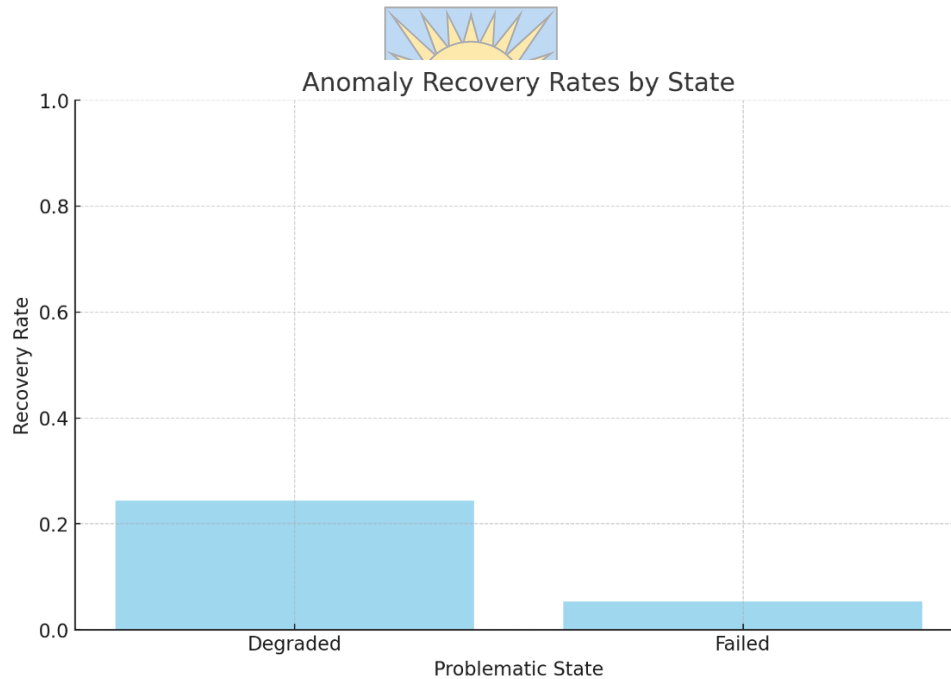


Figure 6.2: Anomaly Recovery Rates by States

6.3.3 Cumulative Failure Over Time

The Cumulative Failure Analysis plot illustrates the accumulation of failures over time; this plot is crucial in highlighting fault trends and, subsequently reliability degradation as devices age. Periods with steeper slopes suggest increased failure rates, potentially linked to environmental or operational factors. Flatter sections indicate stable periods with fewer failures. Initial degradation could also arise from users getting accustomed to configuring and using AmI-AT devices in their care.

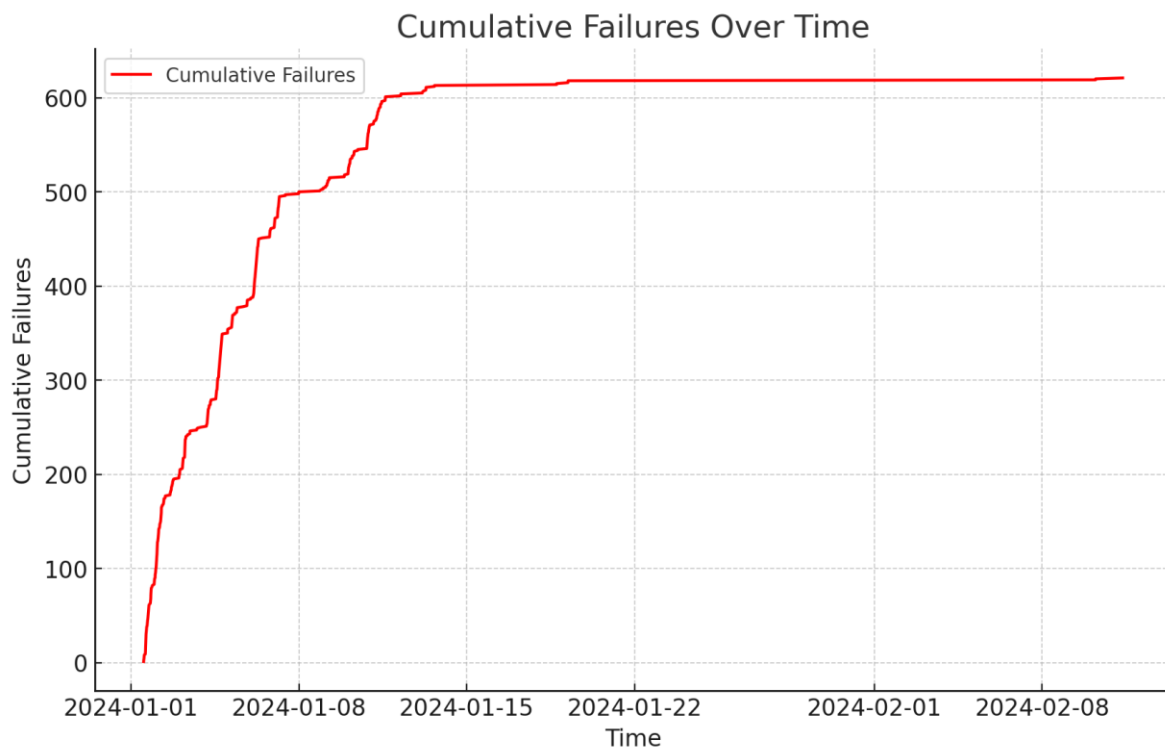


Figure 6.3: Cumulative Failures Over Time

6.3.4 Failure Probability

The failure probability over time plot shows the likelihood of the Amt- AT system failing at any given time. As reported in the literature survey, the variability in reliability of systems can be observed via the presented failure probabilities. The failure probability fluctuates over time, indicating varying levels of system reliability. Periods with elevated probabilities suggest persistent issues or conditions causing frequent failures. Monitoring these trends can help identify and address

factors contributing to increased failure risks. From Fig below, it can be observed that high failure probability is concentrated over a definite period. Analyzing the occurrences around the observed period can contribute to drafting a comprehensive conceptual framework that can cover other aspects of AmI-AT usage beyond the technical aspects.

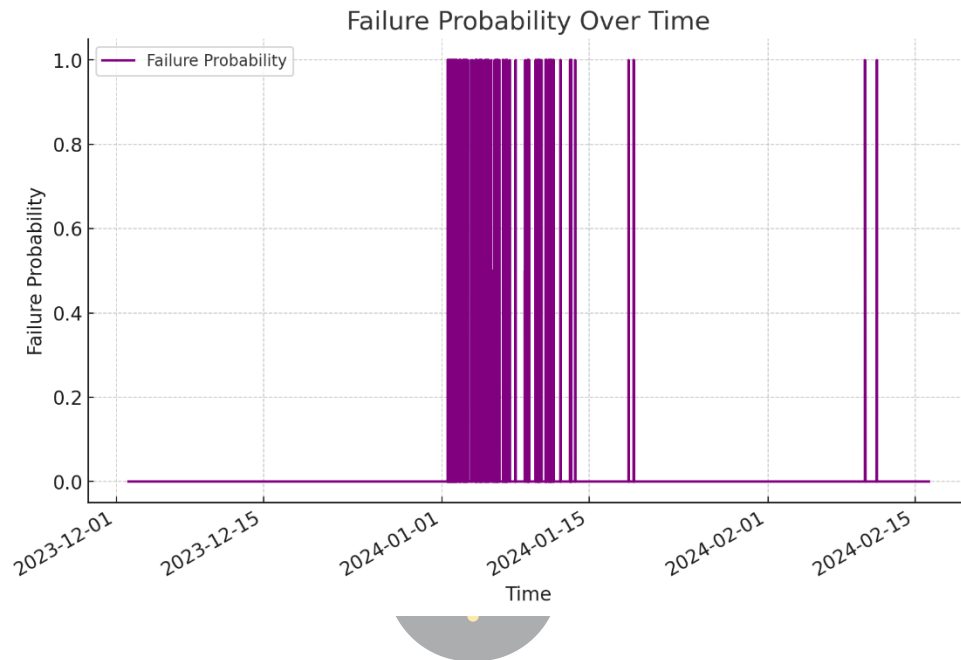


Figure 6.4: Failure Probability
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6.3.5 System Reliability Over Time

The system reliability plot illustrates how the overall reliability of the CGM system evolves over time. Reliability is defined as the likelihood of the system functioning without failure. In the plot, the green line represents the system's reliability, which decreases progressively as failures occur.

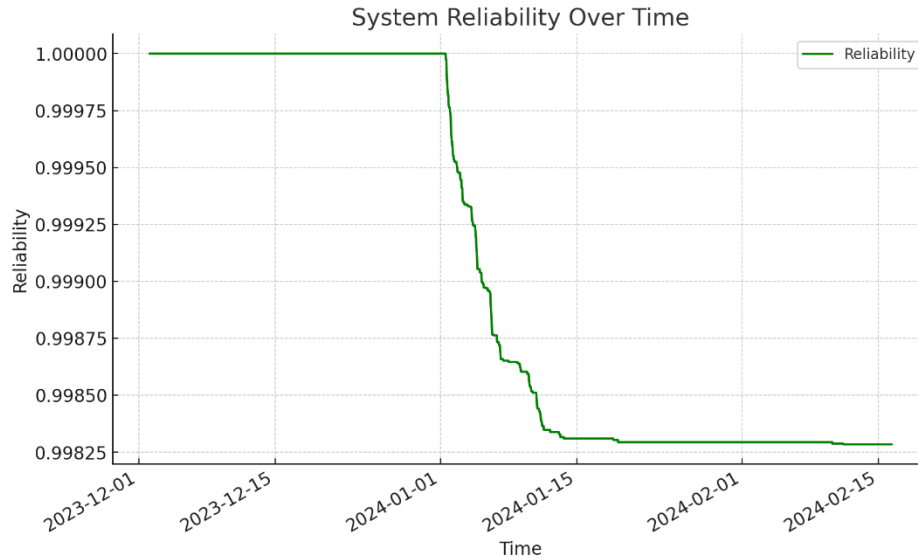


Figure 6.5: System Reliability Over Time

The illustration in Figure 6-3 shows that as time progresses, the cumulative impact of failures reduces the system's reliability. The rate of decline highlights periods of increased vulnerability, where failures occur more frequently. Steep declines in reliability indicate clusters of failures within short timeframes. These periods may correspond to external factors such as environmental changes, sensor wear, or calibration issues. Flat sections suggest stable periods where the system operates without significant failures.

Understanding how reliability trends over time helps identify when and why the system is most susceptible to failures. Proactive maintenance or enhanced anomaly detection can mitigate steep reliability declines, ensuring consistent system performance. By identifying periods of steep reliability decline, system operators, the conceptual framework can provide constructs to recommend targeted interventions to mitigate failures before they escalate, such as algorithmic recalibration, redundancy, or manual intervention. Though the observed cumulation degradation in reliability is for CGM, the insights are not only valuable for CGM systems but also applicable to other AmI-AT technologies. The findings emphasize the importance of designing systems that are resilient to failures and capable of rapid recovery, and further concert the need for a comprehensive framework to factor in such anomalous behaviours in AmI-AT systems.

6.3.6 MCMC Simulation Results

The MCMC simulation results show approximately 98 steps, highlighting the system's expected duration of operation before entering the Failed state. The improved system maintains high reliability, demonstrating the effectiveness of enhanced recovery and prevention mechanisms. The degraded system's reliability is significantly lower, around 80%, highlighting the impact of noise and increased transition probabilities to failure states.

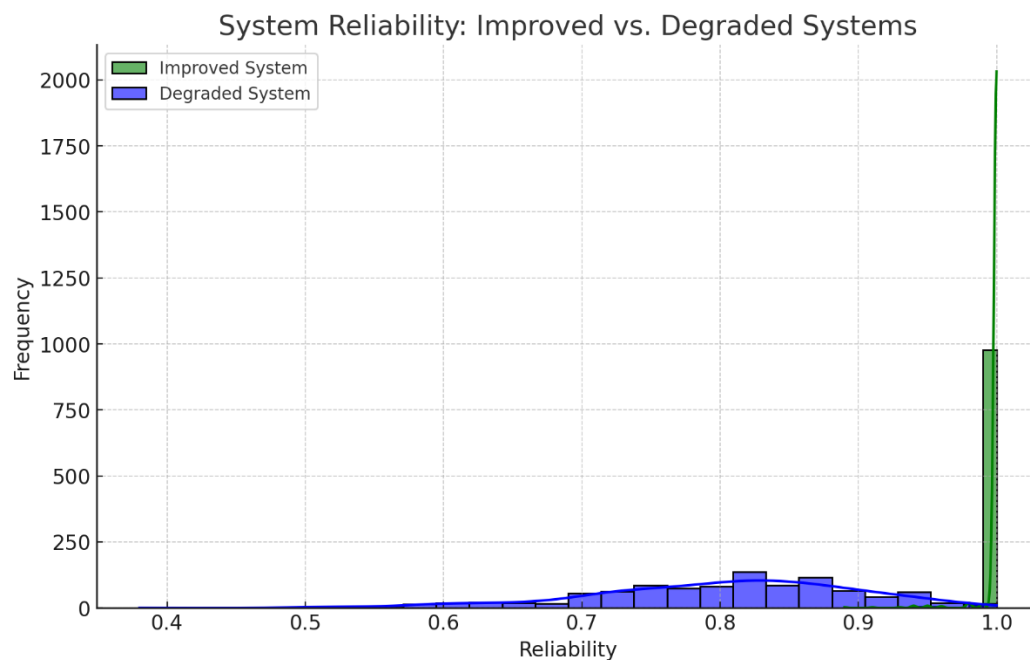


Figure 6.6: System Reliability: Improved vs Degraded Systems

6.3.7 Anomaly Distribution

The histogram illustrates the distribution of detected anomalies over 1,000 simulated iterations, highlighting variability in anomaly counts when sampling subsets of the dataset. The frequency of anomalies helps estimate the reliability of the system under different scenarios, simulating the potential impact of failures on overall performance.

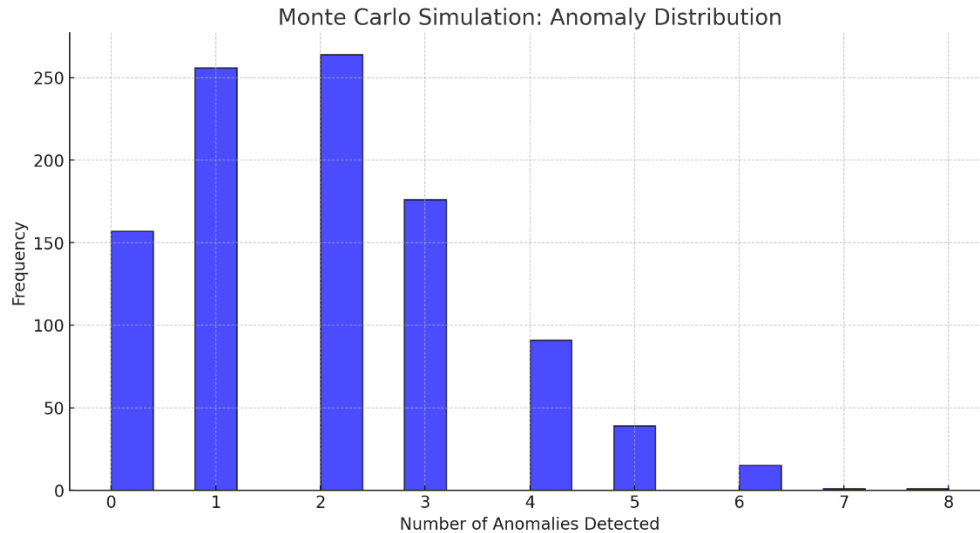


Figure 6.7: Monte Carlo Simulation: Anomaly Distribution

6.3.8 Discussion on CGM

The analysis of state transitions in CGM systems reveals several critical insights into system behaviour and reliability. The high probability of remaining in the Normal state underscores the robustness of the system when glucose levels are maintained within the expected range, while transitions to the Degraded state serve as early warnings of potential issues requiring attention. The inclusion of the Recovered state highlights the system's capacity to return to optimal functioning after degraded or failed conditions, emphasizing the value of timely interventions. Conversely, the Failed state, with its absorbing nature, underscores the urgency of proactive anomaly detection and maintenance strategies to prevent irreversible failures (Modarres & Growth, 2023). By aggregating data across all instances in the dataset, the findings provide a generalized model that is applicable to a wide range of scenarios, offering valuable insights into system behaviour for diverse patient populations and guiding the design of more reliable and resilient CGM systems.

The importance of recovery mechanisms in CGM systems cannot be overstated, as they serve as a critical safeguard to restore functionality after the system transitions to degraded or failed states. The inclusion of the Recovered state in the study's analysis highlights the system's capacity to return to normal operation, which is essential for maintaining reliable glucose monitoring and ensuring patient safety (Singh et al, 2023). Recovery mechanisms are particularly vital in scenarios where glucose

readings deviate significantly from the expected range, as timely stabilization can prevent further deterioration and mitigate the risks associated with prolonged system failure.

It is vital to include recovery mechanisms as a component of the conceptual framework. It is to be noted that devices are not always in perpetual functioning. As such, the ability to recover provided the users with continued services. Effective recovery mechanisms might include automated recalibration of sensors, redundancy in data collection systems, or algorithmic corrections based on historical data trends (Azghiou, El Mouhib, Koulali & Benali, 2020). These interventions can address issues such as signal noise, data transmission errors, or sensor inaccuracies, thereby restoring the system's reliability without requiring immediate manual intervention. Additionally, real-time alerts to healthcare and service providers during degraded states can prompt swift manual adjustments or replacements, ensuring that the system resumes optimal performance with minimal delay.

The problematic state findings reinforce the importance of timely detection and response to anomalies during the Degraded state, as it presents a valuable window for corrective action. By intervening promptly, the escalation of issues to the Failed state can be mitigated, thereby preserving system functionality and reliability (Wu & Cui, 2021). Conversely, the Failed state necessitates robust preventive strategies, as recovery from this state is rare and often resource intensive. Together, these observations highlight the need for effective anomaly detection systems, proactive maintenance, and efficient recovery mechanisms to ensure the consistent performance and reliability of CGM systems in critical healthcare applications (Nadella et al, 2023).

In addition, the observations from the analysis demonstrate that transitions to the Recovered state are not only a reflection of the system's inherent resilience but also an indicator of the effectiveness of these recovery strategies, and, subsequently, an indicator of reliability. Wang, Li, Li and Li, (2024) indicated that without robust recovery mechanisms, transitions from degraded or failed states back to normal operation would be rare, leaving the system vulnerable to prolonged failures and reduced reliability. Therefore, the design and implementation of efficient recovery strategies are pivotal for ensuring the long-term functionality and resilience of CGM systems, particularly in critical settings where consistent performance is imperative (Lee et al, 2015). These mechanisms not only enhance the robustness of the system but also instill confidence in its reliability among users and third-party service providers.

6.4 Case Study 2: Heart Monitoring in Elderly Care

Monitoring heart health in the elderly is crucial due to the increased risk of cardiovascular issues with age. Advancements in heart rate monitoring technologies have enhanced the ability to track cardiac health effectively (Valavanidis, 2023). However, implementing these technologies in elderly care presents specific challenges, including false alarms and connectivity issues. This case study examines the reliability of heart rate monitoring technologies in elderly care, utilizing a dataset to analyse metrics, conduct simulations, and derive insights (Bohr & Memarzadeh, 2020). Heart rate monitors are devices that detect and measure heart or pulse rate, providing real-time data on cardiac activity. They are commonly used in fitness tracking and medical monitoring (Ahmad et al, 2022). The primary technologies include Electrocardiography (ECG) Monitors used to measure the Heart electrical signal activity, and Photo Platyasma Graphy (PPG) Monitors, which utilize light-based technology to detect blood volume changes in the microvascular bed of tissue, often used in wearable devices such as fitness bands and watches.



6.4.1 Heart Rate Monitoring Observations

This section examines the key findings and insights derived from the Heart Rate Monitoring case study. The focus is placed on the technical aspects of the monitoring system, including the reliability and performance of its hardware components and adaptability to various operational conditions. By analysing these elements, the study aims to identify factors that influence the overall reliability and effectiveness of heart rate monitoring in healthcare and elderly living applications, particularly in resource-constrained environments. These observations complement the data-focused analysis presented in the Continuous Glucose Monitoring (CGM) case study, offering a broader perspective on the challenges and opportunities in the deployment of Ambient Intelligent Technologies.

6.4.2 Calibration Errors for Sensors

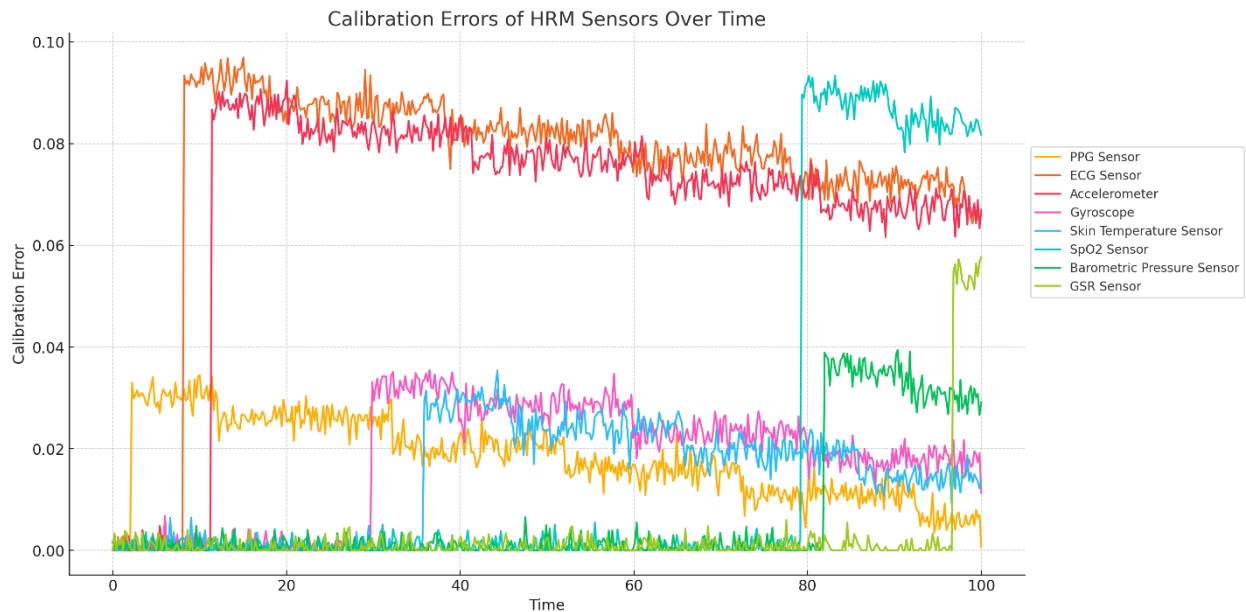


Figure 6.8: Sensor Calibration Over Time

Figure 6-8 shows sensor calibration analysis over time for the different sensors used on an AmI-AT in HRM. The analysis in Figure 6-3 shows that calibration errors of heart rate monitoring sensors evolve over time, influenced by drift, periodic corrections, and environmental variability. The graph illustrates this phenomenon, showcasing how calibration errors increase due to random drift events. Drift events refer to gradual changes or deviations in the accuracy or calibration of a sensor over time. These deviations are typically caused by a combination of internal factors, such as aging components, wear and tear, or changes in sensor sensitivity, and external factors like environmental conditions.

From the observed dataset, these events occur at specific times for each sensor, with magnitudes varying between 2% and 10%, highlighting the differing susceptibilities of the sensors. Periodic corrections play a critical role in mitigating these errors, as recalibrations are conducted at regular intervals, every 20-time units after drift onset, reducing errors by 0.5% per interval. Additionally, realistic noise factors introduce minor fluctuations in calibration errors, showing the real-world variability caused by environmental and operational conditions. Insights from this analysis emphasize

the importance of drift management, where timely recalibrations effectively reduce error accumulation and maintain sensors within acceptable performance bounds. Furthermore, sensors with higher drift rates necessitate more frequent recalibrations to stabilize their accuracy, underscoring the sensor-specific nature of maintenance strategies. In the context of rural South Africa, challenges in accessing trained personnel to aid in recalibrations can exacerbate the impacts of drift event.

6.4.3 Connectivity Reliability Analysis

Figure 6-4 shows the observed connectivity behaviour in operating conditions benchmarked against an ideal baseline performance. It can be observed that connectivity is unstable. Connectivity drops can be attributed to factors such as events like network congestion or temporary outages. The illustration shows periods of poor connectivity and recovery. The system shows resilience by returning to near-baseline connectivity after each disruption, though minor fluctuations persist. While connectivity is crucial on the functioning of an Aml-AT, it is relatively easier to recover from poor connectivity periods, nonetheless, the observed periodic disruptions highlight potential vulnerabilities in network reliability, emphasizing the need for robust recovery mechanisms in Aml-ATs.

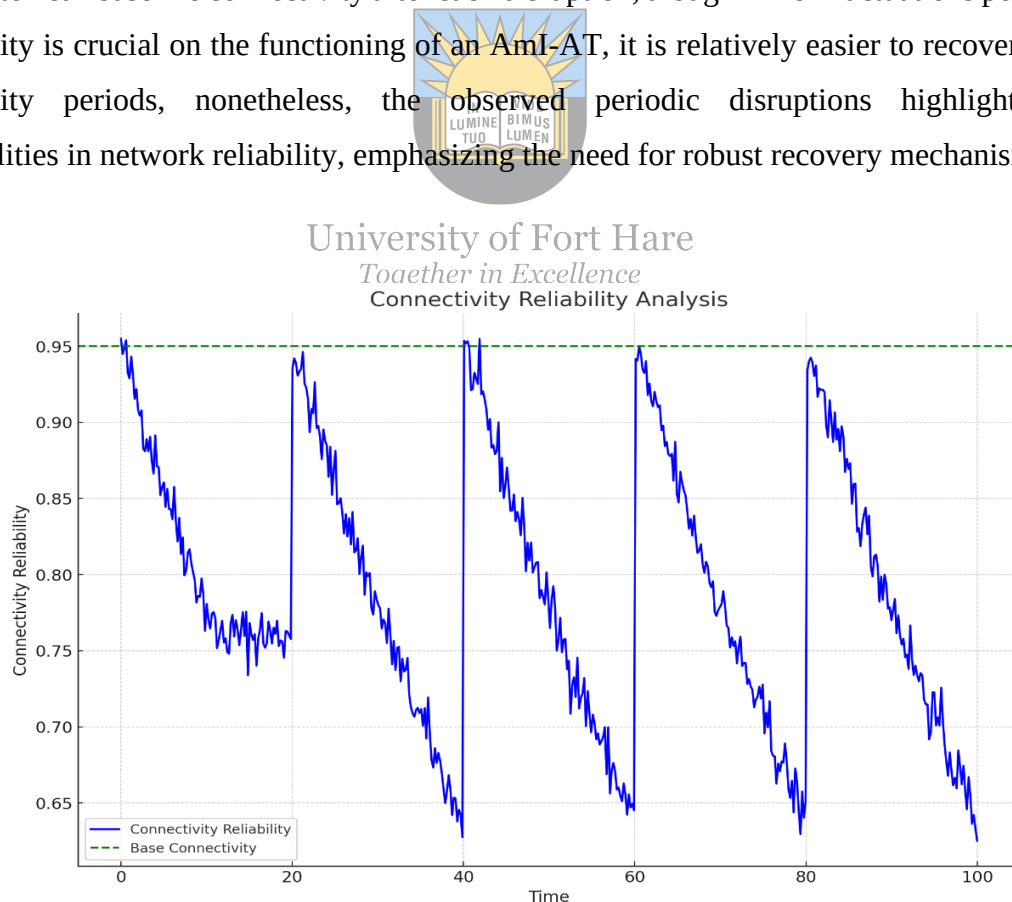


Figure 6.9: Regular Connectivity Analysis

6.4.4 Effects of Individual Factors on System Reliability

The observation in Figure 6-9 shows a comparative analysis of the effects of individual factors on reliability. The analysis of individual factors affecting system reliability highlights the unique roles and vulnerabilities of each component within an AmI-AT system. Battery reliability shows a steady decline over time due to natural discharge, stabilising at a critical threshold of 70%. This trend underscores the importance of adaptive energy management, periodic recharges, and renewable energy integration to sustain system operation.

Furthermore, batteries are normally made to recharge at certain intervals, however, for some devices, especially those implanted into the body, recharge may not be possible, as such battery reliability is crucial. Connectivity reliability exhibits periodic sharp declines which may be due to lack of coverage, signal interference or network overload. The observed connectivity disruptions are followed by gradual recoveries, emphasising the need for failover mechanisms, redundant communication paths, and signal amplification technologies to maintain robust connectivity.

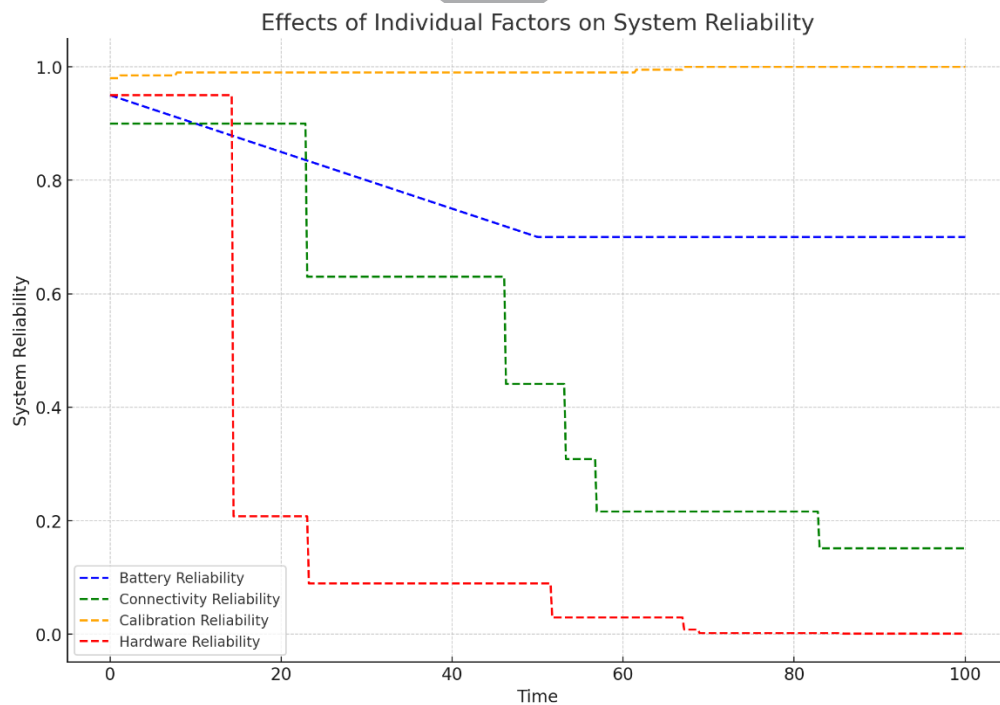
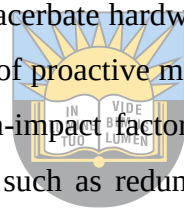


Figure 6.10: Effects of Individual Factors on System Reliability

Calibration reliability demonstrates periodic improvements driven by scheduled recalibration events, reflecting efforts to counteract sensor drift over time. Although calibration reliability remains relatively high, fluctuations highlight the variability of drift across different sensors. Automating recalibration processes and incorporating error-detection algorithms can significantly enhance accuracy and reduce manual interventions. Hardware reliability, in contrast, is characterised by abrupt declines at random intervals, reflecting the sporadic nature of hardware failures. Recovery from these failures is slower compared to other factors, due to the complexity of repairs or replacements. Strategies such as modular hardware design and predictive maintenance are essential to reducing repair times and improving reliability for critical components and sensors.

While each factor is analysed in isolation, their interdependence cannot be ignored. For instance, battery reliability directly influences connectivity, as insufficient power can lead to signal disruptions, and calibration drift may exacerbate hardware stress by producing inaccurate data. The observations underscore the importance of proactive measures, such as early detection of reliability drops and prioritising recovery for high-impact factors like battery and connectivity through the implementation of integrated strategies such as redundancy, adaptive recovery mechanisms, and predictive analytics.



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6.4.5 Reliability of Individual Sensors in an HRM Device Over Time

Figure 6-11 represents the reliability of individual sensors in a Heart Rate Monitoring (HRM) device over time. Each sensor experiences unique failure at specific times in its lifetime, with varying severity. The average impact of failures observed ranges between 40% and 80% reliability reduction reflecting the diverse operational challenges. Variability in sensor reliability underscores the importance of monitoring individual sensors for timely intervention. The observation shows that different sensors recover at rates between 1% and 4%, reflecting the complexity of recalibration or repair efforts. While the AmI-AT is made up multiple sensors, some of the sensors are more critical than others. Sensors like Photoplethysmography (PPG) and Electrocardiography (ECG) are critical to HRM functionality, requiring higher priority in recovery efforts.

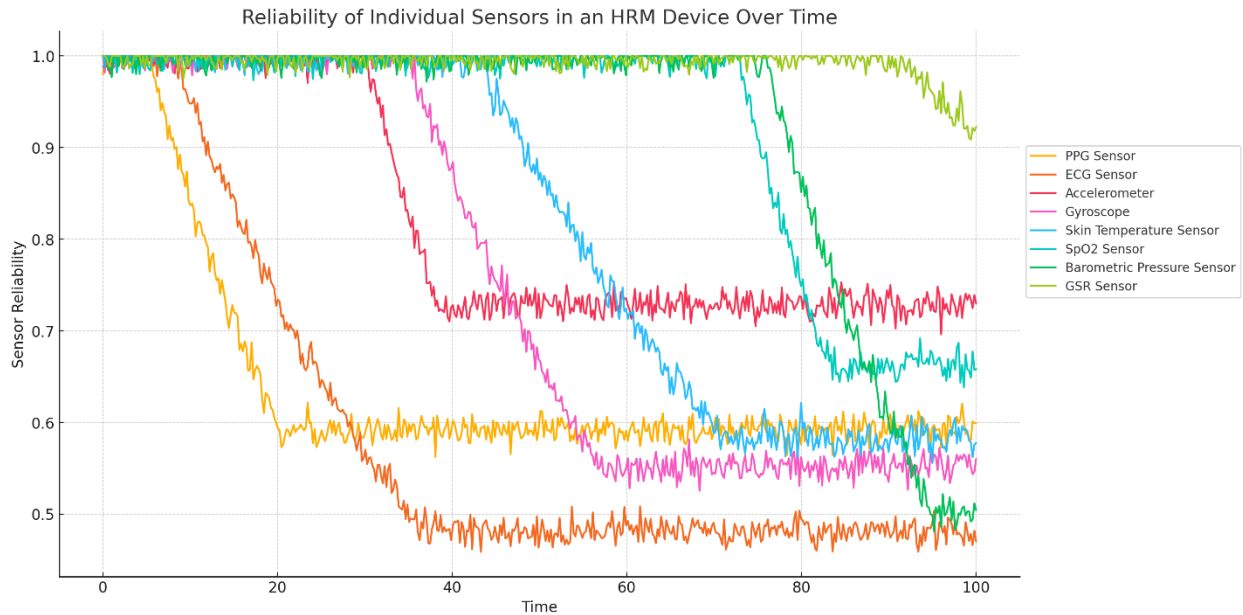


Figure 6.11: Reliability of Individual Sensors in an HRM Device Over Time



6.4.6 Reliability with Failure Dependencies Between Sensors

The graph in Figure 6-12 illustrates the reliability dynamics of heart rate monitoring sensors while considering failure dependencies between sensor types. Key features include failure dependencies, where the failure of a primary sensor partially impacts the reliability of dependent sensors. For instance, the PPG sensor influences the accelerometer and gyroscope, while the ECG sensor affects the SpO2 and skin temperature sensors. Primary failures occur uniquely for each sensor, directly reducing their reliability according to predefined failure impacts. These failures propagate as secondary failures, decreasing the reliability of dependent sensors by 90% of the primary impact.

In addition, recovery dynamics are evident in the gradual restoration of reliability for both primary and dependent sensors, representing repair or recalibration efforts. Figure 6-12 highlights the cascading effects of sensor dependencies, where failures can propagate across multiple components, underscoring the need for robust system design and proactive maintenance strategies. Additionally, critical sensors with multiple dependencies, demand higher monitoring and recovery prioritization to mitigate widespread reliability degradation.

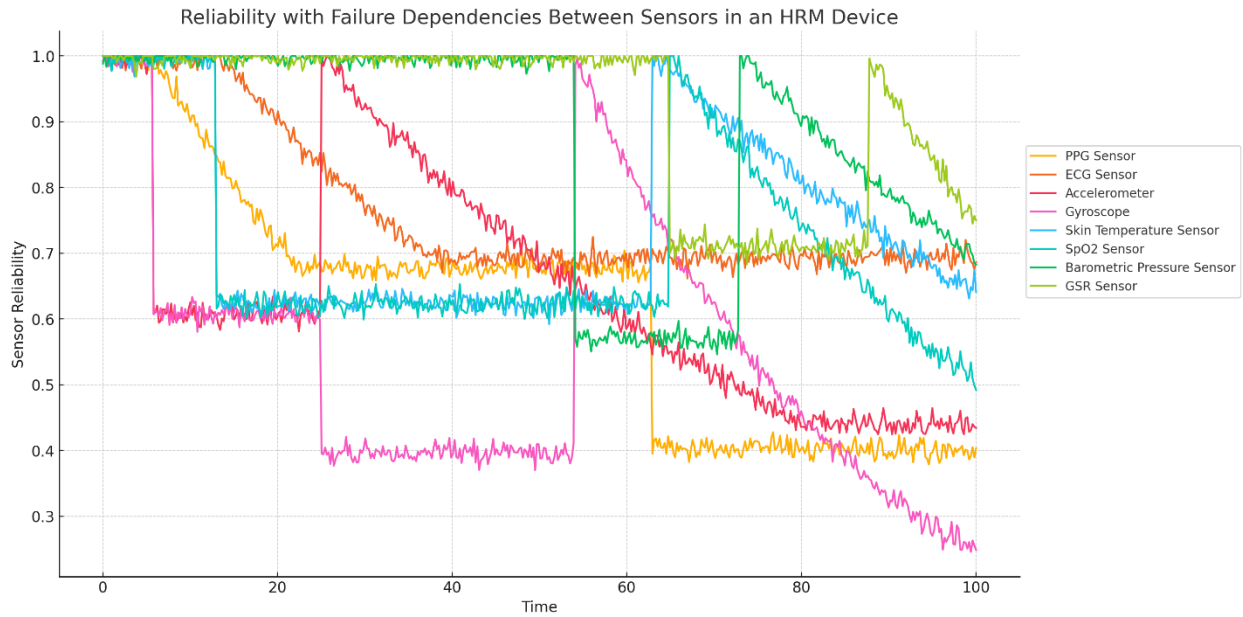


Figure 6.12: Reliability with Failure Dependencies Between Sensors



6.5 Discussion and Insights from Case Studies

The findings from these case studies underscore the importance of integrating advanced anomaly detection and probabilistic modelling techniques into AmI healthcare systems. By leveraging methods Markov Chains Monte Carlo simulation, the case studies provided a comprehensive understanding of CGM and HR device reliability (Chakour et al, 2024). The observation from the case analysis highlighted how sensor failures impact system performance, emphasising on the need for more reliable AmI-AT systems coupled with proactive maintenance.

Furthermore, the case studies reveal the unique challenges of deploying AmI systems in rural environments, where resource constraints and environmental factors can exacerbate reliability issues (Labrique et al, 2020). The lessons learned from these analyses will directly inform the development of a conceptual framework for AmI reliability, ensuring these systems can consistently deliver safe and effective healthcare. These case studies bridge the gap between theoretical modelling and real-world application, providing valuable insights into the challenges and solutions for ensuring the reliability of CGM and HR monitoring devices. By combining real-time anomaly detection with probabilistic modelling, they demonstrate how AmI systems can meet the demands of rural healthcare

(Labrique et al, 2020). These findings lay a strong foundation for the next chapter, where a formalized reliability framework will be developed based on the methodologies and results presented here. This work marks an important step toward building robust, scalable, and reliable AmI systems for healthcare monitoring.

6.6 Main Themes from the Literature

During the literature review, several concepts emerged from the studies reviewed. These main themes are discussed below. The themes present the justification and significance of the presented framework. These themes demonstrate the alignment between the study's framework and the existing studies. The framework evaluation using the themes from literature shows the applicability and relevance of the framework in Chapter 5.

6.6.1 Insufficient Healthcare Systems, Low Patient-to-Doctor Ratios and a Lack of Educational Systems



Based on the studies presented in the literature by Godongwana, De Wet-Billings, and Milovanovic (2021), there are still challenges to healthcare access in South Africa. According to Sehume and Markus (2020), insufficient healthcare systems, low patient-to-doctor ratios, and lack of educational systems have a negative impact on the medical diagnosis of patients among various developing nations, mostly in rural areas. This has a negative impact on the diagnosis of patients in the majority of developing nations, mostly in rural areas. Patients are living in rural areas where the distance between their home and the health institution involves travelling expenses.

6.6.2 Role of Technology

Rapid growth and technological devices have made it possible for the introduction of robotic assistance systems to assist in improving general healthcare access and execute prompt diagnosis of health conditions. Based on the studies presented in the literature by Sehume and Markus (2020), these intelligence systems incorporate wireless monitoring systems, sensor networks, medical equipment, wireless communication, middleware software, and software applications that support the progress of healthcare improvements.

6.6.3 ICT Developments and Challenges in AmI-ATs as Monitoring Systems

ICT advancements in AmI-ATs as monitoring systems are essential for tackling a range of issues and health conditions. Based on the studies presented in the literature by Behrendt et al, (2021), both possibilities and problems arise from the growth of ICT in the context of AmI-ATs as monitoring systems. Gebrehiwet (2023) asserts that companies such as Astronics offer cutting-edge technological solutions that support improvements in monitoring systems. As AI continues to transform industries globally, monitoring these systems is fundamental to carefully considering appropriate AI systems (Devagiri et al, 2022; Rashid & Kausik, 2024).

6.6.4 Reliability for AmI-AT Systems

Different methods and factors are taken into account when identifying and depicting reliability in different systems, stressing the necessity of fault analysis, dynamic elements, and integration with performance indicators. Based on the studies in the literature supported by Torquato, Maciel, and Vieira (2022) elucidate a modelling approach for degradable computing systems that combines performance metrics with availability and reliability metrics. The Bayesian networks for power system reliability evaluation were labelled by Wang, Li, Li, and Li (2024) for a Bayesian network based on fault tree analysis. The definitions of reliability assessment on multi-state systems are also covered by Bao et al, (2021), who applied state transition processes into consideration.

6.6.5 Privacy and Adaptability and Security Considerations

Every element used in AmI-AT systems has an immense impact on reliability, and in order to render AmI-AT systems functional and sustainable, reliability must be evaluated and assured. AmI-ATs monitoring systems' designs are complex due to the many different technologies that are used to develop them and to produce a single autonomous system. Based on the studies in the literature supported by Jordan, (2022), to guarantee privacy and adaptability, it is important to enhance the reliability and maintenance efficiency of systems and components. Consequently, it is crucial for sustainability to evaluate and guarantee AmI-AT systems' dependability.

6.6.6 Financial Support and Regulations for System Development

Based on the studies in the literature by Costello (2016) indicated that to safeguard reliability and maintenance efficacy, Pre-MS AML programmes and ACAT III AML initiatives with significant financial support need to be given careful consideration. According to Saggese et al, (2024), in order to preserve reliability, VASPs must have efficient methods for tracking and guaranteeing adherence to national AML/CFT regulations.

6.6.7 Proper Systems

Reliable and fault-tolerant AmI technologies must be developed. Several approaches have been put forth to improve AmI technologies' reliability and create systems that are more resistant to errors and malfunctions. Based on the studies in the literature supported by Niknahad, Huebner, and Becker, (2010), who described methods that concentrate on attaining reliability in systems with nanoscale components, providing a feasible area overhead and notable increases in reliability. These methods improve the reliability of systems by addressing low defect and fault rates (Niknahad et al, 2010).



6.6.8 Mix of Strategies

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Including redundancy-based design, fault-tolerant designs, fine-grained data channel recovery, and error-resilient strategies, may help to increase the fault tolerance and reliability of AmI systems and devices. Such approaches consider multiple elements of system operation and design in order to provide reliable performance even in the presence of errors and failures. Based on the studies supported by Liu et al, (2011), instead of adding redundancies, the authors suggested fine-grained data path salvaging techniques for on-chip routers by dividing data path components into slices, which is intended to increase the resilience of on-chip communication networks, especially in very large-scale embedded systems that use Network-on-Chip technology.

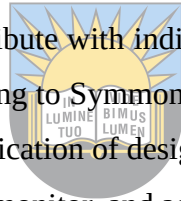
6.6.9 Target Users

AL systems are primarily designed for older individuals with the goal of providing ongoing assistance and extending their lives in a healthy and active manner. Based on the studies in the literature supported by Heta, Robo, Ostreni, Haxhiu, Resuli, Rumano and Kapaj, (2022), medical studies have

categorised elderly people into three different classes, depending on their age. More so, several applications for diabetes control, depression treatment, hypertension control, medication adherence, and psychological support have been developed to allow people to live alone while having the possibility of daily control over their health status (Zhao, Zhao & Song, 2022). Early identification of these risk factors can be prevented in a large portion of the elderly population at the time of retirement by targeting timely interventions and reducing the risks (Haque, Alam, Gow, Neville & Keramat, 2024).

6.6.10 Designers Classification

AmI-ATs monitoring systems cannot be designed by a single person due to their nature of being an amalgamation of various technologies that are operating at software, hardware and network levels. Based on the studies in the literature by Szmeja (2023), for a successful AmI-AT monitoring system to be delivered as an end product ready for the market, a team of different technology and non-technology expertise is required to contribute with individual pieces of information and knowledge to the invention being designed. According to Symmons, (2021), for any AmI-AT tool that requires to be developed, there should be a classification of designers, which are individually chosen on their skill set and based on what the tool shall monitor, and additionally on the set functional requirements of such as systems.



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6.6.11 Collaboration

There should be datasets that are accessible to support human-machine collaboration because of the grey zone issue raised by the healthcare sector's use of big datasets for AI predictions. Based on the studies supported by Vaccaro et al, (2024), little has been discovered about the datasets that are now accessible to support this human-machine collaboration. The necessity for human interpretation of outcomes because of the grey zone is another issue raised by the healthcare sector's use of big datasets for AI predictions (Zicari et al, 2021).

6.6.12 Quality Assurance

Effective and efficient maintenance and improvement of the system are necessary to ensure that the system is well-designed and devoid of any flaws that can cause it to malfunction while in use. Based

on the studies in the literature supported by Rad and Thomas, (2017), since the idea of responsibility cannot be overstated, reliability is strongly advised to guarantee the quality of the product, and quality assurance of a product or system must be maintained and improved effectively and efficiently to ensure that the system developed is well-designed and free from any faults that could result in failure during operation.

6.6.13 Connectivity Reliability Factor

Based on the studies in the literature supported by Sai et al, (2022), mobility is one of the key expectations of an IoT network whereby users of the network can dynamically move between applications while the device onboarding and identification happen seamlessly in the background. IoT is challenging, though, because manufacturers do not work together to provide each IoT device with a universally distinctive brand. This means that the responsibility of assigning unique identification resides within the IoT network itself (Guillemin et al, 2022).

This then leads to reliability concerns when it comes to tracking or auditing the device as it moves through different IoT applications., According to de Barros Filho et al, (2021) the scarce resources and intermittent communication, the network is liable to drop readings, or produce unreliable readings. Farooq and Zhu, (2021) indicated that the notion that readings can be dropped due to the inherent nature of IoT networks is an area for concern, especially given that IoT infrastructure is often responsible for managing mission-critical applications

- Network connectivity protocols: lightweight, lacking QoS (Quality of Service).
- Mobility and network migration
- Intermittent communication

6.6.14 Human User Reliability and System Reliability Factor

Based on the studies in the literature supported by Moore et al, (2020), human reliability can mean preventing accidents and minimizing the consequences of accidents that do occur. When these potential consequences are significant, such as catastrophic loss of equipment, long term damage to the environment, or loss of life, then reliability engineers working collaboratively with others like

risk management, human factors and safety engineers can have an important impact (Pokorni, 2016). Pokorni (2016) has considered human reliability to be an important factor.

6.6.15 Need for More Research

Based on the studies in the literature supported by Xu et al, (2023) and Fadhel et al, (2024) concurred that more detailed research is necessary with the goal to solve these issues and potential negative effects of AI technology to address the shortcomings and gaps in knowledge on the implications of AI in different industries and the role of human-computer interaction in influencing the future of AI.

6.7 Reliability Framework Evaluation Feedback

The evaluation of the reliability framework, as demonstrated through the case studies on Continuous Glucose Monitoring (CGM) and Heart Rate Monitoring for elderly care, highlights its robustness and adaptability across different healthcare monitoring contexts. The framework effectively integrates advanced modelling techniques, such as MCMC and RBDs, to assess reliability dynamically, providing valuable insights into system performance under real-world conditions. Its ability to simulate state transitions and identify critical failure points ensures comprehensive evaluations that are crucial for improving assistive technologies. Additionally, the layered structure of the framework facilitates modular assessments, allowing for targeted analysis of specific components like sensors, connectivity, and software systems.

However, areas for improvement remain. While the framework successfully incorporates statistical models and simulations, future iterations could benefit from integrating more real-world operational data to enhance its predictive accuracy. The inclusion of user-centered metrics, even in a non-user-involved approach, would add depth to the evaluation, addressing usability alongside technical reliability. Moreover, expanding the scope of case studies to include diverse environments and additional AmI-AT applications, such as smart home systems, could further validate the framework's scalability and versatility. These refinements would not only enhance the framework's applicability but also strengthen its contributions to the fields of Computer Science, healthcare monitoring, and device development.

6.8 Chapter Summary

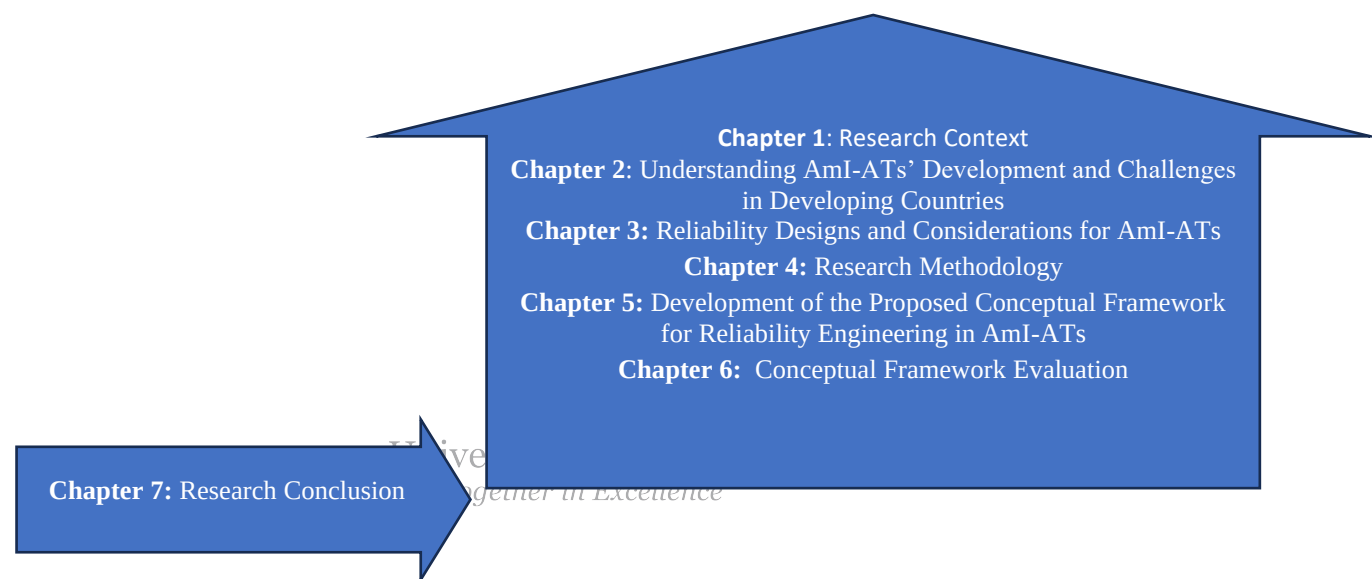
An overview on the experimental application and numeric analysis of the proposed reliability framework was discussed using two case studies which are Continuous Glucose Monitoring and Heart Rate Monitoring in elderly care. This highlighted key reliability challenges and demonstrated the framework's effectiveness in addressing these issues and lays the groundwork for further refinement and application of the framework in broader contexts. Therefore, the next chapter summarises the research, addressing how the research questions were presented and highlights the limitations and future work as well as research conclusions.



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Chapter 7 : Research Conclusion

The final chapter summarises the research, addressing the study's questions and achievements. It highlights the limitations and proposes future directions, emphasising the significance of reliable AmI-AT systems in healthcare and monitoring applications.



7.1 Addressing Research Objectives

The study set out to achieve the primary aim of this study is to develop a framework for evaluating the reliability of assistive technologies based on Ambient Intelligence without direct user engagement. The study employed a methodological approach to achieving its aim. This section examines how the study addressed the research objectives:

Research Objective 1: *To identify the key framework components for AmI-based health monitoring technologies, focusing on dimensions such as fault tolerance, adaptability, and consistency.*

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Through the agency of a systematic literature survey, the study extensively examined the concept of reliability for AmI-ATs. It identified reliability metrics and key framework components such as fault tolerance, adaptability, and consistency through a critical analysis of failures in AmI-AT systems. Furthermore, the study emphasised the role of factors such as hardware reliability, network reliability, software reliability, and human user reliability in achieving the reliability of AmI-AT technologies. Additionally, the study identified context-aware reliability factors, such as the user's environment and the heterogeneity of system components, as critical in developing countries, where operational conditions such as erratic power supply and limited infrastructure pose unique challenges. The literature findings gave basis for the further development the study and the design of the proposed conceptual framework for reliability in AmI-AT systems.

Research Objective 2: *To apply different algorithms and mathematical models that enable a simulation-based framework for evaluating the components in controlled environments, ensuring comprehensive reliability assessments.*

The study proposed a reliability assessment framework using different machine learning algorithms and simulation-based methods, including Markov Chain Monte Carlo (MCMC) techniques and Reliability Block Diagrams (RBDs). These tools were used to model and analyse the reliability of AmI-AT systems under different operational scenarios. The framework was validated with use cases like Continuous Glucose Monitoring and Heart Rate Monitoring, demonstrating its ability to evaluate reliability in a structured and controlled manner. The proposed framework leverages state-based modelling to simulate transitions between operational states such as functional, degraded, and failed states, of AmI-ATs. The proposed framework goes beyond traditional reliability assessments by incorporating stochastic processes to capture uncertainties in system performance, environmental impacts, and user interactions. The proposed framework also provides a platform for experimenting with what-if scenarios, such as power outages, sensor failures, or extreme environmental conditions. By simulating these scenarios, the framework can evaluate the resilience and robustness of AmI-ATs.

Additionally, the proposed framework incorporates failure mode as part of its assessment component to pinpoint critical vulnerabilities and suggest design improvements making the framework adaptable for broader contexts. Furthermore, the ability to evaluate IoT applications under dynamic conditions, including erratic power supplies and network disruptions typical of developing countries, showcases

the framework's robustness. This simulation-driven methodology enables iterative testing and refinement, ensuring that the framework can adapt to varying deployment scenarios and system complexities.

Research Objective 3: *To create an integrated framework for evaluating the reliability of AmI-based health monitoring technologies based on the formulated components.*

The study integrated probabilistic mathematical modelling and reliability quantification techniques into the proposed framework. It detailed the development of tools for failure probability calculation, and reliability estimation over time. The methodologies were tested using experimental setups and simulated environments to validate their effectiveness in assessing reliability. The study delved deeply into the development of advanced tools and methodologies for implementing the reliability framework. These tools included anomaly detection algorithms that identified deviations from expected performance, probabilistic failure analysis tools, and real-time reliability monitoring.

One particularly innovative methodology was the use of hybrid reliability assessment models, combining simulation with empirical data from real-world deployments. The study tested the methodologies against diverse datasets from healthcare systems, focusing on sensor reliability, communication reliability, and human-interaction reliability. Testing included metrics such as the accuracy of reliability predictions, and the time required to generate reliability scores for complex systems. The tools used were modular, scalable, and optimised for low-resource environments typical of developing countries. Lastly, the methodology employed is underpinned by context-specific adaptability, ensuring that tools account for variations in device configurations, user behaviour, and environmental factors.

Research Objective 4: *To validate the framework using selected case studies of AmI-based health monitoring technologies towards drawing up key strengths, weaknesses and recommendations before full implementation.*

Case studies, such as monitoring systems for Continuous Glucose Monitoring (CGM) and Heart Rate (HR) Monitoring, are employed to validate the framework. Additionally, secondary data has been used as well for framework validation. These studies focus on the unique challenges posed by the South African context, including unreliable power supplies, heterogeneous devices, limited access to advanced medical infrastructure, and the need for low-cost solutions. The selected case studies

demonstrated the scalability of the framework and its relevance to South African conditions. The case study findings validate the framework's ability to deliver quantitative reliability metrics, actionable qualitative insights for system improvements, and adaptability to low-resource settings. The incorporation of South African-specific challenges such as infrastructural limitations and healthcare disparities highlights the framework's relevance. The findings affirm the framework's ability to not only quantify reliability but also suggest actionable improvements tailored to localised conditions.

7.2 Research Achievements

The main contribution of this study is the development of a comprehensive framework for evaluating the reliability of health monitoring technologies based on AmI. The primary contribution of this research is the development of a reliability assessment framework specifically designed for Ambient Intelligence Assistive Technologies (AmI-ATs). The proposed framework addresses the critical need for structured, practical, and systematic methods to evaluate the reliability of AmI-ATs operating in ambient intelligent environments, particularly in healthcare and elderly living monitoring scenarios.

The proposed framework serves as a practical toolset that bridges the gap between theoretical reliability modelling and real-world application. It integrates key reliability metrics to comprehensively assess how well these technologies perform under diverse conditions. These metrics were carefully selected to account for both system-level factors (for instance, hardware and software reliability) and user-centric factors (like human interaction and usability). One of the framework's unique strengths lies in its ability to simulate and model the dynamic, resource-constrained, and often unpredictable environments where AmI-ATs are deployed. By leveraging advanced techniques such as Markov Chain Monte Carlo simulations and Reliability Block Diagrams the framework provides a robust and quantitative approach to identifying potential failure points, analysing system behaviour under stress, and recommending design improvements.

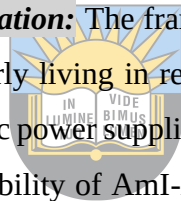
In addition to its theoretical contributions, the framework offers practical guidelines for developers, healthcare practitioners, and policymakers. It provides actionable insights into how AmI-ATs can be designed, implemented, and maintained to achieve higher reliability. By incorporating use-case-driven validation (for instance, Continuous Glucose Monitoring and Heart Rate Monitoring systems),

the framework demonstrates its real-world applicability, especially in resource-constrained settings like those in developing countries. The major outcomes of the study are summarised as follows:

Development of a Comprehensive Reliability Framework: The study introduced a multi-disciplinary framework for evaluating the reliability of AmI-ATs. This framework integrates human-computer interaction, health information systems, data science, machine learning, and assistive device manufacturing, making it applicable across various domains.

Application of Innovative Statistical and Machine Learning Models: The study adopted statistical models, traditionally used in other disciplines like agriculture economics, and applied them to reliability assessment in computer science. Machine learning algorithms were utilised for data analysis and anomaly detection, which were validated through case studies (like Continuous Glucose Monitoring and Heart Rate Monitoring systems).

Case Studies for Context-Specific Validation: The framework was validated using real-world case studies, focusing on healthcare and elderly living in resource-constrained environments like South Africa. By targeting challenges like erratic power supplies, heterogeneous devices, and human errors, the study provided insights into the reliability of AmI-ATs under operational constraints typical of developing countries.



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Defined Metrics for Reliability Assessment: The work presented in the study provides a basis for the introduction and discussion on non-traditional reliability metrics that are more suited to AmI-AT systems. Key metrics for reliability were identified and quantified and were applied systematically to estimate AmI-AT reliability in the presented use cases.

Scalability and Broader Applicability: The framework was designed to be scalable, addressing reliability across different contexts and systems. It aligned with broader Ambient Intelligence (AmI) and IoT fields, promoting the development of real-time reliability monitoring and predictive maintenance strategies for smart environments.

Bridging Research Gaps: The study addressed the lack of models for assessing the reliability of AmI-ATs in developing countries. It provided a context-aware solution that is specifically tailored to South African healthcare needs, with broader implications for other developing regions. It

demonstrated how reliability assessments could consider the human component, a critical factor often overlooked in existing models.

By combining insights from established disciplines like engineering, statistics and mathematics, the study advanced the theoretical understanding of AmI-AT reliability. The findings from the study can potentially contribute significantly to future research directions, particularly in the fields of health informatics, assistive technology design, and reliability engineering. These prospective achievements highlight the study's depth in addressing reliability challenges for AmI-ATs, especially in resource-constrained environments. The proposed framework and its findings provide a robust foundation for both academic exploration and practical applications in healthcare and elderly living monitoring.

7.3 Researcher Contribution

The researcher's contribution to the framework formulation, as outlined in the thesis, leveraged secondary data and technical methodologies without direct user involvement. Below are the specific steps undertaken by the researcher, detailing their technical contributions:



1. Secondary Data Analysis

- **Source Identification:**
 - The researcher identified and gathered secondary data from published studies, datasets, and technical reports on Ambient Intelligence Assistive Technologies (AmI-ATs) reliability.
 - Focused on datasets relevant to health monitoring systems, including glucose monitoring and heart rate tracking.
- **Data Preparation:**
 - Cleaned and pre-processed datasets to ensure consistency and usability for simulations.
 - Structured the data to align with the reliability metrics defined in the study, such as failure rates, recovery times, and transition probabilities.

2. Literature Synthesis

- **Critical Review:**

- Conducted an in-depth analysis of existing reliability evaluation models, including Reliability Block Diagrams (RBDs), Fault Tree Analysis (FTA), and Markov models.
- Synthesised insights from previous studies to identify gaps in current methodologies and inform the framework design.
- **Variable Identification:**
 - Defined key reliability metrics (e.g., accuracy, fault tolerance, recovery rates) and contextual factors (e.g., environmental constraints) from the literature.
 - Developed a taxonomy of factors influencing AmI-AT reliability, including hardware, software, connectivity, and human interaction.

3. Technical Modelling and Simulations

- **Mathematical Modelling:**
 - Used probabilistic techniques, including Markov Chain Monte Carlo (MCMC) simulations, to model state transitions in multi-component systems.
 - Developed mathematical formulations for reliability in series and parallel configurations, integrating redundancy and fault tolerance.
- **Simulation Design:**
 - Designed simulation scenarios to mimic real-world operations of AmI-ATs under varying conditions.
 - Incorporated synthetic failures and environmental challenges to evaluate system robustness.

4. Framework Architecture Design

- **Layered Approach:**
 - Conceptualised a multi-layered framework, with components including sensing, processing, transmission, and application layers.
 - Integrated findings from simulations and literature to structure the framework.
- **Metrics Integration:**
 - Established a set of reliability metrics to guide the evaluation process, ensuring comprehensive coverage of system performance.

5. Validation through Case Studies

- **Use Case Selection:**
 - Chose Continuous Glucose Monitoring (CGM) and Heart Rate Monitoring in Elderly Care as case studies to validate the framework.
 - Justified the selection based on relevance to the thesis's objectives and the availability of secondary data.
- **Evaluation of Results:**
 - Applied the framework to analyse reliability metrics in the case studies.
 - Generated visualisations, such as state transition Heatmaps, to interpret the reliability of systems.

6. Iterative Refinement

- **Framework Refinement:**
 - Adjusted the framework based on insights from simulations and case study results.
 - Ensured the framework addressed gaps identified in the literature, particularly in non-user-based evaluations.
- **Documentation and Contribution:**
 - Articulated the framework's methodology and application, providing a replicable model for future studies.
 - Highlighted the framework's utility in evaluating AmI-T reliability in resource-constrained settings.



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7. Key Contributions by the Researcher

1. **Novel Framework:** Developed a structured, layered framework for reliability evaluation without requiring user input.
2. **Technical Innovation:** Applied advanced modelling techniques, such as MCMC and RBDs, to simulate real-world scenarios.
3. **Validation through Case Studies:** Demonstrated the framework's applicability using practical, secondary-data-driven case studies.

This approach ensured the framework was grounded in technical rigor and practical relevance, addressing the challenges of AmI-AT reliability in constrained environments.

7.4 Research Limitations and Future Work

While this study successfully developed a comprehensive framework for assessing the reliability of Ambient Intelligent Assistive Technologies (AmI-ATs), it is important to highlight areas for further exploration and enhancement. The framework was validated using specific case studies, such as Continuous Glucose Monitoring and Heart Rate Monitoring, effectively showcasing its applicability in real-world scenarios. However, these use cases may not fully encompass the broad spectrum of potential applications, particularly in other healthcare domains or geographic contexts. Additionally, while simulation-based evaluations provided a robust and controlled environment for testing reliability metrics, future research should extend the framework's application to include diverse scenarios to enhance its generalisability and adaptability.

Moreover, expanding the framework's scope to technologies like remote mental health monitoring and assistive robotics, along with real-time field testing and longitudinal studies with diverse user groups, would provide deeper insights into its practical utility. Further integration of advanced AI techniques, such as predictive failure analysis and adaptive interventions, could refine its responsiveness to dynamic environments. The involvement of targeted users is critical before the full implementation of the proposed framework. Finally, collaboration with policymakers and technology developers will be essential to align the framework with global standards, promoting its scalability and adoption in resource-constrained settings worldwide.

7.5 Research Conclusion

This study successfully developed a comprehensive framework for evaluating the reliability of Ambient Intelligent Assistive Technologies (AmI-ATs), addressing a critical gap in healthcare and elderly monitoring systems, particularly as informed by the experiences from the African continent perspectives. By integrating reliability metrics, simulation-based testing, and case studies, the framework offers a robust tool for assessing and improving the dependability of AmI-ATs. The findings highlight the framework's potential to guide the design, development, and deployment of reliable assistive technologies tailored to resource-constrained environments. This research not only advances theoretical understanding but also provides practical insights, paving the way for future innovations in AmI-AT reliability and adoption.

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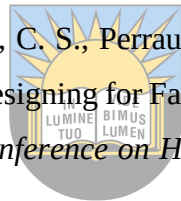
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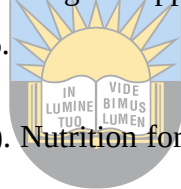
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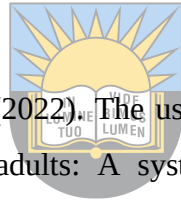
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Appendices

Appendix A Turnitin Report

Shakes Scott
Final PhD Thesis - 27 Dec 2024

-  Research Tasks
-  Research 2024
-  University of Fort Hare

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Appendix B Dataset

Files

diabetes_subset_ecg_data.zip

diabetes_subset_ecg_data.zip

diabetes_subset_ecg_data

001

sensor_data

.DS_Store 6.1 kB

2014_10_01-10_09_39

2014_10_01-10_09_39_ECG.csv 319.1 MB

2014_10_02-10_56_44

2014_10_02-10_56_44_ECG.csv 280.3 MB

2014_10_03-06_36_24

2014_10_03-06_36_24_ECG.csv 332.1 MB

2014_10_04-06_34_57

2014_10_04-06_34_57_ECG.csv 188.4 MB

Files (10.2 GB)

Name	Size	
diabetes_subset_ecg_data.zip	1.7 GB	Download all
md5:3d8928ca1bd43c2aeae3ba7771beb731		Preview Download

Files

diabetes_subset_ecg_data.zip	
002	
sensor_data	
.DS_Store	18.4 kB
2014_10_01-12_35_54	
2014_10_01-12_35_54_ECG.csv	201.1 MB
2014_10_01-20_29_57	
2014_10_01-20_29_57_ECG.csv	77.8 kB
2014_10_02-06_44_21	
2014_10_02-06_44_21_ECG.csv	346.5 MB
2014_10_03-06_33_20	
2014_10_03-06_33_20_ECG.csv	185.5 MB
2014_10_03-14_06_08	
2014_10_03-14_06_08_ECG.csv	165.2 MB



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diabetes_subset_ecg_data.zip md5:3d8928ca1bd43c2aeae3ba7771beb731 ⓘ	1.7 GB		Preview	Download
diabetes_subset_pictures-glucose-food-insulin.zip md5:104a2810050e2c6a6be698f683d862b5 ⓘ	251.7 MB		Preview	Download
diabetes_subset_sensor_data.zip md5:c1aa0e357e550df131310598051ab4e6 ⓘ	1.1 GB		Preview	Download
healthy_subset_ecg_data.zip md5:a6bcea5211b33ba01ed7b4faafe8f7f7 ⓘ	4.1 GB		Preview	Download
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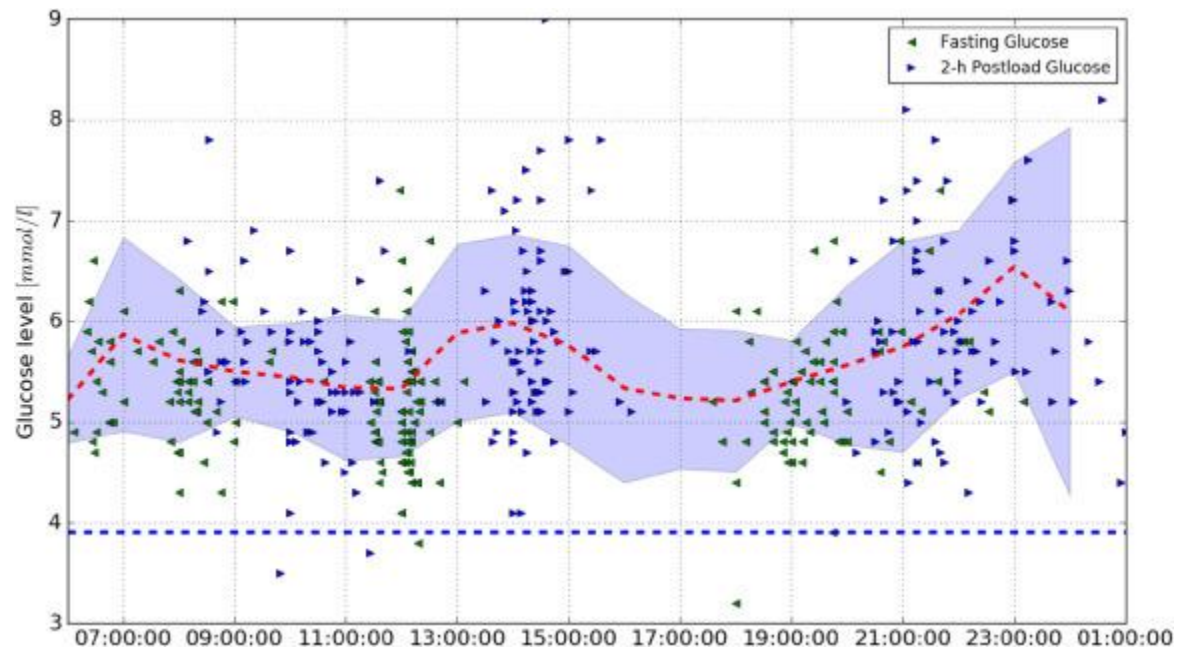
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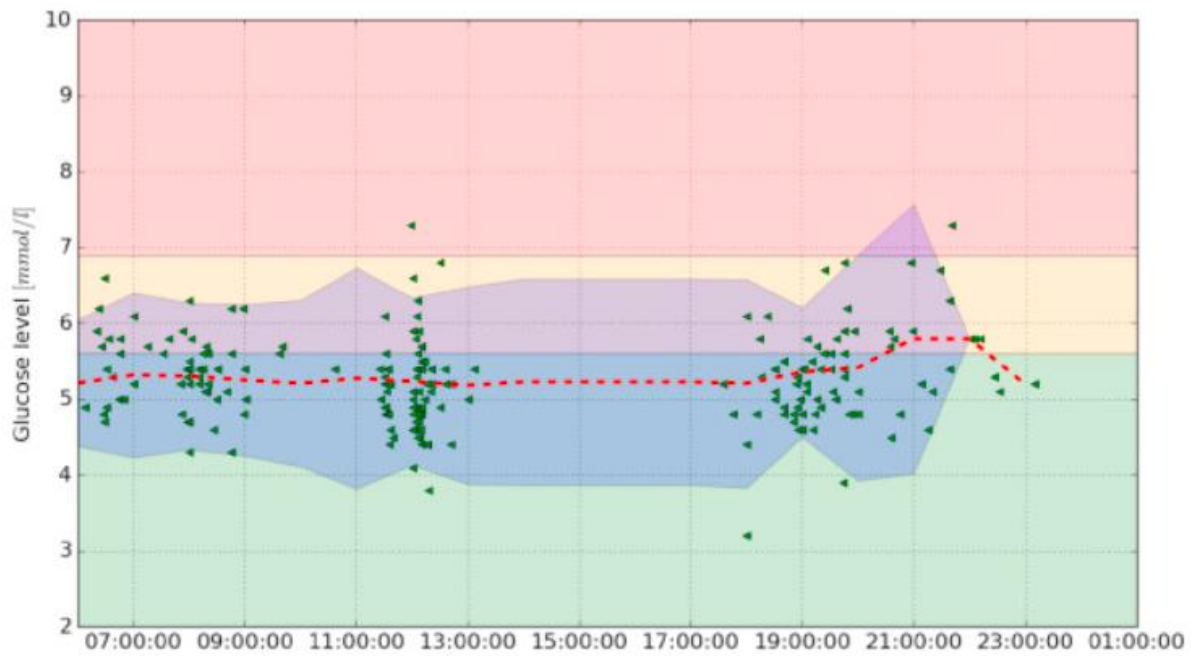
Dataset	ECG	Glucose	Activity	Food Intake	Measurement conditions	Target
MIMIC II[9]	✓	limited	✗	✗	UCI conditions	Monitoring UCI patients
MIT-NIH[11]	✓	✗	✗	✗	Ambulatory	Monitoring ambulatory patients
ECG Physionet datasets	✓	✗	✗	✗	Heterogeneous conditions	Various
UCI MHEALTH[13]	✓	✗	✓	✗	Everyday life	Mobile health
UCI Diabetes	✗	✓	✗	✗	Everyday life	diabetes management
DICARDIA[14]	✓	limited	✗	✗	Everyday life	Cardiac patients
D1NAMO	✓	✓	✓	✓	Everyday life	Diabetes management



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Appendix C Sample Images





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Appendix D Language editing certificate

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This confirms that I edited substantively the document below, including a Reference list. The document was returned to the author with various tracked changes to correct errors and clarify meaning.	
TITLE: A Framework for Evaluating the Reliability of Assistive Technologies that are based on Ambient Intelligence	
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EDITOR'S COMMENT	
The author was advised to effect suggested corrections regarding subject-verb agreement, punctuation and overall academic writing style, to name a few.	
 Signature	
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