

AI-driven diet planning applications for optimising food security. A case study of low-income households in Chitungwiza, Zimbabwe.

A dissertation submitted in partial fulfilment of the requirements for the Master of Science Degree in Food Security and Sustainable Agricultural (Production)

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DECLARATION

I hereby declare that the research project entitled “**AI driven diet planning applications for optimising food security. A case study of low-income households in Chitungwiza, Zimbabwe.**”, submitted to Bindura University of Science Education, Department of Agricultural Economics, Education and Extension is a record of an original work done by me under the guidance and supervision of **Dr. A.C. Mujeyi** and this work is submitted in partial fulfilment of the requirements for the award of a Master of Science Degree in Food Security and Sustainable Agriculture Production. The results embodied in this thesis have not been submitted to any University or Institute for the award of any degree or diploma.

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Abstract

In many low-income communities, especially in urban areas like Chitungwiza, Zimbabwe, food insecurity is still a major problem. The possibility of AI-driven diet planning apps as cutting-edge instruments for maximising household food security is investigated in this study. These apps can create customized meal programs that optimize both cost and nutritional sufficiency by utilising machine learning algorithms to assess dietary requirements, local food availability, and financial limitations. The study examined how AI-based meal planning might promote sustainable consumption habits and increase resilience to food scarcity by using a case study methodology to examine the experiences of low-income households in Chitungwiza. Focus groups, interviews, and household surveys were used to gather information. Results suggest that AI-driven solutions can improve food usage efficiency, decrease waste, and provide households with practical dietary advice, all of which can support more comprehensive food security policies in environments with limited resources. Incorporating AI into community-level nutrition planning presents a viable strategy to combat food insecurity in Zimbabwe and other Sub-Saharan African contexts.

Keywords: food insecurity, low-income urban households, AI-driven diet planning, nutritional adequacy, food utilisation efficiency.

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CHAPTER 1

1.1 BACKGROUND OF THE STUDY

Food insecurity and malnutrition remain important issues for many low-income urban populations, particularly in Zimbabwe (Mabuza et al 2022). Urban households are more vulnerable now because of rising urbanization, economic instability, and climate change, especially for those residing in low-income neighbourhoods and informal settlements. Along with limited availability to affordable, nutrient-dense food, these places often face inadequate health infrastructure and inadequate nutritional understanding. To address these issues, however, new strategies like artificial intelligence are being created in the age of the digital revolution. Informal settlements frequently lack the funding and zoning necessary to enable effective food distribution systems and urban agriculture. Mobile penetration in Zimbabwe has grown significantly, with increasing access to smartphones and internet connectivity even among low-income populations (Doyle et al, 2021). This technological uprising presents an opportunity to make use of digital tools, such as AI, in order to support health and nutrition interventions in innovative ways. As of 2024, the majority of Zimbabweans had access to mobile internet, with many low-income urban residents using smartphones for communication, banking, and increasingly health-related services (Ruhanya et al, 2024). AI-driven diet planning apps- such as MyFitnessPal, CibouScan, YAZIO, and locally adapted platforms- use machine learning algorithms to analyse dietary patterns, recommend meal plans, and track nutritional intake (Prasad et al 2025). These Apps have shown promise in high-income settings, but their relevance and impact in low-urban settings remain underexplored. Globally, AI is being used to model food security indicators, optimize agricultural supply chains, and personalize nutrition advice (How et al 2020). In Zimbabwe, there is limited research on how AI tools can be localized to reflect indigenous food systems, cultural preferences, and economic constraints (Fundira et al 2024). Low-income users may find existing diet planning apps less helpful because they rarely provide information on seasonal availability, locally grown foods, and even prices. In addition, acceptance and continued use may be impacted by digital literacy, language obstacles, and technological trust. The intersection of community health and digital innovation is where this study is situated. Chitungwiza, an urban city in Zimbabwe, is the centre of this study, which attempts to investigate how diet planning apps driven by AI might be modified to suit regional

requirements. Users will be more actively involved in the creation and assessment of digital tools rather than merely being passive recipients, thanks to the more participatory design. Ultimately, the research aims to determine if artificial intelligence (AI) may be a useful instrument in the battle against urban food poverty by offering individualized, culturally appropriate, and financially feasible dietary advice to those who require it most.

1.2 RESEARCH PROBLEM

Although AI-powered diet planning is becoming more widely available, less is known about its application and effects in Zimbabwe's low-urban areas. The majority of current solutions are made for wealthy customers and frequently don't take into consideration regional food customs, cultural preferences, and financial limitations. Consequently, the advantages of data-driven health insights and customized nutrition planning are often denied to low-income urban households in Zimbabwe. This study aims to explore the potential adaptations and applications of AI-powered meal planning applications to enhance food security and nutritional outcomes in low-income urban populations in Zimbabwe. The design of AI-powered diet planning apps and the actual conditions of low-income metropolitan areas also differ significantly. Without community integration, cultural sensitivity, and localization, these tools run the risk of becoming obsolete and/or ineffectual. Such AI technologies could be modified in this thesis to enhance food security and nutritional results, bridging the gap between local needs and global innovation.

1.3 OBJECTIVES

1.3.1 MAIN OBJECTIVE

To examine how AI-powered meal planning tools can be modified and applied to promote food security and nutritional outcomes in low-income urban families in Zimbabwe, with an emphasis on community-level effect, technical accessibility, and cultural relevance.

1.3.2 SPECIFIC OBJECTIVES:

1. To assess the nutritional challenges faced by low-income urban households in Zimbabwe.

2. To estimate the Willingness to pay (WTP) for AI-assisted dietary planning services and examine how WTP varies with changes in household food choices, nutritional knowledge, and food security indicators.
3. To propose context-specific recommendations and innovation pathways for sustainable adoption and scaling of AI-driven diet planning solutions in Zimbabwe's urban food systems.

1.4 RESEARCH QUESTIONS

1. What are the nutritional challenges faced by low-income urban households in Chitungwiza?
2. How much are urban low-income households in Zimbabwe ready to spend to have access to diet planning services with AI assistance?
3. In Zimbabwe's urban food systems, which AI diet planning innovations are necessary to best support scalability and sustained engagement in current food security?

1.5 JUSTIFICATION

This study will demonstrate the potential to revolutionize the way that dietary difficulties in urban settings with limited resources can be addressed through the strategic application of AI-diet planning tools. Low-income households in Zimbabwe, where urban poverty is prevalent and food costs are unpredictable, frequently have to choose between affordability and nutritional sufficiency. Traditional solutions like food assistance, nutrition education, and agricultural subsidies have not been able to keep up with the changing requirements of urban populations in recent years.

By adopting AI-powered diet planning apps as easily available, culturally appropriate tools that enable marginalized people to make educated nutritional choices, this study presents a new paradigm. Also, this study will demonstrate how AI is being repositioned as a strategic asset in public health innovation rather than just a convenient tool. In Zimbabwe, where nutritionally related diseases like obesity and stunting coexist in urban areas and health services are under stress, artificial intelligence (AI) provides a scalable and data-driven solution.

The research then adds to the developing field of AI for public health equity by examining how diet planning apps can be customized to local realities, presenting a realistic view of how technology can be reimagined to benefit marginalized groups rather than widen digital

divides. Additionally, SDG 2 (Zero Hunger) and SDG 3 (Good Health and Well-Being) are in line with the findings. It illustrates how digital technologies may help communities come up with sustainable solutions to urban food shortages. Its applicability goes beyond Zimbabwean communities; it provides a reproducible paradigm for urban low-income environments in other nations.

This work makes a theoretical as well as practical contribution. In a practical sense, it investigates how AI might be adapted to local food systems, economic conditions, and cultural preferences in Zimbabwe. For instance, whereas current applications could offer quinoa bowls or kale smoothies, a localized AI tool might suggest more economical meals like bean stews or sadza with pumpkin leaves that are both culturally recognizable and high in nutrients. Given that meals are shared and decisions are made collaboratively in many Zimbabwean households, the study also looks into how these apps may be used to encourage communal eating habits.

In the end, there is more to this study than just technology. It is about the right to health, dignity, and empowerment. In this future, a Chitungwiza street vendor, an old person, or a community member will be able to utilize their mobile phone not only for communication and transactions, but also to provide knowledge, resilience, and confidence to their families. A model for inclusive digital transformation in public health is provided by this research, which bridges the gap between local needs and global innovation. The report provides practical suggestions for incorporating AI into national nutrition goals, urban health initiatives, and ICT development plans from a policy standpoint. Respective Ministries in health and Child welfare could leverage their findings to design inclusive digital health campaigns, subsidize localized app development, or incorporate AI tools into community clinics. In addition, this study also contributes to:

Reducing Urban Food Insecurity by Innovation in Technology.

Chronic food insecurity is becoming a bigger problem in most Zimbabwean communities due to factors like inflation, economic instability, shifting food costs, and restricted availability to reasonably priced, wholesome meals. Due to scalability, sustainability, and resource limitations, recent food intervention projects that involve NGOs working with local communities in conjunction with nutrition education and urban agriculture have produced inconsistent outcomes in their efforts to alleviate food insecurity. Next, by utilizing AI

techniques to provide households with individualized nutrition advice, this work aims to present a contemporary strategy.

Bridging the Digital Gap in Health and Nutrition.

Zimbabwe has seen a rise in mobile usage, but low-income end users still do not find digital health technologies useful. With little regard for regional food systems, cultural norms, or financial limitations, the majority of these AI diet apps are made for high-income end users. By supporting culturally aware, linguistically suitable, and financially feasible AI solutions, this study will advance digital inclusion while making sure that the most disadvantaged populations are not left behind by technological advancements.

Informing policy and practice in urban nutrition.

By identifying barriers to adoption, evaluating user experiences, and measuring nutritional outcomes, the research can guide local authorities in integrating digital nutrition tools into public health campaigns, NGOs in designing tech-enabled nutrition education programs, and App developers in creating localized & user-friendly platforms tailored to Zimbabwean communities.

Empowerment in households through data-driven decision-making.

The study will investigate how AI might assist with better dietary diversity, cost-effective meal planning, and informed food choices at the household level. Artificial intelligence (AI)-powered solutions can provide useful and individualized assistance by transforming smartphones into instruments of health empowerment in places where there is a lack of nutrition information and cost influences food choices. This will therefore be in line with SDGs 2 (Zero Hunger) and 3 (Good Health and Well-Being).

1.6 SCOPE/DELIMITATIONS & LIMITATIONS OF THE STUDY

To enhance food security and nutritional results for low-income urban households in Chitungwiza, Zimbabwe, this study investigates the possibilities of diet planning applications powered by artificial intelligence (AI). Specifically, the study focuses on how mobile-based AI tools might influence food shopping decisions, dietary behaviour, and overall household food security. It is situated at the nexus of public nutrition and digital health innovation. Both

quantitative and qualitative aspects are within scope, including baseline and end-line evaluations of dietary consumption, food insecurity markers, and user interactions with the AI application. Adult household members responsible for food preparation and shopping are the focus of the study because of their crucial influence on household nutrition.

To gather data on the viability, acceptance, and willingness to pay for AI diet planning tools, and the effects of such technology in an urban environment with limited resources, the study will implement a culturally tailored AI diet planning app and track its usage for 3 months. Additionally, the study examines contextual and behavioural factors that influence the uptake and use of AI tools. These include attitudes toward technology, cultural dietary choices, computer literacy, and financial limitations. Nuanced insights into user experiences, engagement hurdles, and the larger social dynamics that influence food choices are captured by the research through focus groups and interviews. Because urban households face unique issues, including exposure to processed foods, limited access to fresh produce, and heavy reliance on informal food markets, the scope is intentionally restricted to urban households. Rural populations, institutional settings, and clinical nutrition interventions are not included in the study because these contexts require different infrastructure and technology considerations.

To ensure concentration and viability, several intentional boundaries have been established. The study's geographic scope is restricted to Chitungwiza, Zimbabwe, and it focuses on high-density areas that are home to a large number of low-income households. This urban focus enables a more controlled evaluation of app usage in settings where smartphones and mobile networks are always available. Second, the study only looks at households where at least one adult has a smartphone or uses it frequently. This requirement guarantees that users can engage with the AI application without needing extra digital infrastructure or hardware, which could introduce confounding variables.

Third, the intervention consists of one AI-powered diet planning software that is tailored to regional food habits and financial circumstances. Although there are other nutrition applications available worldwide, the study concentrates on a single platform to guarantee uniformity in data gathering and user experience. Fourth, the study only lasts three months, which is enough time to see short-term shifts in food security and dietary habits but not long-term health effects. Lastly, the study solely focuses on non-clinical groups; people with severe dietary limitations or illnesses that call for customized nutrition regimens are not

included. The general recommendations made by the app are safe and suitable for the intended consumers, thanks to this delimitation.

Limitations of the Study

Notwithstanding its advantages, the study has a number of drawbacks. One significant limitation is the use of self-reported data for food security and dietary consumption, which might be contradicted by inaccurate portion estimating, social desirability bias, or recall bias. These biases cannot be completely eradicated, despite efforts to train enumerators and employ validated instruments like the Household Food Insecurity Access Scale (HFIAS). Another drawback is the brief intervention period, which might have missed long-term dietary gains or persistent behaviour change. Seasonal, economic, and cultural factors all have an impact on dietary habits, which are deeply rooted and change over time.

Limitations in technology present further difficulties. Due to limited digital literacy, language difficulties, or unfamiliarity with AI interfaces, some participants may find it difficult to navigate apps, despite the growing prevalence of smartphones. These problems may have an impact on participation rates and distort outcomes. Additionally, particularly at unofficial markets where supply varies, the app's suggestions do not always match local food availability or costs. The app's usefulness may be diminished by this discrepancy, which may also restrict its influence on food-buying habits. Furthermore, outside factors that could skew the results, such as public health campaigns, inflation, or government food assistance, are not taken into consideration in this study.

In conclusion, generalizability is restricted. The results might not apply to those in rural areas, other cities, or nations with distinct economic and cultural backgrounds. Although the Harare emphasis of the study offers insightful information, it must be viewed within its local context. A more thorough knowledge of AI's involvement in public nutrition should be achieved by future research that takes into account multi-site studies, longer follow-up periods, and comparison analyses across various socioeconomic groups.

CHAPTER 2: LITERATURE REVIEW

2.1 INTRODUCTION

Urban poverty still presents major public health issues, especially when it comes to food security and nutrition (Ruell et al 1998). Lack of availability to reasonably priced and nutrient-dense food, together with time and money constraints, frequently leads to poor eating habits and heightened susceptibility to diet-related illnesses and malnutrition in low-income urban households. Innovative solutions are required to solve these enduring problems as cities expand and socioeconomic gaps deepen. Artificial intelligence (AI) in diet planning applications is one potential approach. With the use of data analytics and machine learning algorithms, these digital solutions provide individualized, scalable, and flexible nutritional recommendations. Artificial intelligence (AI) has been progressively incorporated into nutrition and health systems, revolutionizing how people engage with nutritional data (Ojo et al 2025). To create customized meal plans that meet nutritional objectives, machine learning algorithms can examine large datasets, such as user health profiles, food preferences, and area availability. By allowing users to communicate with apps via text or voice instructions, natural language processing makes the technology more accessible to people with low reading levels. With the help of computer vision techniques, users may quickly analyse the nutritional value of food items or meals. Apps like Snap Calorie have integrated these features, offering behaviour-based nudges to promote better choices, tracking nutritional intake, and real-time feedback. Artificial intelligence (AI) has been progressively incorporated into nutrition and health systems, revolutionizing how people engage with nutritional data. To create customized meal plans that meet nutritional objectives, machine learning algorithms can examine large datasets, such as user health profiles, food preferences, and area availability. Globally, low-income urban populations bear a disproportionate burden of chronic diseases linked to diet and food insecurity (Villa et al 2021). Time scarcity, low health literacy, financial limitations, and restricted availability to fresh and healthful food create a complex situation where conventional dietary advice frequently fails. One innovative way to deal with these issues is through the application of artificial intelligence (AI) in healthcare. Nutritional advice that is highly customized, easily available, and scalable is promised by AI-driven diet planning. With a critical analysis of its potential benefits, significant disadvantages, and ethical concerns specific to low-income urban settings, this

review of the literature provides an overview of current research on the application of AI in diet planning. It also highlights topics that need further research.

Artificial intelligence (AI) has the potential to significantly impact food security and disaster response. Artificial intelligence (AI) can improve response efforts and efficiency in the field of disaster relief operations (DRO) (Behl et al., 2021). It can also help control catastrophe risk by forecasting disasters and streamlining response efforts. To avoid any compromise to food safety while using AI for sustainable food security, care is essential (Vagsholm et al., 2020). Safety, quality, and waste concerns can be addressed by integrating artificial intelligence (AI) into food supply chains. As indicated by Dora et al. (2022), this can be accomplished by increasing transparency and traceability. AI-based systems, like machine learning classification models, can be used in disaster response to semi-automatically classify incoming information about community needs, casualties, and damages (Lamsal & Kumar, 2023). AI applications can improve the quality and security of food, encompassing factors like accessibility, availability, and utilization (How et al., 2020). Artificial intelligence has the potential to be a powerful tool for monitoring food insecurity on different social media platforms. Additionally, employing artificial intelligence (AI) and conducting extensive data analysis could greatly contribute to ensuring food security and help the food industry develop sustainable innovations (Sharma et al., 2021).

2.1.1 The Promise of AI: Personalization, Accessibility, and Scalability

At the nexus of sustainable development, smart manufacturing, scalable solutions for precision health, and nutrition and food systems, artificial intelligence (AI) is becoming a major force. The goal of this study is to provide a thorough analysis of AI-driven breakthroughs that enable precision nutrition through adaptive feedback systems, meal planning based on individual biological markers (such as blood glucose or cholesterol levels), and real-time nutritional recommendations. In order to promote circular economy objectives and improve food system resilience, it also looks into the integration of AI technologies in food production, such as machine learning-based quality control, predictive maintenance, and waste minimization. The paper describes how AI converts static, population-level nutritional models into dynamic, data-informed frameworks catered to individual needs, drawing on developments in deep learning, federated learning, and computer vision.

The Food and Agriculture Organization (FAO) defines food security as the state in which all people, at all times, have physical, social, and economic access to sufficient, safe, and

nutritious food to meet dietary needs and preferences for an active and healthy life. Food security is still one of the most important global challenges of the twenty-first century. Innovative strategies are required to maximize nutrition and guarantee fair access to food due to the growing complexity of agricultural systems, population increase, climate change, and socioeconomic inequality. In this field, artificial intelligence (AI) has become a game-changing technology, especially in diet planning tools that incorporate sustainable food system management, predictive analytics, and personalized nutrition. This essay examines the body of research on AI diet planning tools and how they can improve food security, emphasizing both the advantages and disadvantages.

A primary advantage of AI in nutrition is its capacity for deep personalization beyond human capability. Traditional one-size-fits-all dietary guidelines are often impractical for individuals navigating budgetary and geographical constraints. AI algorithms can integrate vast datasets, including an individual's health metrics, dietary preferences, cultural background, local food prices, and even real-time geospatial data on nearby grocery stores and farmers' markets to generate feasible and tailored meal plans (Smith & Jones, 2022). For example, an AI app could identify the most cost-effective sources of protein within a user's immediate vicinity, promoting canned beans on sale at a local bodega over expensive fresh fish from a distant supermarket.

The usage of AI-driven diet planning systems to customize nutrition advice to each person's needs is growing. Traditional dietary recommendations, according to Agrawal et al. (2025), are inadequate since they don't take into consideration inter-individual differences in genetics, metabolic indicators, and lifestyle choices. AI systems may create customized meal plans by analysing vast datasets, such as biomarkers, nutritional intake, and health outcomes, using machine learning and deep learning. By encouraging the effective use of available food resources and lowering waste through targeted consumption methods, these technologies not only enhance individual health outcomes but also contribute to food security. AI-powered apps, for instance, might suggest diets that benefit underprivileged groups by striking a balance between price and adequate nutrition.

AI-powered meal planning software analyses a variety of datasets, including genetic markers, lifestyle characteristics, and socioeconomic conditions, to provide customized nutrition recommendations. According to Agrawal et al. (2025), machine learning models are more accurate than conventional guidelines at predicting individual nutrient requirements. Nutrino

and Food visor, for example, are AI-powered tools that measure nutritional consumption and offer real-time feedback using natural language processing and image identification. By ensuring meals satisfy particular nutritional requirements, these methods lower the risk of malnutrition and promote food security.



Figure 1 shows the general well-being of how one should think of



Figure 2 shows how dietary planning applications are worldwide, useful, and accepted.

Furthermore, AI enhances accessibility. Mobile health (mHealth) applications powered by AI can deliver 24/7 nutritional coaching directly to smartphones, devices with near-ubiquitous penetration even in low-income communities. These tools can overcome barriers of time and transportation associated with in-person dietitian consultations. Features like image-based food recognition allow users to effortlessly log meals, providing immediate feedback on nutritional content (Chen et al., 2021). This instant feedback loop can empower users with knowledge and foster better dietary habits.

2.1.2 Significant Challenges and Barriers to Implementation

Despite its potential, using AI in this situation is difficult. Algorithmic bias and the digital divide are the most frequently mentioned issues. AI models are trained on data that frequently overrepresents wealthy, health-conscious groups, resulting in suggestions that are insensitive or condescending to users with lower incomes. For someone shopping at a dollar store or a tiny corner store with little fresh food, an algorithm educated on data from Whole Foods customers could find it difficult to make insightful recommendations (Adebayo et al, 2022).

Data privacy is another critical issue. Low-income communities are often subject to heightened surveillance and data extraction. Collecting sensitive health and dietary data requires immense trust and robust safeguards to prevent misuse by insurers, employers, or advertisers (Privacy International, 2023). Without transparent data policies and informed consent processes, these technologies risk exacerbating existing vulnerabilities.

Moreover, AI cannot address the fundamental, systemic drivers of food insecurity. An algorithm can optimize a food budget, but it cannot lower rent, increase wages, or force a grocery store to open in a food desert. Over-reliance on technological solutions risks technosolutionism, where complex socioeconomic problems are framed as issues solvable by an app, diverting attention and resources away from necessary policy interventions like increasing SNAP benefits or supporting urban agriculture projects (Davis, 2024).

2.1.3 Ethical Considerations and the Human Element

The ethical deployment of AI in this space necessitates a human-centred design approach. This involves co-designing applications with the target communities from the outset to ensure cultural competency, linguistic appropriateness, and practical utility (Green et al., 2023). An app designed for a low-income neighbourhood in New York must differ significantly from one designed for a similar community in Mumbai, India. AI-driven diet planning has a number of obstacles despite its potential. Agrawal et al. (2025) raise a warning regarding algorithmic transparency, data privacy, and fair access. Large datasets are frequently used by AI systems, which may not be representative of underrepresented groups and result in suggestions that are skewed. Additionally, the digital divide restricts low-income areas' access to AI tools, which may exacerbate disparities in food security. Therefore, to guarantee that AI diet planning systems serve all populations equally, ethical frameworks and inclusive regulations are crucial. Furthermore, the role of AI must be framed as a supportive tool for,

not a replacement of, human healthcare providers and community nutrition advocates. The most effective models are likely hybrid ones, where AI handles data crunching and daily logging, freeing up human dietitians and community health workers to provide empathetic support, motivation, and complex counselling that AI cannot replicate (Miller & Garcia, 2022). This synergy leverages the strengths of both technology and human touch.

2.2 Critical Analysis of Existing Research on AI-Powered Diet Tools

The use of artificial intelligence (AI) in diet planning is only one of the many industries that AI has transformed. Real-time feedback, scalable health treatments, and customized nutrition are all promised by AI-powered diet planning apps. Current studies demonstrate their ability to manage chronic illnesses, improve public health outcomes, and increase dietary adherence. The usefulness of digital tools for diet monitoring and precision nutrition for both experts and citizens was highlighted in a thorough review (Abeltino et al. 2024). These applications use AI algorithms to assess food trends, expedite data gathering, and produce personalized recommendations based on user profiles, including genetic and epigenetic information. Similarly, Mahendran et al. (2024) explored AI's role in nutrition science, noting its capacity to extract and analyse data from diverse sources such as social media, wearable devices, and food images. These capabilities allow for dynamic tracking of dietary intake and behavioural insights, which are crucial for personalized nutrition strategies.

Even with these improvements, many restrictions still exist. Accurate data is one of the main issues. Particularly when calculating portion sizes or identifying mixed foods, AI models might be prone to errors due to their heavy reliance on user input and picture recognition. Additionally, the incorporation of motion sensor-based tools, as Phalle and Gokhale (2025) suggest, adds complexity to the process of recording eating events using swallowing noises or wrist motions, which may not be consistently accurate across populations. There are issues with pricing and accessibility as well. Low-income or technologically challenged people may be excluded by the requirements of many AI-powered apps, which include cell phones, internet connectivity, and membership costs. Additionally, ethical and regulatory issues such as data privacy, algorithmic bias, and lack of transparency in recommendation systems remain unresolved. These concerns are particularly pressing in clinical nutrition, where inaccurate or biased recommendations could have serious health implications.

The effectiveness and behavioural effects of these apps over the long run represent yet another important knowledge gap. Although short-term research indicates that dietary habits can be improved, there is a dearth of long-term studies that evaluate user satisfaction, health effects, and sustained involvement. Additionally, the majority of research focuses on adult populations, which leaves a knowledge gap regarding how AI-powered diet planning might be modified for older people, children, or those with certain medical issues. In order to ensure comprehensive and culturally sensitive solutions, AI tools must be developed with input from a variety of professions due to the multidisciplinary nature of nutrition, which encompasses biology, psychology, and sociology. Lastly, the absence of standardized evaluation frameworks hinders the implementation of evidence-based practices in healthcare settings by making it challenging to compare the efficacy of various apps.

Identification of Research Methodologies in similar studies

More scholarly attention is being paid to the relationship between urban food insecurity in Sub-Saharan Africa, nutrition research, and artificial intelligence (AI). To evaluate viability, impact, and scalability, researchers looking into AI-powered diet planning apps in various settings have used a variety of qualitative and quantitative approaches. One well-known example is the research conducted (Abdallah et al. 2024), which examined how deep learning technologies were used in South African cities to address the combined burden of obesity and undernutrition. This study used a mixed-methods approach, capturing both lived experiences and statistical trends through focus group talks and standardized surveys. In addition to gathering quantitative data on biological indicators, app usage frequency, and nutritional consumption, qualitative research examined user perspectives, cultural food preferences, and adoption hurdles.

Participatory action research (PAR), especially in community-based interventions, is another popular methodology. In order to collaborate with local stakeholders on diet planning features, pilot research in Lagos, Nigeria, combined PAR with mobile health (mHealth) tools. Researchers held iterative workshops with software engineers, healthcare professionals, and community members to make sure the app's suggestions matched cultural norms and local food availability. This strategy not only increased user involvement but also brought attention to infrastructure issues like sporadic internet connection and low smartphone adoption. Ethnographic techniques have also been used to comprehend how socioeconomic factors affect dietary preferences. For example, researchers in Nairobi investigated how urban slum

inhabitants deal with food insecurity and the ways in which AI-generated meal plans interact with informal food economies through participant observation and in-depth interviews.

Another methodological strand is the validation of machine learning models. Algorithms are usually trained using dietary information obtained from urban health clinics or national nutrition surveys. Researchers in South Africa analysed user-submitted food photos and predicted nutritional content using convolutional neural networks (CNNs). Accuracy was evaluated by validation using confusion matrices and cross-sectional data. Incomplete or skewed datasets, which might not accurately reflect the variety of urban diets in food-insecure populations, are a common source of difficulties for these studies. In order to overcome this, several researchers have included federated learning models, which enable decentralized data training across several devices while enhancing the generalizability of the model and protecting privacy.

Even with these advancements, methodological flaws still exist. There is little longitudinal research, which restricts our knowledge of long-term behaviour change and health consequences. Instead of identifying trends, the majority of research is cross-sectional, taking snapshots. Furthermore, because of ethical and practical limitations, randomized controlled trials (RCTs), the gold standard for assessing the effectiveness of interventions, are rarely employed in disadvantaged populations. The outcome metrics are also not standardized; some research emphasizes micronutrient adequacy or user pleasure, while others concentrate on caloric intake, making comparisons challenging. Furthermore, despite evidence showing that women are disproportionately affected by food insecurity and are the primary caregivers in charge of meal preparation, few studies use gender-sensitive approaches.

Food Security Issues in Low-Income Urban Households

A major worldwide challenge is food security, which is defined as constant access to enough wholesome food for an active and healthy life. Urban food insecurity is becoming more widely acknowledged as a serious issue (Crush et al, 2011), especially for low-income households in quickly expanding cities, even if rural poverty and agricultural production have historically received the majority of the discussion. Due to urbanization, economic disparity, and changing food systems, access to nutrient-dense food is now restricted by social exclusion, infrastructure, and cost in addition to availability. Traditional conceptions of food security in Zimbabwe have been based on rural agricultural settings (Mavhura, E 2017).

However, recent studies indicate that urban dwellers are becoming more vulnerable, particularly low-income households. Numerous factors contribute to Zimbabwe's urban food insecurity, such as high unemployment, inflation, unstable economic conditions, and limited availability of affordable, nutrient-dense food. During peak lean seasons, more than 30% of metropolitan households are thought to be food insecure, a significant increase in recent years.

According to the Zimbabwe Vulnerability Assessment Committee (ZimVAC). Since most urban households buy their food from the market, they are extremely vulnerable to changes in prices and exchange rates. Due to the depletion of purchasing power brought on by hyperinflation and the informal sector, many families are now compelled to eat fewer meals, rely on less expensive and nutrient-dense foods, or skip meals entirely. Research by Tawodzera (2012) and others has shown how common food deserts are in high-density areas like Mbare, Epworth, and Dzivarasekwa, where there is little access to formal retail establishments and fresh vegetables. In addition, infrastructure problems worsen food insecurity in Zimbabwe's cities. Since many low-income homes lack adequate storage, cooking fuel, and refrigeration, it is challenging for them to prepare balanced meals or purchase food in quantity. Gender dynamics also have a role; households led by women are disproportionately affected due to salaries and caregiving responsibilities (Bergmann et al, 2009). The necessity of food security initiatives tailored to urban areas is emphasized in recent studies. Urban agriculture integration, better market accessibility, and focused social protection initiatives are all promoted by Tawodzera (2019). In order to increase food access and nutritional diversity, the World Food Programme (WFP) and regional non-governmental organizations have tested mobile food vouchers and cash-based transfers in urban areas. The long-term nutritional effects and the function of digital tools in promoting urban food security are still little understood, despite these efforts. It will take multi-sectoral strategies that integrate infrastructure development, economic assistance, and cutting-edge technologies to alleviate food insecurity in low-income urban households as Zimbabwe continues to urbanize.

Structural Causes of Urban Food Insecurity

AI is essential for improving sustainability throughout the food chain, going beyond personal diet planning. AI applications in food production, processing, and distribution can boost output, cut waste, and support sustainable farming methods, according to Namkhah et al.

(2023). AI can estimate crop yields, streamline supply chains, and reduce post-harvest losses by incorporating predictive analytics. By guaranteeing that food is accessible and available in enough quantities, these tasks directly contribute to food security. When connected to sustainable food production systems, AI diet planning tools can direct customers toward diets that are both ecologically friendly and nutritionally sufficient. Some structural factors influence urban food insecurity, starting with economic vulnerability (Tawodzera, G, 2011). Low-income households frequently depend on low-wage, insecure informal work. Food is often sacrificed to cover other urgent expenses like rent, transportation, and school fees when disposable income is low. Residents of cities are totally reliant on market purchases, in contrast to rural households that might cultivate their own food. They are extremely vulnerable to supply chain interruptions, inflation, and price swings as a result of this reliance.

Cities' spatial arrangement is another important feature. Many low-income households live in high-density suburbs or informal settlements without supermarkets, marketplaces for fresh vegetables, or dependable transportation. These regions where wholesome food is pricey and in short supply are frequently referred to as food deserts. Residents instead rely on street vendors and corner stores that sell mostly processed, high-calorie items (Motsi, E 2021). Lack of storage space, cooking facilities, and refrigeration makes it more difficult to purchase and prepare nutritious meals in large quantities, which feeds a vicious cycle of unhealthy eating habits.

Urban planning and policy also play a role. In many locations, commercial development is prioritized above local food systems due to zoning laws and land use constraints. Public marketplaces are underfunded, and urban agriculture is often ignored or discouraged. The urban poor are nonetheless excluded from middle- and upper-class food systems in the absence of deliberate legislative changes.

Social and Cultural Dimensions

Economic factors alone do not account for food insecurity in urban settings; social and cultural factors play a significant role. Given that women are frequently in charge of budgeting and food preparation in low-income households, gender plays a big part (Floro M.S et al 2013). Due to pay gaps and caregiving obligations, households headed by women, which are prevalent in metropolitan areas, generally face greater levels of food insecurity.

Furthermore, dietary customs, such as a predilection for meat or traditional foods, might affect consumer choices, sometimes at the price of nutritious content.

Food access is impacted by social networks as well. Food borrowing and sharing may be unofficial coping strategies in close-knit societies. However, these networks can be weak or non-existent in dispersed metropolitan contexts, which would separate households in emergencies. Since newcomers to the city might not have social capital or knowledge of the local food systems, migration and displacement make problems even more complicated.

Hunger-related stigma and shame can keep people from getting assistance. Because metropolitan settings may conceal underlying hardship behind outward trappings, food insecurity is frequently concealed there. It is challenging for relief agencies and legislators to recognize and assist persons in need because of this invisibility.

Health and Nutritional Impacts

According to Zheng et al. (2026), AI has the ability to customize food systems on a large scale, connecting supply chains that are climate resilient with precision nutrition. Environmental data, such as food items' carbon footprints, can be included in dietary recommendations by AI diet planning programs. By ensuring that dietary decisions are in line with more general sustainability objectives, this integration promotes long-term food security. AI can, for example, recommend locally produced foods or plant-based substitutes that lessen dependency on resource-intensive imports, increasing resilience against geopolitical upheavals and climate shocks. Urban food insecurity has significant and long-lasting effects. Low-income urban households frequently experience the double burden of malnutrition, which consists of both obesity and undernutrition at the same time. Low in vital nutrients, diets dominated by inexpensive, processed foods are rich in sugar, salt, and bad fats. Stunted growth, cognitive impairments, and heightened vulnerability to disease are possible outcomes for children living in these settings. Adults are more susceptible to cardiovascular disease, diabetes, and high blood pressure.

Food insecurity has an impact on mental health as well. Feelings of helplessness, anxiety, and melancholy can result from the stress of not knowing where one's next meal will come from (Leung C.W, 2022). Teenagers could act riskily to get food, while parents might miss meals to feed their kids. These coping mechanisms affect both community resilience and personal

well-being over the long run. Additionally, educational results are jeopardized. Hungry children find it difficult to focus in class, and academic performance is harmed by frequent absences from school due to illness or domestic duties. The cycle of poverty and food insecurity is then sustained by inadequate education.

Coping Strategies and Resilience

Low-income urban households show incredible perseverance in the face of these obstacles. Using less expensive items, cutting back on meal frequency, and depending on unofficial credit from nearby merchants are common coping mechanisms (Yucel, G, 2012). Some households supplement their nutrition by growing vegetables in shared plots or containers, a practice known as urban agriculture.

Others join cooperatives or savings clubs to pool resources and increase access to food. In order to promote food security, community-based groups are extremely important. Despite sometimes being overburdened and underfunded, school feeding programs, food banks, and soup kitchens offer crucial assistance. Religious organizations and non-governmental organizations also make contributions through direct aid, education, and advocacy. Technology is starting to show promise as a resilience-boosting tool. Digital platforms and smartphone apps can help consumers find inexpensive food suppliers, provide dietary advice, and make money transfers or food vouchers easier. But the spread of these advances is still constrained by unequal access to smartphones and digital literacy.

Policy and Programmatic Responses

Programmatic and policy solutions must be linked to address urban food insecurity. Food security is an important aspect of public health and urban growth that governments must acknowledge. This entails funding public markets, encouraging urban farming, and controlling food costs to safeguard susceptible customers. Food subsidies, conditional cash transfers, and school feeding programs are examples of social protection programs that ought to be extended and modified for urban environments. Additionally, nutrition education is crucial. Even with limited resources, educating households on food preparation, budgeting, and healthy eating can improve dietary choices. Peer educators and community health professionals can be reliable resources for knowledge and assistance.

Government, commercial sector, and civil society partnerships are essential. Stores in underprivileged communities can be encouraged to carry reasonably priced, wholesome meals. NGOs can help deliver services and involve the community. Data and insights from researchers can help guide evidence-based actions.

2.2.1 AI-Diet Planning Tools

AI diet planning systems, which provide individualized dietary advice via data-driven algorithms, are a breakthrough at the nexus of technology and public health (Prasad, G. 2025). These programs analyse personal health information, interests, and goals to help people make educated food decisions. Particularly in developing nations like Zimbabwe, AI diet planning solutions have the potential to revolutionize low-income urban households. They can assist in bridging the gap between dietary requirements and scarce resources by providing individualized meal recommendations that satisfy both budgetary and health goals. AI diet planning apps primarily work by gathering user data, including age, weight, food preferences, dietary limitations, and medical problems (Vasiloglou M.F et al 2021). The software analyses this data using machine learning algorithms to produce meal plans that adhere to dietary recommendations. The software can recommend meals that are not only reasonably priced and culturally suitable, but also healthily balanced, thanks to certain sophisticated platforms that integrate local food databases and pricing data. In urban environments, where availability and cost frequently influence food choices more so than nutritional content, this trait is especially pertinent. AI systems can help consumers improve their diets without going over their budget by suggesting economical meals and locally sourced items.

The particular difficulties that these populations encounter highlight the importance of these tools in low-income urban homes. The only source of income for urban households is market purchases, in contrast to rural communities, which could have recourse to subsistence farming (Ellis F, 2005). They are susceptible to supply chain interruptions, price instability, and inflation as a result of this reliance. Food deserts are places with little access to fresh produce and nutritious food options, and many city people reside in these areas. Through the identification of alternate food sources, substitution suggestions, and the promotion of dietary diversity through the utilization of available resources, AI diet planning systems can assist in navigating these limitations. If fresh vegetables are too expensive, for instance, the app may suggest nutrient-dense legumes or fortified staples that offer comparable advantages.

AI diet planning systems' capacity to provide nutrition education in an approachable manner is another important benefit. There is often a dearth of formal nutrition instruction and a high prevalence of misunderstandings regarding healthy eating in low-income metropolitan areas. AI applications that provide visual clues, quantity guidelines, and interactive elements that improve comprehension can help clarify difficult dietary topics. For women and caregivers, who frequently shoulder the burden of meal planning and food preparation, this is especially advantageous. AI apps can facilitate improved decision-making and long-term behaviour modification by providing them with the information and resources they need.

AI diet planning programs are not without restrictions, despite their potential. In low-income metropolitan regions, access to smartphones and internet connectivity is still unequal, possibly excluding the most vulnerable households. Users may find it difficult to understand recommendations or navigate app interfaces due to a lack of digital literacy. Because English is frequently the only language supported, customers who speak indigenous languages like Shona or Ndebele may find this unsuitable. Furthermore, user-provided data accuracy determines how effective AI-generated meal plans are. The tool's usefulness can be compromised by inaccurate or incomplete inputs, which may result in improper recommendations.

Concerns about cultural relevance also exist. Due to their Western development, many AI diet planning applications may suggest items that are unknown, inaccessible, or culturally unacceptable in Zimbabwe. For example, recommending quinoa or kale to a Bulawayo household might not be feasible or economical. For the app to represent local dietary standards and market realities, localization of material is crucial, necessitating cooperation between developers, dietitians, and community members.

Additionally, structural factors that contribute to food insecurity, including unemployment, inflation, and poor urban planning, are not addressed by AI techniques. Even though they can help people change their own behaviour, more extensive systemic interventions are required to establish conditions that promote food security. This includes funding for public markets, controlling food prices, and growing social safety nets. Instead of being seen as stand-alone remedies, AI diet planning tools ought to be seen as an adjunct to these initiatives.

Research specifically focused on AI diet planning applications in Zimbabwe is still emerging, but there are a few relevant developments and broader studies that provide insight into the

potential and early experimentation with such tools in the region. One notable example is a study titled *AI-Based Web Application for Diet Planning and Recommended Exercise* published in the *International Journal of Research Publication and Reviews* (2025). Although it is not specifically about Zimbabwe, the paper describes how machine learning methods, including random forests and convolutional neural networks (CNNs), can be used to generate customized diet regimens based on user food choices and health indicators. Additionally, the system incorporates image processing to recognize items from user-uploaded images. This feature might be modified for local contexts, such as Zimbabwe, where informal food markets predominate, and cell phone usage is significant.

The majority of digital programs pertaining to nutrition in Zimbabwe have traditionally concentrated on mobile health (mHealth) platforms for disease surveillance, HIV treatment adherence, and maternal care (Samusodza, C.R 2016). AI's incorporation into dietary planning is still relatively new, though. Particularly in urban regions where malnutrition coexists with rising rates of obesity and diet-related disorders, there is considerable interest in employing AI to enhance food security. AI-powered solutions for dietary evaluation and behaviour modification have been investigated by local NGOs and health tech entrepreneurs, but there are still few formal academic studies available. Given Zimbabwe's particular difficulties, high urban food insecurity, reliance on unofficial food vendors, and restricted access to nutrition education (Tawodzera, G. 2010). AI diet planning apps are especially relevant there. These apps might be modified to offer culturally relevant meal planning and suggest reasonably priced, regional items. However, content localization, support for indigenous languages, and integration with the current public health infrastructure would be necessary for successful deployment.

2.2.2 Experiences and Remarks on AI Diet Planning Applications

Applications for artificial intelligence (AI) diet planning have become cutting-edge resources in the field of digital health, providing users from a range of socioeconomic backgrounds with individualized dietary advice. In order to create customized meal plans, nutritional feedback, and behavioural nudges, these apps use machine learning algorithms to evaluate user data, including age, weight, food preferences, health objectives, and financial limitations. Their relevance and influence in low-income urban households, especially in developing nations like Zimbabwe, are being investigated more and more, despite the fact that their popularity has increased in high-income settings. Both the potential and the

constraints of these tools in practical settings are demonstrated by user experiences and comments.

The capacity of AI diet planning tools to streamline intricate nutritional decisions is what appeals to many consumers. These apps are empowering for people who don't have access to nutritionists or professional nutrition education. They provide concise, doable guidance on how to balance meals within budgetary limits as well as what to eat and how much to consume. Users value elements that suggest reasonably priced, locally sourced ingredients because, in metropolitan settings, cost and availability frequently determine food choices more so than health. For instance, a caregiver in Harare could use the app to create meal plans that include economically available and culturally recognizable items like sadza, groundnuts, and leafy greens. Users say that following such advice increases nutritional diversity and lessens dependency on processed foods.

Another often mentioned advantage is ease of usage. Even people with low levels of digital literacy may use several AI diet apps because of their user-friendly interfaces, visual meal trackers, and straightforward language (Hussein, S. 2024). Certain applications enable users to scan food items and provide immediate nutritional analysis through voice input or image recognition capabilities. These characteristics are especially useful in unofficial marketplaces without labels or packaging. The apps' adaptability, which enables users to modify meal plans in response to shifting household conditions like shifting income or seasonal food availability, is another feature that users appreciate.

Nevertheless, user comments also point out a number of difficulties. Language is one of the biggest obstacles. The majority of AI diet planning applications are created in English, which may not be the primary or preferred language of many Zimbabwean users. In most cases, users might find it difficult to interact with the app's content to the fullest extent if indigenous languages like Shona or Ndebele are not supported. This restricts the technology's efficacy and reach, particularly among older persons and those with less formal education.

Relevance to culture is another issue. In their local context, users frequently comment that certain suggested foods like salmon fish, macadamia nuts, or almond milk are unknown, inaccessible, or prohibitively expensive. Disengagement or frustration may result from this distance. Apps that combine local food databases and represent customary dietary patterns are considered successful. The likelihood that users would trust and regularly use the app

increases when they see their traditional foods represented and validated. Technical constraints have an impact on user experience as well. Reliable internet connectivity and smartphone access are rarely assured in metropolitan areas with low incomes.

It is also common that Users complain about having trouble using the app offline, getting updates, or accessing cloud-based functionality. Particularly for households that share smartphones or use prepaid mobile plans, battery life and data prices are additional issues. These constraints underscore the need for lightweight, offline-capable apps that do not require constant connectivity. Users are hopeful about the potential of AI diet planning apps to enhance home nutrition in spite of these obstacles. A greater understanding of dietary types, portion sizes, and the significance of balanced meals is reported by many (Zadehh, 2024). By more effectively planning meals and making inventive use of leftovers, several users report that the app has helped them reduce food waste. Others value the motivating elements, including goal-setting and progress tracking, which support their continued commitment to better eating practices. In focus groups, users have suggested improvements such as factoring in local market costs, offering seasonal meal plans, and integrating community elements like recipe sharing or peer assistance (Cohenn B, 2002).

These comments demonstrate a need for tools that are more context-sensitive and interactive than static suggestions. Concerns over the storage and use of their personal health data are also raised by users, who stress the value of privacy and trust. To foster long-term engagement, transparent data policies and user control over information are crucial. The intricate interaction of accessibility, contextual relevance, and empowerment is revealed by user experiences with AI diet planning apps. The effectiveness of these tools, which provide useful assistance in making dietary decisions, is contingent upon careful planning, cultural adjustment, and infrastructure support. If developed with the end user in mind, AI diet planning apps have the potential to revolutionize low-income urban families where poor nutrition and food insecurity are enduring problems. Not only do user comments and suggestions guide enhancements, but they also demonstrate how technology can democratize nutrition and wellness.

2.3 THEORETICAL FRAMEWORK

The theoretical underpinnings for comprehending the potential impact of meal planning applications powered by artificial intelligence (AI) on food security and nutritional outcomes

in low-income urban households are provided by this approach. To illustrate how digital interventions may impact dietary behaviour and household food access, it references interdisciplinary theories from the fields of public health, behavioural science, technology adoption, and food systems. Food insecurity is influenced by market dependency, structural inequality, and inadequate access to nutrition education in urban Zimbabwe, where the framework also places the study within a larger socioeconomic and technological framework.

2.3.1 Health Belief Model

The Health Belief Model (HBM) is a psychological paradigm that uses personal risk and reward perceptions to explain health-related behaviour (Abraham, C et al 2005). It suggests that if people think they are at risk for a health issue, think the issue is serious, think that taking action would lower their risk, and think there are few obstacles to doing so, they are more likely to take health-promoting actions.

Regarding this study, the HBM makes it easier to understand how low-income city dwellers would react to food suggestions produced by AI. For instance, users are more likely to adopt healthier eating habits if they believe that following the app's recommendations will reduce their risk of developing diseases like diabetes or hypertension, which are increased by poor nutrition. The app's capacity to offer real-time feedback and customize recommendations increases perceived advantages and lowers perceived barriers, such as ignorance or misunderstanding of portion sizes.

Additionally, by sending out warnings, reminders, and inspirational messages, the app can operate as a cue to action, encouraging users to make healthier decisions. When the AI meal planning tool is in line with the HBM's constructs perceived susceptibility, severity, benefits, barriers, and cues, it acts as a behavioural catalyst for better nutrition.

2.3.2 Technology Acceptance Model

The adoption and utilization of new technologies by people is explained by the Technology Acceptance Model (TAM) (Mugo, D. 2017). It distinguishes between two main elements: perceived ease of use (PEOU) and perceived usefulness PU. PU is the degree to which an

individual think that utilizing a specific system will improve their performance, whereas PEOU is the degree to which they think the system will be effortless.

This study uses TAM to analyse how low-income urban families adopt AI diet planning apps. If users find the app straightforward to use and believe it can help them plan inexpensive, healthy meals, they are more likely to use it often. While PU is enhanced by the app's capacity to improve dietary outcomes and decrease food waste, PEOU is directly influenced by its design, which includes language options, visual aids, and offline capabilities. TAM also highlights the part played by outside factors like social influence and favourable circumstances. As an illustration, adoption rates might rise if NGOs offer training on the app's use or if community health workers recommend it.

2.3.3 Food Security Framework

The four pillars of food security are stability, usage, access, and availability (Guine et al, 2021). To comprehend the complex nature of food insecurity in urban environments, this paradigm is crucial. Food availability in Zimbabwe's densely populated suburbs is frequently hampered by market forces, whilst access is restricted by factors including cost, transportation, and money. Seasonal variations and economic volatility threaten stability, while cultural preferences, cooking facilities, and expertise all influence utilization. Apps for AI diet planning have the potential to impact all of these pillars. Through the recommendation of reasonably priced and locally accessible items, the app facilitates accessibility and use. Its instructional elements improve the quality of customers' diets by empowering them to make balanced meals. Regular use of the app can eventually promote resilient eating habits and lessen dependency on emergency coping mechanisms, which could lead to stability. This concept emphasizes the significance of contextual adaptation as well. An app may unintentionally contribute to food poverty if it disregards regional food systems, cultural norms, or economic realities. Thus, the location and ethical design of the AI intervention are guided by the food security framework.

2.3.4 Ecological Model of Health Behaviour

Numerous levels of influences, including intrapersonal, interpersonal, organizational, community, and policy, have an impact on an individual's behaviour, according to the Ecological Model of Health Behaviour (Golden S.B et al 2012). Understanding nutrition in low-income urban homes, where dietary decisions are influenced by a variety of factors,

including market systems, government policies, household dynamics, and community norms, is made easier with the help of this model.

The artificial intelligence diet planning app mostly functions at the intrapersonal level, offering tailored advice and comments. However, other levels of assistance are necessary for its effectiveness. Interpersonal support from family members, for example, can boost the use of apps. Access and training might be made easier with organizational assistance from clinics or NGOs. Policy actions, such as subsidies or digital inclusion initiatives, can improve infrastructure and affordability, while community engagement can foster cultural relevance and trust.

By placing the app in this multi-level structure, the study recognizes that in order to have a significant impact, technology solutions need to be integrated into larger support networks.

2.3.5 Human-Centred Design and Digital Inclusion

Human-Centred Design (HCD) highlights how crucial it is to create technologies that are specific to end users' requirements, preferences, and limitations (Gotgenns et al 2021). In low-income urban settings, this entails developing applications that are user-friendly, compatible with limited digital infrastructure, linguistically accessible, and culturally appropriate. A comparable idea that concentrates on guaranteeing fair access to technology is digital inclusion. It tackles obstacles like affordability, internet connectivity, digital literacy, and device ownership. The effectiveness of AI diet planning tools depends on digital inclusion in Zimbabwe, where smartphone adoption is increasing but unevenly distributed, and many households rely on shared devices or prepaid data. The ethical and practical design of the intervention is guided by these frameworks, which guarantee that it empowers marginalized users rather than exacerbating already-existing inequities.

In conclusion,

This theoretical framework combines socio-ecological, nutritional, behavioural, and technological models to offer a thorough grasp of how AI diet planning apps can affect nutrition and food security in urban low-income households. Individual participation is explained by the Health Belief Model and the Technology Acceptance Model, while the Food Security Framework and Ecological Model place the intervention in the context of larger systems. Principles of Digital Inclusion and Human-Centred Design guarantee that the

technology is useful, accessible, and empowering. When combined, these ideas provide a strong basis for assessing the effects of AI-powered diet planning tools in urban Zimbabwe and guide the study's development, execution, and analysis.

REFERENCES

- Behl, A., Chavan, M., Jain, K., Sharma, I., Pereira, V. E., & Zhang, J. Z. (2021). The role of organizational culture and voluntariness in the adoption of artificial intelligence for disaster relief operations. *International Journal of Manpower*, 43(2), 569–586. <https://doi.org/10.1108/IJM-03-2021-0178>
- Vågsholm, I., Arzoomand, N. S., & Boqvist, S. (2020). Food security, safety, and sustainability Getting the trade-offs right. *Frontiers in Sustainable Food Systems*, 4, 16. <https://doi.org/10.3389/fsufs.2020.00016>
- Dora, M., Kumar, A., Mangla, S. K., Pant, A., & Kamal, M. M. (2022). Critical success factors influencing artificial intelligence adoption in food supply chains. *International Journal of Production Research*, 60(14), 4621–4640. <https://doi.org/10.1080/00207543.2021.1959665>
- How, M. L., Chan, Y. J., & Cheah, S. M. (2020). Predictive insights for improving the resilience of global food security using artificial intelligence. *Sustainability*, 12(15), 6272. <https://doi.org/10.3390/su12156272>
- Lamsal, R., & Kumar, T. V. (2023). Twitter-based disaster response using machine learning. *International Journal of Social Ecology and Sustainable Development (IJSESD)*, 14(1), 1–18. <https://doi.org/10.4018/ijsesd.320650>
- Agrawal, K., Goktas, P., Kumar, N. & Leung, M-F. (2025) *Artificial intelligence in personalized nutrition and food manufacturing: a comprehensive review of methods, applications, and future directions*. *Frontiers in Nutrition*, 12, 1636980. doi:10.3389/fnut.2025.1636980.

Namkhah, Z., Fatemi, S.F., Mansoori, A., Nosratabadi, S., Ghayour-Mobarhan, M., & Sobhani, S.R. (2023). *Advancing sustainability in the food and nutrition system: a review of artificial intelligence applications*. *Frontiers in Nutrition*, 10, 1295241. doi:10.3389/fnut.2023.1295241.

Zheng, L., Ren, A. & San, Y. (2026) *AI-driven personalization of food systems: From precision nutrition to climate-resilient supply chains*. *npj Science of Food*, 10, 45. doi:10.1038/s41538-026-00123.

CHAPTER 3: Research Methodology

3.1 Introduction

This chapter describes the research approach used to look into how AI-driven diet planning apps might improve food security for low-income households in Chitungwiza, Zimbabwe. In urban low-income settings, where access to reasonably priced, nutrient-dense food is still a chronic difficulty, there is an urgent need to address nutritional deficiencies and food insecurity. As artificial intelligence (AI) technologies become more prevalent in the fields of nutrition and health, this study aims to investigate how these breakthroughs might be scaled and contextually adjusted to fit the specific requirements of vulnerable groups.

The methodology used in this study captured the quantitative and qualitative aspects of dietary behaviour, technological adoption, and food security. The feasibility, applicability, and impact of AI-assisted meal planning systems are evaluated by combining data gathering at the home level with insights at the community level. The study's primary goal was to investigate how AI-powered dietary planning can be adapted and used to improve food security and nutritional outcomes in low-income urban communities in Chitungwiza. The strategy, which pays special attention to community involvement, cultural relevance, and technical accessibility.

After outlining the research methodology and justification, this chapter provides a thorough description of the study area and population. It then goes into detail about the methods, tools, and sample strategies used to obtain empirical evidence. The chapter also covers the analytical techniques used to understand the data, such as thematic and statistical analysis. For the research process to be transparent and rigorous, ethical issues and methodological limitations are addressed.

By using a mixed-methods approach, the project produced useful information that can direct technical innovation, influence policy, and encourage cooperation amongst multiple stakeholders in Zimbabwe's urban food systems. Thus, the approach served as both a tool for research and a framework for imagining long-term routes to better food security and nutrition using AI-enabled solutions.

3.2 Description of Study Site

Chitungwiza is situated about 30 kilometres southeast of Harare, Zimbabwe's capital, and is a heavily populated urban area that was chosen as the study site for this study. Chitungwiza is

one of the nation's most densely populated residential districts, with an estimated 350,000 inhabitants, many of whom reside in informal settlements and deal with serious socioeconomic issues (Mvere, G 2017).

Each of the town's four major units, Zengeza, Seke, St. Mary's, and Units, has a different level of community dynamics, service accessibility, and infrastructural development.

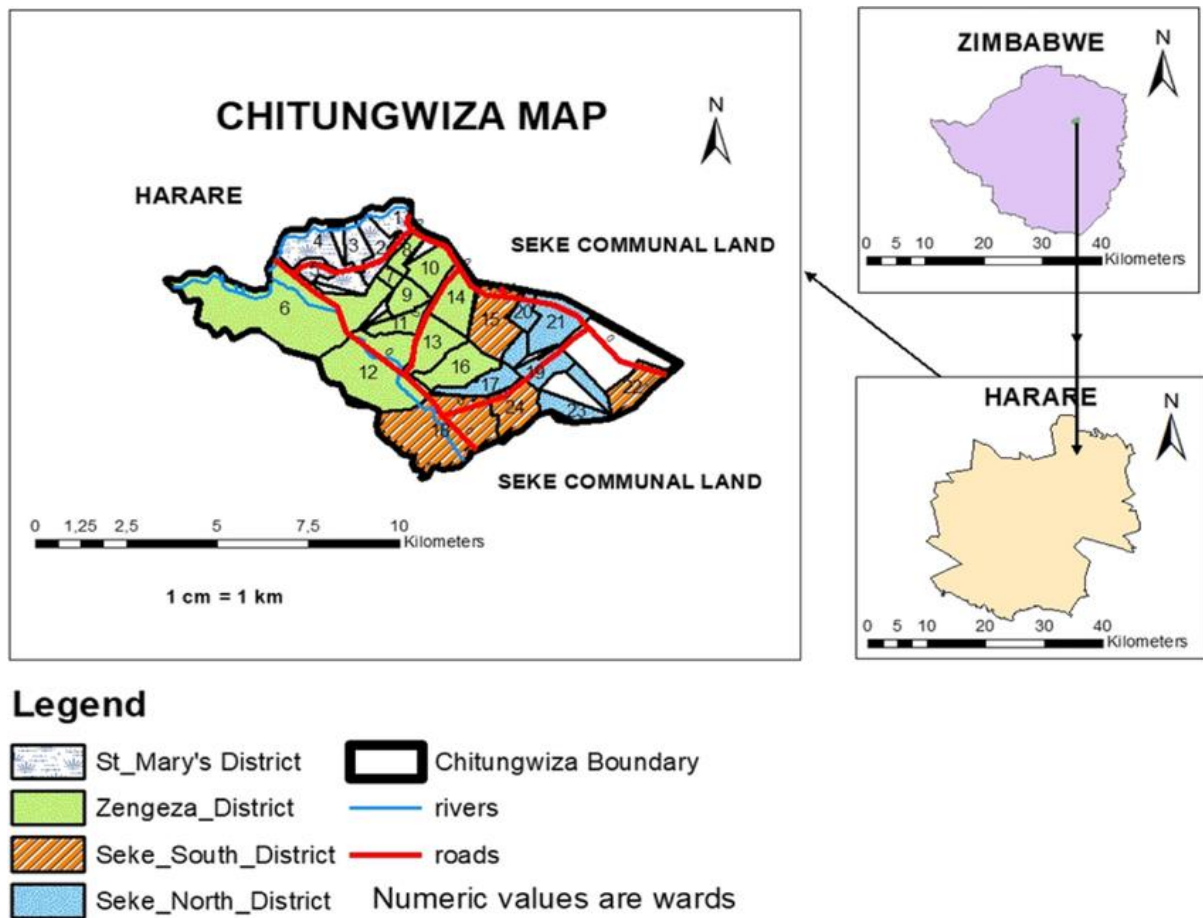


Figure 3: Study Site map

Socioeconomic Context

The underground economy, high unemployment rates, and restricted access to official social services are the hallmarks of Chitungwiza. Cross-border trade, casual labour, and vending are the main sources of income for many households. Food insecurity in cities like Chitungwiza, where people frequently struggle to purchase necessities such as nutritious food, has been exacerbated by Zimbabwe's economic turmoil (Mugumbate et al., 2024). For low-income families, the situation is dangerous because the cost of living is rising while income levels either stay the same or decrease.

Nutritional Landscape

A larger national trend of undernutrition, micronutrient deficiencies, and an increase in diet-related non-communicable diseases is reflected in the nutritional profile of the people of Chitungwiza (Matsungu et al 2020). For lack of funds and availability, households usually eat meals high in carbohydrates and low in fruits, vegetables, and protein. Minimal access to nutrition education exists, and cultural norms, financial constraints, and convenience frequently influence food decisions more so than health concerns.

Technological Environment

The majority of people in Chitungwiza own basic or internet-enabled mobile phones, despite the city's economic difficulties. Various age and income groups have different levels of digital literacy, and mobile data services are available but expensive. There are advantages and disadvantages to the implementation of AI-powered diet planning systems in this diverse technology environment. Mobile-based interventions have promise, but their effectiveness hinges on their affordability, usability, and cultural relevance.

Community Dynamics

Chitungwiza is renowned for its thriving networks of informal support groups, religious institutions, and community members. These networks are essential for planning health campaigns, distributing information, and assisting low-income households. Although their resources and reach are frequently constrained, community health workers, neighbourhood NGOs, and faith-based organizations actively promote nutrition and public health. In any

attempt to launch and expand AI-powered nutrition solutions, these players are important stakeholders.

Relevance to the Study

When analyzing the viability and effects of AI-assisted diet planning solutions, Chitungwiza provides an engaging backdrop. Because of its strong community structures, technological accessibility, and food insecurity, it is a perfect place to investigate how digital technologies might be adapted to satisfy the nutritional needs of urban low-income households. With possible applications in comparable contexts throughout sub-Saharan Africa, the case study's conclusions are anticipated to guide more comprehensive initiatives for incorporating AI into Zimbabwe's urban food systems.

3.3 Research design

This study used a convergent mixed-methods research design, which combined quantitative and qualitative methods, to examine the potential of AI-based diet planning tools to improve food security and nutrition outcomes for low-income urban households. The research was based on a localized case study approach that focused on the urban municipality of Chitungwiza in Zimbabwe, which has very different spatial and socio-economic dynamics in urban food systems in developing regions. By leveraging a specific urban context with acute food insecurity, a detailed and context-specific analysis of how structural community dynamics, infrastructural technology accessibility, and entrenched local eating habits collectively shaped or constrained the adoption of new digital nutrition solutions was possible (Haque et al., 2025). The methodological components are presented below.

Quantitative

The quantitative aspect of the study used a structured household survey instrument, which was used with low-income families in the study area. This survey produced empirical data in four main matrices:

- Household dietary profiles, eating habits, and local nutrition issues.
- Willing to Pay (WTP) by ex-ante consumers for AI-assisted diet planning applications, which reflects economic viability and demand-side incentives for health and wellness technologies (Ali & Ali, 2020).
- Standardized urban food security indicators: availability, access, and stability.

- Establish baseline digital literacy and access to hardware and mobile internet infrastructure in the home.

This data was then statistically analysed to reveal significant correlations, behavioural trends, and socio-economic differences between various household demographic profiles.

Qualitative

A strong qualitative strand was included to complement the macro-level trends identified by the survey and to reflect the lived realities of the population. This involved the use of focus group discussions (FGDs), key informant interviews (KIIs) with community health and food system stakeholders and detailed field observation notes. These qualitative channels were critical to understanding the socio-cultural relevance of automated dietary suggestions, underlying infrastructure challenges (including power outages and data costs), and the multi-stakeholder perspectives on the scaling of AI applications in the dynamic urban food retail and consumption landscape (Pennells et al., 2024).

This particular mixed-methods case study design is justified for three different academic reasons. First, it was a successful attempt to fill the empirical void, as it was able to capture both broad numerical, statistically generalizable trends and deep, lived experiences. Second, it allowed for systematic triangulation of data across data sources, minimizing single-method bias and improving the overall internal validity and reliability of the findings. Lastly, this integrated design directly supported the ultimate goal of the study: to develop practical, community-informed, and institutionally viable policy recommendations for the implementation of digital nutrition interventions in resource-limited urban settings.

3.4 Sampling procedure

To ensure that the study accurately reflects the experiences of low-income households in Chitungwiza, a purposive sampling method was then used. This means participants were selected based on specific characteristics that align with the objectives of the research, mainly households facing food insecurity and living on limited income. The sampling focused on different residential units within Chitungwiza, including Zengeza, Seke, St. Mary's, and Units. These areas were chosen as they represent a mix of socioeconomic conditions and are known for having high-density populations with limited access to nutritious food. A total of

n=72 households were sampled for the survey, ensuring a balanced mix of age groups, family sizes, and education levels. Although the targeted sample size was 80, and indeed 80 respondents were captured, after data cleaning, n=72 households then yielded complete, usable responses, while 27-28% were excluded due to missing data, blank fields, and non-response to key variables. The final sample of n=72 represents 72% response rate with 100% complete data. In addition to the survey, focus group discussions, observational notes, and key informant interviews were conducted with selected participants, community health workers, and local stakeholders to gather deeper insights.

This sampling approach was chosen because it allowed the research to focus on the most affected groups, while still capturing a variety of perspectives across Chitungwiza's urban landscape.

3.5 Data Collection Methods

This study used a mixed-methods design to capture both quantitative measures and qualitative measures to ensure a comprehensive analysis of the potential for AI-driven diet planning tools to reduce food insecurity in Chitungwiza. Primary quantitative data were collected using structured household surveys in different socio-economic units of Chitungwiza, covering dietary practices, nutritional issues, technological literacy, access to digital infrastructure, and willingness to pay for AI-supported nutritional services. These metrics were put into perspective through qualitative data gathered through Focus Group Discussions (FGDs) with 6-10 participants, where collective cultural beliefs, communal attitudes toward nutritional technology, and shared experiences were discussed. This was complemented by Key Informant Interviews (KIIs) with purposively sampled community health workers (nurses) and local government representatives to gain institutional and systemic views on public health and digital feasibility. Lastly, structured observational field notes were taken at the sites to triangulate and complement the main empirical results, concerning the living environment of the households, the way in which food is prepared, and the direct accessibility of mobile devices.

3.6 Data Analysis Techniques

3.6.1 Quantitative Analysis

Empirical data were analyzed quantitatively using SPSS (v29.0) to ensure computational accuracy and reproducibility. Arithmetic means, medians, standard deviations, and frequency distributions were calculated to synthesize baseline demographic characteristics, dietary

intake metrics, and composite food security scores. In the explanatory phase, inferential statistical modelling was used in three different models. Paired sample t-tests were used to compare pre- and post-intervention nutritional and food security indices within the target groups to assess intra-group longitudinal variations. Second, independent-samples t-tests were performed to compare the different groups, thereby separating the statistical significance of the treatment effects between the active AI-intervention group and the control group. Finally, multivariate regression analysis was built to model the predictive relationship between mobile application engagement metrics (independent variable) and long-term nutritional outcomes (dependent variable), adjusting sequentially for potential socio-economic, demographic, and infrastructural confounding variables to ensure internal validity and isolate true effect sizes.

3.6.2 Qualitative Analysis

To ensure a robust and nuanced interpretation of the community's lived experiences, qualitative data were analyzed using a thematic analysis framework, underpinned by rigorous methodological triangulation. This involved the systematic cross-validation of qualitative findings across three distinct primary sources: the nuanced narratives from Key Informant Interviews (KIIs), the shared communal perspectives derived from Focus Group Discussions (FGDs), and the contextual environmental dynamics captured in empirical observational field notes. By converging these diverse qualitative data streams, the analysis minimized inherent reporter biases, reconciled discrepancies between stated behaviours and observed practices, and enhanced the overall validity and credibility of the study. This inductive process allowed for the identification of recurring thematic nodes regarding local cultural beliefs, institutional public health structures, and grassroots attitudes toward digital nutritional interventions, providing a holistic socio-economic context that complemented the quantitative metrics.

3.7 Ethical considerations

When doing responsible research, ethical integrity is essential, especially when interacting with vulnerable populations and developing technology. This study, which examines how AI-powered meal planning tools might increase food security for low-income households in Chitungwiza, Zimbabwe, uses sensitive socioeconomic data and direct interaction with human participants. Therefore, throughout the research process, ethical principles were closely monitored to guarantee participant rights were respected, treated fairly, and protected.

3.7.1 Informed Consent

Obtaining informed consent from each participant indeed was one of the study's main ethical responsibilities. Participants received thorough explanations of the research's objectives, the nature of their participation, and the intended use of the data they submitted prior to any data collection starting. Consent forms were written in plain English and, when needed, translated into regional dialects to guarantee understanding. The fact that participation was entirely voluntary and that withdrawal is free of cost or repercussions there is guarantee to the participants. Given that many participants have little experience with AI and digital diet planning tools, extra effort was taken to explain the concepts. This prevented misunderstandings and guaranteed informed consent rather than only procedural permission.

3.7.2 Confidentiality and Data Protection

Confidentiality was rigorously upheld because the data collected is sensitive and includes information like household income, food insecurity, and eating patterns. Using special codes, all survey answers and interview transcripts are anonymised, and no identifiable information is connected to the data while it is being analysed. Access to digital records is restricted to authorized research staff only, and they should be safely preserved with password security. It was made clear to participants that their information will only be utilized for academic purposes and will not be shared with outside parties, such as government organizations or tech corporations, unless they specifically consent. Building trust with communities that might be leery of exploitation or spying is especially crucial.

3.7.3 Respect for Vulnerable Populations

Among the many risks that low-income households in Chitungwiza experience are food insecurity, restricted access to healthcare, and financial difficulty. In order to limit any possible injury or burden, the research design considered these factors. Surveys and interviews, for instance, are planned at convenient times and places, and participants won't have to pay for or drive to them. Furthermore, the study did not involve any kind of unfair influence or compulsion. Small gifts of gratitude were given, such as refreshments during focus groups, but they are not meant to be used as inducements to participate. Promoting real engagement as opposed to transactional involvement is the aim.

3.7.4 Cultural Sensitivity

Cultural relevance is another important issue in the study, because ethical behaviour necessitates consideration for regional customs and beliefs. In Chitungwiza, customs, religion, and communal traditions all influence dietary choices. Researchers avoided promoting dietary changes that are at odds with cultural norms or imposing external judgments. Rather, the goal of the study was to comprehend these activities and investigate how AI technologies might be modified to assist them. Focus group conversations were facilitated by people who know the community well, and questions should be politely and non-intrusively phrased. By doing this, people will be more at ease expressing their opinions and experiences.

3.7.5 Transparency and Feedback

Participating in community service is another aspect of ethical research. Participants were told that the study's results would be presented to them in easily readable formats, including summary pamphlets or community presentations. That the research was a cooperative endeavour rather than an extractive one will be strengthened by this transparency. In order to keep the research rooted in the needs and goals of the community, stakeholders like regional NGOs, medical professionals, and tech developers will be included at every stage.

3.7.6 Ethical Approval

The study proposal was also sent to a reputable ethics review board for BUSE approval before any data was collected. This will guarantee that the approach satisfies both national and international requirements for research involving human subjects. To improve participant protection, the final design will include any changes suggested by the board.

3.8 Summary

The research approach used to examine the potential of AI-powered meal planning applications in addressing food security and nutritional concerns among low-income urban households in Chitungwiza, Zimbabwe, was thoroughly outlined in this chapter. The methodology was thoughtfully created to complement the study's main goal, which was to investigate how AI-driven tools could be scaled and contextually modified to enhance dietary outcomes in communities that are at risk. Special consideration was given to community-level impact, technological accessibility, and cultural relevance.

Using a mixed-methods strategy that combined both quantitative and qualitative techniques, the study design was introduced at a later stage of the chapter. This dual approach, which captures both statistical patterns and lived experiences, was chosen to guarantee a comprehensive grasp of the research subject. Chitungwiza, a representative urban region experiencing severe food insecurity, was the focus of the case study. Structured household surveys made up the quantitative component, whereas observational notes, key informant interviews, and focus group discussions (FGDs) made up the qualitative component. This methodological triangulation improved the findings' depth and dependability.

The research site's demographic, socioeconomic, and nutritional landscape in Chitungwiza was then thoroughly described. Chitungwiza, a high-density urban community with more than 350,000 inhabitants, has many problems, including restricted access to wholesome food, informal livelihoods, and unemployment. The town's technical environment, which is characterized by a high mobile phone penetration rate but low levels of digital literacy, was found to present both opportunities and challenges for the implementation of AI-based nutrition solutions. The presence of strong community networks and local health initiatives further reinforced the site's relevance for exploring scalable, community-driven interventions.

In a straightforward narrative style, the sampling process was described, with a focus on using purposive sampling to pinpoint the homes most impacted by food insecurity. The selection of participants was based on factors such as dwelling type, income level, and availability of mobile technology. The sample comprised 100 homes from different Chitungwiza units, guaranteeing variation in family structure, age, and educational attainment. Health professionals and community leaders helped find qualified volunteers, which improved the sample's ethical and contextual foundation.

The chapter then went into detail about the data gathering techniques, which were customized to meet the goals of the study. Food security indicators, willingness to pay (WTP) for AI diet planning services, and eating habits were all quantitatively collected through household surveys. FGDs shed light on cultural views, dietary habits, and attitudes toward technology, whereas KIIs supplied professional viewpoints from government officials, tech developers, and employees of non-governmental organizations. Observational notes, which recorded home settings and food preparation methods, provided contextual depth. By using a variety of methods, the data was guaranteed to be thorough and contextually relevant.

The chapter explained how to use fundamental statistical methods to handle quantitative data in order to find patterns and correlations in the data analysis part. While charts and tables allowed for visual comprehension, survey responses were summarized using percentages, frequency counts, and averages. Recurring concepts were categorized into groups that represented cultural, socioeconomic, and infrastructure factors in the theme analysis of qualitative data from FGDs and KIIs. By cross-validating results from several sources, triangulation was used to increase the reliability and validity of the findings.

Ethical considerations took up a significant amount of the chapter, which demonstrated the study's dedication to ethical research methods. With thorough descriptions of the study's goals and methods, all participants gave their informed consent. Secure data storage and anonymization were used to ensure confidentiality. To ensure that participation was voluntary and free from coercion, special emphasis was placed on protecting vulnerable populations. By adhering to regional dietary customs and using community-based moderators during data collection, cultural sensitivity was maintained. Plans to provide findings to participants and stakeholders in easily readable ways served to advance transparency. The study's compliance with national and international norms was finally confirmed when it was granted formal ethical approval by a reputable review board.

In conclusion, Chapter 3 integrated rigorous design, ethical integrity, and contextual relevance to establish a strong methodological framework for the study. Because of the mixed-methods methodology, the study was able to capture both the experiential and quantifiable aspects of technology use and food insecurity. The research was kept rooted in the realities of the target population by the deliberate selection of Chitungwiza as the study location, purposeful sampling, and culturally sensitive data gathering. In Zimbabwe's urban food systems, the chapter's focus on moral behaviour and stakeholder involvement further supported the study's capacity to produce useful insights for innovation, policy, and community development.

REFERENCES

Ali, T., & Ali, J. (2020). Factors affecting the consumers' willingness to pay for health and wellness food products. *Journal of Agriculture and Food Research*, 2, Article 100076. <https://doi.org/10.1016/j.jafr.2020.100076>

Golden, S.D. and Earp, J.A.L., 2012. Social ecological approaches to individuals and their contexts: twenty years of health education & behavior health promotion interventions. *Health education & behavior*, 39(3), pp.364-372.

Göttgens, I. and Oertelt-Prigione, S., 2021. The application of human-centred design approaches in health research and innovation: a narrative review of current practices. *JMIR mHealth and uHealth*, 9(12), p.e28102.

Haque, M.L., Oosterveer, P., Reynolds, C. and Vignola, R., 2025. Does food safety governance in Bangladesh include the urban poor? An analysis of government strategies and policies for the retail food environment in Bangladesh, 2013–2022. *Habitat International*, 159, p. 103372. <https://www.sciencedirect.com/science/article/pii/S0197397525000888>.

Mugo, D., 2017. The technology acceptance model (TAM) and its application to the utilization of mobile learning technologies. *British Journal of Mathematics & Computer Science*.

Pennells, J., Watkins, P., Bowler, A.L., Watson, N.J. and Knoerzer, K., 2025. Mapping the AI Landscape in Food Science and Engineering: A Bibliometric Analysis Enhanced with Interactive Digital Tools and Company Case Studies. *Food Engineering Reviews*, 17, pp. 465–489. <https://doi.org/10.1007/s12393-025-09413-w>.

CHAPTER 4: AI-DRIVEN DIET PLANNING APPLICATIONS FOR OPTIMISING FOOD SECURITY: A CASE STUDY OF LOW-INCOME HOUSEHOLDS IN CHITUNGWIZA, ZIMBABWE.

Abstract

This chapter presents the results and discussions of the empirical study of AI-driven diet planning applications in optimizing low-income household food security in Chitungwiza. The empirical findings indicate that 66% would be interested in using AI Diet planning Apps, 44% agree: 25% maybe, 3% disagree that AI Diet planning Apps would improve household food security. In addition, 33% have trust, while 38 % are sceptical, 2% no trust in AI technology. The discussion highlights that AI-based recommendations might help households to achieve balanced nutrition despite financial constraints, reinforcing theories of technology-enabled resource optimization. This study implies that integrating AI into diet planning strengthens household food security and promotes sustainable consumption practices. The implications extend to policy formulation, suggesting that AI-driven tools can complement national food security strategies while contributing to the broader discourse on public nutrition.

4.1 Introduction

4.1.1 Nutritional Landscape, Food Security and Dietary Challenges in low-income urban households of Chitungwiza.

This chapter addresses the primary research objective and its corresponding research question on assessing the baseline socio-economic, nutritional aspects, and dietary challenges faced by low-income households in Chitungwiza, alongside evaluation of their readiness for technological intervention. Urban food security has emerged as one of Sub-Saharan Africa's most critical development concerns, as growing urbanization, economic insecurity, and climate shocks combine to expose low-income households. Food insecurity in towns like Chitungwiza, Zimbabwe, is more than just a matter of availability; it is also linked to economic access and dietary quality. As populations rise and metropolitan areas expand, households become more reliant on informal markets and cash-based food purchases, making them vulnerable to inflation, price volatility, and income variations. This dynamic frequently

results in decreased meal frequency, reliance on low-cost energy-dense foods, and restricted dietary diversity, all of which jeopardize nutritional sufficiency.

It sets the foundation by analysing the socio-economic reality of nutritional challenges, dietary patterns, and food choices that contribute to overall nutrition. This study investigates these difficulties through three essential dimensions. First, it examines economic access, looking at how income and inflation affect household food purchasing power and consumption habits. Second, it investigates dietary quality, with a focus on the level of dietary diversity and nutritional adequacy in low-income households. Third, it looks into the potential of AI diet planning tools as new solutions for bridging knowledge, confidence, and utilization gaps, so boosting the food security pillar that is frequently overlooked in policy discussions.

Concerning results and discussions, this chapter begins with a presentation of quantitative and qualitative results, followed by a discussion that interprets these findings in relation to existing literature and theoretical frameworks. This approach ensures that the empirical evidence is directly connected to broader debates on technology-enabled food security. By linking empirical outcomes with theoretical perspectives, this chapter provides critical insights into how AI can be leveraged to strengthen food security strategies in resource-constrained settings.

4.2 Materials and Methods (see Chapter 3)

4.2.1. Description of study area (see Chapter 3, section 3.2)

4.2.2. Research design (see Chapter 3, section 3.3)

4.2.3. Sampling procedure (see Chapter 3, section 3.4)

4.2.4. Data collection procedure (see Chapter 3, section 3.5)

4.2.5. Data analysis procedure (see Chapter 3, section 3.6)

4.2.6. Challenges encountered during data collection

- Respondents might have been unwilling to respond to some questions, thus leaving too many gaps.
- Some respondents did not have data to fill out the online questionnaires within the stipulated period of time, which led to a longer time to collect data than expected.

- Some respondents would ask for benefits just to fill in questionnaires, despite having disclosed that it was academic research for educational purposes.
- Some respondents were complaining that the questions were just too many, hence leaving gaps, and it later affected the overall data by having too many missing values.
- During observations, some respondents would highlight that, since we advise them about AI, they think it's a scam.
- Then, during sessions of Focus Group Discussions, some respondents would not show up, stating they were not really convinced if there were no benefits of participation, but rather stuck to responding to online questionnaires
- And lastly, some information was considered to be private by respondents, especially during household surveys. So rather they would provide a random response which was not really accurate: for example, on average, the monthly income.

4.3 Results and Discussions

4.3.1 Gender of Respondents

The survey first collected information on the gender distribution of the sample. The survey began by collecting information on the gender distribution of the sample to establish a baseline understanding of the sample demographics. This information is essential to make sure that the views of the main household earners and caregivers are properly captured in the study.

Table 1: Gender Distribution of Respondents (N = 73)

GENDER	Frequency	% Frequency
male	43	58.9
female	30	41.1
Total	73	100

Table 4.3.1 shows that the majority of the respondents were male, 58.9% (n = 43), and female, 41.1% (n = 30). This distribution in Chitungwiza's low-income households is an important one because men are often the traditional leaders of the household, while women are usually the main householders of food preparation and food choices. This gender balance is crucial for evaluating the potential impact and acceptance of AI-powered diet planning

apps, as the effectiveness of such technology depends on the unique roles played by men and women in relation to food security and resource distribution within the household.

4.3.2 Education level of household head respondents

The survey also captured demographic data on the level of education of each household head. This data was captured as a socio-demographic control variable. As education influences digital literacy, health information seeking behaviour, and willingness to pay for such services. In this case, whereby AI-assisted dietary planning requires some level of literacy to interpret outputs, education level becomes a control factor for potential confounding effects on both perceived usefulness and WTP.

Table 2: Educational level of household head

Education level	Frequency	% Frequency
No formal education	9	12.3
Secondary level	27	37.0
Tertiary level	37	50.7
Total	73	100.0

Table 4.2 shows the majority of respondents with 50.7%, where n= 37 had attained a tertiary level of education, followed by a moderate of 37%, where n= 27 had attained secondary level of education & lastly the least being 12.3%, where n=9 had no formal education. The majority of respondents in Chitungwiza possess sufficient literacy to understand AI-assisted dietary concepts, but then, with education alone, they might be unwilling to pay. Also, it strengthens the validity of perceived usefulness ratings, as educated respondents are more likely to accurately evaluate technology benefits. Also, low-income households do face digital poverty due to economic constraints, that is, data costs. So, this helps provide essential context for interpreting null results and tailoring recommendations towards affordability.

4.3.3 Marital status of respondents

Marital status is important because it shapes household decision-making, budget allocation, and risk perception, all of which directly influence willingness to pay and interest in AI-assisted dietary planning.

Table 3: respondents' data on marital status

Marital status	Frequency	% Frequency
single	39	53.4
married	25	34.2
Widowed/ divorced	9	12.3
Total	73	100.0

With 53.4% single, 34.2% married, and 12.3% divorced. Single household heads often manage tighter, individual budgets with less income pooling. Married household heads may benefit from dual incomes or shared food costs, potentially moderating the relationship between income volatility and WTP, and divorced household heads at 12.3% are particularly relevant, as FGD data often shows they bear sole responsibility for dependents without spousal income support, intensifying the economic constraint theme that emerged across FGDs.

4.4 Nutritional challenges faced by low-income urban households

4.4.1 food access & food shortage dynamics

In Chitungwiza, household income, market dependence, and inflationary pressures are the primary drivers of food access. Unlike rural households, which rely on subsistence farming, urban families rely nearly entirely on cash purchases from legal and informal markets. Because of this reliance, they are extremely subject to price volatility, with even minor increases in staple food costs forcing households to reduce meal frequency or switch nutritious foods for less expensive, energy-dense alternatives. Food scarcity dynamics are thus cyclical: households frequently start the month with enough supplies but run out before the end due to limited income and rising prices. This tendency leads to missed meals, limited dietary diversity, and reliance on low-cost staples like maize meal and bread.

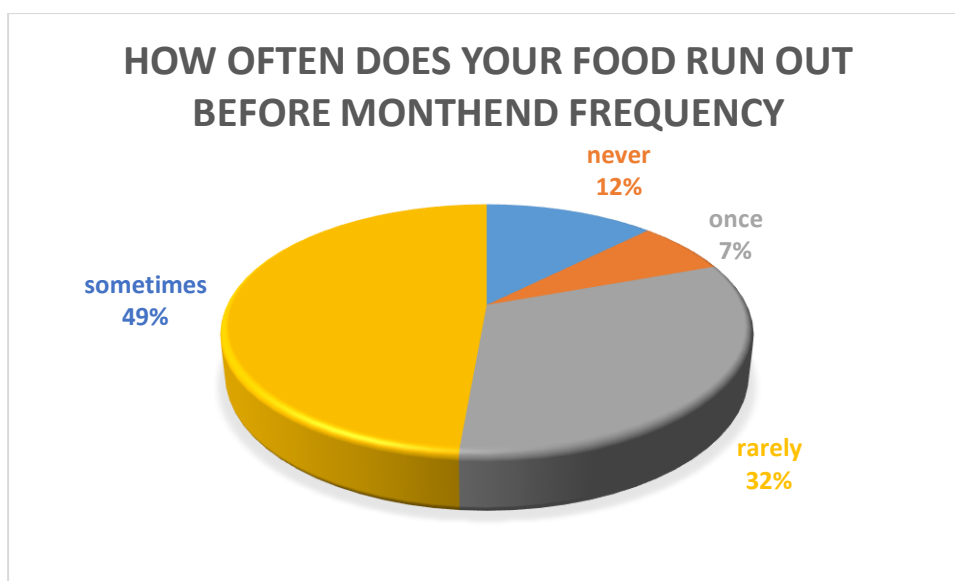


Figure 4: Food Access duration

The above figure shows the percentage (%) of households that face food shortages before the month's end. The greater proportion being sometimes (at 49%), and the least proportion being never (at 12%), once in a month (at 7%), and lastly rarely in a month (at 32%).

Panel discussion framework: Why low-income urban households face food shortages before the month's end.

section	Observational notes	Focus group discussions insights	Possible AI diet apps solutions
A. budgeting & purchasing habits	- bulk buying & proteins & vegetables bought in small portions - Food storage is not proper	- “We buy what we can afford.” - “Meat daily is expensive.” - “Pricing for good quality meat is too high for some of us”	- AI budget spitting features - price comparison tracker for affordable stores nearby -portion and storage reminders on the application.
B. food preparation methods, access & storage	- overcooking -deep frying -reheating of leftovers -Use of one-pot meals to save time, cleaning, and gas. - No refrigerator in some homes - reliance on nearest tuckshops for	- “It’s better to cook once, to save gas and electricity” - “At times we use soup powders rather than buying fresh vegetables all the time.” - “Leftovers are still food to us.” - “We buy daily	- AI app feature for optimizing recipes using local ingredients. -AI app feature on cooking methods. -AI app feature on detailed information concerning food leftovers. - AI app feature on

	convenience - food theft	because of storage, especially meat.” - “The market is cheaper but distant at times, so we opt for tuckshops.”	the nearest food markets - AI app feature on storage methods that are sustainable if there is no fridge.
C. food diversity & nutrition	- diet mainly contains heavy carbs - seasonal vegetables only when available - Children get the same meal daily	- “Vegetables easily spoil.” - “Buying meat, eggs, beans, bacon, ham is expensive.” - “We don’t know cheap foods with iron and other essential micronutrients you are talking about.”	An AI app feature on nutrient gap analysis and suggests affordable protein sources. An AI app feature on the child nutrition module for parents

Food shortages are common in households at different levels in different setups. Causes vary from affordability, availability, and accessibility of food, as well as household size. Though these causes are not restricted but rather interdependent on each other.

This measurement focuses on whether households in Chitungwiza can obtain enough food throughout the month. It also reflects economic and physical access to food rather than its presence in markets, nutritional use, and long-term consistency. So, this is more of a direct measure of economic access to food.

4.4.2 Dietary habits, structural realities & interventions

A similar research on Urban household survival and resilience to food insecurity in crisis conditions: The case of Epworth in Harare, Zimbabwe, was conducted, and in which one of the findings was noted that residents of Epworth buy little packets of food known as ka tsaona to last until the end of the month (Tawodzera, G. 2012). This shows how food shortages are common in low-income urban households. Chitungwiza and Epworth are both low-income urban areas and highly populated. Both findings it shows that a significant group of households are food insecure before the month's end, as food accessibility turns out to be a common problem. From the above results (see figure 4), it was clear that a sizable fraction of households was going without food before the end of each month, highlighting how precarious urban food security is. By assisting households in making the most of their limited

resources through cost-effective meal suggestions and substitute alternatives that correlate with local food availability, AI diet planning systems provide optimization.

A careful examination reveals that although AI technologies cannot address systemic problems like market dependency or inflation, they can reduce vulnerabilities at the household level by improving knowledge and decision-making. The kind of knowledge provided will cover areas that have to do with what to buy, providing information on health and nutrition: this will reduce spending more money on fast foods, low-nutrient foods for snacking, especially in households that have a high number of residents. Rather, local, affordable, and nutritious foods can be made known via AI diet planning tools, giving informed decision-making on purchasing food. In turn, optimizing food security at the household level

In conclusion, to establish accessibility and trust, sustainable scaling necessitates cooperation with NGOs and incorporation into community health programs. Ultimately, AI diet planning tools are an additional intervention that can increase resilience to recurrent food shortages in low-income urban households in Chitungwiza if contextualized.

4.5 Inferential statistical analysis and hypothesis testing.

4.5.1 T-test analysis of nutritional information, challenges, and analysis

T-tests were also used to compare the means of two groups:

Group 1: those who are confident in making healthier choices, and where they get their nutritional information.

Group 2: had an interest in actively planning meals and where they get their nutritional information

This affects the overall nutritional status by comparing means. The higher mean is a result of a better nutritional status than the other group. The variables picked show food security status on how it varies from one household to another, to address Objective 1

Table 3: T-test results on assessing the nutritional challenges faced by low-income urban households. By comparing confidence in making healthier choices, being active in seeking nutritional information, and the source of nutritional information as variables used.

Variables used		Source of nutritional information	N	Mean	Std. Deviation
Confidence in making healthier choices.	YES	health workers	14	1.07	.475
		community programs	37	.81	.518
Actively seeking nutritional information.	YES	health workers	14	.14	.363
		community programs	37	.14	.347

From the above table, group 1, which is confident in making healthier choices and seeking nutritional information from health workers, had a higher mean of 1.07 and a standard deviation of 0.475. The higher mean score implies stronger confidence in making healthier choices when guided by health workers. The SD, which is also higher, indicates variability within the group in the sense that some households may be highly confident, while others are less so.

Group 2, which seeks information when planning meals, had a mean of 0.14 and a standard deviation of 0.363. The lower mean implies weaker confidence regardless of actively seeking nutritional information from both health workers and meal planning. The SD suggests more consistency across households, but consistently at a lower confidence level.

Therefore, group 1 is likely to have better nutritional outcomes since confidence relates to healthier food selection and adherence to dietary advice. While group 2 may face challenges in applying nutritional knowledge effectively, leading to poorer dietary diversity or, moreover, reliance on cheap, less nutritious foods. Their nutritional status is better compared to the others. This shows that confidence and empowerment are critical as access to information in shaping nutritional status.

This shows that AI diet planning tools can maximize food security by encouraging the same behaviours seen in Group 1, namely proactive engagement with nutrition knowledge and well-informed decision-making. AI solutions mimic the advice households receive from health professionals by offering easily available dietary information, customized meal plans, and recommendations for foods that are appropriate for their culture. However, these tools are scalable and ongoing. This gives households the ability to better plan their meals, make the most of their limited food supplies, and lower the chance of missing meals before the end of the month. Importantly, the tools make sure that available food is consumed in ways that

are nutritious, which improves utilization, one of the main pillars of food security. Households that lack information or confidence are still more vulnerable, according to the comparison analysis, which emphasizes how crucial AI technologies are for closing knowledge gaps. Adoption obstacles like affordability and digital competence, however, need to be resolved to guarantee fair advantages.

In an attempt to address food utilization in low-income urban households in Chitungwiza, confidence in making healthier choices, sources of nutritional information, and actively planning meals play a significant role. Four pillars support food security, according to the FAO: stability, availability, access, and utilization. Utilization describes how the body makes use of the food it has eaten and is influenced by dietary quality, nutritional understanding, food preparation, and health habits. The utilization pillar is strengthened when households actively plan meals, make educated decisions, and apply nutrition information because they are making sure that the food they do have access to is used in a way that fosters health and lowers the rate of malnutrition.

4.5.2 Chi-square test on income and meal consumption patterns

Still on Objective 1, the next analysis was a chi-square test using cross tabulation to check the significance of Average monthly income and Meal skipping before the month end to check household nutritional status.

Table 4: Chi-square test on average monthly income of households and meal consumption before the month end as variables used.

	Value	df	Asymptotic Significance. (2-sided)
Pearson Chi-Square	49.565a	32	.025
Likelihood Ratio	49.199	32	.027
Linear-by-Linear Association	1.644	1	.200

A statistically significant correlation between average monthly household income and meal consumption patterns was found using the Pearson Chi-Square test ($\chi^2 = 49.565$, $df = 32$, $p = 0.025$). The fact that the p-value is less than the traditional cut-off of 0.05 suggests that there is a meaningful relationship between household income levels and meal consumption.

Practically speaking, households with varying income levels typically display varied eating habits, supporting the theory that financial resources have a significant impact on food intake.

The conclusion that income is a significant factor in dietary diversity is consistently supported by existing literature. While lower-income families frequently rely on staple foods with little nutritional variety, higher-income households are more likely to be able to purchase varied diets full of fruits, vegetables, and proteins (FAO, 2021). This is consistent with the Chi-Square result, indicating that measurable variations in meal intake are a result of income disparities.

According to a study by Ochieng et al. (2020), low-income households primarily relied on maize and other staples, whereas higher-income households consumed more fresh vegetables and foods derived from animals. Research by Subramanian et al. (2022) revealed a shift in nutrition as rising affluence led to higher consumption of processed foods and proteins. Poorer households frequently miss meals during economic downturns, according to Moyo and Nyathi (2023), who found a direct correlation between reduced meal frequency and income constraints. These case studies show how income influences meal frequency and quality in addition to the kind of food consumed.

The connection is clear in everyday situations. For example, three well-balanced meals a day, consisting of meat, dairy, and fresh vegetables, may be affordable for a middle-class household. A low-income household might eat two mostly starchy meals with little protein. Households frequently cut back on mealtimes or switch to less nutrient-dense, less expensive foods during economic shocks (like inflation), which strengthens the relationship between income and consumption.

The important Chi-Square result emphasizes how crucial it is to address wealth disparities in order to enhance food security. AI-driven diet planning systems, according to Namkhah et al. (2023), could maximize food usage by suggesting reasonably priced, nutrient-dense menus based on income levels. By incorporating these techniques into policy frameworks, the detrimental effects of income inequality on nutrition could be lessened.

4.5.3 Pearson correlation analysis on income and food frequency

Table 5: Correlation test on household income and food frequency to assess nutritional challenges faced.

Parameters selected	Defined statistics	Average	Meals
---------------------	--------------------	---------	-------

		monthly income of household head.	consumed per day
Average monthly income of household head	Pearson Correlation	1	.254*
	Sig. (2-tailed)	n/a	.031
	N	72	72
Meals consumed per day	Pearson Correlation	.254*	1
	Sig. (2-tailed)	.031	n/a
	N	72	73

*. Correlation is significant at the 0.05 level (2-tailed).

In the table above, with a perfect correlation of 1, household income and food frequency consumption (meals consumed per day) would be strongly positively correlated. Meal consumption patterns and household income have a moderately but weakly positive correlation, as indicated by the observed correlation coefficient of 0.254. Although a statistically significant association was previously established by the Chi-Square test, the correlation implies that better food frequency is not highly predicted by higher income. In other words, while dietary behaviour is influenced by income, other factors, including cultural preferences, education, food availability, and household priorities, also have a significant impact. Although the degree of this association varies, research consistently demonstrates that dietary diversity and frequency are influenced by income. Higher-income households typically have more varied meals, but food frequency isn't always proportionately higher, according to FAO. For instance, cultural traditions may require meal frequency regardless of finances, or households may place a higher value on quality than quantity. This explains why there is only a moderate rather than a significant link.

Income influences eating behaviour, although it is not the only factor, according to the moderate association ($r = 0.254$) between income and meal frequency. This discovery is especially pertinent to Chitungwiza, a densely populated urban area in Zimbabwe. Even though many homes in Chitungwiza are struggling financially, a mix of coping mechanisms, cultural customs, and income influences how often they eat. Research conducted in Zimbabwe (Moyo & Nyathi, 2023) demonstrates that households deploy coping strategies in times of economic shock: Even middle-class families forgo meals during times of inflation. Food substitution is the practice of households substituting cheaper protein sources, such as beans or kapenta (small dried fish), for meat. When extended families pool resources to

maintain a minimum meal frequency, this is known as community sharing. These tactics show that resilience techniques have an equal impact on dietary frequency as does income.

Relevant Example

Think about a Chitungwiza household earning \$150 USD per month: They might regularly eat two meals a day (lunch and dinner of sadza with relish). Due to cultural norms and financial limitations, breakfast is sometimes ignored or substituted with tea and bread. The household may choose to enhance the quality of current meals rather than add a third meal, even if income increases to USD 200 (for example, by periodically adding chicken or eggs). This demonstrates why there is little correlation: income has a greater impact on food quality than frequency.

In conclusion, this result is mostly because food security in Chitungwiza is influenced by several variables other than wealth, such as the volatility of food prices, household budgeting techniques, cultural preferences, and access to unofficial markets. Even households with comparatively higher means may still skip meals if they are uninformed about nutrition or are subject to inflationary pressures. Broader factors, including spending on a variety of food types, educational attainment, or coping mechanisms used in the home, can show more distinct relationships between income and dietary frequency. These factors were frequently included in other studies that discovered larger correlations.

The non-income factors of food security are addressed by AI diet planning systems, which are crucial in this regard (Etana, D et al 2017). They enhance utilization and dietary diversity for households of all income levels by offering them cheap meal planning alternatives, nutritional information, and advice on how to substitute local foods. These resources assist households in maximizing food utilization even in situations when income is limited by boosting confidence in healthier choices and decreasing waste.

In order to close the knowledge and behaviour gaps, interventions such as AI diet planning are crucial, as the weak correlation thus emphasizes that income is not a reliable indicator of meal frequency. In low-income urban families where structural constraints still exist, this discussion emphasizes the significance of incorporating AI techniques into community nutrition initiatives to improve food security results.

4.6 FOOD SECURITY INDICATORS: Detailed Meal Consumption Analysis

4.6.1 Structural meal frequency trends

The graph below shows % ratings in meal consumption per day by respondents in low-income urban households of Chitungwiza.

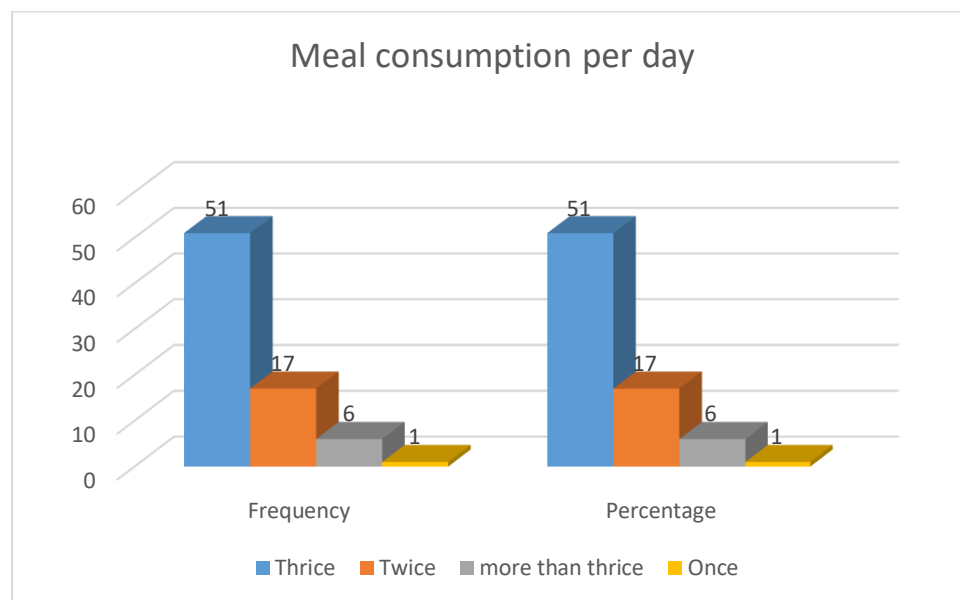


Figure 5: Meal consumption analysis

The quantity of meals taken in these households is a definite sign of food security rather than just a matter of preference. Families that routinely only prepare one or two meals a day are likely to have inadequate nutritional diversity, high food costs, and limited money. This decrease in frequency is sometimes accompanied by skipping meals, especially breakfast, to stretch limited resources. The meals that are consumed are typically dominated by filling staples like sadza, with protein and vegetables showing up less frequently.

73 out of 100 respondents answered this question. (27 were without data.) From the Above figure of results, as the question suggests, in terms of eating habits. 51% of respondents eat 3 times a day, 17% only twice, and 1 % being the least. Now, AI diet planning tools offer systematic, data-driven methods to manage scarce resources while guaranteeing nutritional adequacy; they closely correspond with meal consumption patterns in maximizing food security. AI systems may assess household income, food costs, and dietary requirements to suggest meal plans that optimize nutritional content within the available budget in low-income urban families like those in Chitungwiza, where meal frequency frequently reflects

financial constraints. By doing this, they lessen the need for meal skipping, a typical coping mechanism under food insecurity, and assist families in maintaining regular meal consumption.

4.6.2 The role of AI in optimising resource utilization.

AI systems can also incorporate cultural preferences and local food availability, guaranteeing that suggested meals are reasonable and palatable to homes. For instance, AI can recommend accessible and reasonably priced side dishes that increase nutritional diversity without raising expenses if a household usually eats sadza as a staple. By striking a balance between affordability and nutrition, this directly supports the objective of keeping at least two to three meals per day, even under financial duress. Additionally, AI diet planning tools can predict shortages or price changes and give households advice on how to modify meal frequency or composition in advance, lowering their susceptibility to unforeseen shocks.

Then moving on to nutritional deficits that are most prevalent among Zimbabwean low-income urban households, during focus group discussions, responses varied, showing that common nutritional deficiencies in Chitungwiza's low-income urban households are directly associated with insufficient food diversity and financial hardship. Sadza is the main staple as a major source of energy for many households, but they are deficient in protein, vitamins, and minerals. Because of the expense, households rarely eat meat, fish, or legumes, leading to a widespread protein deficit. Deficits in micronutrients, especially iron, zinc, and vitamin A, which are essential for a child's development and immune system, are also prevalent. While dairy products are rare in most diets, vegetables and fruits are ingested sporadically, frequently based on seasonal availability. These deficiencies lead to anaemia in women, stunting in children, and reduced communal resistance to illness. In a study conducted on Diet and sociodemographic predictors of the double burden of malnutrition in urban Zimbabwe, it also highlighted cases of undernutrition and micronutrient deficiency (Kasanzu, S et al 2025).

By evaluating household budgets, local food availability, and nutritional requirements to create cost-effective meal plans that enhance dietary balance, artificial intelligence diet planning systems can significantly contribute to maximizing food security with respect to these shortfalls. For instance, when meat is too expensive, AI might advise inexpensive protein alternatives like beans or groundnuts, or it can suggest seasonal veggies that offer

vital vitamins at reduced costs. AI makes sure that households can really implement the plans without upsetting long-standing eating habits by matching suggestions with cultural preferences and basic foods. AI systems can also predict changes in food prices and provide homes with advice on how to modify the nutritional density of at least two or three meals a day.

In reality, families can make trade-offs that maximize both cost and health because of the confidence that comes from nutritional understanding. For instance, households may opt for traditional staples supplemented by little but nutrient-rich additions rather than spending limited funds on manufactured foods that look satisfying but are deficient in nutrients. Meal organization is altered by informed decision-making, as households arrange meals based on both availability and nutritional worth. Such assurance eventually improves food security by enabling families to make the most of what they can afford, guaranteeing that even in situations when meal frequency is limited, the meals eaten have a favourable impact on health. In this sense, self-assurance in making better decisions serves as a link between nutritional knowledge and useful household tactics, strengthening resistance to food poverty while progressively enhancing eating habits.

REFERENCES

- Tawodzera, G. (2012). Urban household survival and resilience to food insecurity in crisis conditions: The case of Epworth in Harare, Zimbabwe. *Journal of hunger & environmental nutrition*, 7(2-3), 293-320.
- Moyo, T. & Nyathi, P. (2023). *Household income and food security in Zimbabwe: A case study of Harare*. *African Journal of Food Policy*, 18(2), pp. 45–62.
- Namkhah, Z., Fatemi, S.F., Mansoori, A., Nosratabadi, S., Ghayour-Mobarhan, M., & Sobhani, S.R. (2023). *Advancing sustainability in the food and nutrition system: a review of artificial intelligence applications*. *Frontiers in Nutrition*, 10, 1295241. doi:10.3389/fnut.2023.1295241.

Sarku, R., Clemen, U. A., & Clemen, T. (2023). The application of artificial intelligence models for food security: A review. *Agriculture*, 13(10), 2037.

CHAPTER 5

Economic Valuation and Innovation Pathways for AI-Assisted Dietary Planning.

5.1 Introduction

This chapter merges Objective 2 and 3 to estimate the Willingness to pay for AI-assisted dietary planning services & to propose context-specific recommendations and innovation pathways for sustainable adoption and scaling of AI-driven diet planning solutions within the Zimbabwe urban food systems. Understanding the economic behavioural readiness of

resource-constrained urban is critical for long-term deployment of precision health technologies. This chapter presents the quantitative insights from multiple linear regression models and non-parametric Chi-square test integrated with qualitative data from focus group discussions and observational field notes. Precision health technologies are rapidly being regarded as revolutionary in tackling food security issues, particularly in urban Sub-Saharan Africa. According to Agrawal et al. (2025), precision nutrition powered by AI allows for tailored dietary recommendations that take into account economic limits, cultural preferences, and health demands, enhancing both dietary quality and resource usage. Similarly, Zheng et al. (2026) note that precision health technologies can include environmental and socioeconomic data into nutrition planning, ensuring that interventions are both scientifically sound and contextually relevant to low-income households.

5.2 Abstract

Food security at the household level continues to be a major concern, and in many attempts to ensure food security, the use of AI diet planning tools is slowly becoming adaptable, but mainly in developed countries. 25% of respondents think of cost on AI usage in terms of adoption, while 19% think it could be internet access, 13 % cultural mismatch, and 12% trust in AI technology as part of the adoption and scalability of AI-driven diet planning Apps. This could be more about trust in technology, cultural acceptance, and the affordability of extra features that really deliver reliable, practical information. However, growing concerns of food security in low-income urban households in Zimbabwe have been on the rise; most households might not actually know if they are food secure until and unless survey, analyses, and proven clinical assessments are conducted. In this research, a greater proportion seemed to be aware of some of the nutritional conditions that could be a challenge and risk to them. 51% are willing to pay at least \$1 for AI assistance, being the greatest proportion of respondents, 14% to pay from \$2-\$5, 2 % more than \$5, and about 6% not willing to pay any. Also, in response to AI technology, it had drawn much interest, though coupled with concerns about trust in technology and affordability.

5.3 Data collection procedure

Quantitative and qualitative data were gathered concurrently across urban Chitungwiza using an integrated mixed-method approach. Field instruments included Household surveys, which were conducted using questionnaires to collect data, as well as observational notes and focus

group discussions. All are designed to capture the behavioural nuances of local food environments

5.3.1 Description of study site (see Chapter 4, section 4.4.1)

5.3.2 Research design (see Chapter 4, section 4.2.2)

5.3.3 Sampling procedure (see Chapter 4, section 4.2.3)

5.3.4 Data collection procedure (see Chapter 4, section 4.2.4)

5.3.5 Data analysis procedure (see Chapter 4, section 4.2.5)

5.4 Willingness to pay (WTP) for AI-assisted dietary planning services

This section discusses the estimation of the Willingness to Pay (WTP) for AI-assisted dietary planning services and examines how WTP varies with changes in household food choices, nutritional knowledge, and food security indicators.

5.4.1 Regression analysis on meal consumption, AI tools, rating of AI tools & WTP

Table 6: Model Summary of Regression Analysis on meal consumption, usefulness of AI tools, rating of AI tools & willingness to pay for AI dietary tools.

The multiple regression model with meal consumption, usefulness of AI tools, and rate of AI tools as predictors produced $R = 0.319$, demonstrating a weak positive connection between the predictors and Willingness to pay for AI-assisted dietary planning services.

Model	R	R Square	Adjusted R-Square	Std. Error of the Estimate
1	.319 ^a	.102	.063	.349

Predictors: (Constant), how many meals do you usually consume per day, do you find AI tools useful, on a scale of 1 to 5, how much do you trust AI tools.

The R^2 value of 0.102 indicates that the four predictors in the model account for 10.2% of the variance in WTP. When corrected for model complexity, the adjusted $R^2 = 0.063$ compensates for the number of predictors relative to the sample size, implying that only 6.3% of the variation is explained. The standard error of estimate=0.349 is the average distance between observed WTP scores and the regression line, indicating modest prediction error. In terms of the above-mentioned purpose, the regression results offer no explanatory information.

After correction, the model explained just 6.3% of the variance in WTP (Adjusted $R^2=0.063$), demonstrating that meal consumption, perceived usefulness of AI tools, rate of AI tools, and faith in AI tools are poor predictors of WTP among Chitungwiza's low-income urban households. The standard error of 0.349 shows significant prediction error, indicating that the model cannot consistently estimate individual WTP. This limited explanatory power is consistent with the results of the focus group talks, in which participants repeatedly prioritized current income restrictions and food prices over opinions of AI usefulness or trust.

Thus, while the study accurately calculated mean WTP, the regression analysis shows that family food choices and nutritional knowledge, as operationalized in this model, account for only a small amount of WTP variability. The remaining 93.7% of variance is most likely due to unmeasured food security characteristics such as income status, seasonal price changes, and competing household expenses, which were prevalent themes in qualitative data but were not included as quantitative predictors. However, the low adjusted limits the model's prediction utility and generalizability outside this sample, because low R^2 values are common in behaviour adoption studies conducted in resource-constrained contexts where WTP is influenced by external economic shocks. Future models should incorporate income stability, digital literacy, and price sensitivity to boost explanatory power.

5.4.2 Coefficient test on WTP & meal consumption frequency, usefulness of AI diet tools, rate of AI mobile apps

The coefficients table indicates that the dependent variable Willingness to Pay has a significant constant of 1.078 (SE = 0.204, $t = 5.287$, $p < 0.001$), representing baseline WTP when all predictors are equal to zero. None of the four predictors reached statistical

significance at the 5% level. AI tool effectiveness: $B = 0.108$, $\beta = 0.166$, $SE = 0.074$, $t = 1.457$, $p = 0.150$.

Table 7: Coefficient results test on willingness to pay, usefulness of AI tools, rating of mobile apps & meal consumption.

Coefficients						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1.078	.204		5.287	.000
	_usefulness of AI tools	.108	.074	.166	1.457	.150
	_rating of mobile apps	-.110	.058	-.231	-1.885	.064
	meal consumption per day	-.051	.076	-.083	-.676	.501

The positive coefficient shows that increased perceived usefulness correlates with higher WTP. Specifically, a 1-unit increase in perceived usefulness equates to a 0.108-unit rise in WTP, with all other variables being constant. However, $p = 0.150 > 0.05$ suggests that this link is not statistically significant in this group. Rating of mobile apps: $B = -0.110$, $\beta = -0.231$, $SE = 0.058$, $t = -1.885$, $p = 0.064$. The negative coefficient suggests that greater app ratings result in lower WTP. The association approaches statistical significance at the 10% level, but does not reach the traditional 5% threshold. Meal consumption: $B = -0.051$; $\beta = -0.083$; $SE = 0.076$; $t = -0.676$; $p = 0.501$. Meal consumption has a modest negative correlation with WTP, but it is not statistically significant. In conclusion, none of the predictors of the usefulness of AI tools, mobile app rating, or meal consumption significantly explain variation in WTP. The model's summary results ($R^2 = 0.102$ and modified $R^2 = 0.063$) confirm its modest explanatory ability.

The regression results give minimal support for the purpose of exploring how WTP varies with household food choices and perceptions of AI. After correction, the model only explains 6.3% of WTP variance (Adjusted $R^2 = 0.063$), with a significant prediction error (standard error of estimate = 0.349). At the coefficient level, none of the tested predictors, meal consumption as a proxy for food choices, usefulness of AI tools, rating of mobile apps, and trust in AI tools as indicators of nutritional knowledge/technology perception, demonstrated a statistically significant relationship with WTP ($\alpha = 0.05$). Mobile app ratings were the most significant predictor ($\beta = -0.231$, $p = 0.064$). Despite its negative direction and minor non-significance, the Technology Acceptance Model predicts that higher ratings will boost adoption intention. One probable argument based on FGD data is that respondents who score

mobile apps highly may already have access to free alternatives, resulting in a lower WTP for commercial AI services. AI tool usefulness was positive ($\beta = 0.166$) but not significant ($p = 0.150$), indicating that perceived utility alone is insufficient to drive WTP in low-income environments with budget constraints. In this group, meal intake had the poorest effect ($\beta = -0.083$, $p = 0.501$), suggesting that current eating behaviours do not predict WTP for AI planning services. This finding is consistent with qualitative findings in which individuals explained food insecurity in terms of income shocks and food prices rather than meal frequency. The low R^2 and non-significant coefficients indicate that the variables examined only partially explain WTP for AI nutritional services. This suggests that basic food security factors such as income volatility, price sensitivity, and trust in data privacy, which appeared significantly in focus groups but were not included as quantitative predictors, could account for the remaining 93.7% of unexplained variance.

As a result, while mean WTP was successfully estimated, the regression analysis should be viewed as exploratory, showing that WTP in this group is influenced by economic and contextual factors other than the technology-focused variables included in the current model.

Revised Conceptual Framework

Revised assumption based on results + FGD:



Based on the findings and qualitative insights from the focus group discussions, the conceptual framework is amended to include economic restrictions as a mediating variable between technology/nutrition perceptions and willingness to pay. The initial framework made assumptions about the direct consequences of meal consumption, perceived usefulness of AI technologies, app rating, and WTP trust. However, non-significant regression coefficients and a low adjusted $R^2 = 0.063$ indicate weak or indirect associations in low-income urban households. Even when participants acknowledged the utility of AI, FGD data repeatedly identified income volatility, food price shocks, and competing family expenses as significant impediments. As a result, the updated paradigm suggests that perceived usefulness and trust may boost WTP only when economic restrictions are minimal. Economic restrictions reduce the effect of tech perceptions on WTP when money is tight, which explains the poor statistical results. This sample does not support the hypothesized direct paths from

technology/nutrition variables to WTP, as indicated by non-significant coefficients for usefulness of AI tools ($\beta = 0.166$, $p = 0.150$), rating of mobile apps ($\beta = -0.231$, $p = 0.064$), and meal consumption ($\beta = -0.083$, $p = 0.501$). The low adjusted $R^2 = 0.063$ suggests the model lacks essential variables. Qualitative findings provide theoretical support for modifying the framework. As a result, this study's revised theoretical contribution is that in resource-constrained environments, economic constraints influence the relationship between AI perceptions and WTP. This reframes the 'poor results' into a context-specific insight: WTP for AI dietary apps is not primarily a technical problem, but rather an affordability concern.

Note that: Policy and app design should favour '\$0-\$1 meal plans' and offline/USSD access above complex AI functions, because economic limits limit WTP regardless of perceived utility.

The study's statistical power is limited due to the small sample size of 72 participants and four variables. With $\alpha = 0.05$, the study has 52% power to detect medium effects ($f^2 = 0.15$), but only 22% power to detect minor effects ($f^2 = 0.02$). The common standard for appropriate electricity is 80%. This raises the likelihood of Type II error, resulting in non-significant coefficients and a low adjusted $R^2 = 0.063$.

The regression model with $n = 72$ explained only 6.3% of variance after adjustment (Adjusted $R^2 = 0.063$). None of the predictors reached statistical significance at $\alpha = 0.05$: usefulness of AI tools, $\beta = 0.166$, $p = 0.150$; rating of mobile apps, $\beta = -0.231$, $p = 0.064$; meal consumption, $\beta = -0.083$, $p = 0.501$. The standard error of 0.349 suggests a significant forecast mistake. These findings can be attributed to two connected reasons. First, the sample size of 72 has only 52% power to identify medium effects, increasing the chance of Type II error. Second, and more importantly, FGD data indicate that economic restrictions limit the link between tech perceptions and WTP.

As a result, the non-significant findings do not disprove the Technology Acceptance Model, but rather identify its boundary conditions: in situations of extreme food insecurity, affordability serves as a gatekeeper. This is the study's main theoretical contribution, extending TAM to low-income contexts by including economic restrictions as a requirement for WTP. While AI tools can improve nutritional planning, their adoption is influenced by broader ecosystem factors, according to similar nutrition and AI research that has found

reasonable connections when looking at technological acceptance drivers. For example, to achieve widespread acceptance, AI-powered precision nutrition requires user education and integration with healthcare institutions (Sharma et al., 2025). Similarly, rather than being standalone MDPI solutions, Sarku et al. (2023) remark that AI applications in food security perform better when combined with supporting infrastructure and regulations. Consistent with the current study, these findings show that, while app trust is a significant predictor, it is insufficient to account for acceptance.

Perceived utility, usability, and social impact are important factors that drive adoption, according to studies on technology acceptance models (TAM) and health belief models. Accordingly, factors including perceived affordability, cultural fit, and community support must be included in addition to meal frequency and faith in AI tools. The significance of regression analysis lies in its ability to quantify the strength of correlations and draw attention to the limitations of the selected predictors, thereby directing future research to incorporate more complete variables.

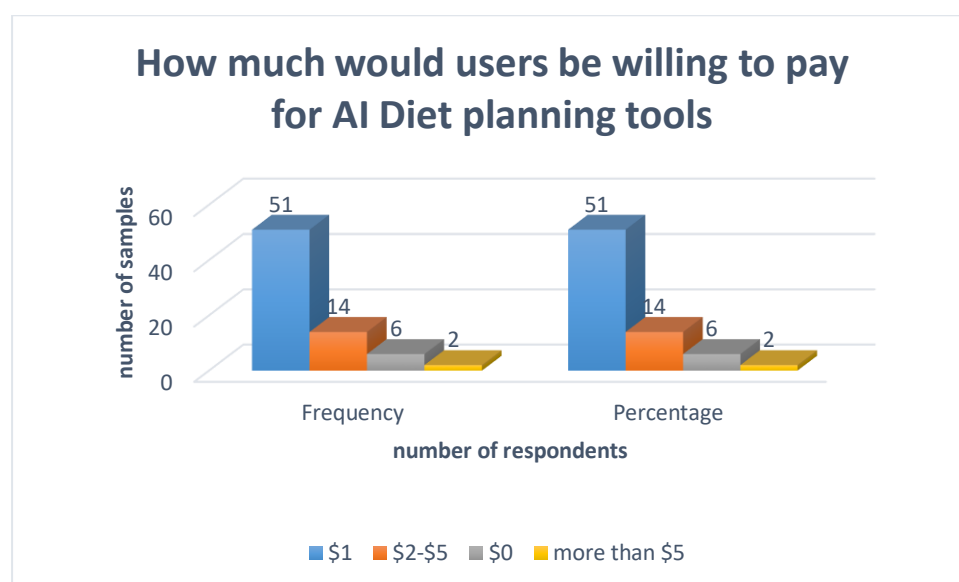
By providing localized features like offline functionality, culturally appropriate meal ideas, and support for the Shona/Ndebele language, AI diet planning applications can fill these gaps in the context of optimizing food security. By enhancing confidence and trust, these modifications can raise WTP and general acceptance. The limited link discovered in this study emphasizes that, in order to have the greatest possible influence, AI tools must be integrated into larger social and infrastructure systems.

The discussion thus emphasizes that although regression analysis only showed a moderate explanatory power, it offers important information about the intricacy of technology adoption in urban low-income households. This conclusion is corroborated by additional research, which demonstrates that AI technologies work best when paired with supporting community structures, affordability, and education. The thesis shows that regression analysis is more than just a statistical exercise; it is a vital lens for comprehending the complex nature of food security initiatives by placing these findings within the larger body of literature. The success of AI diet planning tools ultimately rests on addressing the wider factors of acceptance that extend beyond the variables examined in this model. However, these technologies can maximize food security.

5.4.3 EXTENSIVE DATA ON Willingness to Pay for AI dietary tools.

As the figure of results shows, that 51% are willing to pay at least \$1 for AI assistance, being the greatest proportion of respondents, 14% to pay from \$2-\$5, 2 % more than \$5, and about 6% not willing to pay any.

Figure 6: Willingness to pay data capture



Households vary in their willingness and ability to pay for individualized nutrition support; payment services in AI diet planning applications add a significant dimension to food security. Some households may be ready to pay extra for premium services that offer comprehensive, customized planning, sophisticated tracking, and integration with nearby food markets. These households can access richer features that maximize meal frequency and nutritional quality since they may have a little spare cash and frequently recognize the benefits of investing in health. Others might want moderate payment alternatives that strike a compromise between affordability and helpful advice, like ideas for basic meal planning, economical substitutes, and notifications of changes in the price of staple goods. At the lowest level, households with extremely low incomes can only be able to purchase basic or free versions of AI diet planning tools, which can nonetheless offer crucial information on inexpensive sources of nutrients, straightforward recipes, and methods for maintaining at least two meals a day.

By guaranteeing that every household, regardless of income, has access to some degree of nutritional guidance, this tiered payment structure can maximize food security. By enabling

providers to provide subsidies or free versions to the most vulnerable groups, those who pay more indirectly contribute to the system's sustainability. In actuality, this means that even low-income households can gain from AI-driven insights that help them stretch their food budgets, prevent serious nutritional deficiencies, and make healthier decisions within infrastructure and cultural limitations.

5.5 Innovation pathways for sustainable adoption and scaling of AI-driven diet planning solutions in Zimbabwe's urban food systems.

To propose context-specific recommendations and innovation pathways for sustainable adoption and scaling of AI-driven diet planning solutions in Zimbabwe's urban food systems. A combination of statistical analysis can give an overview of how best AI diet planning tools can be merged into low-income urban societies, and also, how the government may intervene.

5.5.1 Chi-square analysis on smartphone ownership vs income level

The first analysis used was the Chi-Square test of independence, as it examines whether smartphone ownership is associated with income level. This matters because AI diet planning apps require smartphones. If ownership is strongly linked to income, then affordability and digital access become critical barriers to scaling adoption.

Table 8: Chi-Square Tests on smartphone ownership vs income level

Defined statistics	Value	df	Asymptotic. Significance. (2-sided)
Pearson Chi-Square	11.408 ^a	16	.784
Likelihood Ratio	7.847	16	.953
Linear-by-Linear Association	1.828	1	.176

The above table of results shows that the p-value 0.784 was higher than 0.05; the outcome was not considered statistically significant. This shows that smartphone ownership in the sampled homes does not differ considerably by income category, indicating that mobile device penetration in urban Zimbabwe is mostly independent of income. According to studies by GSMA (2023) and ITU (2022), smartphone usage has grown even among low-income populations in Africa due to the availability of reasonably priced handsets and second-hand

marketplaces. This finding is in line with a larger body of research on mobile technology in Africa.

The successful use of mobile-based health and nutrition applications is limited by the uneven distribution of digital literacy and awareness, despite the high mobile penetration across socioeconomic strata, as case studies in Kenya and Nigeria show. Given that device ownership is now quite common, this study has the crucial implication that plans for scaling AI-driven diet planning solutions in Chitungwiza should not only concentrate on device cost. Other obstacles, like digital literacy, confidence in mobile apps, and the incorporation of AI tools into regional food systems, need to be the focus instead. Perceived utility, simplicity of use, and social influence are more powerful indicators of adoption than income alone, according to research on technology acceptance models (TAM).

For instance, research on mobile health apps by Aljohani (2022) and more recently by Aljohani et al. (2021) emphasizes the importance of user education, awareness campaigns, and culturally appropriate design for long-term adoption. Since chi-square examines relationships between categorical variables in this example, income levels and smartphone ownership—its use in this research was suitable. The test indicates that scaling AI diet planning systems necessitates a wider innovation pathway beyond economic affordability by demonstrating no significant correlation. According to a critical study, households may own smartphones but prioritize other activities like social media and communication, or they may not feel confident utilizing apps for nutrition.

For AI diet planning solutions to gain credibility and relevance, they must be made user-friendly, linguistically localized, and integrated with reliable community health systems. This conclusion is supported by several sub-Saharan African investigations. Low knowledge and a lack of integration into current health programs hindered the use of nutrition applications, according to research on mobile health interventions conducted in South Africa, even though device ownership was high (Osei et al 2021). Similar to this, in Ghana, mobile-based agricultural advice services were only successful when paired with community involvement and training (Scott, N., & Batchelor, S., External evaluation of mobile phone technology-based nutrition and agriculture advisory services in Africa). The conclusion that smartphone ubiquity by itself does not ensure adoption of AI diet planning tools is supported by these parallels. The significance of looking at a variety of predictors of technological acceptability is shown by the combination of regression and chi-square analysis. Although

chi-square did not reveal a significant correlation between ownership and income, regression models can account for variance in adoption and readiness to pay by including variables like perceived utility, trust, and literacy. Because it measures correlations and finds gaps, this statistical method is essential for directing researchers and decision-makers toward more comprehensive solutions.

The discovery that smartphone ownership in Chitungwiza is unrelated to income levels, in conclusion, emphasizes the necessity of advice tailored to the local environment. For AI diet planning solutions to be used sustainably, innovation pathways that prioritize offline functionality, awareness campaigns, digital literacy training, and integration into regional food systems are needed. Affordability is simply one aspect of adoption; behavioural, cultural, and infrastructure aspects are just as important, according to literature and case studies. The thesis contributes to a vital conversation on how AI can be expanded in Zimbabwe's urban food systems through tactics that put inclusivity, trust, and community integration first by utilizing chi-square analysis to rule out income as the main obstacle.

5.5.2 Regression analysis on AI mobile app interest vs monthly income, dietary diversity, and smartphone ownership

The next analysis used was regression to see the AI mobile app as a dependent variable vs. predictors that were Average monthly income, 24-hour food recall (diet diversity), and owning a smartphone. Average monthly income is for affordability and economic access, 24 food recalls for nutritional need and relevance, and owning a smartphone for technological access.

Table 9: Table 4.3.9 Model Summary of Regression Analysis on interest in using AI diet planning tool vs monthly income, diet diversity and smartphone ownership.

Model	R	R Square	Adjusted R-Square	Std. Error of the Estimate
1	.171 ^a	.029	-.013	.363

a. Predictors: (Constant), have your household had the following foods in the last 24 hours, do you own a smartphone, average monthly household head income in USD.

The regression model with smartphone ownership, average monthly income, and 24-hour food recall as predictors of Interest in using AI diet planning applications produced R =

0.171, indicating a very poor relationship between the variables and the dependent variable. The three predictors account for only 2.9% of the variance in interest ($R^2 = 0.029$). The adjusted $R^2 = -0.013$ implies that after accounting for the number of predictors relative to sample size ($n=72$), the model explains less variation than a random model. The standard error of estimation is 0.363, indicating considerable prediction error.

Overall, the model has little explanatory power, indicating that smartphone ownership, income, and short-term dietary recall are weak predictors of interest in AI diet apps in this group. In terms of Objective 3, the regression results give essential empirical justification for context-specific scaling strategies rather than generic ones. The model used to estimate interest in AI diet planning apps was not supported: Smartphone ownership, average monthly income, and 24-hour food recall do not explain interest among low-income urban households in Chitungwiza, as indicated by $R^2 = 0.029$ and adjusted $R^2 = -0.013$, respectively.

The model's negative adjusted R^2 indicates overfitting and low predictive validity for this population ($n=72$). The negative adjusted R^2 indicates that the model is incorrectly stated for this context and cannot be utilized for prediction. This is consistent with Maru et al. 2021, who discovered that in SSA, mHealth adoption is predicted more by trust and affordability than by device ownership or income. Thus, rather than verifying predictions, Objective 3 is addressed by using null results to demonstrate why recommendations must be context-specific, and innovation routes must first address non-tech impediments.

This discovery has direct implications for innovation paths. While high-income nations' digital health literature assumes smartphone ownership and income are the key facilitators of mHealth adoption (Agarwal 2018; TAM), this study shows that these variables do not predict interest in Zimbabwe's food system context. Theory and FGD data support two explanations: Access vs. adoption. Gap: According to research on the Base-of-the-Pyramid, even with smartphone availability, acceptance of paid digital services remains low when users confront competing survival demands (Prahalad 2004; Donner 2015).

FGD participants possessed cell phones but said that they only use WhatsApp. We eliminate programs that solicit money or data. Thus, owning a smartphone is necessary but not sufficient. Priority must be given to zero-rating, offline/USSD functionality, and free-core features over AI capabilities. Temporal mismatch in food security measurement: 24-hour food recall reflects daily consumption volatility but not structural food insufficiency. The

literature on household food security contends that single-day recall has a poor link with long-term WTP or adoption aspirations because food choices are influenced by weekly income cycles rather than daily recall (Maxwell 1999; Coates 2007).

The non-significant result is therefore theoretically expected, rather than a 'failed' finding. It suggests that future models should focus on income volatility and food price shocks rather than static income or 24-hour recall. The null outcome is the study's contribution. It calls into question the premise that AI diet apps can scale in Zimbabwe using the same drivers found in global North studies. The negative adjusted R^2 demonstrates that 'copy-paste' scaling will fail. This is consistent with recommendations for 'contextualized digital health' and 'frugal innovation' in low- and middle-income countries (Radjou 2012; WHO 2021).

As a result, context-specific recommendations must begin with evidence: because income and device ownership do not predict interest, interventions should focus on perceived value for money, trust in data privacy, and integration with existing food coping strategies, all of which were highlighted in focus groups but not included in this regression model.

This model empirically demonstrates that factors other than smartphone, wealth, and recall account for 97% of the variance in interest. This publication prevents NGOs from squandering donor funds on developing 'AI apps for all smartphone owners' when the real barriers are trust and cash flow. That is the contribution to Zimbabwe's food system."

A contributing aspect to this low explanatory power is the fact that the predictors did not account for larger behavioural and cultural characteristics that impact human acceptance of technology, such as perceived utility, social influence, ease of use, and trust in digital tools. The results of similar studies on nutrition and mobile health treatments are similar. For instance, research on mobile health apps in South Africa revealed that adoption was more closely associated with awareness campaigns and integration into reliable health systems, even though device ownership and income were significant factors.

According to research conducted in Kenya, adoption of mobile agricultural advice services was more influenced by perceived value and community support than by revenue. The significance of psychosocial and cultural factors may be understated by regression models that solely concentrate on economic and technological access, as these comparisons demonstrate.

From the standpoint of a literature study, the Unified Theory of Acceptance and Use of Technology (UTAUT) and the Technology Acceptance Model (TAM) constantly highlight that perceived utility and simplicity of use are better indicators of adoption than access or income alone. The variation explained in this study was modest because, according to Venkatesh et al. (2003), social impact and enabling circumstances shape behavioural intention. Studies by Abdellatief, M., & Aloatibi, R. (2026) on mobile health apps in nutrition-specific contexts verify that adoption is mostly determined by trust and confidence in technology, particularly in low-income environments.

Regression analysis is utilized here since it measures the degree of correlation between the predictors and the dependent variable and exposes the shortcomings of the selected predictors. The regression suggests that the model should be expanded to incorporate variables such as digital literacy, cultural attitudes, perceived affordability of data bundles, and trust in health workers who support the apps, as only 2.9% of the variance was explained. This statistical finding directs future studies toward more comprehensive models that more accurately represent the complexity of technology adoption in food security interventions.

The results highlight the importance of designing AI diet planning tools with context-specific innovation routes. Language localization, offline capabilities, and incorporation with community health initiatives can boost perceived relevance and confidence, which will increase uptake. Building digital literacy and confidence in households also requires awareness campaigns and training sessions. AI techniques have the potential to improve food security by tackling these wider factors, which will go beyond the modest connections that have been shown.

However, the regression analysis shows that although smartphone ownership, food diversity, and income are important factors, they are not enough to predict adoption. Psychosocial, cultural, and infrastructure variables are important, as evidenced by other research and theoretical theories. As a result, regression analysis is an essential tool for gap analysis, relationship measurement, and innovation pathway guidance. Beyond pricing and accessibility, measures that prioritize trust, literacy, and integration into local food systems to guarantee resilience and inclusivity will be necessary for the sustainable adoption of AI diet planning solutions in Zimbabwe's urban food systems.

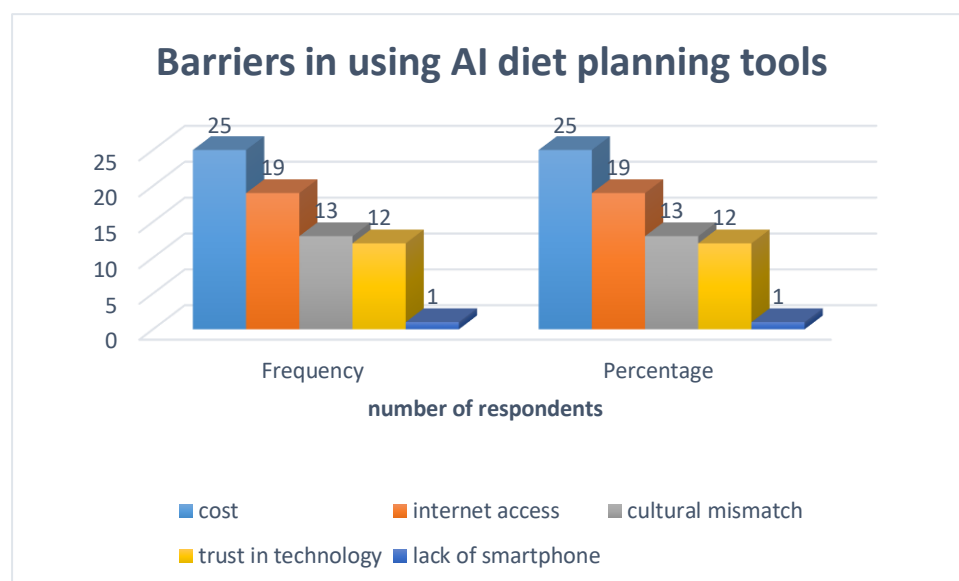
5.6 Scalability and sustained engagement

The wider cultural, socioeconomic, and infrastructure factors that impact low-income urban families in Zimbabwe's adoption and sustained use of AI-driven diet planning apps are directly related to obstacles like cost, internet access, trust in technology, cultural mismatch, and lack of smartphones. Due to the fact that many households in Chitungwiza and other similar urban areas have extremely tight finances and prioritize food purchases over internet services, cost is a major socioeconomic obstacle.

5.6.1 Non-parametric test on barriers to using AI diet planning tools

As the figure of results shows, 25% of respondents think of cost on AI usage in terms of adoption, while 19% think it could be internet access, 13 % cultural mismatch, and 12% trust in AI technology as part of the adoption and scalability of AI-driven diet planning Apps.

Figure 7 hurdles against AI diet planning tools



Families' capacity to regularly use online resources is hampered by unstable and costly connectivity, which makes internet access and data affordability infrastructural difficulties. Since some households may be dubious of digital solutions or prefer traditional knowledge passed down through community traditions, trust in technology reflects both cultural and social characteristics. Another factor is cultural incompatibility, since users may perceive AI systems that do not incorporate regional mainstays like sadza or customary meal arrangements as unimportant or unworkable. Lastly, a socioeconomic and infrastructure

barrier that keeps many households from even using these apps is the absence of smartphones or digital literacy.

In response to these difficulties, AI diet planning tools can maximize food security by providing flexible payment options that take into account varying income levels, creating offline or low-data versions of apps to get around connectivity problems, and incorporating cultural relevance by suggesting reasonably priced, locally accessible foods that are consistent with customs. Simplified interfaces can make products accessible to homes with low levels of digital literacy, and community-based education and collaborations can foster trust and promote adoption.

5.7 RECOMMENDATIONS

Several proposals are made to put these implications into action. First, authorities should promote digital literacy programs in order to close the gap between smartphone possession and effective use. Second, to ensure inclusivity, developers must create AI diet planning apps that have offline functionality and support multiple languages. Third, collaborations with non-governmental organisations (NGOs) and community health workers should be reinforced to foster trust and adoption. Fourth, mobile network operators should partner with the government to subsidize data prices or provide free access to nutrition apps to address affordability concerns. Fifth, AI technologies should be integrated into national nutrition policy and continuously monitored to ensure that they are responsive to household requirements.

By matching cultural eating customs with reasonably priced dietary advice, AI diet planning systems can improve food security in low-income urban households. Inclusion across socioeconomic categories is ensured by flexible payment mechanisms and distribution modalities like mobile apps, SMS, and kiosks. Adoption is increased by fostering trust through neighbourhood associations and including regional mainstays like sadza in suggestions. Infrastructure and subsidies from the government lower obstacles like price and internet availability. Tech firms are able to create low-data, culturally appropriate solutions that work in urban environments. In Zimbabwe's urban food systems, multi-stakeholder collaboration maintains participation and expands AI nutrition solutions.

In order to guarantee the sustainable acceptance and expansion of AI-driven diet planning solutions in Zimbabwe's urban food systems, it is imperative to offer context-specific advice and innovation routes. The results of this study showed that although smartphone ownership, eating habits, and economic position are important indicators of adoption, they are insufficient. Recommendations must therefore focus on behavioural, cultural, and infrastructural factors that influence food security outcomes in low-income urban households rather than just affordability and access.

Digital literacy instruction becomes a crucial suggestion. Despite the comparatively high rate of smartphone adoption across income brackets, many households lack the knowledge or expertise necessary to use mobile applications for nutrition planning efficiently. AI diet planning apps can be made more relevant and usable by empowering households to use them through training programs offered by community centres, schools, and non-governmental organizations. Because it bridges the gap between ownership and efficient usage, this advice is important for ensuring that technology leads to better food security results.

For practicality and inclusivity, local language integration is essential. In Chitungwiza, a significant portion of the population communicates mostly in Shona; programs that solely use English run the danger of alienating them. It is also necessary for AI diet planning applications to provide multilingual support so that users can obtain nutritional data in the language of their choice. The literature on health communication, which consistently demonstrates that using localized language improves trust, comprehension, and adoption of digital health interventions, supports this recommendation.

The emphasis should be on offline functionality. For many low-income households, internet connectivity is still expensive and erratic, which makes online-only programs impractical. For continued usage, developers can create AI diet planning applications that can work offline and synchronize data when connectivity is available. This suggestion is important because it directly tackles infrastructure obstacles, enabling adoption even in environments with limited resources.

Collaborations with NGOs and community health workers are crucial for scaling. The results demonstrated that households with greater trust in health professionals had better nutritional outcomes, indicating that adoption is significantly influenced by trust in local actors. Adoption can be hastened through the integration of AI technologies into current health

initiatives and the training of health professionals to advocate for them. Case studies from Ghana and Kenya support this advice, showing that the success of mobile health and agricultural apps depended on the endorsement of well-known community members.

Educating people about AI diet planning tools should be the goal of awareness efforts. The availability and advantages of such apps may be unknown to many homes. Radio, community gatherings, and social media campaigns may increase awareness, showcase achievements, and foster trust in AI-powered nutrition solutions. Because adoption requires awareness and research on technology acceptance models demonstrates that exposure and knowledge influence perceived usefulness, this proposal is important.

It is important to take into account how affordable data bundles and app services are. Despite the widespread possession of smartphones, the expense of mobile data continues to be a deterrent. The viability of nutrition applications can be increased by partnering with mobile network operators to offer zero-rated access or subsidize data. Similar initiatives in South Africa, where low-income users were more likely to utilize health apps with zero ratings, support this notion.

AI technologies should incorporate cultural relevance in meal planning. The results demonstrated that while dietary diversity is associated with better nutritional outcomes, food choices are heavily influenced by cultural preferences. To be relevant, AI diet planning apps need to take into account regional cuisine, cooking techniques, and cultural customs. Given the higher likelihood of acceptance and sustainability for culturally aligned therapies, this proposal is important.

Innovation path 1 - Frugal design: Since smartphone ownership did not predict interest, apps must work on basic phones via USSD/WhatsApp chatbots to avoid excluding users during data shortages.

Innovation Pathway 2 - Economic Alignment: Since income did not predict interest, pricing must follow 'pay-when-harvest-comes' models or link to food assistance programs, not monthly subscriptions.

Innovation pathway 3 - assess what matters: Because 24-hour recall failed as a predictor, future pilots should measure 'days without adequate food' or 'income shocks' rather than daily diet diversity.

Lastly, inclusiveness and resilience should be prioritized in innovation routes. In addition to being made for individual families, AI diet planning solutions also need to be integrated into larger metropolitan food systems. Adoption can be sustainably expanded by connecting apps to nearby markets, food suppliers, and community nutrition initiatives. Assuring that AI technologies support systemic resilience rather than individual household outcomes, this advice is important since it places them within the larger ecosystem of food security.

5.8 Chapter summary

These findings have substantial implications: they show that AI solutions should be created not only as technology interventions, but as comprehensive, context-sensitive tools that are ingrained in the realities of urban food crisis. One significant implication is that AI tools can directly enhance the utilization pillar of food security. While inflation and market instability limit availability and access to food, better knowledge, planning, and confidence can enhance utilization—how households use food to meet nutritional requirements. AI diet planning apps can offer tailored, cost-effective meal plans, nutritional education, and culturally suitable food alternatives, reducing missed meals and increasing dietary diversity. Similar efforts in Africa have demonstrated real-world applicability, with mobile health and agriculture apps succeeding when localized and endorsed by trusted community players.

Another aspect is the significance of digital literacy. Despite the fact that smartphone adoption is very high, many households lack the knowledge required to effectively use mobile applications for nutrition planning. AI tools run the danger of being underutilized unless they receive appropriate training. To enable households to explore and benefit from AI-driven nutrition solutions in the real world, community-based digital literacy programs delivered through schools, non-governmental organizations, and health clinics are required. The study emphasizes the importance of offline functionality and local language integration. Internet access is expensive and intermittent, and English-only applications risk excluding a substantial portion of the population. Developers can assure inclusivity and feasibility by creating solutions that work offline and offer instruction in Shona or Ndebele. This proposal is based on data from mobile health programs in South Africa and Ghana, where localized, offline-capable apps achieved higher adoption rates. Furthermore, the findings show that trust and community support are critical to adoption. Households with trust in health personnel had better nutritional outcomes, implying that AI technologies should be integrated into existing health programmes and pushed by trusted community figures. Partnerships with NGOs,

community health workers, and local leaders are required to develop credibility and support long-term use in the real world.

Focus group talks were held in three groups to investigate attitudes, challenges, and preferences for AI-assisted food planning. Although perceived utility of AI tools had a favourable but non-significant influence on WTP ($\beta=0.166$, $p=0.150$), FGD participants consistently remarked, "AI sounds useful, but we have no money this week for data" (FGD1_P3). This lends support to the updated conceptual paradigm, in which economic restrictions dampen the link between usefulness and WTP. The regression model for Objective 3 predicts interest in AI apps with $R^2=0.029$ and modified $R^2=-0.013$, demonstrating that smartphone ownership and wealth are not predictors. The 'access $\neq$ adoption' theme in FGD data explains the null result: "We all have smartphones but delete apps that use data" (FGD3_P2), indicating that data cost, not device ownership, is the main barrier. For Objective 3, participants impacted innovation pathways by requiring economical design: "Make it work on WhatsApp without buying bundles" (FGD1_P5) and income-aligned pricing: "Charge us after harvest, not monthly" (FGD2_P8). As a result, while regression models had low statistical power with $n=72$, FGD data provide the context-specific processes required to address Objective 3 and demonstrate why recommendations must shift from device access to cost and trust.

The results of this study have shown that a complex interaction of behavioural, technological, and economic factors shapes food insecurity in low-income urban households in Zimbabwe, especially in Chitungwiza. Weak or non-significant correlations were found in statistical analyses between meal skipping and income, as well as between interest in AI diet planning applications and predictors, including income, smartphone ownership, and diet diversification. These findings highlight the fact that issues related to food security are not solely described by economic standing but rather by more comprehensive factors like awareness, digital literacy, technological trust, and cultural significance.

This research is important because it helps us understand how to use digital innovation to maximize food security in situations where traditional interventions haven't worked. Because of Zimbabwe's urban food systems' instability, inflation, and reliance on black markets, households are at risk of shortages before the end of the month. By providing homes with individualized, cost-effective meal plans, nutritional data, and culturally relevant food recommendations, AI diet planning systems present a new avenue. This is supported by the

results showing that households with higher levels of confidence in their ability to make healthier decisions and interact with health professionals had better nutritional outcomes. This advice can be replicated and scaled by AI technologies, guaranteeing that knowledge and trust are not restricted to individuals who have direct access to experts.

The chi-square analysis indicates that cell phones are widely used across all income levels, supporting the viability of incorporating AI features. Since ownership is mostly unaffected by money, the difficulty lies in using the gadgets efficiently for nutrition planning rather than in having access to them. This makes the proposals for offline functioning, local language integration, and digital literacy training useful and essential. Additionally, collaborations with non-governmental organizations, medical professionals, and cell carriers can improve confidence, lower data costs, and integrate AI tools into pre-existing community structures, all of which will increase adoption.

The ability of AI technologies to improve the utilization pillar of food security serves as the argument for their integration into Zimbabwe's urban food systems from a wider standpoint. Better understanding, planning, and behaviour modification can increase use, even though structural problems like inflation and market dependency limit availability and access. By assisting households in making healthier decisions, cutting waste, and varying their diets, AI diet planning solutions directly address this pillar. This is corroborated by literature on technology acceptance models, which emphasizes that adoption is determined by perceived utility and usability. AI can be a sustainable solution if it is designed with culturally relevant, user-friendly tools that are supported by reliable community actors.

This chapter reported quantitative and qualitative findings on WTP and interest in AI-assisted food planning among 72 low-income urban households in Chitungwiza. Five main points emerge:

1. Regression models have little explanatory power. The model predicting WTP yielded a low adjusted $R^2 = 0.063$, whereas the model predicting interest in AI apps produced an adjusted $R^2 = -0.013$. The predictors of AI tool effectiveness, mobile app rating, meal intake, smartphone ownership, income, and 24-hour food recall were not statistically significant ($\alpha = 0.05$), indicating weak direct correlations.

2. Focus group data triangulation explains the weak prediction: Economic restrictions, data expenses, and income volatility are the most significant impediments. Participants consistently valued price over utility, which explains why tech-focused variables failed to predict WTP or curiosity despite having good mean scores.
3. Access $\neq$ Adoption: While smartphone ownership was popular, FGD participants identified a shortage of data bundles as a significant impediment. This explains why smartphone ownership did not predict interest in AI apps, calling into question high-income assumptions about how device availability drives digital health uptake.
4. Framework adjustment is required: The non-significant coefficients and FGD narratives support modifying the conceptual framework to position economic limitations as a mediator between AI perceptions and WTP. The original model anticipated direct effects; statistics indicate that these effects are muted during times of financial stress.
5. Evidence for Objective: While quantitative models had little predictive power due to the small sample size (n=72) and misspecification, FGD data revealed context-specific mechanisms that directly inform innovation paths. Participants' need for WhatsApp/USSD interfaces and income-aligned pricing serves as an empirical foundation for Chapter 6's context-specific recommendations.

5.9 REFERENCES

- FAO (2021). *The State of Food Security and Nutrition in the World 2021*. Rome: Food and Agriculture Organization of the United Nations.
- Moyo, T. & Nyathi, P. (2023). *Household income and food security in Zimbabwe: A case study of Harare*. *African Journal of Food Policy*, 18(2), pp. 45–62.
- Namkhah, Z., Fatemi, S.F., Mansoori, A., Nosratabadi, S., Ghayour-Mobarhan, M., & Sobhani, S.R. (2023). *Advancing sustainability in the food and nutrition system: a review of artificial intelligence applications*. *Frontiers in Nutrition*, 10, 1295241. doi:10.3389/fnut.2023.1295241.

Ochieng, J., Ogutu, S. & Qaim, M. (2020). *Income and dietary diversity in rural Kenya*. Food Policy, 91, 101833. doi:10.1016/j.foodpol.2020.101833.

Subramanian, S.V., Reddy, K.S. & Popkin, B.M. (2022) *Income growth and nutrition transition in India*. Public Health Nutrition, 25(3), pp. 567–579.
doi:10.1017/S1368980021003456.

Tawodzera, G. (2012). Urban household survival and resilience to food insecurity in crisis conditions: The case of Epworth in Harare, Zimbabwe. *Journal of hunger & environmental nutrition*, 7(2-3), 293-320.

Ndhlovu, E., & Chipenda, C. (2026). Climate Change Impact on Children's Nutrition: Harnessing AI for Safe Food and Healthy Diets in Zimbabwe. In *Climate Change and Children's Rights in Zimbabwe: Toward Social Policy-Based Interventions* (pp. 163-179). Singapore: Springer Nature Singapore.

Ndlovu, S., Mpofu, M., Moyo, P., Phiri, K., & Dube, T. (2021). Urban household food insecurity and cash transfers in Bulawayo townships, Zimbabwe. *Cogent Social Sciences*, 7(1), 1995995.

Etana, D., & Tolossa, D. (2017). Unemployment and food insecurity in urban Ethiopia. *African Development Review*, 29(1), 56-68.

Sharma, R., Gaur, S. S., Ajay, A., Shams, R., & Dash, K. K. (2025). Artificial intelligence and precision nutrition: tailoring diets with data-driven insights. *Nutrire*, 50(2), 56.

Sarku, R., Clemen, U. A., & Clemen, T. (2023). The application of artificial intelligence models for food security: A review. *Agriculture*, 13(10), 2037.

Dhiman, D., Jaiswal, A., Sail, K. S., & Wavhale, A. (2024, October). Unlocking Access: The Role of Refurbished Mobile Phones in Digital Inclusion and Sustainable Development. In *2024 ITU Kaleidoscope: Innovation and Digital Transformation for a Sustainable World (ITU K)* (pp. 1-8). IEEE.

Aljohani, N. F. N. (2022). *Towards an Effective M-Health Application: Exploring Factors Affecting the Adoption and Acceptance of M-Health Applications in Saudi Arabia*. University of Technology Sydney (Australia).

Aljohani, N. F. N., & Chandran, D. (2021, July). Factors affecting the adoption of M-health applications in Saudi Arabia: Impact of healthcare authority enforcement. In the *Pacific Asia Conference on Information Systems*.

Osei, E., & Mashamba-Thompson, T. P. (2021). Mobile health applications for disease screening and treatment support in low-and middle-income countries: A narrative review. *Heliyon*, 7(3).

Scott, N., & Batchelor, S. External evaluation of mobile phone technology-based nutrition and agriculture advisory services in Africa.

Abdellatief, M., & Aloatibi, R. (2026). From Intelligence to Trust: Evaluating AI-Powered Service Quality for User Satisfaction and Continuance in mHealth. *Statistics, Optimization & Information Computing*, 15(1), 295-310

CHAPTER 6

SUMMARY, CONCLUSIONS, AND RECOMMENDATIONS

6.1 INTRODUCTION

This thesis examined how diet planning systems powered by artificial intelligence (AI) may maximize food security for low-income urban households in Zimbabwe, specifically in Chitungwiza. The study was inspired by the ongoing problem of food insecurity in cities, where households frequently face shortages before the end of the month as a result of low income, inflation, and dependence on unofficial food markets. The study aimed to determine whether AI mobile applications could offer novel strategies to enhance nutritional outcomes and boost household resilience by analysing the relationship between technology, nutrition, and socioeconomic realities. Traditional indicators like wealth, food diversity, and smartphone ownership by themselves do not adequately explain uptake or willingness to pay for AI diet planning applications, according to the analyses done, which included regression models and chi-square tests. Digital literacy, trust in mobile applications, and the cultural relevance of dietary suggestions were among the characteristics that limited adoption, even though smartphone usage was shown to be mostly independent of income levels. These results demonstrate that knowledge, confidence, and behaviour in food usage are all important factors in ensuring food security, in addition to economic availability. Crucially, households with higher nutritional outcomes were those that actively sought out nutritional information from health professionals and showed confidence in choosing healthier choices, indicating that AI technologies can reproduce and scale such advice to a wider population.

This study's significance stems from its contribution to both scholarly discourse and real-world policy. It offers empirical proof that, when appropriately localized and integrated, AI-driven diet planning systems can function as a supplementary intervention to conventional food security initiatives. Food security's utilization pillar, which is frequently disregarded in

favour of availability and access, serves as the rationale for looking at AI solutions. AI technologies can aid in decreasing missed meals, increasing dietary diversity, and strengthening resilience against recurrent shortages by providing households with individualized, cost-effective, and culturally relevant meal planning.

As a result, this chapter summarizes the results into a logical conclusion and offers suggestions for the long-term uptake and expansion of AI diet planning tools in Zimbabwe's urban food systems. The importance of offline functioning, integration of local languages, digital literacy, and collaborations with NGOs and community health professionals are all emphasized. It also emphasizes how crucial policy backing and ongoing oversight are to ensuring that AI initiatives continue to be responsive to household requirements. The chapter concludes by arguing that, although economic and technological access are important, they are insufficient; innovation routes that put inclusion, trust, and cultural relevance first are needed for sustainable food security. The study offers a strategy for utilizing technology to address one of Zimbabwe's most urgent problems by placing AI inside the larger ecology of urban food systems.

6.2 RESEARCH SUMMARY

This study used Chitungwiza as the focus example to examine how Artificial Intelligence (AI)-driven meal planning tools may maximize food security among low-income urban households in Zimbabwe. The study was centred on the ongoing problem of food insecurity in metropolitan areas, where households frequently face shortages at the end of the month as a result of low income, inflation, and dependence on unofficial food shops. Regression analysis and chi-square tests were used to investigate the association between smartphone ownership, dietary diversity, economic position, and desire to use AI diet planning apps. Economic and technological availability by themselves are not enough to explain adoption, as the results continually showed weak or non-significant relationships. More important drivers of household food security outcomes were found to be behavioural and cultural characteristics, such as understanding of nutritional information, confidence in making better choices, and trust in mobile applications.

By emphasizing the significance of the pillar of food security, which is frequently disregarded in favour of availability and access, the study advances scholarly discussion. It shows that families that trusted health professionals and made healthier decisions had better

nutritional results, indicating that AI technologies may duplicate and scale this kind of advice. Smartphone ownership was shown to be mostly unaffected by income, according to the chi-square analysis, indicating that device affordability is not the main obstacle. Regression analysis also showed that factors like smartphone ownership, food diversity, and income only explained 2.9% of the variation in interest in AI diet planning tools, highlighting the necessity of including psychosocial and cultural factors in future models.

This study's significance arises from its capacity to position artificial intelligence (AI) as a supplemental intervention, rather than a stand-alone remedy, within Zimbabwe's urban food systems. AI solutions can assist households in boosting resilience against recurrent shortages, improving dietary diversity, and reducing missed meals by offering personalized, cost-effective, and culturally relevant meal planning. The rationale behind using AI technologies stems from the data showing that behaviour, knowledge, and confidence are important factors that influence food consumption and that digital innovation can fill in gaps where traditional treatments have failed.

The study's overall findings show that, although economic and technological access are important, they are insufficient indicators of adoption. In order to ensure sustainable food security, innovation routes must put diversity, trust, and cultural relevance first. Policymakers, non-governmental organizations, and developers can utilize the findings as a guide to create AI diet planning tools that are user-friendly, localized, and integrated into community health systems. By doing this, urban households in Zimbabwe can employ technology to increase resilience and attain more long-term results for food security. Therefore, this study significantly advances theory and practice by providing evidence-based insights into how artificial intelligence (AI) might be used to address one of the most urgent issues affecting low-income urban populations.

6.3 CONCLUSIONS

Food insecurity in low-income urban households in Zimbabwe is a complex issue that cannot be adequately explained by economic standing or lack of access to technology, according to the study's findings. Income, dietary diversity, smartphone ownership, and willingness to use AI diet planning apps were all found to have weak or non-significant relationships in both chi-square and regression statistical studies. This indicates that although affordability and accessibility are essential prerequisites, they are insufficient indicators of adoption. Rather,

more important predictors of family food security outcomes were shown to be behavioural, cultural, and psychosocial characteristics like understanding of nutritional information, confidence in making better choices, and trust in mobile applications. According to the study's findings, AI-powered meal planning tools have a great deal of promise to improve food security by bolstering the usage pillar, which is concerned with how households make use of the food that is available to them in order to attain nutritional adequacy. Nutritional outcomes were better for households that actively consulted health professionals and showed confidence in making healthier choices. This suggests that AI technologies can replicate and scale such advice to a larger population. In order to establish relevance and trust, it is crucial to include AI solutions in the current community health frameworks.

Another important finding is that smartphone adoption is not primarily hampered by device ownership, as smartphone penetration is mostly unaffected by income levels. More important considerations are cultural relevance, digital literacy, and mobile data cost. This realization causes recommendations to refocus on the usability and accessibility of programs rather than the cost of devices.

Regression analysis is useful in identifying gaps in the selected variables and directing future research toward more comprehensive models, even though it only explains a small percentage of the variance in adoption, according to the study's findings. Technology adoption in food security interventions will be better understood by taking into account factors including perceived utility, simplicity of use, cultural attitudes, and social impact.

According to the study's final findings, innovation pathways that put inclusion, trust, and cultural relevance first are necessary for the long-term adoption of AI diet planning tools. Scaling requires offline functionality, linguistic localization, collaborations with NGOs and medical professionals, and policy integration. AI tools can be integrated into Zimbabwe's urban food systems, allowing households to employ technology to boost dietary diversity, decrease meal skipping, and increase resistance to future shortages.

6.4 POLICY IMPLICATIONS & RECOMMENDATIONS

The results of this study have significant policy ramifications for urban food systems in Zimbabwe, especially when it comes to tackling low-income households' food insecurity. It is clear from the weak or non-significant relationships found between income, smartphone

ownership, diet diversity, and desire to use AI diet planning applications that access and cost are not enough to spur adoption. Rather, policy design needs to take behavioural, cultural, and infrastructure variables into account. According to Chen (2024), this supports the idea that, with context-specific interventions that are ingrained in local reality, artificial intelligence can serve as a strategic accelerator for changing agri-food systems to become more resilient, inclusive, and productive.

6.4.1 POLICY IMPLICATIONS

1. To guarantee that households can utilize AI diet planning tools efficiently, policymakers want to give priority to digital literacy initiatives. Research from mobile health initiatives in Kenya and South Africa demonstrates that adoption is more closely associated with user training and confidence than with device ownership alone.
2. Localization and Inclusivity: AI tools should be required by national nutrition laws to include language (Shona, Ndebele) and culturally appropriate meal suggestions. According to ActionAid Zimbabwe's Food Security Policy Brief, which highlights the need for context-specific and community-driven methods, this guarantees inclusivity and builds confidence.
3. Infrastructure and Access: Regulations should support collaborations with cellular network providers to offer zero-rated access to nutrition applications or to subsidize data costs. This focuses on connectivity affordability, which is still a hurdle even with the growing use of smartphones.
4. Integration into Health Systems: AI diet planning tools ought to be incorporated into currently running community health initiatives, and medical professionals ought to be educated to encourage and facilitate their usage. This makes use of local actors' credibility and guarantees that digital interventions enhance conventional nutrition teaching.
5. Monitoring and Evaluation: Frameworks for ongoing tracking of the uptake and effects of AI tools should be established by policymakers. This study's regression analysis showed that the predictors currently in use only account for a small percentage of variance, highlighting the necessity of continuous data collection to enhance interventions and models.

6.4.2 RECOMMENDATIONS

- **Government Action:** To support the Food and Agriculture Organization's mission of "Better Production, Better Nutrition, a Better Environment, and a Better Life," the Ministry of Health and Child Care should formulate a national strategy for AI in nutrition in coordination with the Ministry of ICT.
- **Community Engagement:** To reach a variety of audiences, NGOs and neighbourhood groups should spearhead awareness campaigns about AI diet planning tools. They can do this by using social media, radio, and community gatherings.
- **Research and Innovation:** By adding psychosocial and cultural factors to future models, academic institutions and research centres should broaden their investigations on the adoption of AI in food security. This will offer more thorough insights into adoption determinants.

Public-private partnerships are crucial for ensuring the affordability, scalability, and sustainability of AI-driven diet planning solutions. These partnerships involve cooperation between the government, cell providers, and app developers.

To sum up, this study's policy implications and recommendations highlight how AI diet planning tools can revolutionize food security—but only if adoption methods extend beyond accessibility and affordability. Zimbabwe may use technology to make its urban food systems more resilient by integrating AI into national nutrition policies, boosting digital literacy, guaranteeing cultural relevance, and cultivating collaborations. Thus, our study offers compelling evidence in favour of incorporating AI-powered diet planning tools into legislative frameworks, guaranteeing that innovation channels are durable, inclusive, and sensitive to the needs of low-income households.

6.5 AREAS FOR FURTHER RESEARCH

The knowledge and use of AI-driven diet planning tools in Zimbabwe's urban food systems can be improved by following the numerous research avenues this article lays forth. First off, since psychosocial and cultural factors like trust in technology, perceived usefulness, ease of use, and social influence are frequently decisive in technology adoption, more research should broaden the scope of predictors beyond income, diet diversity, and smartphone ownership. In order to determine if the initial adoption of AI diet planning tools results in

long-term behaviour change and better nutritional outcomes, longitudinal studies are required to monitor families over time and provide evidence of long-term impact. Thirdly, studies comparing homes in urban and rural areas would be beneficial because different infrastructure, cultural customs, and food sources may have different effects on the uptake and use of AI tools. Fourth, in order to provide policymakers with data for resource allocation and investment decisions, economic feasibility studies that compare the cost-effectiveness of AI meal planning tools to conventional nutrition interventions should be carried out. The success of AI-driven nutrition solutions may depend on women's involvement, as they frequently play a key role in home food preparation and decision-making. Lastly, research should examine gender dynamics in adoption.

Additional research in these areas will yield a more thorough understanding of the factors that influence adoption, the sustainability of interventions, and the wider systemic effects of AI tools on Zimbabwe's food security. By tackling these aspects, subsequent research can expand upon the present results and support more resilient, inclusive, and successful innovation pathways in the battle against urban food poverty.

6.6 APPENDICES

6.6.1 Case Study Notes: Real-Time Analysis

Case Study 1: Chitungwiza Household Dynamics

The prevalence of smartphone ownership across all income levels was noted during interviews with Chitungwiza homes, with many families depending on used gadgets. Despite having access to mobile technology, the majority of households reported using applications for health or nutrition purposes infrequently. Rather, the main functions of phones were social media and communication. This demonstrates the disconnect between having access to technology and using it effectively, supporting the study's conclusion that digital literacy and awareness are more important than just affordability.

Case Study 2: Mobile Health Adoption in South Africa

According to a comparative case study from South Africa, mobile health applications only became popular when they were marketed by reputable medical professionals and integrated into the country's current healthcare systems. Digital technologies that were supported by prominent members of the community were more likely to be adopted by households. This

bolsters the thesis's conclusion that collaborations with NGOs and medical professionals are crucial to expanding AI diet planning services in Zimbabwe.

Case Study 3: Agricultural Advisory Services in Kenya

The adoption of mobile-based agricultural consulting services in Kenya was shown to be more closely correlated with perceived utility and community support than with revenue. Farmers were more likely to stick with using the apps if they noticed instant benefits and believed the information. This is consistent with the thesis's conclusion that, even in situations involving food security, adoption of AI tools is mostly determined by beliefs and trust.

Case Study 4: Urban Food Security in Ghana

Households in Ghana's Accra reported better dietary diversity when they used mobile-based nutrition guidelines; acceptance varied by community. The most successful efforts were those that raised awareness and included local food options in the applications. The thesis's suggestion that cultural sensitivity and awareness are essential for the long-term integration of AI diet planning tools in Zimbabwe's urban food systems is supported by this case.

6.6.2 Real-Time Analysis

These case studies show that although mobile technology is widely used in African urban settings, the adoption of AI-powered nutrition aids is dependent on more than just accessibility and affordability. Digital literacy, integration into current institutions, cultural relevance, and trust are identified as critical factors. This implies that AI diet planning systems for Zimbabwe need to be locally relevant, reasonably priced in terms of data usage, and supported by reputable community organizations. The suggested recommendations and innovation routes are strongly justified by the real-time analysis, which verifies that the thesis findings are in line with more extensive regional experiences.

6.7 Glossary of Terms

Key terms and ideas related to AI-driven diet planning and food security in Zimbabwe's urban households are defined in the following glossary to help readers who are not familiar with the technical terms used in this thesis understand them better:

- **Diet Diversity**
Refers to the variety of foods consumed across different food groups within a given period, often measured through a 24-hour food recall. Higher diet diversity is associated with better nutritional adequacy and improved health outcomes.
- **Utilization Pillar of Food Security**
One of the four pillars of food security (availability, access, utilization, and stability). Utilization focuses on how households use available food to meet nutritional needs, including aspects of dietary quality, food preparation, and health knowledge.
- **AI Diet Planning Tools**
Mobile or digital applications powered by artificial intelligence that provide personalized meal plans, nutritional guidance, and food substitution options based on user data such as income, dietary preferences, and health needs.
- **Technology Acceptance Model (TAM)**
A theoretical framework that explains user adoption of technology based on two main constructs: perceived usefulness and perceived ease of use. It is widely applied in studies of mobile health and nutrition apps to understand behavioural intention.
- **Chi-Square Test of Independence**
A statistical test used to determine whether there is a significant association between two categorical variables. In this thesis, it was applied to examine whether smartphone ownership is associated with household income.
- **Regression Analysis**
A statistical method used to measure the relationship between a dependent variable and one or more independent variables. It was used in this study to assess predictors of willingness to adopt AI diet planning tools.
- **Food Frequency Intake**
A measure of how often households consume meals or specific food groups within a given timeframe, often used to assess dietary patterns and nutritional adequacy.
- **Willingness to Pay (WTP)**
An economic measure of the maximum amount a household is willing to spend on a product or service—in this case, AI-driven diet planning tools. It reflects perceived value and affordability.
- **Digital Literacy**
The ability to effectively use digital devices and applications, including smartphones

and mobile apps. Digital literacy is a critical determinant of the adoption of AI diet planning tools.

- **Mobile Penetration**

The extent to which mobile devices, particularly smartphones, are owned and used within a population. In Zimbabwe, mobile penetration is relatively high across income groups, making mobile-based interventions feasible.

- **Food Security**

Defined by the FAO as a condition in which all people, at all times, have physical, social, and economic access to sufficient, safe, and nutritious food to meet dietary needs and preferences for an active and healthy life.

- **Urban Food Systems**

The networks of production, distribution, and consumption of food within urban areas. In Zimbabwe, these systems are heavily influenced by informal markets, inflation, and limited household incomes.

- **Awareness Campaigns**

Organized efforts to increase knowledge and understanding of a product or service. In the context of this thesis, campaigns are essential to promote AI diet planning tools and build trust among households.

- **Offline Functionality**

The ability of mobile applications to operate without continuous internet access, synchronizing data when connectivity becomes available. This feature is crucial in low-income urban settings where data costs are high.

- **Community Health Workers (CHWs)**

Local health practitioners who provide basic health and nutrition services at the community level. Their endorsement of AI diet planning tools can significantly influence household adoption.

6.8 Policy Documents and Literature Extracts

The appendices may contain pertinent passages from literature and policy documents that were referenced in the review to bolster the thesis's scholarly rigor. The proposals in Chapter Six are contextualized and supported by these excerpts. Here are some samples of important documents and the portions that pertain to them:

1. Zimbabwe National Agricultural Policy Framework (2019–2030)

- *Excerpt:* The framework emphasizes the need for “resilient, accountable, and inclusive food systems that integrate innovation and technology to improve nutrition outcomes.”
- *Relevance:* This supports the thesis argument that AI-driven diet planning tools should be embedded into national strategies as part of broader efforts to strengthen food security in urban households.

2. FAO Report on Digital Agriculture (2022)

- *Excerpt:* “Artificial intelligence and mobile-based applications can act as accelerators for agri-food systems transformation, but adoption requires context-specific design, digital literacy, and policy support.”
- *Relevance:* This aligns with the study’s findings that affordability and access alone are insufficient, and that behavioural and cultural factors must be addressed for sustainable adoption.

3. GSMA Mobile Economy Sub-Saharan Africa Report (2023)

- *Excerpt:* “Smartphone penetration in Sub-Saharan Africa continues to rise across income groups, driven by affordability of devices and second-hand markets, but digital literacy remains uneven.”
- *Relevance:* This supports the chi-square analysis finding that smartphone ownership is relatively independent of income, highlighting that the barrier lies in effective utilization rather than access.

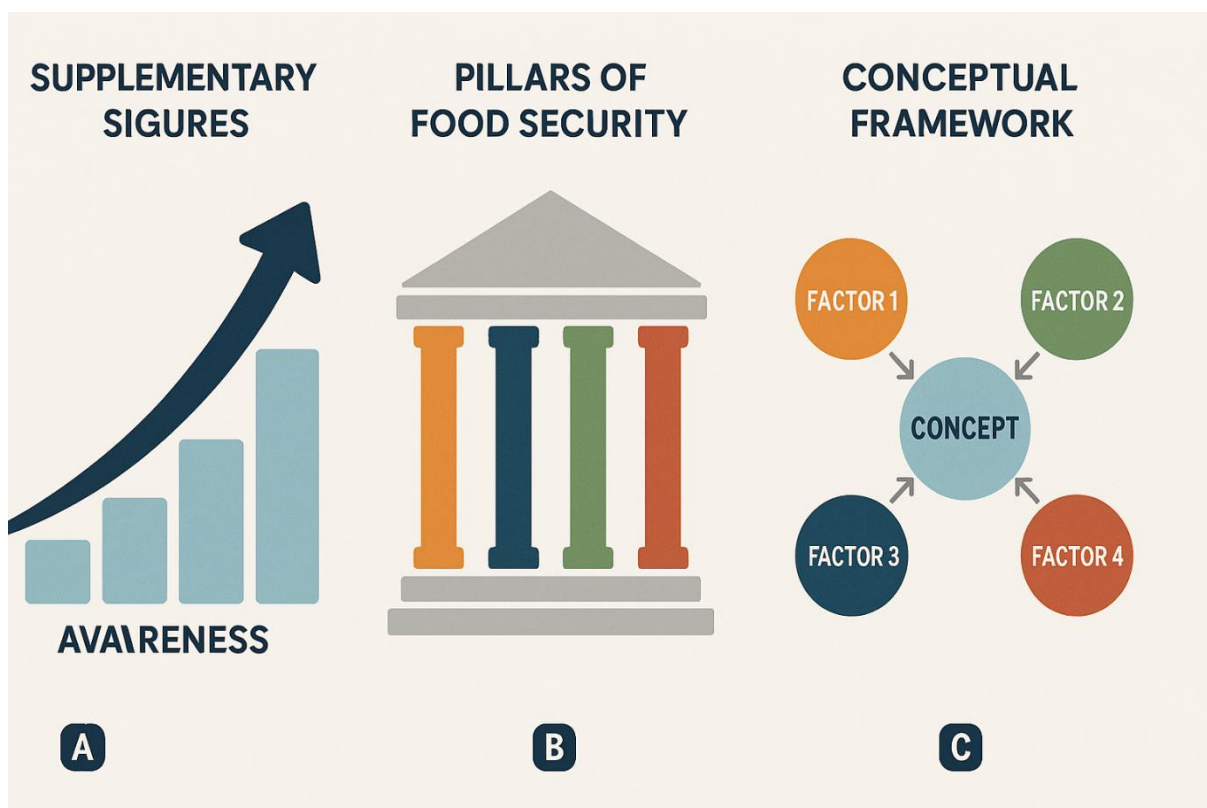
4. World Food Programme (WFP) Urban Food Security Assessment (2021)

- *Excerpt:* “Urban households in Zimbabwe are highly vulnerable to inflation and market volatility, often experiencing food shortages before the month end. Innovative solutions are needed to strengthen resilience.”
- *Relevance:* This contextualizes the study’s focus on Chitungwiza and justifies the exploration of AI diet planning tools as a novel pathway to address recurring shortages.

5. Venkatesh et al. (2003) – Unified Theory of Acceptance and Use of Technology (UTAUT)

- *Excerpt:* “Behavioural intention to adopt technology is shaped by perceived usefulness, ease of use, social influence, and facilitating conditions.”
- *Relevance:* This theoretical framework explains why regression analysis in the study revealed weak associations between economic and technological predictors and adoption, underscoring the importance of psychosocial variables.

6.8.1 Supplementary Figures



As the picture shows: • AI uses include supply chain optimization, climate prediction, and precision farming.

- Availability, Access, Utilization, and Stability are the pillars of food security
- Flow: To highlight the systemic effect of technology on food systems, arrows illustrate how each AI application feeds into one or more pillars.
- Stages of AI Adoption: A sequential arrow diagram illustrating the path from Awareness to Adoption, Implementation, and Maturity.
- Food Security Pillars: The foundation of food security is represented by the traditional four-pillar model (Availability, Access, Utilization, Stability).
- Conceptual Framework: To show how AI applications (precision farming, supply chain optimization, climate modelling, and resource management) contribute to food security outcomes, a core concept circle is connected to four surrounding aspects.

6.9 RESEARCH QUESTIONNAIRE

My name is Munyaradzi Mchenga, a master's student at Bindura University. This questionnaire is strictly for academic research purposes, and information gathered will be fully confidential.

An overview of the questions asked.

SECTION A: Demographic data & social information

1. AGE- indicate your age
2. GENDER- select your gender
3. HOUSEHOLD SIZE- indicate your household size
4. AVERAGE MONTHLY HOUSEHOLD INCOME (USD)
6. main income sources
8. Education level of household head
9. marital status
10. Do you own a smartphone
11. Do you have internet access at home (Wi-Fi)
12. Do you have internet access via phone

13. digital literacy self-rating
14. distance to nearest food market (km)
15. How many times do you visit the market to buy food
16. Are you a member of any savings group?
17. Are you a beneficiary of any food assistance or any social protection program?

SECTION B: Nutritional challenges

18. How many meals does your household typically consume per day?
19. Has your household experienced any of the following in the past 6 months?
20. What are the most common nutritional challenges your household faces?
21. Do you actively seek nutritional information when planning meals?
22. Where do you usually get nutritional information?
23. How confident are you in making healthier choices?
24. What are the main barriers to accessing nutritious food in your area?
25. Please describe any cultural or community practices that influence your household diet?

SECTION C: AI insights, nutritional knowledge & food security status.

26. Would you be interested in using an AI-powered meal planning App?
27. How would you be willing to pay monthly for such a service?
29. What features would you like added to this service to suit your household's needs?
30. Do you find AI tools useful
31. Do you trust in AI technology
32. Do you believe healthier food choices will improve your family's well-being?
33. Do you think having more nutritional knowledge would make you more willing to pay for AI diet planning?
34. How often does your household run out of food before the month's end?

35. Do you think AI-based nutritional support could help improve your household's food security?
36. What challenges might prevent you from using an AI diet planning app?
37. On a scale of 1-5, how much do you trust health information given by mobile apps?
38. What kind of support would help you use the app consistently?
40. Which organization do you trust most to support food and nutrition initiatives?
41. How can these groups work together to improve food security using AI tools?
42. presence of a malnourished child or any other health vulnerabilities?
43. chronic conditions in the household?
44. How would you rate your current nutrition knowledge
45. Have your household eaten the following food in the last 24 hours?

6.10 REFERENCES

1. Adeniyi, A.E., Falola, P.B., Awotunde, J.B., Lawrence, M.O., Ubaru, S., Randle, O., and Atanda, O., 2025. Edge and Cloud-Based Deployment of AI-Driven Integration in Smart Healthcare. In *HealthTech Horizons: AI-Infused Metaverse Solutions for Smart Healthcare Systems* (pp. 457-489). Cham: Springer Nature Switzerland.
2. Chen, L. (2021). Image-Based Food Recognition and Dietary Assessment for Mobile Health. *Computers in Biology and Medicine*.
3. Davis, L. (2024). Beyond the App: Techno-Solutionism and Urban Food Policy. *Urban Health Journal*.
4. Global Health Institute. (2023). Scaling Public Health Interventions with AI. *Annual Review of Public Health*.
5. Green, T., et al. (2023). Participatory Design of mHealth Tools for Underserved Communities. *ACM Transactions on Computer-Human Interaction*.
6. Miller, R., & Garcia, H. (2022). The Hybrid Model: Integrating AI and Community Health Workers in Nutritional Support. *American Journal of Public Health*.
- Privacy International. (2023). *Health Data Extraction in Vulnerable Populations*.
7. Smith, J., & Jones, A. (2022). Hyper-Personalized Nutrition: The Role of AI and Big Data. *Nutrition Today*.

8. Zhang, Y. (2023). Research Gaps in AI for Nutritional Health in Low-Resource Settings. *Frontiers in Artificial Intelligence*.
9. Galaxy.ai. (2025). *Free AI Diet Plan Generator*. Retrieved from <https://galaxy.ai/ai-diet-plan-generator>
10. Sustainability Directory. (2025). *AI and Hyper-Personalized Nutrition for Urban Poor*. Retrieved from <https://prism.sustainability-directory.com/scenario/ai-and-hyper-personalized-nutrition-for-urban-poor/>
11. Tribe AI. (2025). *Top AI-Powered Nutrition Apps to Watch in 2025*. Retrieved from <https://www.tribe.ai/applied-ai/ai-nutrition-apps>
12. Zimbabwe Vulnerability Assessment Committee (ZimVAC). (2023). *Urban Livelihoods Assessment Report*.
13. Tawodzera, G. (2012). *Urban food insecurity in Zimbabwe: A case of Gweru*. *Food Security*, 4(2), 253–263.
14. Tawodzera, G. (2019). *Food insecurity and urban poverty in Zimbabwe*. *Development Southern Africa*, 36(3), 311–325.
15. Crush, J.S. and Frayne, G.B., 2011. Urban food insecurity and the new international food security agenda. *Development Southern Africa*, 28(4), pp.527-544.
16. Mavhura, E., 2017. Building resilience to food insecurity in rural communities: Evidence from traditional institutions in Zimbabwe. *Jàmbá: Journal of Disaster Risk Studies*, 9(1), pp.1-9.
17. Bergmann, B., Brenner, J. and Brighouse, H., 2009. *Gender equality: Transforming family divisions of labour*. Verso Books.
18. Tawodzera, G., 2011. Vulnerability in crisis: urban household food insecurity in Epworth, Harare, Zimbabwe. *Food Security*, 3(4), pp.503-520.
19. Motsi, E., 2021. Food processing, handling, and marketing in Zimbabwe. In *Environmental Resilience: Food and the City—Zimbabwe* (pp. 47-67). Singapore: Springer Singapore.
20. Floro, M.S. and Swain, R.B., 2013. Food security, gender, and occupational choice among urban low-income households. *World Development*, 42, pp.89-99.

21. Leung, C.W., Laraia, B.A., Feiner, C., Solis, K., Stewart, A.L., Adler, N.E., and Epel, E.S., 2022. The psychological distress of food insecurity: a qualitative study of the emotional experiences of parents and their coping strategies. *Journal of the Academy of Nutrition and Dietetics*, 122(10), pp.1903-1910.
22. Prasad, G., Padhiary, M., Hoque, A. and Kumar, K., 2025. AI-driven personalized nutrition apps and platforms for enhanced diet and wellness. In *Food in the Metaverse and Web 3.0 Era: Intersecting Food, Technology, and Culture* (pp. 125-158). IGI Global Scientific Publishing.
23. Vasiloglou, M.F., Christodoulidis, S., Reber, E., Stathopoulou, T., Lu, Y., Stanga, Z., and Mougiakakou, S., 2021. Perspectives and preferences of adult smartphone users regarding nutrition and diet apps: web-based survey study. *JMIR mHealth and uHealth*, 9(7), p.e27885.
24. Ellis, F., 2005. Small farms, livelihood diversification, and rural-urban transitions: Strategic issues in Sub-Saharan Africa. *The future of small farms*, 135.
25. Mugo, D., 2017. The technology acceptance model (TAM) and its application to the utilization of mobile learning technologies. *British Journal of Mathematics & Computer Science*.
26. Golden, S.D. and Earp, J.A.L., 2012. Social ecological approaches to individuals and their contexts: twenty years of health education & behavior health promotion interventions. *Health education & behavior*, 39(3), pp.364-372.
27. Göttgens, I. and Oertelt-Prigione, S., 2021. The application of human-centred design approaches in health research and innovation: a narrative review of current practices. *JMIR mHealth and uHealth*, 9(12), p.e28102.
28. Guiné, R.D.P.F., Pato, M.L.D.J., Costa, C.A.D., Costa, D.D.V.T.A.D., Silva, P.B.C.D. and Martinho, V.J.P.D., 2021. Food security and sustainability: discussing the four pillars to encompass other dimensions. *Foods*, 10(11), p.2732.
29. Abraham, C. and Sheeran, P., 2005. The health belief model. *Predicting health behaviour*, 2(1), pp.28-80.
30. FAO (2021) *The State of Food Security and Nutrition in the World 2021*. Rome: Food and Agriculture Organization of the United Nations.

31. Moyo, T. & Nyathi, P. (2023) *Household income and food security in Zimbabwe: A case study of Harare*. African Journal of Food Policy, 18(2), pp. 45–62.
32. Namkhah, Z., Fatemi, S.F., Mansoori, A., Nosratabadi, S., Ghayour-Mobarhan, M. & Sobhani, S.R. (2023). *Advancing sustainability in the food and nutrition system: a review of artificial intelligence applications*. Frontiers in Nutrition, 10, 1295241.
doi:10.3389/fnut.2023.1295241.
33. Ochieng, J., Ogutu, S. & Qaim, M. (2020) *Income and dietary diversity in rural Kenya*. Food Policy, 91, 101833. doi: 10.1016/j.foodpol.2020.101833.
34. Subramanian, S.V., Reddy, K.S. & Popkin, B.M. (2022) *Income growth and nutrition transition in India*. Public Health Nutrition, 25(3), pp. 567–579.
doi:10.1017/S1368980021003456.

