Utilization of Data Visualization Tools to Inform Decision-Making Among Health Managers in Selected Counties in Kenya

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ABSTRACT

The study aimed to investigate the factors influencing the utilization of data visualization tools among County and Sub County Health Managers in eight selected counties in Kenya. The research focused on how individual characteristics, technological, organizational, and behavioral factors impact the use of these tools in decision-making. The mixed methods approach included quantitative data from structured questionnaires and qualitative data from interviews. Out of the targeted 160 respondents, 149 participated, giving a response rate of 93%. Data were analyzed using SPSS version 26 for quantitative analysis and thematic content analysis for qualitative data. The findings revealed that all four factors significantly influence decision-making. Individual characteristics had a positive correlation coefficient of 0.504, technological factors 0.784, organizational factors 0.776, and behavioral factors 0.404, all statistically significant. The study showed that 82.3% of the variance in data visualization tool utilization could be explained by these factors. The regression analysis demonstrated positive relationships between each factor and the use of data visualization tools. The study concluded that individual characteristics, such as training, significantly influence decision-making and recommended further training for healthcare managers in advanced data analysis, epidemiology, data presentation, interpretation, data mining, modeling, GIS, monitoring, evaluation, data analytics, and predictive analysis.

Key Words: *Health managers, Decision-making, Technological factors, Quantitative analysis, Qualitative analysis*

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1.0 Introduction

A Health Information System (HIS) encompasses a set of procedures and tools used by health programs to collect, process, transmit, and use data for monitoring, evaluating, and controlling health systems. HIS underpins decision-making with four primary functions: generating data, compiling it, analyzing and synthesizing it, and communicating the findings. It ensures the timeliness, relevance, and quality of health data, converting it into actionable information for health-related decisions. Data visualization, which graphically represents data using maps, graphs, and charts, plays a crucial role in this process. It aids in understanding patterns, outliers, and trends, facilitating data-driven decision-making, especially in an era where vast amounts of data are generated continuously. This necessity has driven the development of advanced visualization tools to bridge the gap between abstract data and public needs, providing clarity and new approaches to complex figures.

In Kenya, as in many places, there are significant hurdles to effective data usage, including a lack of essential data skills among personnel, inadequate data availability and accountability, poor data quality, infrastructure constraints, and financial limitations. Implementing live data visualization tools can potentially strengthen data use and management practices. Research suggests that such tools could enhance data quality, availability, and access. However, general infrastructural and financial constraints present significant challenges to these improvements. This study aims to investigate the utilization of data visualization tools in informing decision-making for health service delivery within the HIS, focusing on case study sites at National and County Health Programs in Kenya. The research seeks to determine how available data is used to inform policy and guideline development, the use of data visualization tools like dashboards in decision-making, and the benefits and challenges of implementing and maintaining data use at national and county levels within Kenya's HIS.

1.1 Research Problem

Despite substantial investment in data collection on communities, facilities, and populations, key stakeholders often neglect to use this information for informed programmatic and policy decision-making (Nutley, 2017). This oversight hampers health systems' ability to respond effectively to urgent needs, as decisions are made without considering all empirical evidence (MEASURE Evaluation, 2018). The National Health Sector Strategic Plan (NHSSP 2012-2017) emphasizes the importance of incorporating health information to guide decision-making. However, data remains underused in informing health decisions (MOH, 2018). There is limited information on the use of data visualization tools in evidence-based decision-making within the health sector, and previous assessments have not evaluated their role (Health Metrics Network, 2017). A review reveals a lack of real-world evidence use, with only 42% of health managers in Kenya using data to impact budgeting and clinical services planning (Measure, 2018). Administrative decisions often remain data-independent (Walshe & Rundall, 2017; Pappaioanou et al., 2016). Improving data use is essential due to inadequate data quality and usage in policy formulation, especially in Health Information Systems (HIS) routine service reporting (Sauerborn & Lippeveld, 2018). Despite theoretical information on data visualization tools and decision-making, recent studies on their utilization in healthcare are lacking. This research aims to fill this gap by assessing the relationship between data visualization tool utilization and decision-making capabilities of health managers in selected Kenyan counties, including Machakos, Kisumu, Nyeri, Isiolo, Makueni, Laikipia, Garissa, and Mombasa. The study provides crucial insights into strategies and actions to enhance the use of visualization tools, thereby facilitating decision-making across various health service delivery systems.

1.2 Research Objective

This paper focused specifically on determining technological factors influencing utilization of data visualization tools among health managers in selected Counties, in Kenya

1.3 Research Hypothesis(es)

This study was guided by the following null and alternative hypothesis tested at 0.05 level of significance.

H_{01}: Individual characteristics do not influence data visualization.

H_{A1}: Technological, organizational, and behavioral factors do not influence data visualization.

2.0 Literature Review

2.1 Technological Infrastructure and Integration

Technological factors, encompassing tools, skills, and the IT environment, form a critical dimension in data visualization tools for health managers in decision-making. These tools transform complex data into visual formats like graphs and interactive dashboards, making them more accessible (Islam & Jin, 2019). User-friendly tools are essential to ensure effective utilization, as overly complex or unfamiliar ones can hinder adoption. Analytical competencies are crucial for health managers to extract valuable insights from visualized data. Training in data analysis equips them to make informed decisions (Dunn et al., 2016). The ability to integrate data from various sources enhances the effectiveness of these tools, highlighting the importance of refining data analysis and synthesis skills for better decision-making. The skills and knowledge of health managers and support personnel are vital for effective tool utilization. Specialized training in data visualization techniques significantly improves competence (Gesicho et al., 2018). In-house expertise, including data analysts and visualization specialists, can streamline adoption and resolve issues efficiently (Jeremie et al., 2014). Investing in the skills and knowledge of health managers and support staff is essential to fully unlock these tools' capabilities. The complexity of IT systems within healthcare organizations can either facilitate or hinder the utilization of data visualization tools. A strong and seamlessly integrated IT infrastructure simplifies data extraction and visualization (Gesicho et al., 2018; Jeremie et al., 2014). Conversely, disjointed or outdated IT systems may create difficulties in accessing and aligning data. The degree of IT complexity and an organization's commitment to technological progress profoundly impact the successful incorporation of data visualization tools into decision-making processes.

The study focuses on exploring the theoretical and empirical foundations of using data visualization tools to enhance data-informed decision-making within health management information systems (HMIS), both nationally and at county levels. It emphasizes that capacity building in data visualization and core data use competencies can significantly improve HMIS, enabling better presentation, utilization, and evaluation of information for effective decision-making (Braa et al., 2017). This literature review serves as a crucial basis for understanding the application of data visualization tools among health managers in selected Kenyan counties: Machakos, Isiolo, Nyeri, Kisumu, Makueni, Mombasa, Laikipia, and Garissa. The chapter introduces key concepts, significance, and research objectives, laying the groundwork for a comprehensive exploration of data visualization tools in the Kenyan HMIS.

The Health Management Information System (HMIS) is pivotal in healthcare decision-making, as defined by the WHO, evolving from traditional data collection to actionable information systems aimed at supporting management decisions (Land & Kennedy, 2015; Heeks et al., 2009). Kenya, through its HIS strategic plan (2014-2018), has made strides in reforming its health sector, addressing weaknesses in data collection, quality, and utilization for planning and managing health services (MOH, 2019; WHO, 2018). Despite technological advancements like ICT applications and mobile technologies in data processing and storage, challenges such as fragmented systems and poor data quality persist, hindering effective HIS implementation (Vermij S.L., 2019; Lippeveld, 2018).

Effective data visualization tools play a crucial role in addressing these challenges by enhancing data exploration and comprehension. They facilitate the transformation of complex data into understandable visual formats, aiding quick interpretation and informed decision-making (Jeff Baker, 2016; Avi Parush, 2017). However, the successful implementation of HMIS also hinges on organizational factors such as management commitment, feedback mechanisms, and fostering a culture of data use and accountability (Garrib et al., 2018; Campbell, 2014; Heeks et al., 2009). Variations in data use cultures across different countries underscore the importance of studying management styles that promote effective information utilization within Kenya (WHO, 2018). In conclusion, this study aims to delve into how data visualization tools can empower health managers in Kenya to leverage data effectively for decision-making, contributing to improved healthcare delivery and system performance. By addressing gaps in existing literature and exploring practical applications in selected Kenyan counties, it seeks to provide valuable insights into enhancing HMIS through strategic data visualization interventions.

Data visualization plays a crucial role in improving decision-making processes across various domains. It involves transforming raw data into visual representations that are more understandable and insightful for decision makers. By presenting data visually, patterns, trends, and relationships that might be obscured in raw data become clear, enabling quicker and more informed decisions. This process is essential in sectors ranging from healthcare to business management, where complex data sets are common. Effective data visualization not only aids in understanding current situations but also supports predictive analysis, allowing decision makers to anticipate future trends and outcomes. Moreover, it encourages proactive data demand, where decision makers actively seek specific data to address their information needs. Overall, data visualization enhances decision-making by facilitating a clearer understanding of data, promoting informed choices, and driving organizational and societal progress.

Table 1: Data visualization

Criteria	**Description**
Interactive and Predictive (Optional)	The visualizations can have filters and variable for users to interact in predicting diverse scenarios' results.
Appealing	The visualization should be visually pleasingand captivating.
Efficient	It should not be ambiguous.
Informative	It should be capable of conveying the anticipated information from the data to the reader.

Utilizing data visualization tools to enhance decision-making among health managers in selected counties of Kenya is crucial in today's data-rich environment. Effective utilization of these tools goes beyond their mere adoption, requiring a deep understanding of individual characteristics, technological capabilities, and organizational structures. Individual characteristics such as gender, education level, age, and attitudes towards technology significantly influence the ability of health managers to leverage data visualization tools effectively. Training and support tailored to these diverse profiles are essential to bridge knowledge gaps and foster positive attitudes towards technology adoption (Karuri, 2015; Hazelbaker, 2018). Technologically, the choice of user-friendly data visualization tools plays a pivotal role in accessibility and adoption rates. Tools that simplify complex data into intuitive visual formats like graphs and dashboards are crucial for facilitating decision-making processes in healthcare settings (Islam & Jin, 2019). Furthermore, ensuring that health managers and supporting staff possess adequate skills in data analysis and synthesis is imperative. Training programs aimed at enhancing these competencies enable managers to extract meaningful insights and make informed decisions based on visualized data (Dunn et al., 2016; Gesicho et al., 2018).

Organizational factors, including robust data governance frameworks and well-structured Health Information Systems (HIS), are foundational in supporting the effective integration of data visualization tools. A strong data governance framework ensures data accuracy, security, and compliance, thereby safeguarding against misuse and facilitating consistent decision-making processes (Fu et al., 2011; Bernardi, 2017). An optimized HIS design enhances data interoperability and accessibility, allowing health managers to combine and visualize data from diverse sources seamlessly (Wagenaar et al., 2015). Clear procedures and guidelines for utilizing these tools further streamline their adoption and ensure consistent application across healthcare organizations (Batch & Elmqvist, 2018). The competencies of decision-makers and the design of data visualizations themselves are critical in maximizing the impact of data visualization tools on decision-making. Health managers with strong analytical skills are better equipped to interpret complex visualizations and derive actionable insights, thereby leveraging these tools effectively (Dimara et al., 2021). Moreover, well-crafted visual representations tailored to the needs of decision-makers facilitate clear understanding and enable prompt identification of trends and anomalies in data (Killen, 2017; Leonelli et al., 2013). In conclusion, the successful integration of data visualization tools into decision-making processes within healthcare organizations requires a holistic approach that considers individual competencies, technological infrastructure, and organizational frameworks. By addressing these factors comprehensively through targeted training, supportive technological environments, and robust governance structures, health managers can harness the full potential of data visualization tools to improve healthcare outcomes and operational efficiencies in Kenya and beyond.

3.0 Methods

The study adopted an interventional mixed methods approach to investigate the effectiveness of a training intervention on data analytics among health managers in selected counties of Kenya. Quantitative data were collected through structured and semi-structured questionnaires administered to 44 health managers, complemented by qualitative insights obtained from key informant interviews and focused group discussions. Baseline data was initially established using a sample of 50 health managers, employing both quantitative and qualitative methods. The intervention phase consisted of a six-month training program in data analytics, with ongoing mentorship and field supervision. Evaluations conducted at the end of the intervention involved 44 health managers, 11 key informant interviews, and 2 focus group discussions, assessing the impact of the training on managerial practices. Findings from the study were analyzed and synthesized into a comprehensive report for dissemination, aiming to enhance healthcare management capacities within the context of Universal Health Coverage (UHC) in Kenya. The study focused on four pilot UHC counties: Machakos, Kisumu, Nyeri, and Isiolo, selected for their similarity in demographic profiles and UHC implementation, contributing valuable insights into healthcare management practices in diverse regional contexts within the country. The study population comprised counties where Universal Health Care (UHC) was piloted (Machakos, Kisumu, Nyeri, Isiolo) and those where it had not been piloted (Makueni, Laikipia, Garissa, Mombasa). This division allowed for comparison of healthcare outcomes and accessibility between piloted and non-piloted regions.

In this study, a combination of sampling designs and techniques was employed to gather data on healthcare management across several counties in Kenya. The sampling strategy consisted of a census approach for selecting respondents from a national program, complemented by purposive sampling to identify managers across eight counties and 49 sub-counties. The study included all listed program managers identified from Sub-County and County Health Management offices, ensuring comprehensive coverage within the selected areas. Additionally, key informants were chosen purposively to provide deeper insights into specific aspects of healthcare management.

The sample size determination followed Yamane's formula, which guided the selection of participants. This involved applying a simple random method to select sub-county and county health managers, totaling 162 respondents. Key informant interviews continued until data saturation was reached, ensuring comprehensive coverage of perspectives from relevant stakeholders. Data collection utilized pre-coded closed-ended questionnaires for quantitative data and key informant interviews for qualitative insights. Focus group discussions were also conducted with health partners to explore nuanced issues identified through literature review gaps. A structured questionnaire guide was pre-tested in Machakos County to refine clarity and ensure objectivity before full-scale data collection.

Reliability and validity of study tools were ensured through rigorous pre-testing and supervision of data collection. Debriefing sessions with participants during pre-testing helped refine interview materials for clarity and relevance. Internal consistency was checked through comparisons of participant responses, while validity was enhanced by aligning questions with study objectives and maintaining methodological coherence. Data analysis involved both qualitative content analysis using QSR/Nvivo and quantitative analysis with SPSS Version 20 and 26. Quantitative data were compiled, coded, and analyzed for descriptive and inferential statistics, assessing relationships between variables using regression, correlation analyses, and chi-square tests where applicable. Qualitative data underwent thematic analysis to identify and interpret key themes, with findings triangulated to enrich the overall understanding of healthcare management dynamics in the studied counties. Overall, this sampling and data collection approach facilitated a comprehensive exploration of healthcare management practices, ensuring robust findings that can inform policy and practice improvements in the Kenyan healthcare system.

4.0 Results

The study provides an overview of the demographic characteristics of the respondents. The participants were employed across various counties, with significant representation from Makueni (15.9%), Kisumu (15.2%), Garissa (14.6%), Nyeri (13.9%), and other counties such as Laikipia (9.3%), Machakos (9.3%), Isiolo (6.6%), Mombasa (6.0%), Nairobi (5.3%), and the National Government (2.7%). This diverse county distribution ensured a broad spectrum of perspectives in the study. In terms of gender, the study incorporated both male (55%) and female (45%) respondents, indicating a balanced gender representation. Age-wise, participants were primarily aged between 26-45 years, with 36.2% falling in the 36-45 age bracket and 35.6% in the 26-35 bracket. The study also included older age groups, with 22.8% aged 46-55 years and smaller percentages for those over 55 years (4.7%) and 18-25 years (0.7%). Regarding experience, respondents had varying years of work experience, with 26.2% having 11-15 years, 25.5% with 6-

10 years, and a distribution across other brackets including 16-20 years (10.1%), over 30 years (8.7%), and 1-2 years (2.0%). Educational qualifications varied as well, with 41.6% holding diplomas, 39.6% undergraduates, and smaller percentages for Master's degrees (14.4%), certificates (1.3%), and other qualifications. This comprehensive demographic profile ensures that the study findings represent a wide range of perspectives across gender, age, experience, and educational backgrounds among the respondents.

In this study, the influence of individual characteristics on data management skills, task performance, and use of data visualization tools was investigated. Participants rated their training across various aspects of data management using a Likert scale, revealing significant training in data collection and reporting, moderate training in data presentation and analysis, and a neutral stance towards computer software proficiency. They expressed a need for further training in advanced data analysis, epidemiology, and software-specific skills like SPSS and Python. In terms of task performance, participants rated themselves highly in tasks such as data accuracy checking, percentage calculation, and identifying gaps in data, indicating proficiency in these areas but less so in others, with overall responses showing low variability. Regression analysis highlighted that individual characteristic significantly influenced the use of data visualization tools for decision-making, explaining 24.9% of the variance. The study found a statistically significant relationship ($F(1, 200) = 50.104$, $p < 0.05$) between these characteristics and tool utilization, affirming the model's validity in predicting outcomes related to data visualization tool use. This suggests that attributes such as training, task proficiency, and other personal traits play a crucial role in how effectively individuals utilize data visualization tools for decision-making purposes. These findings underscore the importance of tailored training programs and skill development initiatives to enhance data literacy and optimize the use of visualization tools in professional settings.

4.1 Regression Analysis

In examining the impact of technological factors on the adoption and utilization of data visualization tools for decision making in healthcare settings, several key aspects were evaluated. First, the availability of equipment and infrastructure crucial for data visualization was assessed using a Likert scale, revealing that dashboards and computers were rated as adequately available, while software and printers were considered neutral or inadequate by respondents. Significant variability in responses indicated notable differences in infrastructure readiness across facilities.

Secondly, the influence of technological factors was gauged through participant agreement on various statements. It was found that healthcare managers perceived assurance in data protection, access to reliable data for visualization, and the impact of local contexts and existing technological setups on tool utilization. Factors such as affordability, technological infrastructure adequacy, and compatibility with mobile platforms were also noted as influencing adoption. However, participants were neutral regarding software suitability and the availability of supportive training programs, highlighting potential barriers to full integration.

Lastly, regression analysis underscored the significance of technological factors in predicting the utilization of data visualization tools, revealing a substantial 61% variation attributable to these factors. The high statistical significance (p-value of 0.001) and a calculated F-value exceeding critical thresholds confirmed the robustness of the regression model. The regression equation indicated a baseline utilization rate of 0.619 in the absence of technological factors, with each unit increase in these factors correlating with a 0.342 increase in tool utilization. Overall, the study underscores the pivotal role of technological readiness in shaping the effective implementation of data visualization tools in healthcare decision making. It highlights both strengths, such as adequate availability of certain equipment, and challenges, including the need for improved software and training support, which collectively influence the adoption landscape. These findings provide valuable insights for policymakers and healthcare administrators aiming to enhance the strategic integration of technological advancements in healthcare management practices.

Table 2 Regression Analysis

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.497	.111		4.489	.001
	Behavioural factor	.275	.051	.404	5.355	.001

The study focused on assessing how behavioral factors influence the utilization of data visualization tools, employing a Likert scale to gauge participant responses. Scores were interpreted across a spectrum ranging from "No extent at all" to "Very large extent," with standard deviations used to indicate significant differences in responses. Key findings highlighted that participant strongly emphasized the importance of data gathering for monitoring facility performance (Mean 4.09). Behavioral factors such as user confidence in health information (Mean 3.66), clarity on roles in handling health data (Mean 3.64), and encouragement for planning and tracking outputs (Mean 3.63) were noted to significantly influence tool utilization. Additionally, factors including demand for information, recognition of staff efforts, commitment to community health, and confidence in data accuracy also played substantial roles.

The study revealed that motivational incentives and attitudes towards data collection were areas of concern, with varying impact on tool adoption (Means ranging from 3.16 to 2.60). Notably, responses indicated significant variance in the influence of behavioral factors on decision-making processes involving data visualization tools. Key informant interviews affirmed that clear understanding of roles was crucial at county levels, underscoring the practical impact of behavioral factors. Regression analysis demonstrated that behavioral factors explained 16.3% of the variance in data visualization tool utilization related to decision-making processes (R2 = 0.163), suggesting a moderate but significant influence. This metric provides insight into the extent to which changes in behavioral factors contribute to tool effectiveness, with implications for enhancing data-driven decision-making in organizational contexts. In conclusion, the study highlighted the multifaceted influence of behavioral factors on the utilization of data visualization tools, emphasizing the importance of addressing motivational incentives, attitudes, and role clarity to optimize their impact in decision-making processes within health information systems.

4.2 Model Summary

The study conducted correlation analysis to investigate relationships between variables, yielding correlation coefficients that indicate the strength and direction of these associations. Positive correlations were found between the use of data visualization tools in decision making and various factors: individual characteristics ($r = 0.504$), technological factors ($r = 0.784$), organizational factors ($r = 0.776$), and behavioral factors ($r = 0.404$), all significant at $p < 0.001$. These results suggest meaningful connections between these variables, reducing the likelihood of chance findings.

Furthermore, multiple regression analysis was employed to assess how individual characteristics, technological factors, organizational factors, and behavioral factors collectively impact the use of data visualization tools in decision making. The analysis revealed an R Square value of 0.823, indicating that 82.3% of the variance in tool usage can be explained by these factors. This high explanatory power suggests that the model effectively captures the influences on decision-making practices involving data visualization tools, with implications for understanding and enhancing their adoption and effectiveness in organizational contexts.

Table 3 Model Summary

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.907[a]	.823	.818	.116
a. *Predictors: (Constant), Behavioural factor, Organizational factors, Technological factors, Individual Characteristics*				

Further examination of the ANOVA, as depicted above, showed that the significance of the F-statistic is 0.001, which is lower than 0.05. Additionally, the F-value (167.317) is statistically significant at a confidence level of 0.00.

Table 4: ANOVA

ANOVA[a]						
Model		**Sum of Squares**	**Df**	**Mean Square**	**F**	**Sig.**
1	Regression	9.080	4	2.270	167.317	.001[b]
	Residual	1.954	144	.014		
	Total	11.034	148			
a. Dependent Variable: Utilization of data visualization in decision making						
b. Predictors: (Constant), Behavioural factor, Organizational factors, Technological factors, Individual Characteristics						

The study explores how decision-making processes in healthcare are influenced by various factors, particularly focusing on the use of data visualization tools. It reveals that health managers rely heavily on monthly reports from the field, uploaded online, and utilize dashboard communications, maps, charts, and graphs to gather evidence for decision-making. These tools facilitate critical analysis at management levels, enabling the interpretation of gathered information.

Regarding individual characteristics, the research finds that health managers are moderately trained in data collection, reporting, presentation, and analysis, although they express neutrality towards computer software training. This training landscape reflects broader trends noted in previous studies by Bernardi (2017) and Gatero (2017), indicating a consistent emphasis on equipping health managers with foundational data skills. Technological factors significantly impact the effectiveness of data visualization tools. The study highlights the adequacy of resources such as dashboards, computers, and internet access, which are crucial for facilitating data-driven decision-making. However, challenges with software availability and printer adequacy suggest areas for improvement, echoing findings by Huber et al. (2018) on the technical complexities influencing tool utilization in healthcare settings.

Organizational factors also play a pivotal role in shaping the utilization of data visualization tools. Leadership support, access to reliable data, and a culture promoting transparency and accountability are identified as key enablers. Studies by Fu et al. (2011) and Park et al. (2021) support these findings, emphasizing the importance of robust data governance frameworks and well-defined procedures in enhancing data visualization tool effectiveness within healthcare organizations. Behavioral factors, such as staff confidence in using health information, understanding of roles, and demand for information, are crucial determinants of tool utilization. These factors underscore the significance of user competence and organizational culture in fostering effective data utilization practices, aligned with research by Dimara et al. (2021) highlighting the role of analytical skills in leveraging data visualization tools effectively. In conclusion, while data visualization tools offer substantial potential for enhancing decision-making in healthcare, their effectiveness hinges on a complex interplay of individual, technological, organizational, and behavioral factors. Addressing gaps in training, improving technological infrastructure, fostering supportive organizational cultures, and enhancing user competencies are critical steps towards maximizing the impact of these tools in healthcare management.

5.0 Conclusions and Recommendations

5.1 Conclusions

The study explores how individual characteristics, technological factors, organizational factors, and behavioral factors influence the utilization of data visualization tools in decision-making among health managers. Firstly, it reveals that health managers generally possess moderate to high levels of training in data collection, reporting, presentation, and analysis. However, there's a noted neutrality towards computer software training, which may impact tool utilization efficiency. Technological factors such as the availability of dashboards, computers, and internet access significantly support the use of data visualization tools, although challenges with software availability and hardware adequacy remain. Issues like data security, infrastructure obsolescence, and occasional technical disruptions also affect tool effectiveness, highlighting areas for improvement in healthcare settings.

Organizational factors play a crucial role in fostering a conducive environment for data-driven decision-making. Leadership support, access to reliable data, and a culture emphasizing transparency and accountability are identified as key facilitators. Conversely, organizational challenges such as insufficient infrastructure, lack of integration with existing databases, and inadequate storage pose barriers to effective tool utilization. Behavioral factors, including user confidence in health information, clarity of roles, and motivation to collect and utilize data, significantly influence the adoption of data visualization tools. These factors underscore the importance of fostering a supportive organizational culture and enhancing staff competencies to maximize the impact of visualization tools in decision-making processes. Overall, the study's findings suggest a strong correlation between individual characteristics, technological resources, organizational support, behavioral aspects, and the effective use of data visualization tools in healthcare decision-making. Addressing these factors comprehensively can enhance the strategic implementation and utilization of these tools, ultimately improving healthcare management and outcomes.

5.2 Recommendations

The study's findings highlight several key recommendations to enhance the utilization of data visualization tools in healthcare decision-making. Firstly, healthcare managers in the studied counties should receive comprehensive training in advanced data analysis skills, basic epidemiology, data presentation, and interpretation, as well as proficiency in tools such as SPSS, SAS, Python, Plunk, R, and GIS. Updating skills in data cleaning, mining, modeling, and predictive analysis using updated KHIS systems is also crucial. Secondly, addressing technological factors involves replacing outdated resources like computers and providing advanced software for effective data visualization. Thirdly, management should allocate resources for training and infrastructure to support the regular use of these tools. Lastly, promoting awareness and attitudinal change through sensitization campaigns is recommended to foster a culture of utilizing data visualization in decision-making processes. Additionally, the study suggests further research in more counties to explore broader challenges hindering effective data visualization tool utilization in healthcare decision-making contexts beyond the pilot study areas.

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