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LUISS
School of Government

Joint Master in Global Economic Governance and Public Affairs

A Comparative Study On The Adoption Of Artificial Intelligence And Its Perceived Impact On Operational Efficiency In Maternal And Child Health Nonprofit Organizations.

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2024/2025

THESIS PITCH

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STATUTORY DECLARATION

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26/07/25

ACKNOWLEDGEMENTS

First and foremost, I thank God Almighty. His grace and strength have brought me this far, and without Him, none of this would have been near possible.

I am deeply grateful to my family and friends who stood by me with love and encouragement in countless ways. To my partner, Abraham, thank you for showing me what true support means. Your belief in me gave me the courage to keep going.

To my sisters and backbone, Alero, and to Abigail, Bukky, Mofe, and Bolu, thank you for loving me and being there, especially on the difficult days.

I am thankful to my institutions, the Centre International de Formation Européenne (CIFE) and Libera Università Internazionale degli Studi Sociali Guido Carli (LUISS). These universities provided not only a high-quality academic experience but also helped me grow personally. Through challenging workshops, group projects, and debates, I was encouraged to push my limits and see the world from new perspectives.

Thank you to my thesis supervisor, Professor Riccardo Viale, for introducing me to behavioral economics and guiding me through this research. Your insight and direction were invaluable.

I also want to thank my program director, the academic support staff, and all the lecturers and facilitators who played a role in my academic journey. Your commitment to teaching and your support made a lasting difference.

Finally, thank you to the interview participants in Nigeria and Germany who trusted me with their time and experiences. Your contributions made this thesis possible.

Thank you.

ABSTRACT

This study presents a comparative analysis of the adoption of Artificial Intelligence (AI) and its perceived impact on operational efficiency in maternal and child health (MCH) nonprofit organizations (NPOs) in Nigeria and Germany. While many research has globally explored the clinical application of AI, there is still a gap in demonstrating its impacts in operations in terms of workflow efficiency, resource allocation and delivery in organizations, especially in NPOs that serve vulnerable communities. A qualitative methodology was employed grounded on the Technology–Organization–Environment (TOE) framework and Nudge Theory. In this study, 13 professionals, 8 from Nigeria and 5 from German Organizations were interviewed. The findings reveal that Nigerian NPOs are adopting AI tools reasonably in their internal operations despite their limited infrastructure, however German NPOs show a slower adoption of AI into their system structure than expected, mainly due to issues such as regulatory policies, ethical concerns and cultural hesitations. Both countries demonstrate some common barriers including digital literacy gap and donor partnerships being a core concern. The study concludes that AI has a significant value in enhancing MCH-focused nonprofits, but can only be in perfect alignment when integrated in specific contextual realities of each system. Also applying behavioural economics, organizations can introduce subtle prompts to encourage staff and leadership to gradually embrace AI tools without imposing rigid mandates. By providing evidence based insight, this research presents insightful recommendations for non profits leaders, policy makers, AI developers and donors who aim to implement AI solutions.

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CHAPTER 1: INTRODUCTION

1.1 BACKGROUND OF STUDY

Maternal and child health (MCH) remains a crucial component of public health policy as it directly affects the well-being of people in society as well as economic development. Although from the global standpoint, a lot of efforts have been made, the World Health Organization (WHO) estimates that over 295,000 women die annually from pregnancy and childbirth-related problems, with low- and middle-income countries such as Nigeria bearing the brunt of this burden (World Health Organization, 2005; World Health Organization 2022). At the same time, avoidable problems like under nutrition, hunger, infectious illnesses, and delays in getting medical care continue to take the lives of millions of children under the age of five. Nonprofit organizations (NPOs) have for decades played an important role in filling gaps in MCH service delivery, especially in the most neglected regions. However, the same organizations often face constraints such as inadequate finances, disjointed workflows and processes, and insufficiently trained personnel, which hinder their ability to operate smoothly and scale in productivity and reach (Prentice et al., 2020). Artificial Intelligence (AI) has been noted to show benefits in addressing those challenges through its capacity to automate workflows, conduct predictive analysis, and provide critical data-driven decision support. In clinical settings, AI has been argued to lead to a decrease in diagnostic inaccuracies, optimize supply chains, and accelerate patient triage (Chui, M., & Francisco, S. 2017). While NPOs in technologically sophisticated countries such as Germany have begun experimenting with AI-powered instruments for monitoring program delivery and optimizing outreaches, adoption is still nascent in resource-limited countries such as Nigeria (Sinha, 2025). This disparity highlights a gap and prompts the need for a comparative study of how MCH-focused NPOs across these two distinct contexts are integrating AI, as well as the factors that shape its perceived impact on operational efficiency.

1.2 RESEARCH PROBLEM

Even though Artificial Intelligence (AI) has gained a lot of attention in global health, its real use in maternal and child health nonprofit organizations (MCH NPOs) is still relatively unexplored, particularly between high- and low-resource environments. To date, majority of academic and Industry conversation has focused on clinical AI advancements (such as image-based diagnostics and virtual triage), consistently ignoring how AI could transform the daily operational foundation of NPOs such as beneficiary outreach, reporting processes, inventory management and donor involvement. As a result, NPOs run the risk of two equally harmful consequences. On one side, they might spend limited resources on misplaced "AI for health" experiments that produce little more than costly pilot studies, undermining stakeholder trust and increasing technology exhaustion. Conversely, they might completely disregard AI due to concerns for its complexity or expenses, thus missing out on chances to cut out pointless tasks, speed up data-driven decision-making, and reach out to underrepresented populations. In both cases, ongoing inefficiencies, fragmented data flows, created supply bottlenecks, and reporting backlogs that are left unaddressed, weakening program effectiveness and ultimately jeopardizing maternal and child health outcomes. This stark lack of evidence regarding AI's organizational applications in maternal and child health non-profits also affects service delivery, causing supply-chain backlogs and reporting delays that slow down critical care and put a strain on front-line staff, who manage error-prone manual workflows or invalidated AI systems without necessary training. Funding priorities are distorted, leading donors to either pump limited resources into un-scalable pilots or avoid digital innovation entirely. Additionally, governments are left to maneuver through a regulatory gray area that can either put organizations at risk of data privacy issues or hinder the responsible use and adoption of AI. Ultimately, when AI solutions are misused or implemented incorrectly, they exacerbate health inequities, undermine community confidence in both technology and the nonprofits that promote it, thereby jeopardizing the very objective of enhancing maternal and child health results. This research tackles this significant gap by examining not only the "if" but the "how" of AI adoption across vastly diverse contexts. It aims to reveal the institutional, technical, and cultural divides that decide whether AI serves as a catalyst for nonprofit impact or an unachievable goal, thereby providing decision-makers with the thorough, comparative evidence they urgently require.

1.3 RESEARCH QUESTION

Primary Question:

How does the adoption of Artificial Intelligence influence operational efficiency in maternal and child health focused nonprofit organizations in Nigeria as compared to Germany?

Sub-Questions:

1. What is the extent of AI adoption among maternal and child health NPOs in Nigeria and Germany?
2. How do perceptions of AI's effectiveness in improving operational efficiency differ between NPOs in these nations?
3. What are the main barriers and enablers influencing the adoption of AI in these organizations

1.4 RESEARCH AIMS

The primary aim of this research is to produce contextually relevant insights that guide strategies to improve AI adoption and maximize operational efficiency in MCH NPOs across various economic and geo-political contexts.

1.5 SPECIFIC OBJECTIVES

To realize this aim, the study will:

1. To evaluate the extent of AI adoption in MCH NPOs across Europe and Africa with Germany and Nigeria as case study countries.
2. To compare the perceived effectiveness of AI tools in improving operational efficiency between these regions.
3. To identify critical barriers and enablers affecting the deployment and adoption of AI in nonprofit organizations in both contexts.
4. To suggest tailored recommendations for improving the implementation of AI in MCH NPOs in Europe and Africa.

1.6 JUSTIFICATION FOR THE STUDY

The increasing complexity of global health concerns requires maternal and child health (MCH) nonprofit organizations (NPOs) to embrace new and creative strategies to enhance effectiveness despite worsening limited resources. However, the majority of current studies focus on clinical AI uses like diagnostic imaging or patient triage while ignoring the organizational procedures that are essential for the successful provision of services by NPOs. This gap is especially noticeable in cross-context analyses: we do not have systematic data on how AI integration plays out in resource-constrained settings versus technologically advanced ones, or whether insight gained in one context can be applied to another. This study directly bridges the gap by comparing MCH NPOs in Nigeria with their German counterparts, thereby providing a detailed, comparative perspective that can be used to uncover both universal principles and context-specific strategies for utilizing AI in the nonprofit sector. First, the study's comparative framework will reveal excellent practices that cut across economic and infrastructural barriers. In Germany, it is argued that strong digital infrastructures, strong technical skills and proficiency, and supportive policy environments are advantages for NPOs. Conversely, Nigerian NPOs often deal with the infrastructural challenges that the country faces, including unreliable electricity, restricted broadband access, and severe skill deficits. By recording these varied experiences concurrently, the study will shed light on organizational models and adaptive methods that can benefit NPOs worldwide, whether they are based in a major European city or a small West African suburban area. Practical evidence-based recommendations for various stakeholder groups will be produced by this research to provide some insights into navigating their various operations. Nonprofit leaders will learn which AI tools provide the highest operational return on investment, whether it involves automating repetitive data entry, enhancing supply-chain logistics for life-saving supplies, or facilitating real-time field reporting through mobile devices. Donors and funders will gain a detailed understanding of how to effectively distribute limited digital-innovation grants, while steering clear of a "one-size-fits-all" funding approach and instead adjusting support based on the infrastructural capacity and maturity level of recipient organizations. In turn, technology creators will gain practical insights into exploring factors affecting the proper adoption of technology that need to be incorporated into AI solutions, like linguistics, culture, and regulatory factors. By emphasizing organizational aspects of AI adoption over purely clinical ones, the study creates a substantial theoretical contribution. It broadens existing models like the Nudge Theory and Technology–Organization–Environment (TOE) framework into the nonprofit sector, evaluating their efficient suitability and improving them while taking into consideration mission-oriented institutional logics, reliance on donations, and community-focused governance structures. This theoretical development will enhance both information systems and literature on nonprofit management, creating new opportunities for researchers to examine the relationship between algorithmic tools, organizational purpose, and stakeholder principles. Lastly, the research has significant findings for sustainability and health equity. In numerous LMICs, the records of maternal and child mortality are still alarmingly high, and the same old method of interventions alone has been proven inadequate to deal with the difficult situation. This study offers a pathway towards demonstrating how AI can be utilized to speed up decision-making processes, optimize workflows, and minimize waste in MCH programs that can increase resilience and be cost-efficient. It recognizes the role of nudging, subtle cues and design choices that steer organizations and stakeholders toward adopting AI tools without restricting their freedom of choice, helping to accelerate meaningful, context-sensitive change (Viale, 2022). Equally significant, by recognizing the facilitators and obstacles to AI adoption, the research will help guide policy changes, either via incentives for innovation in digital health, funding for broadband infrastructure, or capacity-building training programs targeted at local nonprofit personnel. By doing this, it aims to stimulate a global shift toward data-driven, inclusive, and fair MCH service delivery that acknowledges the diverse realities of businesses functioning across economic backgrounds.

1.7 CONCLUSION

This chapter has emphasized the necessity of exploring AI implementation in maternal and child health nonprofit organizations by presenting the background, outlining the important research problem, and formulating precise questions, aims, and objectives. By contrasting the resource-scarce context of Nigeria with Germany's digitally mature environment, we have identified a pressing need for comparative, organizationally focused evidence on how AI reshapes workflows, data management, and program delivery. The following chapter of this thesis would shed more light on this foundation by undertaking a thorough synthesis of existing literature, as well as understanding the theoretical frameworks and findings across studies on AI across clinical and non-clinical health environments, and identifying gaps in cross-context evaluations of nonprofit activities. Subsequently, Chapter 3 will provide a qualitative methodology sampling of MCH NPOs, semi-structured interviews, and will apply a themed technique analysis intended to produce results that are profound and give context-specific insights. Chapters 4 and 5 will discuss the findings, respectively: Identifying common facilitators and barriers to AI adoption, assessing perceived operational efficiencies, and interpreting results via our theoretical frameworks. The final Chapter 6 will consolidate findings, recommend practical recommendations for nonprofit executives, funders, technology creators, and policymakers, as well as potential directions for future research. The encompassing goal of this is to close the absent evidence gap on organizational AI and provide a guide for utilizing intelligent technologies to enhance MCH outcomes in various settings internationally.

CHAPTER 2: LITERATURE REVIEW

2.1 INTRODUCTION

Over the years, Artificial Intelligence (AI) has evolved in its integration into many systems of society and has become a tool recognised for its unique problem-solving potential. Nonprofit organizations (NPOs) that are focused on maternal and child health (MCH) have been instrumental in solving some of the challenges facing the health care industry in both underserved and developed regions (Anyanwu et al, 2024). However, these organizations are seen to face operational inefficiencies, and this has been attributed to issues such as limited resources, outdated infrastructure, and fragmented processes (Bamidele & Pikirayi, 2023). The integration of AI has been argued by experts to present an opportunity towards optimizing the delivery of healthcare as well as streamlining resource allocations and ultimately improving patient care (Aminizadeh et al, 2024). This chapter of this Thesis would identify existing literature on the adoption of AI in the health sector, focusing especially on nonprofit organizations that are involved in maternal and child health (MCH).

2.2 ARTIFICIAL INTELLIGENCE IN HEALTHCARE

Artificial Intelligence refers to computational technologies that allow machines to be able to stimulate and replicate the processes that ordinarily are organized by human intelligence, including learning, reasoning, and the ability to make decisions (Jarrahi, 2018). AI-powered tools have been deployed in health contexts for risk prediction, diagnostic imaging, electronic health record management, and telemedicine (Patel et al, 2024). Jikiemi (2024) describes the power of AI in its ability to compensate for the shortage of skilled workers and also its ability to optimize limited resources.

A recent significant contribution by Capraro et al. (2024) gives insights into how generative AI is more of a transformative tool than a neutral tool; it highlights how it can reduce and make obvious socioeconomic inequality in our society. This reinforces the need to evaluate AI in maternal and child health nonprofits for both operational efficiency and its broader implications for health equity. Nonetheless, some scholars express some caution about the fact that excessive reliance on AI systems without adequate clinical oversight can lead to a breach in the safety of patients, especially as the decision-making may not fit the context (Amann et al., 2020). AI has several forms and models and one of these is based of it been used in the processing of unstructured medical texts, virtual consultations, as well as serving as digital health assistants providing medical advice and scheduling patient visits (Nazi & Peng, 2024). AI models such as LLMs offer innovative capabilities, nevertheless there have been questions about if they are a ready-fit for high-stakes healthcare tasks, especially considering risks like generating clinically incorrect advice and difficulties in validating outputs against guidelines and evidence (Benjamens et al., 2023).

2.3 NONPROFIT ORGANIZATIONS IN MATERNAL AND CHILD HEALTH

Nonprofit organizations are of great importance in delivering maternal and child healthcare services. By offering free clinics, mobile health units, and telemedicine, they are crucial in accessing the most vulnerable populations and inaccessible communities (Weaver et al., 2017; Griffith et al., 2010). They pursue several partnerships, including with the government and donors; however, these can sometimes lead to a compromise of NPO autonomy, and consequently lead to a drift in focus and values as they become forced to prioritize donor-driven metrics over local health needs (Banks et al., 2015). NPOs still posses some gaps in service, especially in their processes, as they often encounter challenges operationally, such as insufficient workflow, poor data management, and funding constraints (Rajabi, M., 2021). In addition, a shortage of skilled personnel further limits the quality of services delivered (Bendell, 2006; Burger & Owens, 2010; Rajabi, 2021).

2.4 OPERATIONAL EFFICIENCY IN NONPROFIT ORGANIZATIONS

Operational efficiency in Nonprofit Organizations (NPOs) is defined as the ability to make the best use of resources, time, money, personnel, and materials to achieve set objectives (Liket & Maas, 2015). In maternal and child health (MCH) NPOs, efficiency is often evaluated through cost-effectiveness, service delivery speed, error reduction, and the ability to scale interventions (Liket & Maas, 2015). There are several ways in which NPOs improve operational efficiency and deliver high-quality services while reducing costs and waste (Balidemaj, 2024). Resource utilization ensures that essential inputs, staff, funds, and facilities are deployed optimally to deliver the greatest impact (Balidemaj, 2024). Optimization of processes deals mainly with the streamlining of workflows, often using automation or standard protocols to reduce instances of duplication (Balidemaj, 2024). Cost efficiency is mostly achieved when organizations are able to minimize expenses without sacrificing quality (Lempert, 2015). It has been observed that key indicators for success in the processes within NOPs include reduced error rates, shorter waiting times, improved record accuracy, and measurable outcomes in maternal and child health (Lempert, 2015; Poister, 2008). Yet scholars emphasize that over-reliance on quantitative metrics can neglect softer outcomes such as empowerment and cultural sensitivity, which are essential in community health work (Ebrahim & Rangan, 2014).

2.5 COMPARATIVE PERSPECTIVES: AI IN MATERNAL AND CHILD HEALTH NPOS IN NIGERIA AND GERMANY

There is a significant contrast in the operation of healthcare in Nigeria and in Germany, especially in terms of technology, policy frameworks, and service delivery models. Germany has robust support systems for AI, especially within its healthcare sector, with a high digital infrastructure, government-backed initiatives, and trained professionals who are otherwise digitally aware (European Commission, 2021; BMG Digital Health Survey, 2022). On the other hand, Nigeria is faced with challenges that are largely structural and systemic, and these have been argued to limit the utilization of technology within the health system, including maternal and child health (MCH) NPOs (Jacob et al., 2020).

These contrasts in systems are equally in syn with Capraro et al.'s (2024) argument that AI adoptions give a bigger perspective into social inequalities. Such countries with better governance and infrastructure are tailored to gain more benefits, and the not-so-strong low to middle-income countries are at risk of further widening already present gaps. According to WHO data, only 39% of health facilities based in Nigeria had stable internet connectivity in 2021 (Tung, Press and Peek, 2024.). Researchers argue that Nigeria's healthcare limitations are primarily down to inadequate funding for health, as the expenditure was only 3.1% of GDP in 2020 compared to Germany's 11.7% (Omoleke & Taleat, 2017;). This is also accompanied by poor policy implementation and technological infrastructure, which is weak (Omoleke & Taleat, 2017;). This contrast is consistent with findings by Bhaskar et al. (2020), which demonstrate that the policies in Germany, which are largely structured to expedite AI-driven telemedicine rollouts, while the fragmented nature of policies in Nigeria ultimately risks the limitation of sustainability (Dittrich et al., 2021). It is also noteworthy that even in Germany, the high infrastructural position that is present there does not always guarantee that AI technologies will be seamlessly adopted. There have been several debates about the ethical and cultural concerns, which many argue could be affect adoption (Floridi et al., 2021). A 2023 study on AI implementation in German nonprofits highlighted that the organizations displayed a rather passive position as they were mostly cautious owing to the complexities related to GDPR compliance and concerns that had stemmed from the public about how their data was being managed and used (Panteli et al., 2025). Comparatively, in Nigeria, some scholars have argued that NPOs have to, out of necessity, innovate and begin to deploy AI solutions that are low-cost, such as SMS-based triage or WhatsApp-enabled consultations to bridge workforce gaps, but these efforts are limited in scale due to infrastructural decay such as unreliable power supply and scarce digital literacy (Gooyabadi et al., 2023).

2.6 PERCEPTIONS OF AI IN IMPROVING OPERATIONAL EFFICIENCY OF HEALTHCARE NONPROFITS

In various regions, the perspectives on the perceived effectiveness of AI in improving operational efficiency in MCH differ. The receptiveness of key stakeholders goes a long way in determining the success of the adoption of AI in healthcare for NPOs (Gillespie et al., 2021; Bogumil-Uçan & Klenk, 2021; Sarfo et al., 2024). Yet, receptiveness alone does not guarantee that implementation of these technologies would be successful; organizational inertia and complex workflows often delay scale-up despite supportive attitudes (Greenhalgh et al., 2017). Some organizations, including NPOs, have acknowledged the potential benefit of AI to improve efficiency; they are, however, concerned about the cost of implementation, the availability of digitally skilled personnel, data management systems, privacy concerns, and the adaptability of AI solutions to the Nigerian context (Omoleke & Taleat, 2017). In Nigeria, there have been alot of qualitative evidence that have shown that even though community health leaders value AI-enabled tools, many of them are still very unable to integrate these tools in their work and surveyed staff indicating that additional training is required before full implementation (Tung, Press and Peek, 2024) Furthermore, studies show that health workers often express skepticism about AI tools, as many of them fear the possibility of job displacement or loss of professional autonomy (Petersson et al., 2022). A 2022 cross-sectional survey of 15 Nigerian MCH NPOs found that over 60% of health workers were of the opinion that jobs may be replaced by AI, especially roles which were regarded as administrative, and this in turn contributed to the resistance despite the gain they recognized. (Anyanwu et al., 2024). In Germany, perceptions are shaped more by the caution that most organizations take regarding regulatory concerns than by resource gaps. A 2023 review by Panteli et al. reported that approximately 55% of German nonprofit staff were confident about the ability of AI systems to improve the way that they operate, however many of them reported that compliance with GDPR and ethical guidelines were the main barriers to scaling beyond administrative tasks (Safdar et al., 2020; European Commission, 2021). This divergence in perception in these two regions influences the extent and pace at which AI is implemented in MCH NPOs.

2.7 ADOPTION OF AI

The willingness to adopt AI is strongly influenced by an organization, the availability of funding, and the regulatory environment (Jöhnk et al., 2021). Even in high-income countries, adoption is noted to be largely not uniform. Many organizations struggle with approvals that may be required for ethical control, as well as having to adjust their legacy systems to accommodate the new technology, and the cost of retraining staff, all of which can delay or limit implementation (Petersson et al., 2022). In these contexts, adoption is supported by advanced digital literacy attainment and availability of sizeable resources, but even then, success is often hinged on the ability to achieve clear implementation pathways as well as support from the internal leadership (Jöhnk et al., 2021). Adoption is also shaped by access and skill. Capraro et al. (2024) share an argument that generative AI shows an “inverse skill-bias,” which mainly means that it will unevenly benefit the less skilled and less experienced workers over the more qualified.

In low-income countries, however, the situation is quite different in some ways Hadley et al. (2020) highlight that organizations in these regions face constraints that are linked to the inadequacy of necessary technological infrastructure, inability to access high-quality data, lower digital literacy, and a shortage of skilled workforce, which come together to impede the attainment of the full potential of AI technologies. This, in turn, results in a slower adoption rate, or, where adopted, the restriction to simplified applications that do not fully exploit AI’s capabilities (Ciecierski-Holmes, 2022; Davenport & Glaser, 2022). Within healthcare, AI adoption varies widely depending on the domain.

2.7.1 ADOPTION OF AI IN MCH NPOS

AI has increasingly been embraced by corporate healthcare institutions, but its adoption within nonprofit organizations (NPOs), particularly those focused on maternal and child health (MCH), has been more gradual. In Nigeria, there has been growing traction in the use of digital tools such as telemedicine platforms and AI-enabled applications in urban centers, (Ibironke, 2021). Several NPOs and local health initiatives have begun using services such as remote consultation, AI chatbots for antenatal care reminders, and mobile decision-support tools to cope with the challenges of not having enough trained healthcare professionals, especially in regions that are underserved (Ibironke, 2021). This progress, however, remains uneven, as the adoption and utilization of AI as well as digital transformation are still in their formative stages (Abel & Obeten, 2015). Digital literacy gaps among frontline workers further slow the integration of AI into routine workflows, particularly in rural regions where healthcare access is most constrained (Ibironke, 2021; Mustapha et al., 2024). These mirror patterns observed across many African contexts. For example, research done in Kenya and Uganda shows that although AI-driven SMS health reminder systems led to an increase in patients adhering to appointment by over 20%, weakness in infrastructure such as networks being unstable and the inconsistency of funding lead to it not being adopted readily (Makulilo, 2012; Mate et al., 2022). Despite these barriers, innovation has largely been spurred by necessity; African MCH nonprofits have been noted to often pursue and pioneer low-cost solutions that are adapted to their unique context and have the ability to directly address urgent service delivery gaps. In Germany, by contrast, there have been substantial efforts made regarding adopting AI within MCH NPOs, albeit this has happened at a more measured pace. The health care ecosystems within which German nonprofits operate are one that benefits from near-universal broadband access, as well as structured funding and policy from government, such as the Digital Healthcare Act (DVG), and this largely ensures that the deployment and integration of AI tools are incentivized (European Commission, 2021; Panteli et al., 2025; Safdar et al., 2020). This has resulted in it being explored firstly with administrative or supportive roles before being integrated into direct health decision-making (Floridi et al., 2021). Studies show that 60% of European healthcare nonprofits use AI in administrative functions, while fewer than 30% have integrated AI directly into patient care pathways due to concerns around ethical and regulatory compliance (Van Noordt and Misuraca, 2022).

2.7.2 BARRIERS AND ENABLERS OF AI ADOPTION IN MCH NPOS

Organizational willingness, technology infrastructure, leadership support, the availability of a skilled workforce, local and cultural contexts, trust in technology, and enabling policies all affect how AI is integrated into operational and clinical workflows (Petersson et al., 2022). Agbeyangi and Lukose (2025) emphasize that funding that is directly obtained from donor relations, as well as the presence of a leadership that favors innovations, act as pivotal enablers, yet barriers such as unclear governance structures and low digital literacy remain significant impediments. In high-income countries like Germany, factors that enable the adoption and use of these systems are often based on the financial strength, especially from stakeholders, including the government, with a detailed framework in mind, (Panteli et al., 2025). However, these same regulations can become barriers. Strict compliance processes most of the time would go hand in hand with extensive documentation, legal review, and data protection assessments, which sometimes may contribute to the slowing down of adoption of AI, especially within NPOs that are small-scale and lack the technical structure (Floridi et al., 2021). A 2023 survey found that 42% of managers within German nonprofits faced complexity in regulatory and cited this as one primary reason why AI was not integrated into core workflows (Panteli et al., 2025). In contrast, LMICs such as Nigeria experience barriers of a different nature. While there is less regulatory red tape, infrastructural challenges are far more pronounced. Power instability, unreliable broadband, and high costs of digital tools make it difficult for NPOs to sustain AI interventions (Mustapha et al., 2024). A WHO digital readiness report (2023) noted that less than 40% of primary healthcare facilities in sub-Saharan Africa have continuous internet access, and this fact directly constrains the application of AI-dependent systems. Furthermore, concerns around the Cultural undertone prevalent within these regions also play a role: some communities express distrust in automated decision systems, fearing errors or loss of the "human touch," which can limit how much care delivered by AI systems can be accepted by the people who receive them (Okolo, 2022). Despite these constraints, Nigeria and similar LMICs often show a flexibility in adopting some of these technologies, which has been largely remarkable. This aligns with findings in Kenya and India, where health systems have gone ahead to pursue the adaptation of AI to solve needs despite limitations in the structure and environment (Mate et al., 2022; Mate et al., 2022). Globally, studies note that factors which enable easier and quicker adoption include: international funding, cross-sector collaborations, tailored workforce training, as well as the development of low-cost AI tools, which can bridge these gaps (Arakpogun et al., 2021).

2.8 THEORETICAL FRAMEWORKS FOR AI ADOPTION IN NONPROFITS

2.8.1 TECHNOLOGY ACCEPTANCE MODEL (TAM)

The Technology Acceptance Model (TAM) developed by Davis in 1989 reflects two factors for acceptance, the first is the perceived ease of Use which defines the extent to which a user believes that technology would be free of effort and easy to comprehend, while the other is perceived Usefulness which beliefs that the technology will enhance job performance or personal tasks, (Davis, 1989). Several experts argue that in developed worlds, the users are more willing to prioritize ease of use, while in developing regions, the perceived usefulness of AI applications in addressing pressing issues like Healthcare access may take precedence (Ariza-Montes 2020;

Ritchie 2011). However, critiques of TAM highlight that it may oversimplify adoption by neglecting broader social, cultural, and organizational influences (Legris et al., 2003).

2.8.2 NUDGE THEORY

Nudge Theory, developed by Richard Thaler and Cass Sunstein, posits that small, non-restrictive cues can subtly guide people toward making choices that are in their best interest without limiting their freedom of decision.Within maternal and child health (MCH) nonprofit organizations, these nudges have been seen to accelerate how AI is adopted at both the organizational and workforce levels. Rather than relying solely on formal policies or mandates, nudges help in shaping the environment to allow for decisions that would integrate AI as a more natural and easy choice.

As Viale (2022) describes in Nugdging, nudges are not just a concept limited to human behaviour; they can effectively be applied at both institutional and policy levels. He demonstrates its progressive power in influencing how organisations adopt innovations such as AI. And central to this reshaping is the "Choice architecture" which explains ways in which options are presented and framed to decision makers, such that the preferred options are almost natural and much easier to choose (Viale, 2022). For example, automated prompts that are embedded within the company's current workflows can encourage front-line workers to begin to use AI-enabled data entry systems immediately after patient visits, thus leading to improved timeliness and accuracy.

This aligns with behavioural economics demonstrating how subtle cues can influence decision-making without restricting choices, leveraging human tendencies to follow easier or more salient options. However, it is safe to say that nudges alone are not a panacea and they are only functional best when they are part of a broader adoption strategy (**Viale, 2022)**.

2.9 THE ROLE OF AI IN ENHANCING OPERATIONAL EFFICIENCY IN MCH NPOS

In the last couple of years, AI has been able to demonstrate its potential to contribute to enhancing operational efficiency in various industries, with healthcare being quite receptive to its necessity in this sector. For maternal and child health (MCH) nonprofit organizations (NPOs), AI's ability to demonstrate efficiency in optimizing processes and service delivery in different ways, such as reducing repetition of manually done tasks, providing additional support to clients, and allowing for data-driven resource mobilization (Naamati-Schneider & Salvatore, 2024). Evidence from Global studies prove AI's efficiency in high income healthcare systems like Germany by showing how AI enabled technology has helped reduced emergency wait time by up to 30%, and predictive analysis has also cut appointment no show rate by 15-20% due to its ability to define high risk patients and sending strategic timely reminders (Schwalbe and Wahl, 2020). In low-income healthcare systems, like in Nigeria, pilot projects in vaccine distribution programs have been seen to create a more enhanced delivery chain process and reduce out-of-stock challenges of resources in rural regions by about 12% when compared to the traditional logistics systems (Anyanwu et al, 2024). Reports on the field actually show that automated processing can ironically make the workload more than intended when the systems are poorly developed for local context environments. An example is when staffs in Nigerian NPO pilots had to perform the same task twice, one of inputting data both on paper logs and also on AI devices, because of unforeseen and often foreseen barriers like regulatory requirements, connection reliability, thereby creating some level of administrative fatigue (Seneviratne & Peiris, 2018). Overall, while the benefits are clear to see, including a strong accountability through fraud detection algorithms and operational efficiency, the pathway to achieving them requires careful planning and evaluation.

2.10 GAPS IN LITERATURE

With a growing interest in the adoption of AI in maternal and child health (MCH) within non-profit organizations (NPOs), there are still several gaps in research. A major gap that has been noted in most literature is the fact that there is limited research on what the exact barriers and enablers faced by MCH NPOs in adopting AI technologies are. Although some research has been done in this field most of them have been around private sector and Government based programs with very little and almost nothing on barriers in NPOs like; financial resourcing, low funding funding and technical and infrastructure dynamics, all these which makes implementation of AI more complex to influence AI (Gooyabadi et al, 2023). Secondly, there is a lack of understanding regarding the contextual factors that influence AI adoption for operational efficiency in low- and middle-income countries (LMICs) where many MCH NPOs operate. NPOs face several challenges, so there is a need for specific research on how AI technologies can be environment-specific. While Capraro et al. (2024) advocate for an interdisciplinary study on AI's societal impact in healthcare, there is still an important gap that needs to be addressed, which is nonprofit organisations in maternal and child health. This reinforces the need for comparative, context-sensitive research such as the present study. This comparative study between regions could shed some insights into how varying environmental conditions influence the effectiveness and outcome of AI being implemented. Also, with the rise in ethical concerns in AI applications, there is a research gap in the context of MCH NPOs aligning with regulatory frameworks globally. Understanding and addressing these gaps would help in developing strategic and practical adoption of AI in MCH NPOs, particularly in resource-constrained environments like low- and middle-income countries (LMICs) when compared with developed settings.

2.11 CONCLUSION

This literature review has gone ahead to explore what the evolving landscape of Artificial Intelligence (AI) adoption within maternal and child health (MCH) nonprofit organizations is. It has also highlighted key insights that are largely comparative between Nigeria and Germany, demonstrating that infrastructural readiness, regulatory environments, cultural perceptions, and organizational capacity potentially determine the patterns of adoption of AI. Importantly, the review was able to identify gaps that exist in current literature, especially with regard to how there is limited focus on operational realities faced by NPOs, as well as how context-sensitive AI solutions have been leveraged. It describes the mechanisms through which enablers and barriers interact in diverse regions. Chapter 3 will build upon the foundations that have been established here, and will shed more light on outlining the research methodology.

CHAPTER 3: METHODOLOGY

3.1 INTRODUCTION

This Chapter provides the methodology that was used to achieve the objectives of this study. It outlines the theoretical framework, research philosophy, research design, sampling technique, and overall data collection and analytical process used. It also focuses its discussion on some ethical concerns, trustworthiness, rigour to ensure a valid process and followed by the barriers noted in the study.

3.2 RESEARCH DESIGN

This study employed a qualitative research approach, which helps demonstrate a deep understanding of subjective narratives, organizational approaches, and context-based realities.

3.2.1 THEORETICAL FRAMEWORK

The present study is engaged in a juxtaposition of theoretical perspectives, amalgamating the Technology–Organization–Environment (TOE) Framework and Nudge Theory, thus providing a very wide view of AI uptake within maternal and child health nonprofit organizations in Nigeria and Germany. The TOE Framework as seen in figure 1 below, proposed by Tornatzky and Fleischer (1990), has earned great consideration in technology adoption research as it brings to the fore those various determinants of organizational behavior that should be considered in a very complex environment. In its description, three interdependent contexts-techniques-organization-environment are together carried into the adoption process.

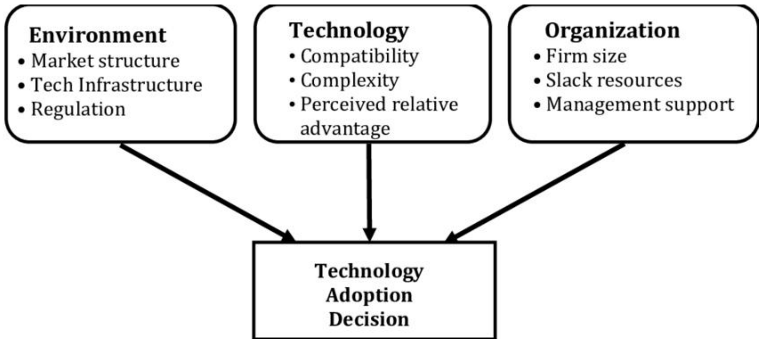

Figure 1: Technology Organization Environment (TOE) Framework (Tornatzky and Fleischer, 1990)

In the context of this study, technological issues are concerned with the availability of AI, its perceived benefits, and the complexity of its tools being deployed in NPOs. The organizational context looks internally at structures, managerial support, budgetary provisions, and human capacity on whether AI projects can be implemented in an applicable manner. In terms of the environmental context, an elaborate construction would embrace the external constructs of regulatory framework, donor expectations, cultural factors, and even infrastructure readiness insofar as these may constrain or enable AI adoption. This tripartite framework, hence, provides a comprehensive view of how the internal and external factors interact to impact operational efficiency results. Another such theory is Nudge Theory (Thaler & Sunstein, 2008), which is about subtle interventions in decision-making contexts that produce an undesired behavior without mandatory impositions. Within the NPO context, such nudges may consist of disseminating evidence-based success stories about AI implementation toward societal benefit; low-cost trial programs; or an extended communication strategy that frames AI adoption as a boon to social impact rather than just another tech upgrade. Thus, nudges may sway organizational leaders and staff toward a positive viewpoint on AI adoption-and therefore towards substantive behavioral change within the NPO over time.

3.2.2 RESEARCH PHILOSOPHY

This study engaged an interpretive research philosophy, which is largely dependent on understanding individuals lived experiences within their context of environment. It does utilise Positivism which seeks to understand the universal laws through quantitative data, but it risks a possibility of not taking into account cultural dynamics and organization informed dynamics. For cross-country comparison in studies, the interpretivist paradigm helps the researcher to appreciate the value of cultural norms, economic situations, organizational structures, and how stakeholder's beliefs shape behaviour and decision making in Nigeria and Germany.

3.2.3 RESEARCH APPROACH AND STRATEGY

This research embedded multiple approaches of reasoning, putting into account both deductive and inductive strategies, able to enhance the research robustness and diversity of the process. The initial line of shaping the focus of the research, enquiry process, and designing the interview guide was guided by the deductive approach. While the inductive element was demonstrated during the process of data collection analysis, it provided insight, themes, and patterns in an organic way from the participants' narrative. This approach was necessary to reveal sensitive context-specific factors and unanticipated barriers.

3.3 SAMPLING

The sampling technique used was a purposive one as it identified and selected the organizations that are either actively considering adopting AI, and especially those that have adopted the integration into their operations. The organizations that were selected were focused mainly on several aspects of maternal and child health (MCH) NPOs operating in Nigeria and Germany. It comprised a total of 13 organizations, with 8 from Nigeria and 5 from Germany, and this ensured that there was a balanced comparative perspective. The size of the companies, whether large or small, was also taken into consideration. Key informants included program managers, technical leads, and organizational leaders with direct involvement in AI-related initiatives, ensuring that the data captured stemmed from knowledgeable and experience-rich perspectives. This sampling strategy was deliberately chosen over alternatives such as random sampling or stratified probability sampling because the research seeks depth rather than breadth or generalization.Purposive sampling, by contrast, allows the researcher to focus on information-rich cases within diverse organizational settings. Although this method inherently limits the generalizability of findings to the wider population of NPOs, it is particularly well suited to qualitative, comparative studies.

3.4 DATA COLLECTION METHODS

Primary data for this study were collected through semi-structured interviews with key informants from each selected organization, ensuring that core themes are explored while still allowing room for probing emergent issues or context-specific insights. Interview guides were carefully developed based on the research objectives, ensuring that each question aligned with the study's aims and targeted operational realities. The questions that were generated underwent a pilot test to ensure that they were clear and appropriate. I was able to reduce ambiguous areas and ensure that they were culturally adjusted, especially considering the cultural differences between the two regions. This enhanced the reliability and validity of the instrument for data collection. The interviews were conducted via Google Meet, which is a secure channel and helps high levels of confidentiality. Each interview session lasted approximately 45–60 minutes. With informed consent, audio recordings were made and later transcribed verbatim, ensuring the opinions and thoughts of the participants were accurately captured. In addition, some notes were taken to record some of the non-verbal cues and contextual overtones.

3.5 DATA ANALYSIS

The analysis of the data for this study was based on the Braun and Clarke (2025) six-phase thematic analysis process as seen in figure 2 below. It began with familiarization, where interview transcript notes were read several times in order to get a very full understanding of the data that participants provided. The second phase was about developing codes, which means systematically identifying data segments. Deductive and inductive coding were both used, even while being guided by the research question. This dual process ensured that analysis remained open to discovery while maintaining alignment with the study's focus. Next, the search for themes required grouping codes that were related into categories from a broader sense. For instance, codes related to "lack of technical expertise," "funding constraints," and "policy barriers" were clustered under a larger theme of "Barriers and Constraints." Following this, the reviewing of themes was done and preliminary groupings against the coded data and the entire dataset were carried out to confirm coherence and internal consistency. The fifth stage, which involved defining and naming themes, required in-depth analysis of each theme's scope and significance, ensuring that each theme accurately represented participants' experiences while contributing to answering the research questions. Finally, producing the report involved weaving together the different themes that were generated into a cohesive narrative.

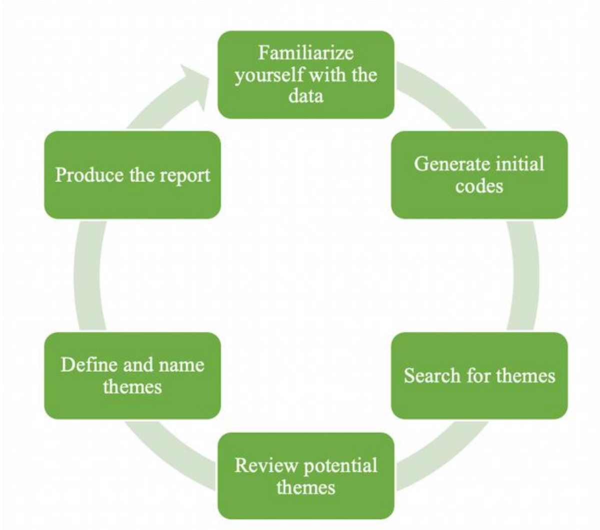

Figure 2: Braun and Clarke (2025) 6 steps of Thematic analysis

3.6 ETHICAL CONSIDERATIONS

The study was designed and conducted in strict adherence to established ethical standards. Before participation, each prospective informant was provided with a comprehensive information sheet detailing the study's purpose, procedures, and the nature of questions, and written consent was obtained electronically before any interviews commenced. Participation was selected based on voluntary participation, and they were told about the fact that they could withdraw at any stage of the study without any repercussions. Within the persons interviewed, three (3) initial key informants withdrew, citing discomfort with discussing AI initiatives within their organizations, and their decisions were respected. All remaining participant's identities were protected through pseudonyms in transcripts. Audio recordings, transcripts, and notes were securely stored on encrypted, password-protected devices.

3.7 TRUSTWORTHINESS AND RIGOUR

Based on Lincoln and Guba's (1988) four key criteria for trustworthiness: credibility, dependability, confirmability, and transferability, this study ensured methodological rigor. To enhance credibility, triangulation was applied by comparing data from multiple organizations across two countries and participants occupying different roles (e.g., program managers, technical leads, and organizational leaders), reducing the risk of relying on a single source or viewpoint. Furthermore, member checking was done in this process (Birt et al., 2016). A clear audit trail was maintained, and this included a record of the process, including the methodological decisions, interview protocols, coding structures, and analytic memos. This documentation is aimed at ensuring that external reviewers or future researchers are able to follow the process step by step subsequently (Shenton, 2004). Also in the same manner, to promote confirmability, reflexive journaling was integrated throughout the research process (Finlay, 2002).

3.8 LIMITATIONS

Although the chosen methodology enabled the generation of rich, context-specific insights, certain limitations were noted in this study. The use of a purposive sampling strategy, while intentional for obtaining in-depth perspectives, inevitably limits the generalizability of results. The study focuses on a targeted set of organizations with specific characteristics and operational profiles, which means the findings may not be representative of all maternal and child health NPOs, either within the two countries or globally. Given the qualitative and cross-country nature of the research, extensive time was required to identify participants, schedule interviews, and conduct detailed thematic analysis. However, despite the careful preparation that was put into designing the interview guides and efforts to ensure culturally sensitive phrasing, differences in language and cultural norms have the potential to have influenced participants' responses and the researcher's interpretations and so participants had a chance to ask for clarification where necessary. Also, the findings rely on participant's self-reported experiences and perspectives, which can be shaped by organizational agendas, social desirability, or personal motivations.

3.9 REFLECTIONS OF THE RESEARCHER

As a postgraduate student and an early career researcher with experience in policy, this process was intellectually enriching and challenging for me personally. Reflecting on the process, one part that was most demanding for me was being able to recruit participants for the interviews. I had reached out to several MCH NPOs across Nigeria and Germany, and the responses demonstrated the realities that AI was largely unexplored by a lot of these organizations. Many of the organizations approached either did not actively use AI in their operations or expressed reluctance to participate. Several issues, including time constraints, capacity issues, or perceived irrelevance of the topic to their current priorities, were. To be able to recruit participants, I had to send numerous emails and follow-ups, and this was time-consuming. However, responses often reflected the operational pressures and differing readiness levels of these organizations. For instance, some feedback highlighted resource and focus limitations: *"We currently are preparing a huge event and thus are unfortunately too busy to conduct an interview... the usage of AI... is currently not within our focus, also because it still is rather costly to hire a supplier of AI services."* Others politely redirected the researcher to other individuals without guaranteeing availability: *"I think the more appropriate person to talk to within our NGO would be the Chairman of the Board... Please contact her either on LinkedIn or via email."* In several cases, organizational fit was a challenge, as departments contacted did not have relevant expertise: *"Unfortunately, I cannot support you with your request... our role in the German office has more to do with fundraising and grant management. The technical expertise for Maternal and Child Health sits with our regional and country offices in countries of the global South."* Through these interactions, the researcher gained invaluable experience in navigating organizational gatekeeping, refining outreach strategies, and managing professional communication with busy stakeholders.

3.10 CONCLUSION

In this chapter, this study has demonstrated a methodological framework with which this study was carried out, providing details on the design, theoretical orientation, and specific methods employed. By doing this in a scientific manner, this chapter sets the foundation for findings that are credible and contextually rich. The next chapter will present the data findings as well as their analysis and interpretation.

CHAPTER 4: RESULT

4.1 INTRODUCTION

This chapter presents the findings of the study, which drew insights from a total of thirteen participants representing a broad spectrum of organizations across Nigeria and Germany. Eight participants were based in Nigeria, several non-profits delivering digital and in-person health services focused on MCH, large national NGOs working on public health, foundations supporting children with disabilities, global organizations providing reproductive and family planning services, and small NGOs improving health education and well-being for women in remote communities. Five participants were based in Germany, drawn from humanitarian aid organizations, small Community centers providing counselling and family planning support, and collectives advocating for reproductive justice for marginalized groups. This diversity of respondents created a rich basis for comparing operational realities and contextual challenges across the two countries.

From the data analysis, six overarching themes emerged, each supported by carefully developed categories: (*1) Extent of Adoption, (2) Motivations Driving Adoption, (3) Perceived Operational Efficiency Gains, (4) Barriers and Constraints, (5) Enabling Factors and Supports, and (6) Future Recommendations.* To derive these themes, a detailed coding process was undertaken, with key codes emerging repeatedly in participant responses. Examples of these codes include *"AI tools currently in use," "staff training needs," "policy push," "decision-making improvement," "infrastructure gaps," "technical skill limitations," "partnership benefits," "internal support structures," and "recommendations for future AI use."* These codes were iteratively refined and clustered into meaningful patterns, forming the basis for the themes and categories discussed in the sections that follow.

Table 1: Comparative Findings: Nigerian vs. German Respondents

Area of Comparison	Key Findings – Nigeria	Key Findings – Germany
Tools in Use	• Broad mix of AI and digital tools (Gemini, Claude/DeepSeek, AI-chatbot, SMS reminders, mobile health platforms, digital records, WhatsApp follow-ups).	• Mostly informal use of ChatGPT for idea generation; organisations still rely on e-mail, Excel, paper records; little to no AI integration.
Stage of Adoption	• Several organisations at moderate-to-mature stage (1-2+ yrs of active AI); smaller/rural orgs still early or pre-adoption.	• Predominantly pre-adoption; AI used ad-hoc by individuals rather than institutionally.
External Motivations	• COVID-19 disruptions and donor/partner opportunities accelerated adoption.	• Sudden staffing gaps prompted limited AI use to maintain momentum.
Internal Needs	• Drive for efficiency, 24/7 client service, data insights, advocacy reach.	• Need to craft stronger proposals and organise ideas; streamline comms.
Policy/Regulation	• Leadership interest emerging but AI still viewed as 'luxury'; limited formal policy push.	• Strict data-privacy rules and conservative culture restrain adoption.
Operational Impact	• Faster, data-driven decisions; evidence-based resource allocation. • Routine tasks cut from hours to minutes; paperless dashboards; chatbot reduces staffing costs. • Improved training, remote monitoring, 24/7 information access; reduced field workload.	• AI used mainly for brainstorming and quick info, not formal decisions. • Anecdotal gains in drafting proposals and coordinating volunteers; many report no measurable impact yet. • Minimal direct service impact; some better referral tracking where digital tools used.
Success Indicators	• Tangible metrics: ↑ client return rates, ↓ missed appointments, 4/5 satisfaction scores.	• Few metrics; success tied to winning grants or qualitative feedback.
Barriers to adoption	• Unreliable power, costly/slow Internet, limited devices, especially rural. • Scarcity of trained AI staff; heavy reliance on single experts; need capacity-building. • Informed-consent gaps; fears of data misuse among clients. • Early mistrust of 'impersonal' tech; fears of job loss easing with results.	• High cost of secure tools and connectivity issues for marginalised groups. • Limited internal tech capacity; dependence on a few digitally savvy staff. • Compliance with stringent GDPR rules; concerns over bias and surveillance. • Conservative attitudes; marginalised communities wary of surveillance.
Enablers to adoption	• Active ties with Microsoft, Meta, etc.; international digital units boost adoption. • Strong leadership buy-in and clear strategies spur rollout; external govt support helps.	• Few to no structured AI partnerships reported. • Donor apathy and staff-replacement fears dampen commitment.
Future Recommendations	• Invest in connectivity, stable power, and rural outreach; provide staff/community training; government policy support; reassure on job security.	• Expand staff training, reform privacy policies, secure leadership champions, and affordable ethical tools.

4.2 THEMES AND CATEGORIES

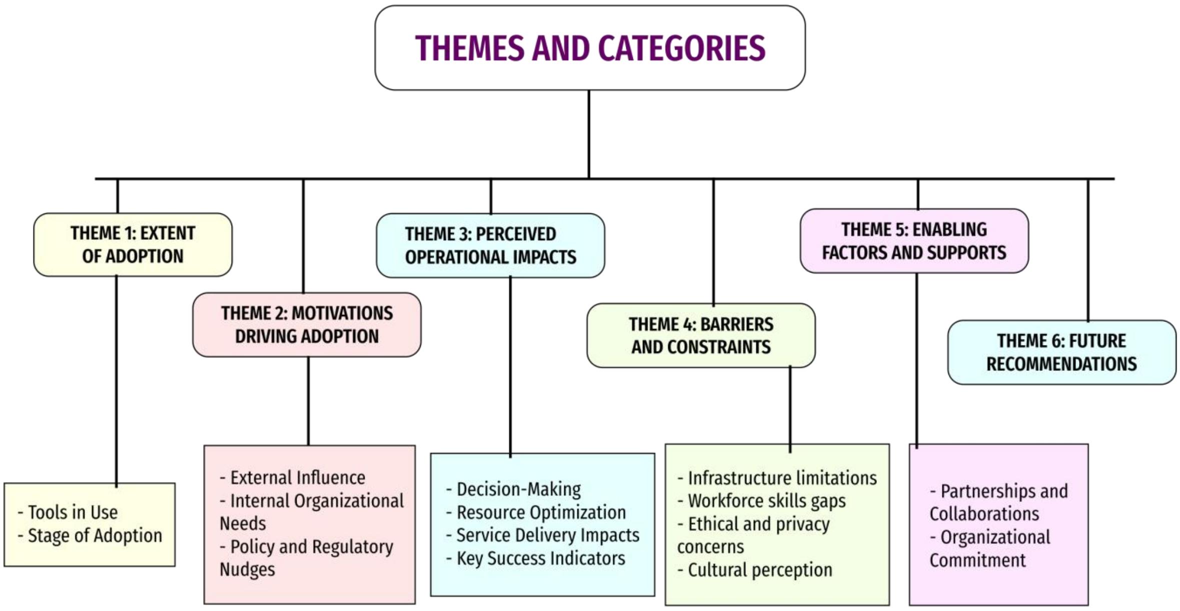

Figure 3: Themes and categories of thematic analysis

4.2.1 THEME 1: EXTENT OF ADOPTION

The extent of adoption of artificial intelligence (AI) and digital technology varied significantly across participants in Nigeria and Germany. This variation has been influenced by organization size, public infrastructure, funding profiles, and workforce readiness. These themes gave rise to two clear categories: the specific tool the organization uses and the stage of adoption within the operational work system.

4.2.1.1 Tools in Use

In Nigeria, most participants interviewed expressed that the integration of both AI and broader digital technology is in use within their programs.. For instance, a participant from Nigeria highlighted a blend of AI and advanced reasoning tools, stating: *"I use Gemini for Google-related reports due to its large dataset and Claude/DeepSeek for constructive reasoning and thought processing…."* Another participant, while noting that no formal AI systems were deployed, described a mature use of conventional digital tools: SMS reminders for appointment tracking, digital record-keeping, mobile health platforms, and WhatsApp groups to follow up with mothers in hard-to-reach areas. A more advanced application of AI was described by a respondent from Nigeria: *"Our organization currently uses an AI-powered chatbot in our maternal and child health program, specifically for family planning inquiries…."* A participant in a Nigerian organization spoke about AI being embedded in their data analysis and health tracking systems: *"These technologies monitor patient health data, predict risk factors for maternal and child complications…"* In Germany, the landscape was more cautious. An interviewee from Germany described an unofficial, individual use of AI: *"We use ChatGPT, but it's not really official. It's just here and there… but it's not like official that,….'"* Similarly, another participant from Germany said they only rely on basic email systems, Excel lists, and paper records, with no AI integration in service delivery. A slightly different picture emerged with another organizational representative from Germany, who explained that ChatGPT was used for idea generation in child welfare activities. Another participant reflected on a new adoption journey: *"We use AI… to support the development of grants and programs… helping us articulate ideas better, especially when we need to tailor our program descriptions to the specific needs and preferences of funders."* Finally, a team lead from the German organization indicated reliance on AI-related digital tools like Google Workspace but expressed interest in exploring AI for data analysis and privacy-sensitive communications.

4.2.1.2 Stage of Adoption

A wide stage of adoption was recognized across countries. In Nigeria, participants described that they use AI to support core programmatic functions and make the optimization of workflow more compact. This supports that Nigeria has moved beyond mere experimentation into actual active operation and integration of AI. They reported the timeline of using these tools has been for one to two years or more, showing an encouraged moderate to mature stage of adoption. For others, especially organizations operating in a rural setting and generally smaller organizations, the adoption of AI has remained in its early phases. With a participant describing a scattered, informal use of ChatGPT, signaling an individual-level rather than an organizational-level integration.

Another interviewee's description of minimal digital tools, *"All client documentation is done on paper,"* places that organization firmly in the pre-adoption stage with AI far from consideration.

4.2.2 THEME 2: MOTIVATIONS DRIVING ADOPTION

Across the various participants interviewed in Nigeria and in Germany, various motivations were highlighted for either adopting AI and digital technologies in their maternal and child health (MCH) programs or delaying their organization's adoption.

4.2.2.1 External Influence

Notably for several interviewees, the driving force for adoption was generally stirred by factors outside their direct control. It was either influenced by opportunities externally or a crisis that forced *"the decision to use digital tools was in view but became urgent only during the COVID-19!) pandemic, as it disrupted traditional service delivery."* This external pressure was a compelling reason for the change in operations, especially because it was crucial to find new ways of doing things for pregnant women and mothers remotely. Another Participant also acknowledged an external driver. She stated that *"the opportunity came externally through a partner platform offering the digital tool."* However, she also noted challenges in low-resource contexts, observing that *"Schools (or clinics, by extension) were lacking computers or digital infrastructure,"* and that many caregivers only had basic phones. In Germany, a professional engaged in nonprofit work described a different kind of external pressure: a sudden loss of human capacity within the group. *"A major member of our group, who typically supported us with this kind of work, stopped being available,"* she said, explaining that this gap created urgency to lean on AI to maintain momentum.

4.2.2.2 Internal Organizational Needs

For most Nigerian participants, internal operational needs were the dominant motivation. A source from the interview pool in Nigeria highlighted that *"the use of AI was driven by the need to check databases, access previous research, and generate insights for stakeholders."* His organization relied on AI for presentation preparation and evidence gathering in maternal health work, which reflects a proactive search for efficiency rather than donor or policy demands. This position emphasized with a key focus on internal efficiency: "*Before we created the chatbot, a challenge we faced was not having an available staff to attend to people 24/7.*" He explained that since human agents worked from 8 AM to 5 PM, it left some gaps in service, so external help was necessary; hence, they had to introduce a chatbot to extend availability beyond those hours. Similarly, another Interviewee from Nigeria added another layer by linking adoption to advocacy needs. She said, "*We needed to push for more government involvement in maternal healthcare, and these digital technologies helped us amplify our messages more effectively.*" A respondent from Nigeria illustrated how internal efficiency needs intersected with creative challenges. *"...we faced a challenge with visual representation. Often, when searching for stock photos to accompany stories about African men, all the photos available featured white people,"* he said.

4.2.2.3 Policy and Regulatory Nudges

While policy or regulatory factors were not primary drivers in many contexts, they did appear as considerations in some settings, particularly in Germany. A participant in Germany stated plainly: *"The reason we don't use AI is mainly because of data privacy policy, cultural hesitancy among older leadership…."* Similarly, another respondent in Germany pointed to a cultural and structural rigidity: *"No one really believes in that. So they would rather use regular traditional methods of gathering information and not rely on AI."* Also, cities differ in integration; for a city like Berlin, integration was more advanced, and for more rural places like *Gifhorn, people are not really that receptive."* Another response from a participant touched on the fact that the slow and cautious process of adoption was mainly based on policy, regulatory, and ethical concerns, especially with healthcare in the mix. In contrast, a source from Nigeria described a context where technology is *"seen as a luxury"* rather than a necessity, suggesting that leadership buy-in and policy emphasis are still developing. *"If the leaders don't buy into it, it can only be wishful thinking,"* she said. A pattern that was traceable in both countries: in Nigeria, motivation was majorly due to internal activities that were driving the adoption, like trying to either solve an operational or communication gap challenge, while in Germany, the motivations were more constrained by regulatory policies and cultural environments.

4.2.3 THEME 3: PERCEIVED OPERATIONAL IMPACTS

4.2.3.1 Decision-Making

Across participants in Nigeria, the feedback received was that AI and digital technology helped improve the decision-making process in such a way that information accessed and used was more streamlined. A participant from Nigeria narrated his observation with AI tools and said*, "it enhanced productivity in such a way that the time spent on researching and drafting documents is shortened and it's obvious."*. Another respondent from Nigeria noted that AI *"has improved the organization's operational efficiency in several ways. Decision-making has become more data-driven, allowing health workers to allocate resources more effectively, especially in prioritizing high-risk cases."* In Germany, participants described a more exploratory use of AI for decision-making. An individual engaged in the research process from Germany said ChatGPT is used *"to get ideas for planning…. It has helped determine what might be needed in terms of resources,"* but she added it is not part of official structured decision-making. Another interviewee from Germany similarly emphasized that AI is helpful in *"quickly accessing information," giving her "extra perspective,"* but she admitted, *"of course it's not 100% efficient."* demonstrating that while AI tools are valued for inspiration, they have not been integrated into formal organizational decisions in many German settings.

4.2.3.2 Resource Optimization

Participants in Nigeria repeatedly mentioned that AI adoption reduced the time and resources spent on routine tasks. A team lead from Nigeria shared that *"tasks that used to take two or three hours could be completed in under twenty minutes with the help of AI tools."* She explained that AI monitoring allowed her team to *"reallocate resources to more impactful channels"* during maternal health campaigns, maximizing limited budgets and staff time. Another interesting perspective was the statement from a participant in Nigeria who described a *"fully paperless office" and the use of*

Power BI to generate interactive donor dashboards, which *"improved the feedback gotten from our work and also how decisions are made about program direction."* Similarly, another respondent from Nigeria highlighted that their AI chatbot reduced staffing costs by *"allowing human agents to take necessary rest without interrupting the service."* In Germany, where it was seen that formal AI integration was less advanced, resource optimization appeared more anecdotal and informal. A participant disclosed, *"AI has improved our operational efficiency by helping us to organize and expand our ideas into clear, actionable proposals."* This enabled the organization to secure funding and attract collaborators, which indirectly optimizes resources by unlocking new streams of support. Another interviewee mentioned that AI *"helps us streamline our communication pathway, schedule coordination, and enhance mutual aid tracking,"* showing progressive resource efficiency. However, the case for resource optimization is different in Germany, as it has not been realized. A participant explained, *"There has been no influence because we do not use AI or any advanced digital technologies in our process yet. Our operations are still mostly manual and routine-based."* This difference demonstrated a regional and organizational gap in AI adoption and the benefits it brings.

4.2.3.3 Service Delivery Impacts

In Nigeria, AI has had a more direct effect on service delivery, especially in training and education, and access to information. A participant noted that digital tools made communication easier and *"reduced some of the workload of field staff,"* with remote monitoring alternatives helping with rural clients. Another participant explained that their chatbot ensured *"users have access to reliable information at all times"* and helped prevent staff burnout while enhancing availability. He also highlighted positive client feedback: *"users have rated the AI's responses as more satisfactory than those from human agents."* One of the voices captured in this study mentioned that AI tools support the training of community health workers in rural settings, providing *"guidance on maternal and child health diagnoses"* when doctors are not available. Another participant described how digitizing records means that *"when you put it on a database, anybody anywhere who needs to assess it can see it… You can hear real-time information… and it makes work easier."* In Germany, service delivery impacts were less tangible, often because AI had not been formally embedded into health programs. A key respondent admitted, *"There are no AI tools in use, so no indicators have been used to assess any impact from such technologies,"* though she personally found AI useful for quick information retrieval. Two participants confirmed no direct use in service delivery contexts. However, another participant described qualitative improvements in referrals and internal coordination: *"We assess impact through community feedback, improvements in response times, accuracy in service referrals, and internal workflow efficiency."* This shows that where AI or digital tools are applied in Germany, the impact tends to be in administrative support rather than direct healthcare delivery.

4.2.3.4 Key Success Indicators

Participants in Nigeria frequently referred to clear success indicators. An organizational representative said improved care outcomes and *"over 1,000 clients/patients returned due to the success of care provided,"* showing validation of AI processes. Another participant tracked *"reduced missed appointments and improved continuity of care."* One of the many respondents mentioned exit surveys with *"an average satisfaction rating of 4 out of 5,"* and another participant measured improvements in task efficiency and campaign reach. In Germany, many organizations lacked formal metrics. A participant said usefulness is judged *"on a case-by-case basis."* A different individual engaged in the research process, however, shared that they track success through funding outcomes: *"Since we began using AI, we have successfully received at least one grant and advanced to the second round for another."* This illustrates that where metrics do exist, they often relate to organizational growth rather than direct health outcomes. The findings reveal a stark contrast in how operational impact is perceived in Nigeria and in Germany. Nigerian participants reported that there is a lot of impact in the decision-making process (faster data processing, prioritization based on evidence), service delivery impact (more consistent health care workers, improved client support service), and resource optimization (reduced time and cost impact, paperless sustainable options, better proposal writing quality drafting). Some success indicators identified were tied to definite outputs like a higher patient return rate due to the service process, reduced appointment gaps, and better rating of performance scores. In Germany, AI and digital technology use remained little or mostly informal. And the impacts were tailored towards a more anecdotal or explanatory basis rather than measurable changes in operational efficiency. When success indicators were detailed, they were tilting more to a more indirect benefit like funding acquisition or better planning outcomes rather than a more service direct base view.

4.2.4 THEME 4: BARRIERS AND CONSTRAINTS

The findings give insights that bring to light the infrastructural limitations, such as unstable power supply and poor internet connectivity, presenting themselves as a barrier in Nigeria, while Germany focuses on issues like cost, regulation policies, and tool availability. The workforce skill gap is a shared concern, with Nigerian organizations having to battle foundational technical capacity and German organizations on sustainability and knowledge sharing. Ethical concern is also a shared concern, but although it surfaces differently, in Nigeria, they have to deal with informed consent issues and fear of data mishandling, and in Germany, they are shaped by external strict data protection regulations and sensitivity to the marginalized and vulnerable society. Finally, cultural perception also plays a role in adoption, with Nigerian communities scared of impersonal AI technologies and the German context showing a much more conservative resistance and marginalized-group concerns about surveillance. A key observation from all interviews is that participants acknowledge the effectiveness and support of AI but agree that its success is also greatly hinged on addressing these barriers. As a key interviewee from Nigeria summed up, despite benefits, *"There's a constant concern about what would happen if I were to leave, since no one else in the organization has the technical expertise to manage the AI infrastructure."* Similarly, a respondent from Germany highlighted the human side of these constraints: *"Tech burnout, digital exclusion, and fatigue from managing multiple platforms can reduce overall participation."*

4.2.4.1 Infrastructure limitations

Across both Nigeria and Germany, infrastructure is an important constraint in adoption, though it manifests in different contexts for both countries. In Nigeria, participants pointed more towards poor internet connectivity, bad power supply, and lack of adequate devices as serious barriers.

A participant stated clearly that *" access to internet, poor power supply, and limited technical know-how (e.g., prompting skills)"* affected effective AI use. A different respondent added that *"Electricity is a big problem, even especially in rural areas. Phones are dead half the time. Also, airtime is expensive for our clients." are significant barriers, especially in rural areas."* In Germany, infrastructure was less of a technical issue but surfaced in relation to access costs and the availability of secure tools. One of the participants highlighted*"high cost of ethical and secure tools* and*"unreliable internet access"* for marginalized groups. Another key participant also mentioned *"financial capacity constraints and resistance from older leadership generation"* as barriers to adoption, despite having full major physical infrastructure within the organization. These varying differences show that while Nigerian Organizations are struggling with basic connectivity, German organizations have to deal with policy and cost difficulties.

4.2.4.2 Workforce skills gaps

Skill deficits emerged as a shared challenge, though with different emphases. In Nigeria, limited technical expertise often forced organizations to depend on a few trained individuals. One respondent remarked: *"Currently, I am the only AI engineer, which poses a risk in terms of maintaining and scaling the system."* An interviewee described *"staff readiness and technical expertise also pose challenges, as some team members require substantial training to use AI tools effectively."* Another participant further stressed the need to hire young tech-savvy staff to support senior professionals. In Germany, workforce challenges around internal capacity and how individuals are being heavily relied upon. A participant shared: *"It highlighted the extent to which individuals are dependent upon for administrative tasks like writing… the need to find supportive and sustainable tools would enhance some work."* Another interviewee's team also pointed to *"little internal tech capacity"* as a barrier to adoption in MCH programs.

4.2.4.3 Ethical and privacy concerns

There is a wide acknowledgement of ethical considerations in how organizations approach AI adoption. In Nigeria, an interviewee noted that: *"Some women didn't even know what they were agreeing to when we asked to send them SMS,"* highlighting gaps in informed consent. Another respondent explained that *"some users are hesitant to ask sensitive or personal health questions because they fear their data might be reused or exposed."* A different contributor underscored strict internal guidelines: *"We emphasized the importance of consent… They also had the option to withdraw consent at any time."* In Germany, concerns often revolved around regulatory environments. An interviewee described: *"The issue of data is a very sensitive issue… It's not well received, and the issue of data protection makes it complicated."* Yet another participant shared their approach: *"They do not input any personal or sensitive data about children or families into AI tools… ChatGPT is only used to generate general ideas."* Another participant further emphasized the risks for marginalized communities: *"We are especially concerned about consent for storing sensitive information, the potential for bias in AI tools, and surveillance or data misuse."* These testimonies reveal that ethical barriers in Nigeria relate more to community trust and clear consent processes, while in Germany, they relate to compliance with stringent data protection policies and safeguarding vulnerable groups.

4.2.4.4 Cultural perception

Cultural views and attitudes marked critical constraints. In Nigeria, the early periods of adoption were confronted with a lot of fears and mistrust of the adoption, and it slowed integration. A response received note that *"some early fears existed, especially around job security, but this has slowly diminished as people are now seeing the support AI provides ."* A participant stated that *"People don't trust what they don't understand and would rather stay away." If you send a message and they can't link it to a real person, they ignore it or even delete it."* An additional interviewee emphasized that *"AI-generated visuals can create a disconnect if the imagery does not align perfectly with local realities."* In Germany, cultural perceptions also played a role, though more subtly tied to conservative attitudes. An interviewee explained: *"Germans are very* *conservative. They take time to change certain things."* Another participant echoed that *"many clients do not have digital access or understanding, so they may not trust or feel comfortable using AI systems."* Yet another interviewee added that *"among Black, migrant, or undocumented people, there's fear that AI tools could enable more surveillance, discrimination, or exclusion from services."* However, a separate participant reported no major cultural trust issues, suggesting that perceptions vary widely even within the same country.

4.2.5 THEME 5: ENABLING FACTORS AND SUPPORTS

4.2.5.1 Partnerships and Collaborations

Across some participants, the recognition of partnership and collaboration was noted as an enabler for adopting AI or digital technology in maternal and child health (MCH) and related programs. In Nigeria, several participants mentioned both local and international collaborations. A participant stated: *"We've had partnerships or integrations here and there with Microsoft, NSX, and Twitter/X. These platforms indirectly support AI adoption..."* These collaborations played a role in their reach. He acknowledged that it was not without some challenges. A different participant highlighted how their partnership works: *"We benefit from our International Digital Engagement Unit, which maintains relationships with major tech companies like Facebook, Twitter, Microsoft, Canva….".* A participant in Nigeria also gave a more different view saying that they experienced a mismatch with their partners digital learning platform*"Limitations: Lack of contextual fit, communities preparedness, and device fit for access. These lessons could be translated to digital partnerships considerations in MCH."* In Germany, the picture was different. Many participants noted an absence or weakness in partnerships. An interviewee stated plainly: *"At the moment, there are really none. Except for the internal processes..."* Another participant added: *"No, there are no such partnerships right now. If something like that were to happen, it would be many years from now."* A separate interviewee also confirmed: *"The organization has not engaged in any partnerships or collaborations related to AI or digital technologies."* Overall, Nigerian organizations are leveraging partnerships, while German organizations report fewer structured collaborations.

4.2.5.2 Organizational Commitment

Organizational commitment is a big benchmark for whether AI flourishes or is delayed, especially when expressed through leadership buy, funding decisions, and strategic alignment. In Nigeria, several participants mentioned that a recurring reason for AI buy-in has been *"Leadership buy-in and a clearly defined transformative strategy for implementation."*. Another interviewee echoed this sentiment: *"Key factors facilitating AI and digital technology integration include strong leadership buy-in from senior management…"* Yet another participant added that external government initiatives also help cultivate commitment internally. For another participant, leadership support became stronger after data showed results. However, not all Nigerian participants had the same experience. Another participant admitted that internal readiness was lacking: *"The lack of internal readiness, infrastructure, and digital engagement from community members discouraged further use of the digital tool.* In Germany, organizational commitment varied and was often more cautious. An interviewee described donor apathy as a significant discourager: *"…Rather than getting more funding for AI, rather invest in other things like actual programs that help people. It's not really a priority."* This financial hesitation was coupled with concerns about staff displacement: *"In some circles, it may be seen as a threat to actual work that people do."* Another participant noted cultural resistance: *"A factor that has discouraged its usage is cultural resistance especially among older staff, and strict data privacy policies."*

4.2.6 THEME 6: FUTURE RECOMMENDATIONS

Across both Nigeria and Germany, participants emphasized that enhancing AI adoption in maternal and child health (MCH) nonprofits will require a combination of supportive policies, infrastructure improvements, funding streams, and intentional organizational development. Many Nigerian participants highlighted the same need, which was the non-AI infrastructures to run smoother operations, like the roads and emergency response systems, a better power supply, and internet connectivity, which would truly be a game-changer in the effectiveness of AI-health education and advocacy. In the role of a stakeholder, a participant stressed that*"training is still very much needed for communities and staff. Also, there is a need for stronger support for digital health from the*

Government". A different responder from Nigeria focused more on reaching the rural settings, saying that *"in the rural areas, AI usage is almost non-existent. Many people in these communities are not digitally connected and lack access to the internet."* Similar reflections emerged from German participants. A participant in Germany pointed to training as a critical factor, explaining that people need to know *"what is this AI, how do I use it, and how best can I also profit from it,"* while avoiding misuse or oversharing. Another participant emphasized policy reform and generational shifts in leadership, stating that *"to make this possible, there would need to be changes in policy, especially around data privacy,"* One of the many participants from Nigeria highlighted the need to demonstrate AI's benefits internally to ease fears of job displacement, stating, *"we must also address fears that AI is here to replace jobs by clearly communicating that it is meant to assist and not replace human input."* German participants echoed similar organizational recommendations. One of the interviewees spoke about equipping staff with practical knowledge and discernment in AI use.

4.3 CONCLUSION

The findings presented in this chapter highlight the diverse and context-specific realities of AI and digital technology adoption across maternal and child health (MCH) nonprofit organizations in Nigeria and Germany. The analysis revealed key contrasts and shared challenges. The next chapter will critically interpret these results, linking them to the literature reviewed earlier, exploring their implications for practice, policy, and future research.

CHAPTER 5: DISCUSSION

5.1 DISCUSSION OF FINDINGS

The integration of artificial intelligence (AI) and digital technologies in maternal and child health (MCH) nonprofit programs is noted to take different turns across various regions. Findings from this study are seen to be in consensus with what was noted by a wide body of literature, and show what the factors behind AI adoption are, as well as offer deep insights into how it is employed impactfully in diverse day-to-day operations. In Nigeria, the use of artificial intelligence (AI) in maternal and child health (MCH) nonprofits has been propelled by necessity and shaped by several infrastructural challenges, such as resource scarcity. These study findings reveal that many organizations within the Nigerian context have gone beyond administrative uses of AI and have begun to deploy it in core operational areas. In some of these instances, AI chatbots have been seen to handle family planning inquiries, predictive analytics, monitor trends in maternal health, and support real-time decision-making and resource management. This kind of adoption have been described by scholars as “leapfrogging innovation,” and involves a phenomenon whereby low- and middle-income countries (LMICs) are seen to bypass incremental stages of technological development due to fact that they have to grapple with pressing needs and limited infrastructure (Watson and Sauter, 2011). Similar examples can be seen in Ghana, where midwives have been noted to employ AI-enabled ultrasound interpretation to support identifying high-risk pregnancies, and this has largely led to a reduction in diagnostic delays (Cockburn et al., 2022). Tanzania’s AI-powered SMS reminder system, which has been deployed among expectant mothers, is seen to have also cut missed appointments (Lund et al., 2014). These examples demonstrate how the limited infrastructure faced by these LMICs has sparked the development of AI solutions that may be locally grounded but are indispensable in the service they provide.

Yet, concerns remain that poorly designed AI systems can unintentionally amplify inequities. Obermeyer et al. (2019) and Capraro et al. (2024) give insights into how hospital allocation of resources algorithm functions in systematically offering more care to white patients compared to those with similar health risks in the United States. The result of this is mostly due to its reliance on cost rather than health data, which exposes the need for more equity-focused design in adopting AI.

The pattern observed in Nigeria has also been mirrored in other regions of the Global South. In Brazil, AI-supported telehealth kiosks in urban areas have been seen to enable health isntitutions achieve rapid triage and reduced waiting times (Marcolino et al., 2018), while in Peru, AI chatbots have been deployed in providing maternal nutrition advice especially during COVID-19 lockdowns improved prenatal engagement (Tzelios et al., 2022). These achievements have not been without some drawbacks. In another study, an AI-based WhatsApp counseling program faced early setbacks, which were attributed to issues around insufficient staff training and a mismatch in cultural expectations, especially when deployed in rural populations (Chianumba et al., 2024). Similar patterns were seen in Eastern Europe, where an AI platform that was designed for scheduling was seen to be unable to scale due to issues surrounding low internet penetration and mistrust of the community in the data collection processes (Barreiro, 2012). These outcomes are better understood in the light of the Institutional Theory, which argues that organizations respond to their environments by mimicking or resisting external norms (DiMaggio & Powell, 1983). In India, the SEWA pilot integrating AI chatbots was noted to reduce the workload that nurses had to deal with (Mustapha et al., 2024), while the SAHELI platform, using Restless Multi-Armed Bandit (RMAB) algorithms, reduced maternal engagement dropouts (Verma et al., 2023). In some regions, AI solutions have had to undergo a redesign to fit into the context-specific requirements of the population where they are deployed (Duffy et al., 2022). In Indonesia, an AI-driven maternal nutrition monitoring project had to be stalled because frontline workers found that the interface with which it was designed was unintuitive (Rafsanjani et al., 2024). Across these cases, the Technology Acceptance Model (Davis, 1989) is further demonstrated, especially regarding how perceived usefulness and ease of use drive adoption.

In addition to the operational examples, some theoretical frameworks also help explain these dynamics that are observed within AI adoption. This study provides a great perspective of Viale's (2022) concept of choice architecture in practice: Nigerian Nonprofits adopted AI systems more smoothly because it is more embedded as automated, whereas German Nonprofits, where such nudges were not present, adoption remained slower and more sporadic. Nudge Theory and the Institutional Theory also clarifies why certain innovations succeed rapidly. In countries like Nigeria and Kenya, urgent gaps in service delivery as well as flexible institutional environments lay a foundation for a more experimental effort at AI adoption, while in Germany and parts of Eastern Europe, the fact that there is a stable institutional context and concerns around strict compliance norms, innovation is sometimes dampened. Operational impacts further illustrate that there is an existing divide, as seen in this study. In Nigeria and Kenya, AI systems have impacted the clinical service delivery and have led to several impacts, such as reduced missed antenatal appointments, faster donor reporting, and improved triage of high-risk cases. Zambia's maternal health programs saw missed antenatal visits drop after machine-learning integration (Mlandu, 2023), while Bangladesh reported a 50% increase in reporting speed as a result of implementing the AI dashboards (Labrique et al, 2013). These operational impacts resonate with findings from even countries in Asia like Vietnam, where AI risk scoring improved prioritization of home visits (Tun et al., 2025).

As with the findings of this study, in Germany, AI is primarily used for administrative activities such as grant writing and internal scheduling rather than transformative health-based functions. This pattern was also observed in Italy and Canada, where AI integration was seen to have remained largely peripheral despite strong infrastructure (Ghanem et al., 2025; Cingolani et al., 2023). Longoni et al. (2019) showed that patients are reluctant to medical AI due to perceptions that it lacked human empathy, and this mirrors what German non-profit professionals described in this study. For the pilots that have been successful, they have employed a user-centered design, iterative implementation, strong partnerships, and leadership support. On the other hand, failed pilots have been initiated based on a poor understanding of local context, running counter to cultural norms, lacking sufficient training, or being untrustworthy concerning data privacy protections. These findings emphasize that AI adoption in MCH nonprofits is not a simple function of national wealth or technological readiness; rather, it considers contextual urgency, cultural fit, and institutional adaptability. Nudge Theory and the Technology Acceptance Model combined remind us how human behavior and perception can be central to the adoption process. Institutional Theory and Resource Dependence Theory show us the influence of broader environments and inter-agency collaborations. Taken together, the evidence points to the fact that

AI, in contexts such as Nigeria, Kenya, India, and Bangladesh, directly assists service-rendering, filling in for infrastructural and workforce shortages. In contrast, in high-income contexts such as Germany, Italy, and Canada, cautious and mainly administrative AI adoption is a direct consequence of regulatory hesitancy and cultural conservatism. To move forward now, nonprofits globally need to use human-centered design, strengthen partnerships across sectors, invest in local capacity building, and, finally, design strong, yet flexible governance structures so AI's potential can be used to improve maternal and child health care outcomes, while protecting civic ethics and community trust.

These barriers to adoption vary by region, as our study has noted, and as the greater literature has shown. Nigerian organizations are caught in infrastructure fragility: unreliable electricity, intermittent internet, and few commercial devices compel staff to rely on generators and banks for charging to maintain minimum connectivity, in line with broader LMIC literature (Gooyabadi et al., 2021). Similar concerns are voiced in Kenya and Bangladesh, albeit with a limited framework, meaning data governance issues on privacy and consent. For Germany, the major barriers are regulatory and financial. Data protection laws, like the GDPR, make implementation more costly and complex, while procurement processes tend to favor tried-and-tested solutions that compete poorly with experimental ones, thereby limiting the integration of AI (Dittrich et al., 2021). Workforce capacity gaps further compound these issues. Frequently, Nigerian nonprofits may depend on a single AI-literate staff; it is a risky "single point of failure" (Abel & Obeten, 2015), and oftentimes, senior staff are not digitally literate, thus leaving the young, computer-literate staff members to carry through implementation, as documented in Kenya and Nepal (Rajabi, 2021; Vatsa et al., 2025). Still, the study also highlights important enablers. In Nigeria, strategic partnerships with universities and technology firms have provided crucial resources and expertise, a path also taken through university–NGO collaboration in Bangladesh (Labrique et al, 2013). and the public–private telehealth networks of Brazil (Valentim et al., 2021). Another key enabler is leadership commitment. In Nigeria, organizations more often secured leadership buy-in only after showing the impact of AI by means of data, thus being in line with evidence from maternal health AI in South Korea, where leadership advocacy was the driver (Kim, and Yu, 2025). German nonprofits, conversely, report donor indifference and cultural inertia, though exceptions exist where visionary leaders have championed AI integration (Hahn et al., 2025). AI adoption in nonprofit organizations across Germany is proving to be rather slow and cautious, in sharp contrast to what is seen in many low and middle-income countries across the continents. Findings indicate that occasionally, staff members use tools like ChatGPT for idea generation or document drafting, but there is hardly any institutional purchase of such tools. Paper records are still very much present, and GDPR compliance is strictly enforced, cultivating a culture of risk aversion within these organizations. AI use is limited to the administrative activities of the organizations-grant writing, scheduling meetings, internal communications, etc.-rather than being deployed in frontline service delivery activities or clinical operations. A similar pattern emerged in Europe, where nonprofit organizations interplay with restrictive procurement policies that ironically prioritize stability and regulatory compliance at the cost of innovation (Saputra et al., 2024). Japan also speaks similarly; despite ambitious national AI roadmaps, nonprofit integrations in Japan are slowed down by a culture that favors human interaction and heavy regulatory oversight (Dirksen and Takahashi,, 2020. Canada's nonprofit sector, while technologically ready, often thinks of AI as something speculative and therefore restricts the use of AI to pilot projects, citing the absence of a grand-scale model (Phillips and Wyatt, 2021). In a much broader sense, several parallels arise in Latin America, where, in Chile and Argentina, nonprofits started AI donor management, telehealth in rural areas, projects, and then abandoned them for lack of sustained funding and rigid procurement laws (Marcolino et al, 2018). In Eastern Europe, NGOs in Poland and Hungary continue with very cautious forms of experimentation, mostly in back-office analytics while confronted with EU data compliance restrictions (Saputra et al., 2024). Southeast Asian scenario diverges as nonprofits take on somewhat hybrid approaches by putting in place AI chatbot systems for multicultural support while struggling with patchy infrastructure (Tun et al, 2025). Technology Acceptance Model (TAM) further offers an insight into the dynamics. On the other hand, German organizations express uncertainty about the perceived usefulness of AI in their contexts, and their heightened perception of risk inhibits the intention to adopt (Davis, 1989;). Nudge Theory (Leal and Oliveira, 2025.) makes apparent how minor shifts in policy related to, for example, clear opt-in instructions or a simplified procurement template, easily promote AI adoption. In contrast, the absence of secular nudges in Germany and France sustains organizational inertia. In keeping with the Institutional Theory nonprofits in Nigeria, Kenya, and even parts of Brazil navigate institutional voids, embracing external collaborations and improvisations, while German NGOs conduct orientation within institutional ecosystems that are stable, albeit rigid, and paradoxically inhibit radical experimentation.

Nigerian organizations adopt AI primarily to fulfill immediate operational needs: accelerating report generation, triaging patient calls after hours, and extending service reach beyond staff shifts. Similar thematic motives surface in Kenya and India, where AI chatbots and decision support systems provide after-hours support and reduce patient loads during peak hours (Joshi et al., 2023; Angubasu, 2022). The COVID-19 pandemic was an adoption catalyst in the guise of an external shock. Nigerian nonprofits reported a 40% spike in deployments after the pandemic (Gooyabadi et al., 2023). Similar surges were seen for the mHealth programmes of India (Joshi et al., 2023). A study saw a threefold increase in telehealth chatbot usage during the lockdowns; however, many reverted to pilot statuses once emergency funds were over (Chagas et al., 2021). On the other hand, due to regulatory limitations and cultural conservatism, Germany remains less motivated. Panteli et al. (2025) stress that the stringent compliance regimes generate hesitations even where operational merits are evident. In contrast, South Korea found that strong leadership advocacy in maternal health initiatives overcame similar compliance concerns to result in enduring funding and scaled AI adoption (Kim, and Yu, 2025). In Nigeria, AI tools strengthen decision-making practically, prioritizing high-risk cases and journaling reports. AI-enabled scheduling, meanwhile, reduced missed antenatal visits by 18% in Zambia (Mlandu, 2023). On the other hand, in Bangladesh, the AI dashboard helped cut the donor report-and-approval times in half (Labrique et al, 2013). The maternal mortality rate dropped by 15% through Kenya's AI triage (Angubasu, 2022). At the same time, in Brazil, AI-powered SMS reminders increased vaccination compliance for remote communities in the Amazon (Revolutionizes, 2024). On the flip side, Germany mostly focuses on operational impacts in the sense of administrative efficiencies to streamline grant applications and internal communications. Similarly, in Italy, largely back-office applications of AI are being observed, with some use of AI for donor engagement (Cingolani et al., 2023), whereas in UK nonprofits, even under the categorical encouragement from the government, AI remains a process management tool (Abbasi et al., 2023). . In Indonesia, in the meantime, the promising AI-based mental health triage pilot was halted since local law precluded automated clinical advice unless directly overseen by a human (Rafsanjani et al., 2024). So barriers come in various forms. Erratic electricity supply in Nigeria and Kenya... and patchy internet connectivity create recurring operational bottlenecks, consistent with studies on infrastructural fragility (Gooyabadi et al., 2023). In addition to workforce issues, some organizations, such as smaller businesses, often rely on a key person with AI know-how, creating sustainability risks (Abel & Obeten, 2015). The barriers in Germany include regulatory complexity and prudence in funds. Since complying with GDPR raises implementation costs, the duration of procurement processes also gets stretched, long and risk-averse (Dittrich et al., 2021). The same dynamics emerge in Europe, administrative burdens at times stifle the adoption of even the most advanced solutions. Resistance comes through culture: older staff emerge as blockers to the uptake of digital tools while management teams almost consciously sabotage innovation by prioritizing data privacy (Rasheed et al., 2023). Argentina and Peru saw a breakdown of AI adoption due to a lack of trust in data governance and scant technical support (Puertas-Bravo et al, 2024). Ethical issues dictate how AI is adopted in specific instances. In Nigeria, data protection illiteracy breeds fear of abuse, similar to Uganda and Malawi, where parents generally tend to withhold sensitive information (Makulilo, 2012). Strict data protection legislation and a tense atmosphere of hesitancy prevail in Germany, especially when marginalized groups such as undocumented migrants are involved. NGOs talk of fears over data misuse related to migrant health initiatives (Nagy, 2024). Culturally, Nigerian respondents reported skepticism regarding AI taking over human jobs, while German respondents mentioned conservative organizational cultures, with a generational divide. Even with barriers, a few key enabling factors are responsible for the successful integration. Nigerian nonprofits proactively seek alliances with universities and tech companies to gain resources and expertise, just as Bangladesh does for its rural AI pilots and Kenya for its community health platforms (Vatsa et al, 2025; Labrique et al, 2013). In Brazil, NGO-governmental alliances paved the way for shared AI infrastructure in vaccine scheduling ((Valentim et al., 2021). To set the commitment of leadership as essential, Nigerian organizations often go on data-driven pilots to attest to the true value of AI in inducing leadership buy-in (Rajabi, 2021). In South Korea, persuasive leadership helped secure funding continuity and scale operations (Kim, and Yu, 2025). Dutch NGOs, in contrast, fare poorly when it comes to innovation networks and external collaboration (Saputra et al., 2024; Dirksen and Takahashi, 2020). Nudging by the policy also matters: streamlined procurement and regulatory sandboxes have proved to work in several settings, where NGOs deploy AI chatbots for multilingual outreach to communities within carefully monitored compliance frameworks (Sultan et al, 2025). The findings thus present strategic layers for promoting responsible and effective AI adoption. In LMICs like Nigeria and Kenya, investing in infrastructure, reliable electricity, internet connectivity, regulatory clarity, and rural digital inclusion becomes paramount, in line with the scholarly emphasis for ecosystemwide interventions (Petersson et al., 2022). For high-income contexts like Germany, policy reform for compliance streamlining, leadership training, and trust-building exercises thus stand as priorities. Transparent communication, placing AI in context as a tool of assistance rather than full-scale replacement of a job, can lessen prevailing fears of impending job displacement, analyzed through the lenses of nudge theory (Viale, 2022; Puaschunder, 2022). Proper adoption of AI across the globe must be co-developed with the end users; it must include governance such that it maintains a fine balance of being neither so rigid as to stifle innovation nor so loose as to lose accountability; and it embeds the AI alongside other interventions aimed at strengthening health systems locally. These results converge with proposals for a tiered AI network in India (Guo & Li, 2018), Canadian models for policy advocacy (Naamati, Schneider & Salvatore, 2024), and Brazilian health technologies ecosystems (Valentim et al., 2021). Building local capacity, participatory design, and strong cross-sector partnerships represent our sustainable future.

5.2 CONCLUSION

The next and final chapter of this thesis will put together the insights that have been synthesized and offer a set of clear conclusions and recommendations for actions. These would be based on proposed strategies that would lead to better uptake of AI technologies to cater to the pressing needs that plague LMICs and HICs. These recommendations would be informed by evidence and set in motion a path towards utilizing AI as a truly equitable, sustainable, and effective tool to drive operational efficiency in maternal and child health worldwide.

CHAPTER 6: CONCLUSION AND RECOMMENDATIONS

6.1 CONCLUSION

This study explored the comparative adoption of Artificial Intelligence (AI) and its perceived impact on operational efficiency on maternal and child health (MCH) nonprofit organizations (NPOs) in Nigeria and Germany. Comprehensive qualitative data were collected within both countries ' organizations, and the data received from the interviewed participants showed some significant differences in infrastructural settings, organizational readiness, and cultural views towards the adoption of AI. The study also revealed both enablers and barriers in the process of adoption and integration. In Nigeria, the key driver for adoption was mainly due to necessity, and its barriers were mainly infrastructural difficulties and deficient resource mobilization. Its organizations actively revealed an improved operational efficiency (enhanced data planning process driven by data and service reliability outside standard work times) in its programs with the active use of AI tools such as chatbots, automated reporting systems, predictive dashboards, and translation tools. An important factor from participants was the impact on service delivery by reducing the amount of missed appointments, the increase in client satisfaction ratio, and also a more compact donor reporting process. In contrast, in Germany, a varying difference was seen as its adoption remains in an early stage and is often only highlighted in administrative operations like generating program ideas, drafting applications for grants, and meeting coordination with the organization. Active and strong regulatory frameworks like the General Data Protection Regulation (GDPR) are a compelling driver for the slow adoption of AI into the direct frontline service delivery process and impact. Cultural perception and views are also evidence of its slow pace. Participants within the organizations reported limited transformation in operations but cited more significant gains in organizational training and planning efficiency efforts. Participants reported limited operational transformation, citing instead incremental gains in organizational learning and planning efficiency. Hesitations to fully adopt AI into its systems reveal, in some cases, create an environment that was heavily paper record-reliant and mostly traditional in the flow of operations despite its very strong infrastructural technology.

The barriers observed were multifaceted. In Nigeria, challenges like unreliable electricity, poor internet connectivity, limited access to affordable devices, and over-reliance on available technically skilled staff were highlighted. Another challenge was ethical issues in forming community trust and informed consent, which was most notable in rural settings where information and digital literacy were low. In Germany, the complexities centered around regulations, strong privacy concerns, and cost caution and cultural hesitation emerged as key inhibitors. Both contexts still find a skilled workforce as a gap to deal with, although in different ways. Nigeria particularly grapples with a shortage of AI-literate staff, while Germany is often dealing with a generational gap in digital fluency. Enabling factors across both contexts also emerged. In Nigeria, the enablers to AI integration were mainly Leadership buy-in, international partnerships, targeted training for specific staff to help the organization surpass its infrastructural delays and innovate creatively. In Germany, where the regulations around usage are paramount, internal teams use AI in really low-risk administrative areas, which is laying a foundation for the future of expansion. These factors give an opportunity to confirm that while a nation's wealth is key to the adoption of Technology, in this case AI, it is not the sole reason; it is deeply influenced by the local context of application, organizational structure, and stakeholder influence and culture.

This research summary demonstrates that AI holds a strong opportunity to impact Organizational operational efficiency and service delivery in MCH NPOs, especially when its usage is tailored to the reality of the context it is exposed to and strategic collaborations, which are both achievable under the foundation of strong Leadership commitment. However, sustainable integration requires changes in system structure, from capacity building and infrastructural transformations to regulatory flexibility and cultural adaptation.

6.2 FUTURE RESEARCH DIRECTIONS

While this thesis provides great perspective and insights, there remain several areas that are ripe for future investigation to give deeper reasoning and expand the scope of work:

1. **Longitudinal Studies on AI Adoption and Impact:** Future research needs to track the implementation of AI usage over an extended period to observe areas around sustainability,

progression of the impact, and unintended consequences and trade-offs in both low and high economic contexts.

2. **Cross-Sectoral and Cross-Regional Comparisons:** In order to give more reflection on the adoption of AI and surface unique barriers globally, it is important to broaden the scope of regions in the comparative study to include regions like East Africa, Latin America, and Southeast Asia.
3. **Beneficiary-Centric Perspectives:** The organizational perspective of this research was an important addition, but further research is needed to give voice to actual grassroots members like mothers, families, and frontline workers in order to understand how AI affects trust, engagement, and health-seeking behavioural patterns.
4. **Economic and Cost–Benefit Analyses:** The return on investment of AI tools needs to be truly assessed to be able to truly provide enough evidence to influence founders and policymakers to support AI intervention in MCH programs.
5. **Governance, Ethics, and Policy Studies:** Additional research is needed into regulatory innovations such as data governance frameworks, ethical AI guidelines, and sandbox policies that balance innovation with the protection of sensitive health data.

6.3 POLICY RECOMMENDATIONS

Based on the findings found through this research, there are multiple layers of recommendations proposed for policy makers, technology experts, and non-profit leaders to draw insights to facilitate an impactful yet responsible way of adopting AI in Maternal and Child Health:

1. Strengthening Infrastructure and Enablers

- **For Governments:** Investment in critical infrastructure like electricity, internet, and affordable digital tools is key. In low-resource settings, the provision of targeted subsidies and better public-private partnerships would enhance faster AI integration in rural areas.

- **For Donors:** Funding flow should cut across ongoing operational support, maintenance, and staff training for better integration and not solely on AI pilot projects, as it's an encompassing process.

2. Regulatory Flexibility and Innovation Sandboxes

- Develop regulatory frameworks that include an experimentation phase for Non-profit NPOs, even if it would be in a controlled environment setup. Instructions on clear data guidelines specifically within the context of NPOs should be provided to streamline compliance and ensure innovation is not degenerating due to strict directives.

3. Workforce Capacity Building

- Establish a nationwide reach for digital literacy training specifically for organizations. These areas should also be accompanied by setting up mentorship opportunities for senior and junior staff to bridge the general gap in operation to some extent.

4. Building Trust and Ethical AI Culture

- Clearly defined protocols for transparent, clear, and detailed consent on how data would be used, stored, and protected should be communicated. Ensure communication around AI adoption narratives stays in place as a support to human roles and not a job replacement strategy.

5. Fostering Partnerships and Ecosystems

- Leverage the power of collaboration by encouraging partnerships between NPOs and private sector tech, universities, and international agencies to exchange value in Knowledge. All this should be done in a way that the adoption and integration align with local language, cultural norms, and the needs of the society.

6. Integration into National Health Strategies

- A shift in the way AI adoption goals are employed within Health strategies should be organized in such a way that it aligns with existing Health systems in a broad national view. There is a need for close monitoring to ensure lessons learnt and next steps are captured for proper advancement.

This research study highlights that AI is not the ultimate cure for all, but it holds a strong opportunity as a transformative tool when it is incorporated into the operations of maternal and child health nonprofit programs. For Organizations that are set up within low-income resource regions like Nigeria, AI can help jump past some foundational barriers like infrastructural gaps, digitally improved advocacy, and manage the already limited resources. And for higher resources regions like Germany, a well-thought-out engagement with the regulations and cultural adaptations can help create a better possibility for deeper integration into the system than just administrative adoption of its usage. This study underscores that while AI is not a silver bullet, it offers transformative potential when carefully integrated into maternal and child health nonprofit operations. For organizations operating in low-resource settings like Nigeria, AI can leapfrog infrastructural gaps, improve outreach, and optimize limited resources. In higher-resource contexts like Germany, thoughtful engagement with regulatory frameworks and cultural adaptation can pave the way for deeper integration beyond administrative functions. Ultimately, unlocking AI's promise in MCH NPOs requires a collaborative, context-sensitive approach, one that combines strong leadership, enabling policies, sustained investment, and a commitment to ethical, inclusive innovation.

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APPENDICES

APPENDIX 1

INTERVIEW QUESTIONS

OBJECTIVES 1: TO EVALUATE THE EXTENT OF AI ADOPTION IN MCH NPOS ACROSS EUROPE AND AFRICA.

Question 1 Can you describe any AI technologies or any digital technology currently in use within your organization's maternal and child health programs? (Prompt: How long have you been using them? Which specific functions do they serve?). Follow up: Looking back, was there a particular challenge or opportunity that made the decision more urgent?

Justification: This directly measures the extent and scope of AI adoption, identifying tools in use and operational domains as established in adoption studies (WHO, 2021). Also, Understanding triggers for adoption (e.g., funding cycles, pandemic response) clarifies regional patterns and urgency drivers.

Question 8: Are there any partnerships or collaborations (local or international) that have or would play a role in your AI journey? (Prompt: What have been the benefits or limitations of these partnerships?)

Justification: Partnerships are key enablers of adoption, especially in low-resource settings, and provide insights into regional networks and capacity (Moucheraud et al., 2019).

OBJECTIVE 2: TO COMPARE THE PERCEIVED EFFECTIVENESS OF AI TOOLS IN IMPROVING OPERATIONAL EFFICIENCY BETWEEN THESE REGIONS.

Question 2: What motivated your organization to begin (or not begin) adopting AI technologies? (Prompt: Was it donor-driven, policy-influenced, or internally initiated?). Follow up: What key success indicators did you use to determine that impact?

Justification: Motivation and measurement criteria reveal organizational rationale and how efficiency improvements are assessed (Lee et al., 2020).

Question 3: In what ways, if any, has the adoption of AI or any digital technology influenced your organization's operational efficiency? (Prompt: Can you share examples of changes in decision-making, resource allocation, or service delivery?)

Follow up: Were there any trade-offs or unintended effects in using those tools?

Justification: This directly evaluates perceived operational impact and uncovers both positive and negative outcomes (Rajkomar et al., 2019).

Question 4: How would you describe the overall impact of AI or any digital technology on maternal and child health outcomes in your programs? (Any example related to MCH would be accepted) (Prompt: Have you seen measurable improvements or mostly anecdotal evidence?)
Follow up: Can you share more about the context in which AI or any digital technology was implemented such as rural vs urban settings and whether the impact varied across different populations?"
Justification: This question shows links between operational improvements and programmatic outcomes, accounting for contextual variability (Sinha et al., 2020).

OBJECTIVE 3: TO IDENTIFY CRITICAL BARRIERS AND ENABLERS AFFECTING THE ADOPTION OF AI IN NONPROFIT ORGANIZATIONS IN BOTH CONTEXTS.
Question 5: What challenges do you foresee or have experienced in trying to explore or adopt AI or digital technologies in your organization? - Have there been moments where a tech-based solution didn't resonate with your community or team?
Follow up: If you've navigated any of these barriers, what strategies or support systems helped you the most?
Justification: Identifies barriers and effective mitigation strategies (Greenhalgh et al., 2017).

Question 6: Are there any ethical or data privacy concerns you've encountered with AI use in your work? (Prompt: How do you navigate issues of consent, bias, or community trust?)
Follow up: Do you struggle with keeping track of data ?
Justification: This question probes ethical and governance challenges, which are critical in sustaining adoption (Leslie et al., 2021).

Question 7: What key factors or supports have helped facilitate (or discouraged) AI/any digital technology integration in your organization? (Prompt: Think about leadership buy-in, donor funding, technical partners, or government support.)
Follow up: How do you make sure the communities you serve understand, trust, or feel included in decisions about technology or AI tools whether you're using them now or not? What approaches or messages have helped build confidence or reduce hesitation?
Justification: This question explores internal and external enablers while considering community engagement, a key factor in technology acceptance (Kotter, 2012).

Question 9: From your perspective, how does the context in your country (Nigeria/Germany) influence the adoption and use of AI in nonprofit health settings? (Prompt: Consider policy, infrastructure, workforce, or culture.)

Follow up: Are there cultural perceptions or trust issues around AI that you've had to navigate?

Justification: This question captures macro-level determinants of adoption, highlighting regional contrasts (ITU, 2022).

OBJECTIVES 4: TO PROPOSE TAILORED RECOMMENDATIONS FOR ENHANCING THE IMPLEMENTATION OF AI IN MCH NPOS IN EUROPE AND AFRICA.

Question 10: Looking ahead, what do you think is needed to enhance AI adoption in maternal and child health-focused NPOs like yours? (Prompt: Any policy, funding, training, or advocacy recommendations?). Follow up: How can governments or global health bodies help create a more enabling environment for AI in nonprofit MCH work?

Justification: Generates forward-looking recommendations based on firsthand experience, aligning with calls for enabling ecosystems (Chen et al., 2021).

APPENDIX 2

PARTICIPANT CONSENT FORM

Study Title: A Comparative Study on the Adoption of Artificial Intelligence and Its Perceived Impact on Operational Efficiency in Maternal and Child Health Nonprofit Organizations in Nigeria and Germany.

Researcher:
Your full name: Okorodus Bawo
Your Institution: Luiss School of Government and CIFE
Contact Email: Okorodusb@gmail.com

1. Purpose of the Study

You are being invited to take part in a research study that seeks to explore how maternal and child health (MCH) nonprofit organizations in Nigeria and Germany adopt Artificial Intelligence (AI) and how this affects their operational efficiency. Your experience and insights will help shape recommendations for nonprofit leaders, donors, technology creators, and policymakers.

2. Procedures

If you agree to participate:
- You will take part in an interview (online or in person) lasting approximately 45–60 minutes.
- The interview will be audio-recorded (with your permission) to ensure accuracy in capturing your views.
- You may decline to answer any question that makes you uncomfortable.

3. Voluntary Participation and Right to Withdraw

Your participation is completely voluntary. You may withdraw from the study at any time, without giving a reason, and without any negative consequences. If you choose to withdraw, any data collected from you before withdrawal will be destroyed if you request it.

4. Risks and Benefits

Risks:
There are no known risks beyond those encountered in everyday life. Some questions may prompt reflection on organizational processes, but you are free to skip any.

Benefits:
Although you may not benefit directly, your contribution will help generate knowledge to improve AI adoption and operational practices in similar organizations.

5. Confidentiality and Data Protection

- Your identity and organization name will not appear in any report or publication. Pseudonyms or codes will be used instead.
- All audio recordings, transcripts, and notes will be stored securely on password-protected devices and accessible only to the researcher.
- Data will be retained for [specify duration, e.g., 5 years] in line with ethical guidelines, after which it will be permanently deleted.

6. Use of Data

The information you provide will be used solely for academic purposes, including:
- Research analysis and reporting in the thesis.
- Possible academic presentations or journal articles.
Your anonymity will always be maintained.

7. Consent

Please read and check the boxes to confirm your agreement:

☐ I have read and understood the information above.
☐ I have had the opportunity to ask questions and received satisfactory answers.
☐ I voluntarily agree to participate in this study.
☐ I agree to the audio recording of the interview.
☐ I understand I can withdraw at any time without consequence.

Participant's Name: ________________________________
Participant's Signature: _____________________________
Date: ___________________

Researcher's Name: ________________________________
Researcher's Signature: _____________________________
Date: ___________________