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TECH SOLUTIONS ON EFFECTIVENESS OF MONITORING AND EVALUATION IN HEALTH PROGRAMS IN KENYA

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ABSTRACT

Despite significant investments in health programs in Nairobi County, Kenya, the effectiveness of monitoring and evaluation (M&E) practices remains a critical challenge, often hindered by outdated methods and inadequate technological support. This study investigated the impact of technological tools on the effectiveness of M&E practices in these health programs. As health programs increasingly rely on accurate and timely data to guide decision-making and improve outcomes, the integration of advanced technological tools becomes essential. This research focused on two key technological areas: data collection tools and data analysis tools and how they influence the effectiveness of M&E processes. A descriptive research design was adopted for the study, targeting a population of 60 management-level employees working across various health programs. Given the relatively small size of the population, a census sampling approach was used, ensuring that all eligible participants were included in the study. Data was collected using a structured questionnaire, which combined both closed-ended and open-ended questions to gather comprehensive insights from respondents. The collected data was analyzed using descriptive and inferential statistical techniques, including regression analysis, to explore the relationships between the use of technological tools and the effectiveness of M&E practices. The findings provide valuable insights for policymakers, health program managers, and technology developers, highlighting the importance of investing in technology and capacity building to maximize the effectiveness of M&E practices in resource-constrained settings. This research contribute to the broader understanding of how technology can be leveraged to improve public health outcomes. The findings revealed that technological components had a statistically significant and positive relationship with M&E effectiveness. Among them, data analysis tools emerged as the strongest predictor, followed by data collection tools. The study concludes that integrating digital tools at all stages of the M&E cycle enhances data accuracy, timeliness, decision-making, and stakeholder communication. The study recommends strategic investments in analytical capacity, interoperable data systems, digital literacy training, and collaborative platforms to strengthen M&E performance in health programs. These findings provide practical guidance for policymakers, development partners, and program managers aiming to enhance evidence-based decision-making through technology-enabled M&E systems.

Key Words: Tech Solutions, Monitoring and Evaluation, Health Programs, M&E practices, data collection tools, data analysis tools

Background of the Study

In the rapidly evolving field of health care, Monitoring and Evaluation (M&E) are essential processes that ensure programs are effective, accountable, and capable of delivering the intended outcomes (Topol, 2019). As the demand for robust health programs increases, so does the need for innovative M&E practices. Technological advancements have ushered in a new era for M&E, transforming traditional methods and offering unprecedented capabilities for data collection, analysis, and dissemination. These technologies are particularly vital in resource-limited settings, where conventional methods often fall short (Mehl & Labrique, 2019).

The advent of technological solutions has revolutionized M&E, providing essential insights that guide decision-making, enhance program effectiveness, and ensure accountability (Mehl & Labrique, 2019). The integration of technology in M&E has gained considerable attention, especially in health programs that operate in resource-limited settings (Kruse et al., 2019). The influence of these advancements is profound, reshaping how health programs are designed, implemented, and evaluated.

Statement of the Problem

Despite the potential benefits of tech solutions in Monitoring and Evaluation (M&E) practices, their influence on the effectiveness of health programs in Kenya remains underexplored and underutilized. The health sector in Kenya faces significant challenges that hinder the full realization of these benefits. Limited resources, fragmented data systems, and inadequate technical capacity are major obstacles that impede the demonstration of long-term impact in health programs (Mwangi et al., 2021).

Data fragmentation is a critical issue in Kenya's health sector. A study by the Ministry of Health (2020) found that 60% of health facilities in Kenya still rely on paper-based data collection methods, which contribute to data fragmentation and inefficiencies. The lack of interoperability between different health information systems further exacerbates this problem, making it difficult to compile and analyze comprehensive health data. Technical capacity and infrastructure constraints also pose significant challenges. According to the World Health Organization (2019), only 40% of health facilities in Kenya have reliable internet access, and many rural areas suffer from inadequate power supply. This lack of infrastructure limits the ability to implement and utilize advanced tech solutions effectively. Furthermore, a survey by the Kenya Health Informatics Association (2021) revealed that 70% of health workers reported insufficient training in using digital health tools, highlighting a significant skills gap that needs to be addressed.

Resistance to change and the adoption of new technologies is another major challenge. Health workers and stakeholders often show reluctance to transition from traditional methods to tech-based solutions due to a lack of familiarity and confidence in these new tools. A report by the Kenya Medical Research Institute (2020) indicated that 55% of health workers were hesitant to adopt new technologies, citing concerns about complexity and reliability. Privacy and data security concerns also limit the adoption of tech solutions. With the increasing volume of health data being collected and stored electronically, ensuring data privacy and security has become paramount. However, the Kenya Health Data Protection Act (2019) implementation remains inconsistent, and a significant number of health facilities lack robust data security measures. This poses risks of data breaches and undermines trust in digital health solutions.

These challenges necessitate a systematic evaluation of how tech solutions impact data collection, analysis, and decision-making processes within health programs. By examining the influence of these technologies, particularly within the context of the Kenya Medical Research Institute (KEMRI), this study aims to identify best practices and propose strategies to overcome existing barriers. The findings provide valuable insights into enhancing the effectiveness of M&E practices, thereby improving health outcomes in Kenya.

Objectives of the Study

The study was guided by a general objective and four specific objectives.

General Objective

To examine the influence of tech solutions on effectiveness of monitoring and evaluation in health programs in Kenya.

Specific Objectives

The study was guided by the following specific objectives;

i. To examine the influence of data collection tools on effectiveness of monitoring and evaluation in health programs in Kenya.
ii. To assess the influence of data analysis tools on effectiveness of monitoring and evaluation in health programs in Kenya.

LITERATURE REVIEW

Theoretical Review

Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM) was developed by Davis (1989) and is one of the most influential models used to explain and predict user acceptance of technology. The model posits that two primary factors—perceived usefulness (PU) and perceived ease of use (PEOU)—determine an individual's intention to use a technology, which in turn influences actual usage behavior. Perceived usefulness is defined as the degree to which a person believes that using a particular system would enhance their job performance, while perceived ease of use refers to the degree to which a person believes that using the system would be free of effort (Davis, 1989).

TAM has been widely supported through empirical research across various contexts, including health information systems, e-learning platforms, and mobile technologies (Venkatesh & Davis, 2000; King & He, 2006). Venkatesh and Davis (2000) extended the model to include additional factors such as social influence and cognitive instrumental processes, which further reinforced its robustness. In the context of health programs, studies have shown that TAM effectively predicts the acceptance of electronic health records (Holden & Karsh, 2010) and other data collection tools in healthcare settings (Mortenson & Vidgen, 2019).

Despite its widespread application, TAM has faced several critiques. One major critique is that it oversimplifies the complexities of human-computer interaction by focusing predominantly on individual-level factors, thus neglecting broader organizational, social, and cultural influences (Bagozzi, 2007). Additionally, TAM has been criticized for its deterministic nature, which assumes that perceived usefulness and ease of use will inevitably lead to technology acceptance, without considering the possibility of resistance or rejection (Chuttur, 2009).

Despite these critiques, TAM remains valuable to the current study as it provides a clear and testable framework for understanding the factors that influence the adoption of data collection tools in health programs. By identifying and measuring perceived usefulness and ease of use, the study can offer insights into how these perceptions impact the effectiveness of monitoring and evaluation (M&E) processes in health programs. The model's simplicity and empirical support make it a practical tool for assessing technology acceptance within the specific context of Kenyan health programs.

Diffusion of Innovations Theory

The Diffusion of Innovations Theory was introduced by Rogers (1962) and describes how new ideas, technologies, and practices spread within a society or organization. The theory outlines five key attributes that influence the rate of adoption: relative advantage, compatibility, complexity, trialability, and observability. According to Rogers, the adoption of an innovation follows an S-curve, with early adopters leading the way, followed by the majority, and finally, laggards.

Rogers' theory has been widely supported across various fields, including healthcare, where it has been used to explain the adoption of new medical technologies and practices (Greenhalgh, Robert, Macfarlane, Bate, & Kyriakidou, 2020). In the context of health programs, the theory has been instrumental in understanding how innovations such as electronic health records and telemedicine are adopted by healthcare providers (Berwick, 2023). The theory's emphasis on communication channels and social systems highlights the importance of organizational culture and peer influence in the adoption process (Rogers, 2023).

Despite its utility, the Diffusion of Innovations Theory has faced critiques for its linear and deterministic view of the adoption process (Fichman, 1992). Critics argue that the theory oversimplifies the complex social and organizational dynamics that influence the adoption of innovations, particularly in diverse and resource-constrained settings (Lyytinen & Damsgaard, 2001). Additionally, the theory has been criticized for its lack of focus on the role of power, politics, and resistance within organizations, which can significantly impact the diffusion of innovations (Tornatzky & Klein, 1982).

Despite these critiques, the Diffusion of Innovations Theory remains valuable to the current study as it provides a robust framework for understanding how data analysis tools are adopted in health programs. By examining the attributes of these tools—such as their relative advantage and compatibility with existing systems—the study can identify factors that facilitate or hinder their adoption within health programs. This understanding can help design strategies to improve the uptake of innovative data analysis technologies, ultimately enhancing the effectiveness of M&E processes.

Conceptual Framework

Orodho (2012) defines a conceptual framework as a graphical or a diagrammatical model of presentation of the relationship between variables in the study. It is a road map that the study intends to follow with the aim of looking for answers to the problems raised by the research questions. The conceptual framework in this paper shows the relationship between the independent and dependent variables. The framework helps the reader see at a glance the proposed relationships between the variables in the study graphically or diagrammatically. The independent variables are mobile surveys, digital dashboards, big data and Artificial Intelligence (AI), and geospatial mapping while the dependent variable is effectiveness of monitoring and evaluation in health programs in Kenya.

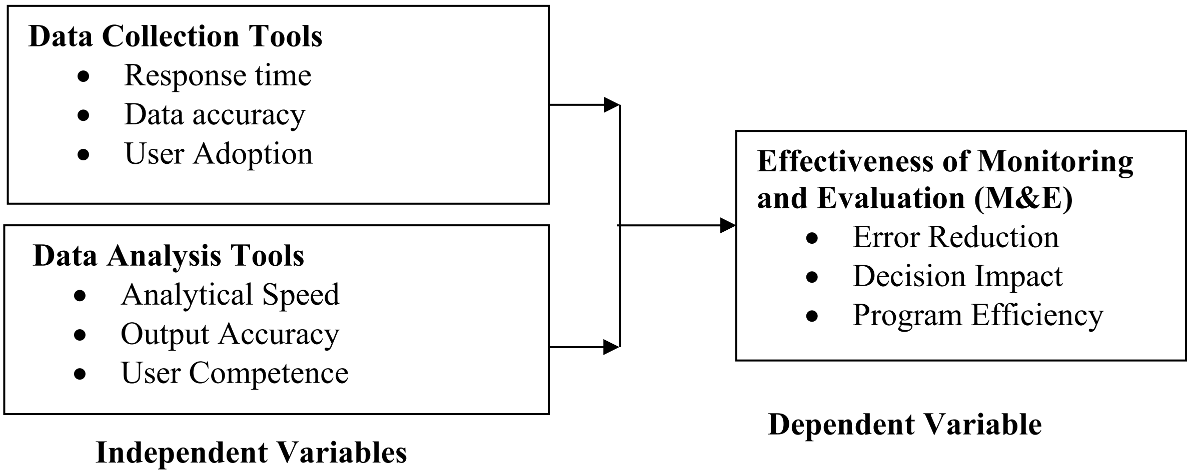

Figure 2. 1: Conceptual Framework

Data Collection Tools

Data collection tools refer to the various methods, devices, or systems used to gather information in monitoring and evaluation (M&E) processes. These tools are vital in collecting accurate, timely, and relevant data, which form the backbone of any M&E system. In your framework, the effectiveness of these tools is evaluated through three key indicators: response time, data accuracy, and user adoption. As noted by Ahmad and Kasim (2019), efficient data collection tools are essential for gathering reliable data, which is critical for making informed decisions in health programs.

The importance of response time in data collection cannot be overstated, especially in the context of health programs where timely data is crucial for decision-making and intervention. The faster data is collected, the quicker it can be analyzed and acted upon, which is vital in scenarios such as disease outbreaks or emergency response situations. Recent studies have highlighted that digital data collection tools, particularly mobile-based surveys, have significantly reduced response times compared to traditional paper-based methods (Ahmad & Kasim, 2019). This has been particularly effective in remote areas where access to healthcare facilities is limited, allowing for real-time data collection and transmission.

Data accuracy is another critical factor, as it directly impacts the quality of the conclusions drawn from the data. Inaccurate data can lead to erroneous conclusions, which in turn can affect program outcomes. For instance, Wamba et al. (2020) discussed how inaccuracies in data collection can lead to flawed public health policies and inefficient resource allocation. The use of automated and digital tools has been shown to improve data accuracy by reducing human errors commonly associated with manual data entry.

User adoption is equally important as it determines the extent to which these tools are utilized in the field. Tools that are not user-friendly or that require extensive training are less likely to be adopted by field workers, which can undermine the effectiveness of M&E efforts. Heckman & Geissler (2020) emphasized that for data collection tools to be successful, they must be designed with the end-user in mind, incorporating intuitive interfaces and minimal complexity to encourage widespread adoption. They also noted that user adoption is influenced by the perceived ease of use and the perceived usefulness of the technology, aligning with the Technology Acceptance Model (TAM).

Effective data collection tools that ensure rapid response times, high data accuracy, and wide user adoption are critical for enhancing the effectiveness of M&E systems. They contribute to reducing errors, making timely and informed decisions, and improving overall program efficiency. By ensuring that data is accurate, timely, and collected through user-friendly tools, health programs can enhance the reliability of their M&E processes and ultimately improve program outcomes.

Data Analysis Tools

Data analysis tools refer to the software and methodologies used to process and analyze collected data, turning it into actionable insights that drive decision-making in M&E processes. In your framework, the effectiveness of data analysis tools is evaluated based on three indicators: analytical speed, output accuracy, and user competence. As Batra et al. (2020) highlight, the role of data analysis tools is increasingly important in health programs where quick and accurate data processing can lead to better decision-making and program outcomes

Analytical speed is critical in health programs where timely decisions are essential for effective interventions. The ability to process large volumes of data quickly allows program managers to respond to emerging issues promptly (Batra et al., 2020). The integration of advanced data analysis tools, such as machine learning algorithms and artificial intelligence (AI), has significantly improved analytical speed, enabling real-time data processing and faster decision-making (Chen et al., 2019).

Output accuracy refers to the precision of the results generated by data analysis tools. Accurate analysis is fundamental for making informed decisions that positively impact program outcomes. Misleading or inaccurate results can lead to incorrect conclusions, resulting in poor program implementation and resource allocation. As noted by Chen et al. (2019), the use of sophisticated algorithms and robust statistical techniques can enhance the accuracy of data analysis outputs, ensuring that M&E processes are based on reliable data.

User competence is another vital factor, as the effectiveness of data analysis tools is largely dependent on the ability of users to operate them effectively. Tools that are overly complex or require specialized skills may not be fully utilized, limiting their potential benefits. Bajwa et al. (2021) argue that training and capacity building are essential for ensuring that users can leverage data analysis tools effectively. They also suggest that user-friendly interfaces and built-in guidance features can help improve user competence and tool adoption.

Data analysis tools that provide rapid, accurate outputs and are easy for users to operate are essential for the effectiveness of M&E processes. By enabling quick and accurate analysis of data, these tools contribute to timely and informed decision-making, reducing the likelihood of errors and enhancing the overall efficiency of health programs.

Effectiveness of Monitoring and Evaluation (M&E)

The effectiveness of M&E is assessed based on its ability to reduce errors, impact decision-making, and improve program efficiency. These indicators are critical in ensuring that health programs achieve their intended outcomes and use resources efficiently. According to Cousins and Bourgeois (2019), the effectiveness of M&E systems is fundamental in guiding program interventions and ensuring that resources are optimally allocated to achieve desired outcomes.

Reducing errors in M&E processes is fundamental to ensuring that decisions are based on accurate and reliable data. Cousins & Bourgeois (2019) emphasize that errors in data collection, analysis, or reporting can lead to flawed conclusions and ineffective program interventions. They argue that robust M&E systems that incorporate checks and balances, regular audits, and quality assurance processes are essential for minimizing errors and improving data integrity.

The impact of M&E on decision-making is another critical indicator of its effectiveness. M&E systems that provide timely and accurate data enable program managers to make informed decisions that positively impact program outcomes (Patton, 2020). By providing insights into program performance, areas for improvement, and potential risks, effective M&E systems help ensure that programs are responsive to changing needs and conditions.

Program efficiency is closely linked to the effectiveness of M&E systems. Efficient programs use resources wisely, achieve their goals within budget and on time, and deliver high-quality outcomes. Effective M&E systems contribute to program efficiency by identifying inefficiencies, monitoring progress, and providing feedback that allows for course corrections (Cousins & Bourgeois, 2019). They ensure that resources are allocated effectively and that program objectives are met in a timely manner.

Empirical Review

Data Collection Tools

The study conducted by Aiello, Renson, and Zivich (2020) explores the use of participatory surveillance systems for monitoring public health trends in the USA. It highlights the significant impact of real-time data collection and individual-level monitoring, which have substantially improved data accuracy and timeliness, thereby enhancing public health response capabilities. The study employed a mixed-methods design, combining quantitative surveys with qualitative interviews. The target population included public health officials, community health workers, and participants from various public health programs. A stratified random sampling technique was used to select a sample size of 300 participants. Data collection involved structured questionnaires for the quantitative survey and semi-structured interviews for qualitative insights. Quantitative data were analyzed using descriptive and inferential statistics, while qualitative data were subjected to thematic analysis. The study identifies key challenges such as data privacy concerns and the need for continuous engagement with participants.

Assefa et al. (2019) examined the impact of participatory learning and action on health outcomes in Ethiopia, particularly focusing on maternal and child health programs. The study underscores the importance of community engagement in achieving accurate data collection and program sustainability. Employing a case study approach, the research combined focus group discussions, in-depth interviews, and health records review. The target population included healthcare providers, community health workers, and program beneficiaries, with a purposive sampling technique selecting 150 participants. Data analysis involved both qualitative thematic analysis and quantitative methods. Despite the positive outcomes in community engagement, the study calls for more robust data management systems to ensure the effective use of collected data.

Kebede, Zegeye, and Taye (2020) conducted a study to assess the effectiveness of mobile data collection tools in enhancing the quality of data collected in public health programs in Ethiopia. The study utilized a cross-sectional research design targeting public health workers who had transitioned from paper-based to mobile data collection systems. A sample of 250 respondents was selected through random sampling. The data collection involved surveys and key informant interviews, with the analysis conducted using both descriptive statistics and thematic analysis. The findings indicated a significant improvement in data accuracy and response time with the adoption of mobile tools, although challenges such as technical glitches and resistance to technology were noted.

Wu and Raghupathi (2019) explored the impact of electronic data collection tools on the efficiency of health information management in community health programs in China. The study used a mixed-methods approach, incorporating both quantitative surveys and qualitative interviews with healthcare workers and program managers. A sample of 300 participants was chosen using stratified random sampling. The analysis revealed that electronic data collection significantly improved the timeliness and completeness of data, which in turn enhanced the overall effectiveness of M&E processes. However, the study also pointed out the need for ongoing training and support for users to fully realize the benefits of these tools.

Wambui, Mwangi, and Kariuki (2019) conducted a study in Kenya to evaluate the effectiveness of mobile data collection tools in monitoring maternal health programs in Nairobi County. The study used a descriptive research design, targeting healthcare workers and program administrators. A sample of 200 respondents was selected using purposive sampling. Data were collected through structured questionnaires and interviews, and analyzed using both quantitative and qualitative methods. The findings indicated that mobile data collection tools significantly improved data accuracy and response times, leading to better program outcomes. However, challenges such as limited technological infrastructure and resistance to change were noted, emphasizing the need for capacity building and infrastructure development.

Data Analysis Tools

Batra et al. (2020) explored the impact of data analysis tools on decision-making speed and accuracy in healthcare programs in India. The study employed a quantitative research design, using a survey method to collect data from 400 healthcare professionals. The sample was selected using stratified random sampling. Data were analyzed using descriptive and inferential statistics. The findings revealed that advanced data analysis tools significantly improved the speed and accuracy of decision-making, leading to better health outcomes. The study also highlighted the importance of training programs to enhance user competence in using these tools.

Chen et al. (2019) conducted a study on the effectiveness of machine learning algorithms in improving the accuracy of data analysis in public health programs in China. The research employed a mixed-methods design, involving a survey of 300 healthcare data analysts and in-depth interviews with program managers. The sample was selected through random sampling. The study found that machine learning algorithms significantly improved the accuracy of data analysis, leading to more precise health interventions. However, challenges related to the interpretability of the algorithms and the need for specialized skills were identified.

Gupta and Nath (2021) investigated the role of artificial intelligence (AI) tools in enhancing the analytical capabilities of health information systems in India. The study utilized a cross-sectional research design, targeting IT professionals and healthcare administrators. A sample of 250 respondents was selected through purposive sampling. Data were collected using online surveys and focus group discussions, and analyzed using both quantitative and qualitative methods. The study found that AI tools significantly enhanced the analytical speed and output accuracy of health information systems. However, the researchers noted that the high cost of implementing AI tools could be a barrier for resource-constrained settings.

Bajwa et al. (2021) examined the impact of user competence on the effectiveness of data analysis tools in healthcare settings in Pakistan. The study employed a descriptive research design, using questionnaires and interviews to collect data from 350 healthcare providers. The sample was selected through stratified random sampling. Data analysis involved both descriptive statistics and thematic analysis. The findings indicated that higher user competence was associated with more effective use of data analysis tools, leading to better program outcomes. The study recommended ongoing training and capacity-building initiatives to enhance user competence.

Muchiri et al. (2019) conducted a study in Kenya to assess the effectiveness of data analysis tools in improving the management of health programs in Nairobi County. The study employed a cross-sectional research design, targeting healthcare providers and program administrators. A sample of 250 respondents was selected using purposive sampling. Data were collected through structured questionnaires and interviews, and analyzed using both quantitative and qualitative methods. The findings indicated that advanced data analysis tools significantly improved the accuracy and speed of decision-making in health programs, leading to better resource allocation and program outcomes. However, the study also identified challenges related to user competence and the need for continuous training and support.

RESEARCH METHODOLOGY

In this study, a descriptive research design was employed. According to Lavrakas (2008), a descriptive survey research design is a comprehensive method used for collecting data from a representative sample of individuals by using instruments such as structured questionnaires and interviews. The unit of observation was the management-level employees within these health programs, including roles such as Program Managers, Monitoring and Evaluation Officers, and Health Information System Managers. These employees are directly involved in the day-to-day operations and strategic decisions of the programs, making them the most relevant sources of information for understanding the effectiveness of management r5practices. By collecting data from these individuals, the study accurately assessed how management practices influence the success of the health programs, thereby providing valuable insights that are specific to the operational context of each program. Therefore, the target population was 60 management employees.

Table 1: Target Population

Health Program	Number of Employees
National HIV/AIDS Control Program	6
Malaria Control Program	6
Maternal and Child Health (MCH) Program	6
Tuberculosis (TB) Control Program	6
Nutrition and Food Security Program	6
Non-Communicable Diseases (NCD) Prevention Program	6
Reproductive Health Program	6
Community Health Strategy	6
Expanded Program on Immunization (EPI)	6
Water, Sanitation, and Hygiene (WASH) Program	6
Total	**60**

Given the relatively small size of the target population in this study, a census sampling approach was used. Ngechu (2018) suggests that census sampling is an appropriate method when dealing with a small population size, as it ensures that every individual within the population is represented, thereby minimizing sampling error and enhancing the reliability of the findings. For this study, the primary data was collected using a questionnaire. The questionnaire used in this study included both open-ended and closed-ended questions, allowing respondents to express their views comprehensively while also enabling the researcher to collect quantifiable data. The use of Likert scales was employed to capture the intensity of respondents' opinions on the effectiveness of various technological tools in M&E practices (Chandran, 2020). The data collected in this study included both quantitative and qualitative information. Quantitative data was analyzed using the Statistical Package for Social Scientists (SPSS), which was used to generate descriptive statistics (such as frequencies, means, and standard deviations) and inferential statistics (including regression and correlation analyses).

RESEARCH FINDINGS AND DISCUSSION

The study initially targeted a census of 60 management-level employees working in various health programs across Kenya. However, a pilot group of 6 respondents was excluded from the final sample to ensure the integrity of the research results. This adjustment brought the effective study sample size to 54 participants. Out of the 54 questionnaires distributed, 48 were correctly completed and returned, yielding a response rate of 88.9%. This is considered excellent for academic research in the social sciences, as a response rate above 70% is deemed sufficient for generating reliable and generalizable findings (Mugenda & Mugenda, 2003). The high response rate ensured that the data collected was representative of the target population and suitable for both descriptive and inferential statistical analysis.

Descriptive Analysis of Study Variables

This section provides a descriptive statistical analysis of the responses collected on the core variables of the study: data collection tools, data analysis tools. These variables represent the technological dimensions explored to determine their influence on the effectiveness of Monitoring and Evaluation (M&E) in health programs in Kenya. The study utilized a structured questionnaire in which respondents rated their level of agreement with various statements using a five-point Likert scale. The Likert scale was coded such that 1 represented "Strongly Disagree," 2 represented "Disagree," 3 was "Neutral," 4 indicated "Agree," and 5 indicated "Strongly Agree."

To analyze the data, the study computed mean scores and standard deviations for each item within the variables. The mean score reflects the average perception of respondents toward each statement, while the standard deviation indicates the degree of agreement or variability in those responses. A lower standard deviation suggests higher consensus among participants, whereas a higher value indicates more variation in perceptions. For accurate interpretation and alignment with the Likert scale, the following ranges were used: a mean score of 1.00 to 1.49 indicates Strong Disagreement, 1.50 to 2.49 represents Disagreement, 2.50 to 3.49 reflects a Neutral position, 3.50 to 4.49 signifies Agreement, and 4.50 to 5.00 denotes Strong Agreement. These classifications guide the interpretation of how respondents perceive the influence of each technological tool on the effectiveness of M&E systems. Each subsection below focuses on one of the study variables and interprets the findings accordingly.

Data Collection Tools

This subsection presents descriptive findings on the influence of data collection tools on the effectiveness of Monitoring and Evaluation (M&E) activities in health programs. Data collection tools, in this context, include mobile devices, digital survey applications, and electronic data capture platforms that support field-level data acquisition. Respondents evaluated five statements using a five-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree), reflecting their perceptions of accuracy, efficiency, user experience, and error reduction related to these tools.

Table 2: Descriptive Statistics for Data Collection Tools

Statement	Mean	Std. Dev.
The data collection tools used in our program are user-friendly.	3.979	0.788
The tools help reduce the time spent on data entry.	4.063	0.751
The data collection tools enhance the accuracy of data collected.	4.271	0.611
The tools are reliable in capturing all necessary program information.	4.104	0.732
Staff receive adequate training on how to use data collection tools effectively.	3.938	0.774
The data collection tools are compatible with other systems used in the program.	4.021	0.689
Regular updates are provided to improve the functionality of the data collection tools.	3.875	0.767
The tools support real-time data capture and reporting.	4.188	0.663
Aggregate Score	**4.121**	**0.709**

The results indicate that respondents generally perceive data collection tools as beneficial to the effectiveness of M&E processes. The highest-rated item was the ability of these tools to enhance the accuracy of data collected (M = 4.271, SD = 0.611), which reflects a strong confidence in the reliability of digital tools over traditional methods such as paper-based forms. The tools' capacity to support real-time data capture and reporting also received a high score (M = 4.188, SD = 0.663), suggesting that respondents appreciate the immediacy with which field data can be transmitted and acted upon. Reducing the time spent on data entry (M = 4.063, SD = 0.751) and ensuring reliability in capturing all necessary program information (M = 4.104, SD = 0.732) were also strongly agreed upon. These findings highlight the efficiency gains digital tools offer in minimizing workload and ensuring comprehensive data collection in dynamic field environments.

The perception that data collection tools are compatible with other systems used in programs (M = 4.021, SD = 0.689) suggests that integration between tools is generally effective, a critical feature for streamlined data flow across organizational departments. However, the slightly lower score for user-friendliness (M = 3.979, SD = 0.788) indicates that while the tools are generally accessible, there may still be minor challenges for some users, perhaps due to interface design or varying levels of digital literacy. Two items—training adequacy (M = 3.938, SD = 0.774) and frequency of system updates (M = 3.875, SD = 0.767)—received the lowest ratings, though still within the agreement range. These results point to areas where improvement is needed. While the tools themselves are generally well-received, ensuring that staff are consistently trained and that tools are regularly improved is critical for long-term success and adaptability of M&E systems.

Overall, the aggregate mean score of 4.121 (SD = 0.709) indicates strong agreement that data collection tools significantly contribute to effective M&E practices. These tools enhance data quality, support real-time reporting, and offer operational efficiencies, making them a vital component of technology-enabled M&E systems in health programs. These findings are consistent with Keter (2022) that digital data collection tools such as ODK and KoboToolbox significantly enhance data accuracy, minimize delays in reporting, and reduce manual errors in field evaluations. The results also reinforce observations by Kurgat and Okello (2021), who noted that mobile technologies play a critical role in increasing operational efficiency and response time in real-time M&E systems. The high agreement levels found in this study support these earlier conclusions, confirming that data collection tools are not only widely adopted but are also seen as instrumental in improving the credibility and timeliness of M&E functions in Kenya's health programs.

Data Analysis Tools

This section presents the descriptive analysis of how data analysis tools influence the effectiveness of Monitoring and Evaluation (M&E) in health programs. These tools include statistical software, spreadsheets, dashboards, and other digital platforms used to transform raw data into meaningful insights. Respondents evaluated eight statements related to the effectiveness, usability, training, compatibility, and decision-support capability of these tools. Each item was rated on a 5-point Likert scale where 1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, and 5 = Strongly Agree.

Table 3: Descriptive Statistics for Data Analysis Tools

Statement	Mean	Standard Deviation
The data analysis tools used in our program are effective in generating accurate results.	4.188	0.643
Our data analysis tools are compatible with the data formats we use.	4.021	0.712
Data analysis tools allow for in-depth analysis and reporting.	4.125	0.712
We receive adequate training on how to use data analysis tools effectively.	3.896	0.774
Data analysis tools help in identifying trends and patterns in the data.	4.229	0.627
Our analysis tools are regularly updated to incorporate new features.	3.875	0.768
The tools we use for data analysis are easy to learn and apply.	3.854	0.796
Data analysis tools support decision-making processes in our program.	4.063	0.728
Aggregate Score	**4.058**	**0.710**

The results In Table 3 show a high level of agreement among respondents on the value of data analysis tools in enhancing M&E processes. The highest-rated item was the role of analysis tools in identifying trends and patterns in data (M = 4.229, SD = 0.627), which reflects the critical importance of analytical tools in generating meaningful insights for program evaluation. This was closely followed by their effectiveness in producing accurate results (M = 4.188) and enabling in-depth reporting (M = 4.125), showing strong confidence in the analytical power of the tools currently in use. Respondents also acknowledged that data analysis supports decision-making within programs (M = 4.063), underscoring the role of analytics in translating findings into actionable strategies. Compatibility with data formats (M = 4.021) was positively rated, suggesting that the tools integrate well with existing systems and datasets, minimizing conversion or formatting challenges.

However, some areas received slightly lower but still positive responses. Training adequacy on the use of analytical tools (M = 3.896), tool updates (M = 3.875), and ease of learning and use (M = 3.854) scored the lowest among the eight indicators, although they remained within the agreement range. These results imply that while the tools themselves are effective, there is room for improvement in building user capacity, ensuring tools remain current, and simplifying interfaces for broader adoption. The overall aggregate mean score of 4.058 (SD = 0.710) indicates that respondents strongly believe data analysis tools significantly enhance the effectiveness of M&E. By enabling data interpretation, trend identification, and strategic decision-making, these tools serve as a cornerstone for data-driven health program management.

These results support the findings presented by Kurgat and Okello (2021), who emphasized that analytical tools such as SPSS and Tableau improve the validity of M&E reports by reducing human error and promoting standardized interpretations. Additionally, Chebii and Ndung'u (2021) noted that integrating data analysis software into project cycles not only improves reporting speed but also enables better tracking of health indicators. The findings in this study affirm these conclusions, suggesting that digital analysis platforms are not just supplementary tools but are becoming core components of efficient, evidence-based M&E systems within Kenya's health programs.

Effectiveness of Monitoring and Evaluation

This subsection presents descriptive statistics on the dependent variable—effectiveness of Monitoring and Evaluation (M&E) in health programs. Effectiveness refers to the extent to which M&E systems achieve their intended purpose, including improving program decision-making, reducing reporting errors, enhancing timeliness, and ensuring accountability. Respondents were asked to rate five statements assessing key indicators of M&E effectiveness using a 5-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree).

Table 4: Descriptive Statistics for Effectiveness of M&E

Statement	Mean	Standard Deviation
The M&E system supports evidence-based decision-making in the organization.	4.188	0.682
The system improves the timeliness of data reporting and analysis.	4.146	0.701
M&E processes reduce program implementation errors.	4.021	0.728
M&E findings contribute directly to program adjustments or redesign.	3.938	0.764
M&E results are used to enhance accountability among teams and partners.	3.896	0.790
Aggregate Score	**4.038**	**0.733**

The findings indicate that respondents generally view their M&E systems as effective. The highest-rated item was the support for evidence-based decision-making (M = 4.188, SD = 0.682), underscoring the critical role M&E systems play in generating credible data to guide interventions. Timeliness of data reporting (M = 4.146, SD = 0.701) also scored highly, reflecting improvements in how quickly program teams access and act on evaluation findings. Reducing program errors through M&E (M = 4.021, SD = 0.728) and contributions to program redesign (M = 3.938, SD = 0.764) were also positively rated, though slightly lower. This implies that while M&E data is being used in shaping programs, there is still room to strengthen how findings are incorporated into strategic decisions. The use of M&E for accountability purposes received a mean score of (M = 3.896, SD = 0.790), which, though within the agreement range, suggests some variability in perceptions—possibly due to organizational or donor dynamics.

Overall, the aggregate mean score of M = 4.038 (SD = 0.733) shows that respondents perceive M&E practices as generally effective within the health programs studied. The results mirror the assertions made by Kurgat and Okello (2021), who observed that integrating digital M&E practices significantly enhances program responsiveness, accountability, and planning accuracy. Furthermore, Omondi (2022) emphasized that M&E is only effective when its findings are fed back into programmatic decisions—a view reflected in this study, where most respondents agree that M&E results contribute meaningfully to program redesign. These findings reinforce the notion that strong M&E systems, supported by appropriate technological tools, play a central role in driving data-informed decision-making and continuous improvement in Kenya's health sector.

Correlation Analysis

This section presents a Pearson correlation analysis to evaluate the strength and direction of relationships between each independent variable (data collection tools, data analysis tools) and the dependent variable—effectiveness of Monitoring and Evaluation (M&E) in health programs. Pearson's correlation coefficient (r) indicates the degree of linear relationship between variables, ranging from –1 (perfect negative) to +1 (perfect positive). In this study, all variables demonstrated strong positive relationships (r > 0.5) with M&E effectiveness, and all correlations were statistically significant at the 0.01 level (2-tailed).

Table 5: Pearson Correlation Matrix

Variables		Data Collection Tools	Data Analysis Tools	Effectiveness of M&E
Data Collection Tools	Pearson Correlation	1.000		
	Sig. (2-tailed)			
	N	48		
Data Analysis Tools	Pearson Correlation	0.584	1.000	
	Sig. (2-tailed)	0.095		
	N	48	48	
Effectiveness of M&E	Pearson Correlation	0.576**	0.603**	1.000
	Sig. (2-tailed)	0.000	0.000	
		48	48	48

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

The correlation between data collection tools and M&E effectiveness was strong and positive ($r = 0.576$, $p < 0.05$), indicating that as the use and functionality of digital data collection tools increase, so does the effectiveness of M&E practices. This suggests that mobile apps, electronic forms, and real-time data capture platforms contribute significantly to improving data accuracy, reducing errors, and enhancing the timeliness of field reporting. This finding reinforces the conclusion by Keter (2022), who reported that digital data collection tools like ODK and KoboToolbox significantly improve efficiency and minimize manual input errors. These tools help create reliable data streams that serve as the foundation for robust decision-making and timely program adjustments in health interventions.

Among all the independent variables, data analysis tools showed the strongest positive correlation with M&E effectiveness ($r = 0.603$, $p < 0.05$). This strong association indicates that the more effectively tools such as SPSS, Excel, and Power BI are used to analyze data, the more effective M&E systems become. This reflects the critical importance of transforming raw data into actionable insights for planning, accountability, and improvement. Kurgat and Okello (2021) emphasized that data analysis tools enhance the precision of evaluation findings and ensure standardized interpretations, thus reducing human bias in reporting. These tools also allow for easy visualization of KPIs and trends, helping program managers to identify gaps and take corrective action swiftly.

Regression Analysis

This section presents a multiple linear regression analysis to examine the extent to which the four independent variables—data collection tools, data analysis tools—predict the effectiveness of Monitoring and Evaluation (M&E) in health programs. The model tests whether technological solutions significantly contribute to improved M&E outcomes, including accuracy, timeliness, and data-informed decision-making. The regression was computed using the enter method at a 95% confidence level, with statistical significance considered at $p < 0.05$.

Table 6: Regression Coefficients

Predictor Variable	Unstandardized B	Std. Error	Beta (β)	t	Sig. (p)
(Constant)	0.918	0.255	–	3.600	0.001
Data Collection Tools	0.267	0.084	0.282	3.179	0.003
Data Analysis Tools	0.312	0.080	0.342	3.900	0.000

The coefficient for data collection tools (β = 0.267, $p = 0.003$) indicates a statistically significant and positive relationship with M&E effectiveness. This means that an increase in the use and effectiveness of digital data collection tools is associated with a corresponding improvement in M&E performance. These findings are consistent with Keter (2022), who reported that tools such as KoboToolbox and ODK have transformed field-level data accuracy and responsiveness, leading to more credible and timely program assessments.

Data analysis tools emerged as the strongest predictor (β = 0.312, $p < 0.001$) of M&E effectiveness. This implies that improved analytical capability has the greatest impact on turning raw data into actionable insights. Tools such as SPSS, Power BI, and Excel enhance data interpretation and visualization, thus enabling faster, evidence-based decisions. This outcome supports the conclusions of Kurgat and Okello (2021), who emphasized the role of analytical platforms in streamlining program evaluation processes and improving the accuracy of impact assessments.

Conclusions

The study concludes that data collection tools have a significant positive impact on the effectiveness of M&E. Digital tools such as mobile applications and electronic forms were found to improve data accuracy, reduce field errors, and enhance the timeliness of reporting. The results revealed strong levels of agreement among respondents, with a statistically significant correlation and predictive influence. These findings suggest that the integration of efficient data collection technologies at the field level is essential for improving the reliability and speed of M&E activities. Well-designed and accessible digital collection tools form the foundation for all subsequent M&E processes, thereby increasing the overall efficiency and responsiveness of health programs.

Data analysis tools emerged as the most influential factor in predicting M&E effectiveness. The study concludes that analytical platforms empower M&E teams to convert raw data into actionable insights through timely interpretation, visualization, and performance tracking. High ratings from respondents, alongside the strongest correlation and regression coefficient, demonstrated that analytical capacity is central to meaningful evaluation. The implication is that M&E systems must prioritize not only data collection and storage but also the ability to analyze and interpret information in a way that informs decisions and fosters accountability. Analytical tools are therefore the engine of evidence-based practice within M&E.

Recommendations

Recommendations on Data Collection Tools

To optimize the effectiveness of M&E, health programs should prioritize the widespread adoption and consistent use of digital data collection tools, such as mobile-based survey platforms and electronic forms. Organizations should ensure that all M&E field staff are equipped with user-friendly and standardized digital tools that can operate both online and offline. Moreover, continuous training and refresher programs should be implemented to enhance the digital literacy of field officers and ensure that the full potential of these tools is realized. Attention should also be given to technical support and real-time troubleshooting to reduce the risk of data loss or collection delays in remote settings. Strengthening the initial data capture process will have a cascading effect on the overall efficiency and reliability of M&E functions.

Recommendations on Data Analysis Tools

Given that data analysis tools were the strongest predictor of M&E effectiveness, health programs should make them a strategic focus. This includes not only the procurement of advanced analytics software but also investing in building internal analytical capacity. M&E personnel should be trained in statistical analysis, data visualization, and reporting best practices. Programs should also adopt tools that automate routine analysis processes, generate real-time dashboards, and allow for scenario-based evaluations. Integrating data analysis into daily M&E workflows can increase responsiveness, improve decision-making, and ensure that the insights derived from data are timely, meaningful, and actionable.

Contribution of the Study to Knowledge

This study contributes significantly to the growing body of knowledge on the integration of technology into Monitoring and Evaluation (M&E) systems, particularly in the context of health programs in developing countries. By examining the individual and combined influence of four distinct technological components—data collection tools, data analysis tools—the study provides a holistic understanding of how digital transformation can improve the effectiveness of M&E. Unlike many previous studies that examine these tools in isolation, this research presents a comprehensive model that quantifies their collective impact, offering empirical evidence of their predictive strength.

Moreover, the study makes a methodological contribution by using both descriptive and inferential statistics—including correlation and multiple regression analysis—to determine the significance of each variable. This analytical rigor not only validates the relationships between technology use and M&E effectiveness but also establishes a basis for prioritizing interventions. For instance, the identification of data analysis tools as the most influential factor provides practitioners and policymakers with actionable insight into where capacity-building and investment should be focused.

From a contextual perspective, the study enriches the literature by situating the research within the operational realities of Kenyan health programs. By using a sample drawn from professionals working directly in M&E roles, the findings offer grounded, practice-based perspectives that reflect both the opportunities and challenges of using technology in real-world program settings. This context-specific contribution is valuable to other researchers and institutions seeking to adapt digital M&E strategies in similar socio-economic and institutional environments.

Finally, the study lays a foundation for future research by highlighting the interconnectedness of technological tools within M&E systems. It underscores the importance of designing integrated solutions rather than standalone interventions. By mapping out the relationships between different digital components and their cumulative effect on M&E outcomes, this research encourages a shift from siloed technological adoption to systems thinking in the planning and implementation of evaluation frameworks.

Suggestions for Further Research

This study focused on the influence of technological tools on the effectiveness of Monitoring and Evaluation (M&E) in health programs, but it opens up several areas for future research. First, longitudinal studies could be conducted to assess the long-term impact of digital tools on M&E performance over time. Second, similar research can be extended to other sectors such as education or agriculture to compare how technology functions in different M&E contexts.

Future studies could also explore the cost-effectiveness of digital M&E investments, helping organizations evaluate whether the benefits outweigh implementation costs. Additionally, expanding the respondent base to include field officers or community workers could offer a more inclusive view of how technology is used at different operational levels. Lastly, as emerging technologies such as artificial intelligence and real-time analytics evolve, future research should examine their potential to further transform digital M&E practices.

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