AI Analytics in Enhancing Patient-centered Care Through Wearables: A Cross-country Analysis

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Abstract:
Artificial Intelligence Analytics (AIA) and wearable technologies offer significant opportunities to advance global healthcare systems by providing personalized health insights, promoting healthy lifestyles, and delivering real-time data to support diagnosis and treatment. However, research into the application of these technologies within developing countries remains notably limited. In response, this study explores the impact of AIA capability, supported by wearable technology, on patient-centered care in the healthcare systems of low- and middle-income countries (LMICs). Focusing on Cameroon and Ghana, a cross-country survey assessed how these digital health tools influence perceptions of effective patient-professional communication, empathy, patient involvement, and access to essential healthcare. Using big data analytics capability theory adapted to healthcare and structural equation modeling, the findings reveal that AIA capability significantly improves perceptions of patient-centered care, particularly regarding communication and empathy, with differences between the two countries. Although eHealth literacy enhances positive perceptions of care, it does not significantly moderate the relationship between AIA capability and patient-centered care. This study highlights the importance of context-specific approaches in adopting wearable health devices in LMICs and adds to the growing literature on AI-powered wearables in underrepresented regions.

Keywords: Artificial Intelligence; analytics; wearable; patient-centered care; eHealth literacy; big data analytics capability

1. Introduction

Smart wearable devices, such as watches, wristbands, and earwear, are accessories with embedded computers worn by individuals that enable the personalized processing of information from the user's body (Niknejad et al., 2020). They use technologies such as artificial intelligence (AI) and big data analytics to collect and analyze vast amounts of physiological and behavioral data, offering unprecedented opportunities to transform patient care, enhance disease management, and improve clinical decision making (Al Kuwaiti et al., 2023; Aminizadeh et al., 2024; Niu et al., 2024). Their pervasiveness holds considerable promise for transforming global healthcare systems by offering personalized health insights, helping users maintain healthy lifestyles, and providing real-time data for diagnosis and treatment (Lu et al., 2020; Yang et al., 2025).

Roughly one-third of Americans use these devices to monitor their health and fitness, with over 80% willing to share information from their device with their doctor to aid in monitoring their health (Chandrasekaran et al., 2020; Dhingra et al., 2023). Relevant to the context of this study, the market value of wearable devices in Africa is projected to increase from USD 1.04 billion to reach USD 2.38 billion by 2031 (6WResearch, 2024). Yet, the implementation of such devices in research within low- and middle-income countries (LMICs) settings has not progressed at the same pace as in high-resource environments such as the United States. Furthermore, there is limited research focused on understanding user experience, readiness, and the specific challenges associated with integrating smart wearable devices into health studies in these contexts (Swahn et al., 2024). Therefore, understanding how healthcare organizations can leverage the capabilities of AI analytics (AIA) derived from wearable device data to enhance patient-centered care is of great interest to healthcare professionals and policymakers.

In this study, we define AIA as the systematic application of adaptive machine learning algorithms and AI methods for data processing, analysis, and interpretation, aiming to derive actionable insights that enhance decision-making through continuous learning and adaptation. Unlike traditional descriptive analytics, which can summarize past data without the aid of AI, AIA emphasizes predictive and prescriptive capabilities through adaptive learning (Sharma et al., 2022). Predictive analytics involves forecasting health issues, such as fatigue or arrhythmias, to inform preventive measures. In contrast, prescriptive analytics provides real-time guidance or alerts, as seen when an *Apple Watch* detects a fall and prompts the user to contact emergency services. Specific AIA features in smart wearables include real-time traceability of physiological data, analytics engines that synthesize behavioral and biometric patterns, and interoperability, allowing integration with health information systems or mobile health apps (Lui et al., 2022; Raja et al., 2019; Velmovitsky et al., 2022). For instance, *the Google Pixel Watch 2* combines a new multi-path heart rate sensor with an AI-powered heart rate algorithm to help users understand their health and take action, such as managing stress. *Garmin Connect+* leverages AI to deliver increasingly personalized insights and suggestions throughout the day, utilizing users' health and activity data to become more tailored to their goals as they engage with the platform.

Previous studies (i.e., El-Haddadeh et al., 2023; Kankanhalli et al., 2016; Witt et al., 2019) that examined the potential of big data and AI in healthcare have established that smart wearable devices are designed to gather and transform raw physiological, behavioral, and environmental data into meaningful health insights, making AIA a distinguishing characteristic of such devices. These integrated AIA features of wearables, which provide personal health information, are a primary driver of adoption (Rha et al., 2022). However, sharing this data and insights with healthcare professionals to support patient care is a different level of patient engagement that remains under-researched. More precisely, the impact of AIA capability on patient satisfaction and experiences, particularly in resource-constrained settings, remains understudied.

This research aims to bridge this knowledge gap by examining the relationship between AIA capability and patient-centered care. The study focuses on LMICs to provide insights into contexts where healthcare systems frequently face challenges related to resource availability and infrastructure. The study aims to assess the impact of AIA capability derived from wearable data on patient-centered care experiences. Specifically, we aim to understand how this capability affects patients' perceptions of care, their communication with healthcare providers, and their access to essential healthcare services. Thus, we formulate the following research question (RQ):

RQ: How does AIA capability derived from wearable health data influence patient-centered care experiences among individuals in health resource-constrained environments?

This study employs the Big Data Analytics Capability (BDAC) theory (Gupta & George, 2016), adapted for healthcare settings, as a theoretical framework that posits healthcare organizations must develop specific capabilities to effectively leverage big data. By adapting this theory to the context of analyzing data from wearables using AI algorithms, such as machine learning, we can identify the core capabilities required for successful AIA implementation and assess their impact on patient-centered care and personalized medicine. This study employs a quantitative research design, utilizing Partial Least Squares Structural Equation Modeling (PLS-SEM) to analyze data collected from users of smart wearables in Cameroon and Ghana. By examining the relationships between AIA capability and patient-reported outcomes, we uncovered underlying mechanisms through which AIA can enhance patient experiences.

Therefore, this study contributes to research by providing theoretical insights and empirical evidence on the impact of AIA on patient-centered care in LMICs, particularly within the context of utilizing smart wearable health devices in healthcare systems. The findings provide valuable insights for healthcare policymakers, administrators, and practitioners in these regions to optimize wearable technology and AI, thereby enhancing patient-centered care and personalized medicine.

The remainder of the paper is structured as follows: the next section synthesizes recent literature on wearable technology and AIA in reshaping healthcare delivery. The theoretical foundation and hypothesis development, methodology, and presentation of results follow this section. We then discuss the findings, outline the theoretical and practical implications, highlight the limitations, and provide directions for future research, concluding with a conclusion section.

2. Literature Review

2.1. Integrating AIA with Wearable Health Devices

Wearable health devices are increasingly enhancing health monitoring by enabling personal fitness tracking and providing clinicians with valuable data for early diagnosis and treatment (Dias & Paulo Silva Cunha, 2018; Jin et al., 2017). Miniaturization technology has made them more reliable and adaptable, with more sophisticated sensors for vital signs such as heart rate and blood pressure (Dias & Paulo Silva Cunha, 2018). These wearables are available for all parts of the body. They can be categorized into four main areas: (i) health and safety monitoring, (ii) chronic disease management, (iii) disease diagnosis and treatment (including drug delivery), and (iv) rehabilitation (Iqbal et al., 2021; Lu et al., 2020). Various types of wearables exist within these categories, including skin-based (e.g., tattoo-based), textile-based, and biofluidic-based (Iqbal et al., 2021). These wearables help healthcare professionals overcome their current challenges related to disease prevention and patient care through components like ultrasound imaging (Contie, 2022), blood pressure tracking (Wang et al., 2018a), continuous vital sign tracking (Leenen et al., 2020), and alcohol biosensing (Kim et al., 2016).

Wearables have advanced to the point where they can execute AI algorithms in real-time at the point of sensing, enabling direct analytical insights from the measurement data (Mirmomeni et al., 2021). Thus, AIA has become an essential component of most wearable health devices and support systems, aiding in the early detection and accurate diagnosis of disorders (Sivarajah et al., 2023; Zheng et al., 2021). For example, machine learning algorithms have been embedded in some wearables to monitor and predict heart disease based on heart rate data; some have been used to detect early signs of Parkison's disease and sports injuries based on data from accelerometers within wearables (Nahavandi et al., 2022; Zadeh et al., 2021); others for the early detection of mental diseases based on sleep pattern data (Tutun et al., 2023; Wang et al., 2024). This has led to the development of patient-centered technical frameworks that integrate AI and wearables to provide intelligent suggestions by analyzing a patient's physiological data from wearable devices for disease diagnosis and treatment (Xie et al., 2021). Despite their potential, the wearable health device industry faces significant challenges that hinder broader adoption in medical practice, including difficulties leveraging AIA in patient care (Mirmomeni et al., 2021; Nahavandi et al., 2022; Zheng et al., 2021).

2.2. Patient Adoption of AIA-Enabled Wearable Health Devices

The success of wearables in healthcare directly depends on how much patients are willing to share AIA-driven insights with healthcare professionals (Nahavandi et al., 2022). From a user perspective, the likelihood of adopting wearables may be higher for devices that ensure strong data privacy, are perceived as easy to use, and deliver reliable data with accurate health references (Bettiga et al., 2020; Huarng et al., 2022). The usefulness, social influence, technology promptness, innovativeness, and prevention awareness may also significantly influence the intention to adopt and the willingness to pay for them (Bettiga et al., 2020). The alignment between task and technology could positively influence users' satisfaction and intention to use wearable health devices as well (El-Masri et al., 2023; Wang et al., 2020). Perceived convenience and perceived irreplaceability may be crucial factors influencing perceived usefulness, which, alongside health beliefs, enhance users' intention to adopt wearable health devices (Chau et al., 2019). Intrusiveness and comfort may not significantly affect the intention to use smart wearable health devices; however, intrusiveness may significantly affect the perceived usefulness of these devices, while comfort may have a strong and significant influence on usefulness and ease of use (Papa et al., 2020).

Research also underscores the impact of demographics on technology adoption. For instance, age is a critical determinant of intention to use technology, with specific attention paid to senior citizens due to their unique health needs and perceptions of technology (Schroeder et al., 2023). Senior citizens' intention to use wearable health devices may be strongly influenced by their perceptions of the devices' usefulness and information accuracy, as well as their self-efficacy, perceived severity, and perceived vulnerability (Singh et al., 2022). The effect of cognitive age on seniors' intention to use a device may also be influenced by their level of subjective well-being. Specifically, when seniors have low subjective well-being, cognitive age could unexpectedly increase their intention to use the device (Farivar et al., 2020). A study in Hong Kong found that the intention of Generation Z consumers to adopt wearable devices is driven by their perceived credibility, ease of use, and usefulness (Cheung et al., 2021). Another study in India found that consumers' adoption intentions were determined by the availability of real-time health information, the normative environment, and decision self-efficacy (Nayak et al., 2022). However, the economic costs associated with these devices and services tend to decrease the intention to adopt them. Consequently, carefully considering the price and payment mechanisms is essential (Huarng et al., 2022; Johnson et al., 2023).

From an organizational perspective, healthcare providers and systems aiming to establish new care models that incorporate smart wearables should consider the following essential elements during the health program design phase to increase chances of success: a clearly defined problem, integration within a healthcare delivery system, technological support, a personalized experience, emphasis on the end-user experience, alignment with reimbursement models, and involvement of clinician advocates (Smuck et al., 2021; Wang et al., 2023).

While previous research has examined the potential of wearable technology and AI in healthcare, the specific impact of AIA capability, derived from wearable data, on patient-centered care, particularly in LMICs, remains understudied, justifying the interest and area of contribution of this research.

3. Theoretical Foundation and Hypotheses Development

3.1.Theoretical Framework: Big Data Analytics Capability

This study addresses the research gap through the BDAC theory proposed by Gupta & George (2016). It posits that while many organizations invest heavily in big data, investing in technology is insufficient to gain a competitive advantage. Instead, firms must develop specific capabilities to effectively leverage big data, which is continuously flowing data that necessitates advanced management, analytical, and processing methods to derive meaningful insights. The theory is grounded in resource-based theory (RBT), which suggests that a firm's competitive advantage stems from its unique bundle of resources and capabilities (Barney, 1996). In the context of big data, these resources and capabilities are (i) tangible resources: Data, technology, and financial investments; (ii) human skills: Managerial and technical expertise in big data analytics; and (iii) intangible resources: Data-driven organizational culture and a strong learning environment (Gupta & George, 2016). These resources, when combined effectively, form a firm's BDAC. The theory suggests that a strong BDAC is associated with superior firm performance and a competitive advantage (Gupta & George, 2016; Mikalef et al., 2018).

The existing literature highlights a growing recognition of the potential of BDAC in healthcare, which is increasingly relying on AI algorithms for analytics, whether descriptive, predictive, or prescriptive (Galetsi et al., 2019, 2020). Thus, BDAC theory offers a valuable framework for understanding how healthcare organizations can harness the potential of AIA, including data from wearable devices. By focusing on building the necessary capabilities and understanding their impact on organizational performance, healthcare providers can effectively leverage AIA to drive innovation and transformation, improving patient care and achieving a sustainable competitive advantage. Thus, extant research has identified and validated five BDACs in healthcare: traceability, analytical capability, speed-to-decision capability, predictive capability, and interoperability capability (Wang et al., 2018b; Wang & Hajli, 2017). Together, these elements can help reduce average excess readmission rates and improve patient satisfaction in healthcare organizations (Wang et al., 2019).

Given this background, the adaptation of BDAC theory to the healthcare domain can be used to develop theoretical insights into the mechanisms through which AIA could enhance patient experiences, as algorithms used for BDA are increasingly AI-powered. In the specific context of health data from commercial wearable health devices, BDAC theory can help explain how wearable data can be integrated into existing healthcare data systems to create a more comprehensive view of patient health and help explain how AIA capability can be leveraged to personalize care based on individual patient data from wearables, leading to improved patient outcomes and satisfaction.

While BDAC theory was initially developed to assess organizational-level big data capabilities (Gupta & George, 2016), its adaptation to the healthcare context, especially when evaluating AIA derived from wearable health devices, necessitates a more patient-centered lens. In this study, we conceptualize organizational AIA capability not solely as internal technical assets, but also as capabilities that are operationalized through patient-facing processes, and therefore perceivable and measurable from the patient perspective. We argue that patient perceptions serve as a valid and meaningful proxy for assessing the functional maturity of AIA capability in healthcare organizations. This perspective is particularly relevant in service-based domains, such as healthcare, where organizational capabilities are manifested through real-time service delivery and interactions with patients (Wang et al., 2019). For example, the BDAC dimension of traceability is captured in our model through items assessing whether patients believe their wearable data is consistently monitored. Predictive capability is assessed through patient-reported perceptions of whether data from wearables is used to anticipate health events or provide early warnings. Likewise, interoperability capability is gauged through the extent to which patients perceive integration of their wearable data into broader hospital or provider information systems.

This perception-based measurement aligns with emerging healthcare BDAC research, which recognizes the value of stakeholder-facing assessments of capability performance, particularly where advanced technologies like AIA are expected to enhance patient outcomes and communication (Schulte & Bohnet-Joschko, 2022; Wang et al., 2019). By focusing on how patients experience these capabilities, we extend the theoretical utility of BDAC theory beyond organizational inputs to include capability enactment in lived patient experiences, which is critical for evaluating patient-centered innovations. Accordingly, our approach contributes to the ongoing evolution of BDAC theory by incorporating the service recipient's perspective, a necessary adaptation in evaluating the use of wearable AIA systems by healthcare organizations in low- and middle-income contexts.

3.2.Hypotheses Development

This research aims to understand the effect of AIA capability on patient-centered care using BDAC theory adapted to healthcare, which comprises five capabilities: traceability, analytical capability, speed to decision capability, predictive capability, and interoperability capability (Wang & Hajli, 2017). In this study, traceability refers to the consolidation and monitoring of patient information from wearable devices. Analytical capability refers to the ability to handle vast quantities of clinical data from wearables (ranging from terabytes to exabytes), diverse formats (including text to graph), and varying speeds (from batch processing to real-time streaming) using analytics methods. Speed-to-decision capability refers to the capacity to efficiently produce outputs related to patients, care processes, and services from wearable devices, informing diagnostic and treatment decisions. Predictive capability refers to the ability to analyze data from wearables to discover valuable correlations, patterns, and trends and to project these insights to predict future occurrences. Interoperability capability refers to the capability to integrate data from wearables and processes to facilitate collaboration and other healthcare activities.

Meanwhile, to better understand patient-centered care, patient-reported measures are arguably the most effective means of assessing patient-centeredness (Tzelepis et al., 2015). Patients are uniquely qualified to evaluate whether their care aligns with their values, preferences, and needs. They are the only ones who can accurately report whether they received the desired amount of information, understood it, and can recall it. Additionally, patients alone can describe the severity of their physical symptoms and whether their medications provide sufficient relief. Therefore, regularly utilizing patient-reported measures to assess patient-centered care is essential for identifying areas in healthcare patient-professional interactions that require improvement. It implies that patient-reported measures are arguably the most effective means of assessing how patients believe the AIA capability of health systems affects the quality of patient-professional interactions and care received. Thus, the effect of AIA capability on patient-centered care can be understood based on patients' perspectives on its effect on patient-professional interactions and access to essential health services.

Patient-centered care from the patient's perspective of patient-professional interactions can be measured from a general perception of the matter (Tzelepis et al., 2015) or in terms of effective communication (EC), interest in the patient's agenda (IPA), empathy, and patient involvement in care (PIC) (Casu et al., 2019). The general perception of patient-centeredness refers to patients' overall impression of how their needs, values, and preferences are respected and addressed (Tzelepis et al., 2015). It captures patients' holistic impressions of their care experience, encompassing not only specific interactions or behaviors but also the broader aspects of their care. In contrast to the more specific, observable aspects of patient-centered care, this general perception dimension allows us to assess whether patients perceive the overall approach to care as patient-centered, even if not all sub-dimensions are strongly expressed. It also provides an opportunity to identify disconnects between overall impressions and specific patient-centred care behaviors, which is especially relevant in settings where patients may conflate professionalism or politeness with patient-centeredness in the absence of substantive engagement. A strong AIA capability enables healthcare organizations to deliver more personalized care, aligning with patient preferences and needs and enhancing patients' perception of patient-centeredness (Alowais et al., 2023; Johnson et al., 2021). Thus, we hypothesize that:

H1: AIA capability has a positive effect on patients' overall perception of patient-centeredness.

Effective communication encompasses transparent and open interaction between healthcare providers and patients (Casu et al., 2019). A strong AIA capability enables healthcare providers to access and analyze patient data from smart wearables, resulting in a deeper understanding of individual patient needs and preferences (Wang et al., 2018b; Wang & Hajli, 2017). This knowledge can facilitate more tailored and effective communication. Thus:

H2: AIA capability has a positive impact on effective communication between patients and healthcare professionals.

Interest in a patient's agenda refers to the degree to which healthcare providers demonstrate concern and curiosity about patients' priorities and goals (Casu et al., 2019). By analyzing patient data from wearables, healthcare providers can identify individual goals and priorities (Galetsi et al., 2020; Wang et al., 2018b). This knowledge can foster a greater interest in patients' agendas and a more patient-centered approach. Thus:

H3: AIA capability positively affects clinicians' interest in patients' agenda.

Empathy refers to the ability of healthcare professionals to understand and share patients' feelings (Casu et al., 2019). By leveraging AIA to gain insights into patients' experiences and perspectives, healthcare providers can develop a stronger sense of empathy (McColl-Kennedy et al., 2017; Morrow et al., 2023). Understanding patients' backgrounds and challenges based on such analytics can foster a more compassionate and supportive approach. Thus:

H4: AIA capability positively affects the empathy of healthcare professionals towards patients.

Patient involvement in care refers to the extent to which patients participate in decision-making and care planning (Casu et al., 2019). AIA from wearables can support shared decision-making by providing patients with relevant information about their health conditions and treatment options alongside information from their healthcare professionals, which can increase patient involvement in care decisions (Schulte & Bohnet-Joschko, 2022; Shay & Lafata, 2014). Thus:

H5: AIA capability has a positive impact on patient involvement in care decisions.

Perceived access to essential healthcare services refers to patients' perception of their ability to obtain necessary healthcare services. Effective use of AIA by healthcare professionals can optimize resource allocation and enhance service delivery, resulting in increased patient satisfaction with access to care (Groves et al., 2013; Wang et al., 2018b). Thus,

H6: AIA capability has a positive impact on patients' perceived access to essential healthcare services.

eHealth literacy refers to the ability to seek, understand, appraise, and use health information from electronic sources to make appropriate health decisions (Norman & Skinner, 2006). Although not part of BDAC theory, extant literature holds that eHealth literacy is crucial for patients to benefit from the potential of AIA. Specifically, patients with higher eHealth literacy are more likely to understand and engage with data-driven care, which may strengthen the relationships between AIA capability and patients' experiences with data-driven patient-centered care (Schulte & Bohnet-Joschko, 2022; Singhania & Reddy, 2024). Thus:

H7: eHealth literacy moderates the effect of AIA capability on patients' experiences with data-driven patient-centered care.

Figure 1 presents the proposed research model and hypothesized relationships.

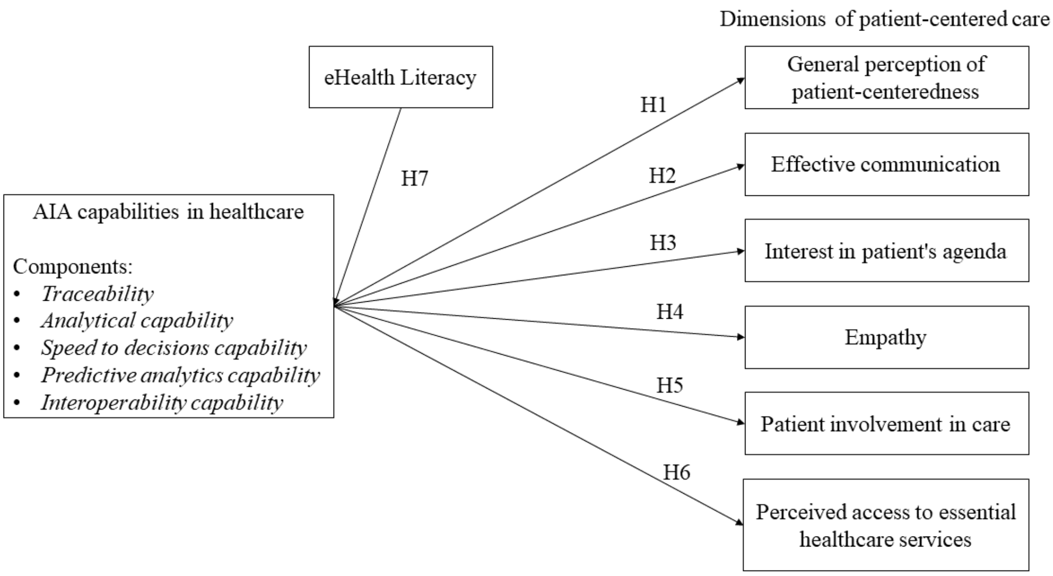

Fig. 1 Proposed research model

4. Methodology

This study employs a quantitative research design to investigate the relationship between AIA capability and patient-centered care. This approach was chosen to measure and quantify the variables of interest, enabling statistical analysis and hypothesis testing, thereby minimizing subjective interpretation and bias. Also, it enables our findings to be generalizable to the larger population through statistical inference. A cross-sectional approach is adopted to collect data from smartwatch users in Cameroon and Ghana, aiming to predict and inform healthcare organizations, professionals, and policymakers before they make significant investments in this practice. This approach also allows for collecting data from a large sample size through questionnaires, making it relatively efficient in terms of time and resources. Ghana and Cameroon have comparable LMIC health landscapes. Both countries represent Sub-Saharan African contexts where the adoption of wearables for health care is nascent but growing and where assessing AIA-enabled patient-centered care can yield policy-relevant insights.

According to the World Health Organization (WHO), Cameroon's health system faces significant challenges but shows gradual progress in key areas. With a population of over 28 million in 2023, expected to increase by 80% by 2050, the country allocates 3.82% of its GDP to health (2021), indicating limited investment in the sector. Life expectancy at birth has improved from 53 years in 2000 to 61.8 years in 2021. The leading causes of death are predominantly communicable diseases such as lower respiratory infections, malaria, HIV/AIDS, tuberculosis, and diarrhoeal diseases, which account for over half of all deaths. Maternal and neonatal mortality, though declining, remain high, alongside significant incidences of malaria and tuberculosis. Non-communicable diseases like stroke and ischaemic heart disease are also rising concerns. Despite these challenges, progress is being made toward universal health coverage and emergency preparedness, with millions projected to gain access to essential services by 2025. However, overall health and well-being indicators still lag, underscoring the need for strengthened health infrastructure and more robust public health interventions.

Ghana's health system is structured around a decentralized primary health care model aimed at improving accessibility and community participation. With a population of over 31 million (2020) and a life expectancy of 64.1 years, health expenditure remains modest at 2% of GDP, with a significant portion (over 60%) paid out of pocket. The system operates on three levels: district hospitals provide comprehensive care, subdistrict facilities deliver outreach and referrals, and the foundational Community-based Health Planning and Services (CHPS) units serve populations of 3,000 to 4,500, focusing on promotive and preventive care. Ghana's health priorities include achieving Universal Health Coverage (UHC) through integrated national policies (such as the "One Health" and "Life Course" approaches. Despite limited resources, Ghana demonstrates commitment to strengthening its health system through policy innovation, community involvement, and a whole-of-society approach.

4.1.Data Collection

Data was collected through a structured online questionnaire administered to individuals in the target population, which consisted of adults (18 years and above) in Cameroon and Ghana who used smart wearable devices and received healthcare services within the past six months. A device was considered a relevant smart wearable health device if it collected and reported aggregated data on at least one basic personal health metric, such as heart rate and blood oxygen levels. Smartwatches were the devices all participants reported using. The questionnaire consisted of two main sections: demographics and research constructs, adapted from validated scales to ensure reliability and validity, using 7-point Likert scales. Measures for AIA capability (traceability, analytical capability, speed-to-decision capability, predictive capability, and interoperability capability) were adapted from Wang & Hajli (2017). Measures of patient-centered care (general perception, effective communication, interest in patient's agenda, empathy, patient involvement in care, perceived access to essential healthcare services) were adapted from Casu et al. (2019) and Tzelepis et al. (2015). eHealth literacy scale was adapted from Norman & Skinner (2006).

To further validate the reliability and validity of the survey instrument in this context, it was pretested with a group of 20 users of smart wearables to assess face validity. A pilot test was followed by another group of 20 individuals from the target population, during which exploratory and confirmatory factor analyses were conducted to identify measurement scale issues before the full-scale distribution. A stratified sampling technique was employed to select participants, ensuring representation of both male and female participants to prevent gender bias in the data. The recommended minimum sample size was calculated using G*Power Version 3.1.9.7 software (Erdfelder et al., 2009), with an a priori power analysis for an F-test using an effect size of 0.04 and an error probability of 0.05, resulting in a recommended total sample size of 248 respondents per country.

After applying attention checks to filter out inconsistent responses, the questionnaire was distributed from May 1 to May 30, 2022, and received 306 valid responses from Cameroon and 281 valid responses from Ghana. Common method bias was addressed by following the procedural and statistical guidelines proposed by MacKenzie & Podsakoff (2012). Harman's single-factor test indicated a variance of 42.6%, which is below the 50% threshold, confirming that common method bias is not a concern in this study and thereby validating our dataset for further analysis. The demographics of the respondents are provided in Table 1.

Table 1 Participant demographics

Variable	Number of respondents from Cameroon (sample size = 306)	Number of respondents from Ghana (sample size = 281)
Household income (monthly)		
1 - 50 USD	68	105
51 - 100 USD	40	48
101 - 150 USD	48	23
151 - 200 USD	34	23
201 - 250 USD	34	30
251 - 300 USD	19	16
Over 300 USD	63	36
Health expenditure (yearly)		
1 - 50 USD	117	145
51 - 100 USD	96	54
101 - 150 USD	43	26
151 - 200 USD	21	18
201 - 250 USD	8	17
251 - 300 USD	4	6
Over 300 USD	17	15
Health insurance		
No	111	217
Yes	195	64
Gender		
Male	158	158
Female	139	120
Non-binary/third gender	7	0
I prefer not to say	2	3
Age		
18 - 24	192	2
25 - 34	95	239
35 - 44	9	34
45 - 54	4	5
55 - 64	5	1
65 - 74	1	0
Marital status		
Legally married	11	11
Not married	236	232
Divorced	5	1
Cohabiting	22	3
Widow/widower	0	1
I prefer not to say	32	33
Level of education		
Doctorate or equivalent	3	0
Master's degree	118	0
Bachelor's degree	103	38
Higher education diploma	46	28
High school diploma	32	85
Below a high school diploma	2	7
No formal education certificate	2	123
Employment status		
Employed full-time	49	23
Employed part-time	35	24
Seeking employment	128	56
Retired	2	0
Available for work	33	144
I prefer not to say	59	34

4.2. Data Analysis

PLS-SEM is a widely recognized data analysis method in research. We consider it relevant for this study because it is particularly adapted to complex studies that aim to adopt a causal-predictive approach to developing theoretical and practical insights into the effects of AIA capability as a formative construct on multiple reflective patient-care constructs (Hair et al., 2024; Lowry & Gaskin, 2014). We employ the two-stage approach to PLS-SEM implementation proposed by Sarstedt et al. (2021) because it offers a systematic framework for applying PLS-SEM, which is crucial regardless of the estimation technique (Schuberth et al., 2023).

The first stage of Sarstedt et al.'s (2021) approach involves evaluating the reflective measurement model. Outer loadings above 0.708 but below 0.95 indicate satisfactory reliability levels for indicators. Constructs with Cronbach's alpha and composite reliability values between 0.70 and 0.95 demonstrate internal consistency reliability; however, values above 0.60 are also acceptable in exploratory research. Average Variance Extracted (AVE) values of 0.5 or higher indicate convergent validity. Recent PLS developments advocate using the Heterotrait-Monotrait (HTMT) ratio of correlations to assess discriminant validity due to its higher sensitivity and specificity, clear thresholds, bias correction, simplicity, empirical support, and theoretical justification (Evermann & Rönkkö, 2023).

The second stage involves assessing the structural model. It is essential to ensure that all variance inflation factor (VIF) values are conservatively below 1, indicating the absence of collinearity among predictor constructs. Values above 5 indicate strong collinearity. Path coefficients and their significance should also be determined. Sarstedt et al. (2021) recommend using R^2 to measure the model's explanatory power, considering 0.75, 0.50, and 0.25 as substantial, moderate, and weak, respectively. In line with recent PLS developments, we focus on the model's explanatory power rather than its predictive power (Evermann & Rönkkö, 2023). We also report Q^2 since this study aims to predict the effect of AIA capability on patient-care variables (Evermann & Rönkkö, 2023). SmartPLS 4.1.0.6 (Ringle et al., 2024) was the primary software used for the PLS-SEM analysis.

5. Results

5.1. Measurement model results

Table 2 reports the measurement instrument and its item reliability. All item loadings exceed the 0.708 threshold, indicating item reliability.

Table 2 Item reliability of measurement scale

Measurement items	Outer loading: Cameroon	Outer loading: Ghana	VIF: Cameroon	VIF: Ghana
Analytical capability (Wang & Hajli, 2017): I would like my healthcare providers to:				
Run broad studies that extract important insights from large amounts of data from my wearable.	0.736	0.868	2.016	2.354
Analyze health information from my wearable in near real-time.	0.772	0.890	2.706	2.420
Automatically monitor my health continuously using data from my wearable device.	0.768	0.805	2.856	1.871
Compare "what if" scenarios regarding my health using data from my wearable.	0.947	0.783	1.787	1.707
eHealth literacy (Norman & Skinner, 2006):				
I know how to find helpful health resources on the Internet.	0.720	0.747	2.140	1.684
I know how to use the Internet to answer my health questions	0.763	0.849	2.540	2.348
I am aware of the various health resources available on the Internet.	0.829	0.880	2.944	2.986
I know where to find helpful health resources online.	0.865	0.863	3.604	2.722
I know how to use the health information I find online to help me.	0.865	0.782	3.186	1.822
Effective communication (Casu et al., 2019; Tzelepis et al., 2015): I believe my healthcare provider would:				
Provide me with clearer information.	0.799	0.898	2.052	1.507
Talk to me in a calm and quiet tone.	0.916	0.879	4.101	1.507
Access to essential health services (Casu et al., 2019; Tzelepis et al., 2015): I believe:				
I would be able to afford all essential vaccines.	0.792	0.864	2.697	1.960
Children in my family would have access to essential health services.	0.721	0.885	3.110	2.310
Empathy (Casu et al., 2019; Tzelepis et al., 2015): I believe my healthcare provider would:				
Listen.	0.865	0.903	2.824	2.515
Put themselves in my "shoes".	0.927	0.899	3.242	2.635
Inspire confidence when treating me.	0.906	0.911	3.302	2.606
Interoperability capability (Wang & Hajli, 2017): I would like my healthcare providers to:				
Integrate data from my wearable device with data from all hospital systems and devices.	0.701	0.956	1.397	2.250
Integrate data from my wearable with that found in other hospitals, clinics, and data sources.	0.977	0.909	1.397	2.250
Interest in Personal Agenda (Casu et al., 2019; Tzelepis et al., 2015)**:** I believe my healthcare provider would:				
Be more interested in what I feel about my current health status.	0.875	0.936	2.714	2.215
Be more interested in what I know about my disease/prognosis.	0.893	0.930	2.947	2.215
Predictive analytics capability (Wang & Hajli, 2017): I would like my healthcare providers to:				
Use the data from my wearable device to determine if I require additional medical attention.	0.762	0.795	1.832	1.527

Use data from my wearable to predict the effectiveness of various treatment options for me.	0.747	0.926	2.035	2.369
Use data from my wearable to perform a "what-if" analysis using predictive modeling.	0.879	0.813	2.042	1.960
General perception of patient-centered care (Casu et al., 2019; Tzelepis et al., 2015): I believe the current healthcare services in my country:				
Are coordinated and integrated.	0.899	0.867	3.829	2.011
Provide information, communication, and education.	0.874	0.845	3.238	1.974
Involve family and friends.	0.734	0.825	1.907	1.485
Patient involvement in care (Casu et al., 2019; Tzelepis et al., 2015): I believe my healthcare provider would:				
Give me time to talk about my disease/prognosis	0.896	0.932	3.182	2.269
Offer me the opportunity to discuss the next steps to take.	0.903	0.938	2.997	2.269
Speed to decision capability (Wang & Hajli, 2017): I would like my healthcare providers to:				
Be automatically notified of critical health issues based on data from my wearable device.	0.821	0.771	2.027	1.756
Generate detailed visual reports on my health status based on data from my wearable.	0.816	0.867	1.725	1.721
Generate proactive clinical recommendations for any health condition detected using data from my wearable.	0.837	0.892	1.785	1.834
Traceability (Wang & Hajli, 2017): I would like my healthcare providers to:				
Track the health data generated by my wearable.	0.872	0.846	1.925	2.011
Monitor my health condition through my wearable device daily.	0.957	0.899	1.925	1.697

Table 3 presents the results on the validity and reliability of the constructs used. Cronbach's alpha and composite reliability values all range between 0.70 and 0.95, demonstrating internal consistency reliability. Meanwhile, all AVEs are above 0.50, demonstrating convergent validity.

Table 3 Construct reliability and validity

Construct	**Cameroon**				**Ghana**			
	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
Effective communication	0.903	0.914	0.932	0.776	0.734	0.737	0.882	0.790
Empathy	0.935	0.937	0.951	0.795	0.889	0.893	0.931	0.818
General perception of patient-centeredness	0.932	0.935	0.947	0.749	0.802	0.806	0.883	0.715
Interest in the patient's agenda	0.927	0.930	0.948	0.820	0.851	0.852	0.931	0.870
Patient involvement in care	0.925	0.927	0.947	0.817	0.856	0.857	0.933	0.874

Perceived access to essential healthcare services	0.870	0.874	0.902	0.607	0.862	0.863	0.916	0.784
eHealth literacy	0.927	0.933	0.940	0.664	0.882	0.885	0.914	0.681

Table 4 reports the HTMT ratio between the constructs. All values are below 0.9, demonstrating discriminant validity. It confirms that the constructs are conceptually distinct from one another.

Table 4 Discriminant validity: Heterotrait-monotrait ratio (HTMT) matrix

Variable	**Cameroon**							
	1	2	3	4	5	6	7	8
Effective communication (1)								
Empathy (2)	0.878							
General perception of patient-centeredness (3)	0.407	0.540						
Interest in the patient's agenda (4)	0.772	0.894	0.526					
Patient involvement in care (5)	0.728	0.878	0.491	0.838				
Perceived access to essential healthcare services (6)	0.467	0.498	0.395	0.364	0.433			
eHealth literacy (7)	0.249	0.384	0.401	0.379	0.329	0.449		
eHealth literacy x AIA capability (8)	0.221	0.144	0.079	0.078	0.060	0.115	0.068	
Ghana								
Variable	1	2	3	4	5	6	7	8
Effective communication (1)								
Empathy (2)	0.820							
General perception of patient-centeredness (3)	0.728	0.547						
Interest in the patient's agenda (4)	0.804	0.884	0.656					
Patient involvement in care (5)	0.807	0.869	0.586	0.819				
Perceived access to essential healthcare services (6)	0.501	0.474	0.386	0.433	0.386			
eHealth literacy (7)	0.364	0.298	0.427	0.281	0.309	0.469		
eHealth literacy x AIA capability (8)	0.345	0.243	0.225	0.220	0.187	0.215	0.291	

5.2. Structural model results

All VIF values are below 5, indicating that collinearity issues are at or below acceptable levels (Table 2). The percentile bootstrapping results, based on 10,000 subsamples, revealed the path coefficients and their corresponding significance levels (Table 5).

Table 5 Path coefficients and their significance levels

		Cameroon	Ghana

	Relationship	Path coefficient	P values	Path coefficient	P values
H1	AIA capability -> General perception of patient-centeredness	0.058	0.370	0.148	0.041
H2	AIA capability -> Effective communication	0.281	0.000	0.196	0.012
H3	AIA capability -> Interest in patient's agenda	0.193	0.004	0.098	0.173
H4	AIA capability -> Empathy	0.211	0.001	0.116	0.113
H5	AIA capability -> Patient involvement in care	0.234	0.001	0.128	0.095
H6	AIA capability -> Perceived access to essential healthcare services	0.228	0.000	0.158	0.021
H7	eHealth literacy x AIA capability -> Effective communication	-0.112	0.067	-0.090	0.056
H7	eHealth literacy x AIA capability -> Empathy	-0.070	0.223	-0.072	0.180
H7	eHealth literacy x AIA capability -> General perception of patient-centeredness	0.085	0.130	-0.028	0.524
H7	eHealth literacy x AIA capability -> Interest in patient's agenda	-0.016	0.795	-0.065	0.257
H7	eHealth literacy x AIA capability -> Patient involvement in care	0.012	0.845	-0.032	0.580
H7	eHealth literacy x AIA capability -> Perceived access to essential healthcare services	-0.036	0.513	-0.016	0.734
	eHealth literacy -> Effective communication	0.145	0.012	0.198	0.001
	eHealth literacy -> Empathy	0.303	0.000	0.198	0.002
	eHealth literacy -> General perception of patient-centeredness	0.371	0.000	0.309	0.000
	eHealth literacy -> Interest in patient's agenda	0.301	0.000	0.186	0.003
	eHealth literacy -> Patient involvement in care	0.241	0.000	0.217	0.002
	eHealth literacy -> Perceived access to essential healthcare services	0.341	0.000	0.354	0.000

Figure 2 and Figure 3 summarize the PLS path analysis results and the R^2 values of all variables explained in Cameroon and Ghana, respectively.

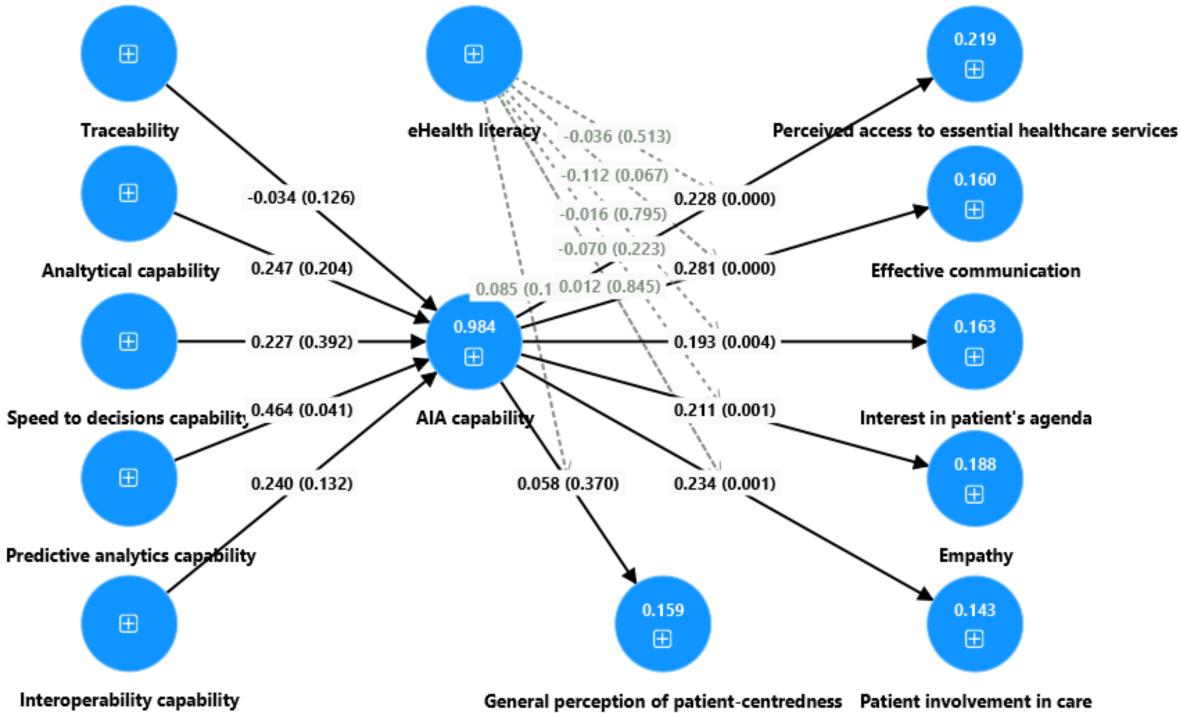

Fig. 2 Structural model results: Cameroon

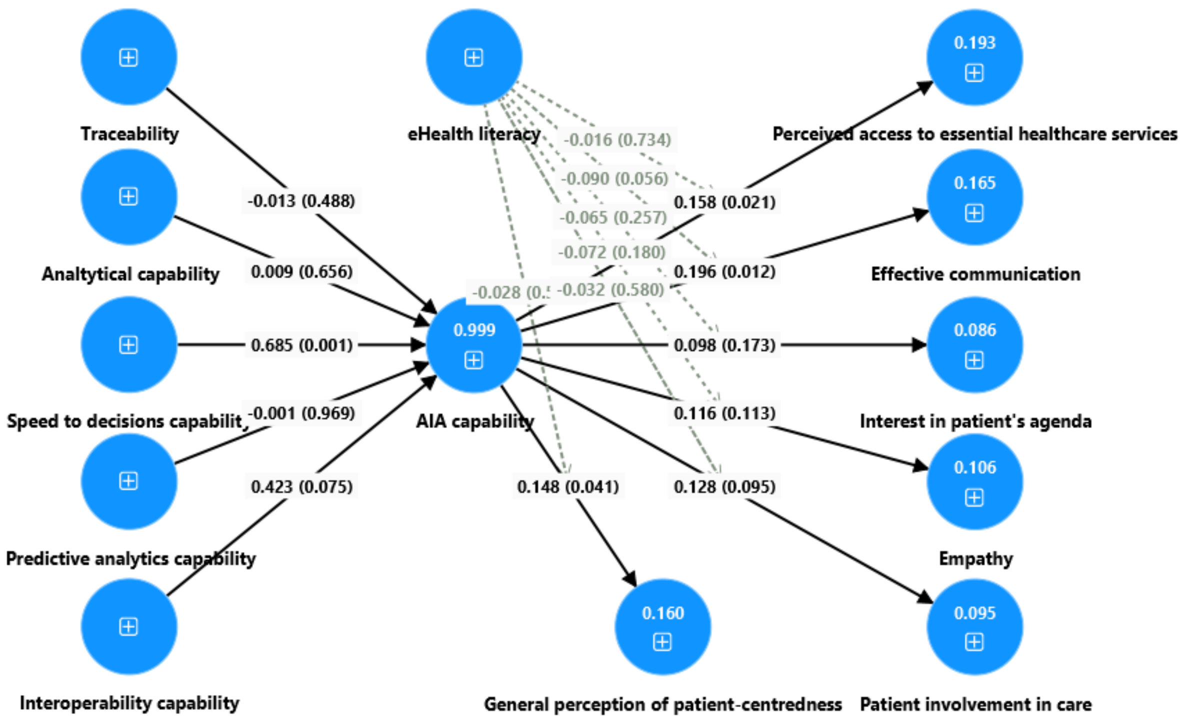

Fig. 3 Structural model results: Ghana

Table 6 presents the PLSpredict results that evaluate the model's predictive capabilities by comparing its performance against two naïve benchmarks. The algorithm was run with ten folds and ten repetitions. The Q^2 values are all positive, indicating that the prediction error of the

PLS-SEM results is smaller than that of simply using the mean values; thus, the model can be used to predict latent variables outside the sample.

Table 6 Outer of sample predictivity scores

Latent variable	Q^2predict	
	Cameroon	Ghana
AIA capability	0.980	0.998
Effective communication	0.119	0.119
Empathy	0.149	0.060
General perception of patient-centeredness	0.136	0.128
Interest in patient's agenda	0.126	0.039
Patient involvement in care	0.107	0.047
Perceived access to essential healthcare services	0.190	0.158

6. Discussion

Using Cameroon and Ghana as examples, this research explored how AIA capability based on wearable health data could influence patient-centered care experiences among individuals in health resource-constrained environments. This research informs healthcare stakeholders about user acceptance and expectations of wearable health devices, guiding investment decisions in strengthening health systems. The results reveal interesting contrasts between Cameroon and Ghana, with varying degrees of alignment with the existing literature.

For Hypothesis 1, which explored the relationship between AIA capability and the general perception of patient-centeredness, the findings show a significant positive relationship in Ghana but not in Cameroon. This discrepancy is notable because it suggests that while AIA capability is generally associated with improved perceptions of patient-centered care in developed contexts (Rha et al., 2022), the effectiveness of AIA in this regard may be highly context-dependent. In Ghana, the positive outcome aligns with studies from more developed healthcare systems, suggesting that Ghana might have better infrastructure or higher levels of digital readiness that could facilitate the impact of AIA capability. In contrast, the lack of significance in Cameroon could indicate that other barriers, such as inadequate healthcare infrastructure or provider resistance (Bawack & Kala Kamdjoug, 2018), may hinder the potential benefits of AIA in patient-centered care. For Hypothesis 2, which examined the link between AIA capability and effective communication, Cameroon and Ghana showed significant positive relationships. This consistency aligns with the broader literature, where AIA has been credited with enhancing communication between patients and healthcare providers through real-time data and insights (Azzi et al., 2020). Despite the different healthcare contexts of

Cameroon and Ghana, AIA's positive impact on communication suggests that this is one area where AIA capability can transcend local challenges, providing a universal benefit to healthcare systems.

Hypothesis 3, which explored the relationship between AIA capability and interest in the patient's agenda, produced mixed results. In Cameroon, a significant positive relationship was observed, indicating that AIA may help healthcare providers better understand and respond to patient concerns, consistent with the existing literature (Wang et al., 2020). However, in Ghana, the relationship was insignificant, suggesting that factors other than AIA capability might be more influential in determining the extent to which healthcare providers engage with patient agendas. This divergence may indicate differences in healthcare provider workload, system inefficiencies (Bonenberger et al., 2016), or cultural factors that could affect how patient engagement is realized. Regarding Hypothesis 4, which focused on AIA capability and empathy, the results were significant in Cameroon but not in Ghana. The significance in Cameroon supports the literature, which suggests that AIA can enhance empathy by providing healthcare providers with detailed insights into patient conditions (Al Kuwaiti et al., 2023). However, the lack of significance in Ghana implies that while AIA can provide valuable insights, it may not automatically translate into empathetic care, which could depend more on other factors, such as training and patient interaction protocols. This finding raises a potential concern during the implementation of AIA capability in Ghana's healthcare system, where the technical benefits must be fully integrated into the interpersonal aspects of care.

Hypothesis 5, which examined the relationship between AIA capability and patient involvement in care, showed a significant positive relationship in Cameroon but a non-significant relationship in Ghana. The significance in Cameroon aligns with the literature, which suggests that AIA facilitates greater patient involvement by providing tailored information and care options (Tzelepis et al., 2015). The result in Ghana may suggest that barriers, such as cultural differences in patient autonomy or varying levels of digital integration (Abedini et al., 2015), could be limiting the impact of AIA on patient involvement. Hypothesis 6 examined the relationship between AIA capability and perceived access to essential healthcare services, revealing significant positive correlations in Cameroon and Ghana. These results are consistent with the broader literature that links AIA capability to improved healthcare access through optimized resource allocation and service delivery (Wang et al., 2018b, 2019; Wang & Hajli, 2017). However, the stronger relationship in Cameroon suggests that AIA might be particularly beneficial in resource-limited settings, where efficiency gains can have a more pronounced impact on access to care.

Finally, the study found that the moderating role of eHealth literacy was generally non-significant across both countries, which contrasts with much of the existing literature, which often positions eHealth literacy as a crucial factor in the effectiveness of digital health interventions (Cheng et al., 2020; El Benny et al., 2021; Trocin et al., 2023). Several context-specific explanations may account for this divergence. First, the nature of eHealth literacy in LMICs may skew toward functional literacy, whereby the basic ability to search for and understand online health information, while lacking interactive and critical literacy, which are required to comprehend AI-generated analytics from wearables and integrate them into healthcare discussions (Neter & Brainin, 2012; van der Vaart & Drossaert, 2017). In our sample, even if patients reported high levels of eHealth literacy, this may not translate into active engagement with advanced, algorithm-driven health insights in practice. Structural and systemic barriers in both countries may also diminish the potential of eHealth literacy to enhance the effect of AIA on care outcomes. In Cameroon and Ghana, healthcare encounters are typically brief and provider-dominated, leaving little room for patient-driven, data-informed dialogue (Abedini et al., 2015). As such, patients, even those who are eHealth literate, may not feel empowered to present or interpret data from wearables during consultations, erasing the moderating influence of their eHealth literacy. These insights suggest that while eHealth literacy has a direct effect on patient-centered care, its moderating effect on AIA's impact is highly dependent on contextual factors, which warrant further investigation.

The contrasting results between Cameroon and Ghana underscore the critical need for context-specific approaches in deploying AIA capability, highlighting that a one-size-fits-all model is insufficient even between LMICs, and that effective implementation must consider each country's unique healthcare landscape.

6.1. Theoretical Implications and Contributions

This research has several implications regarding the transformative potential of smart wearable devices and AI in enhancing patient-centered care. For instance, similar to the conclusions drawn by previous research (Rha et al., 2022; Witt et al., 2019), this study supports the notion that AIA capability derived from wearable devices can play a crucial role in enhancing communication between patients and healthcare providers, thereby positively influencing patient satisfaction and engagement.

However, this research extends beyond the existing literature by focusing on resource-constrained environments, such as Cameroon and Ghana, where healthcare systems frequently struggle with infrastructure and resource limitations. Previous studies have discussed the challenges of integrating AIA into healthcare settings, but these studies have typically focused on more developed contexts (Al Kuwaiti et al., 2023; Azzi et al., 2020). The positive effects of AIA on patient-centered care observed in this study suggest that, despite the challenges, AIA capability can be effectively leveraged in LMICs to improve patient outcomes. This finding extends the applicability of AIA in healthcare beyond more affluent regions.

The lack of significant moderation effects of eHealth literacy on the relationship between AIA capability and patient-centered care perceptions also provides a nuanced understanding of the role of digital literacy in healthcare. The results of this study suggest that while eHealth literacy directly affects patients' expectations and experiences, its role in moderating the effects of AIA capability on patient-centered care may not be as critical as previously thought, especially in resource-limited settings.

Given these implications, this research contributes to the theoretical understanding of BDAC theory within the healthcare domain, particularly in AIA and wearable health devices. By leveraging the BDAC theory adapted to the healthcare setting (Wang et al., 2018b; Wang & Hajli, 2017), this research validates the evolution of BDA towards AI algorithms, which is crucial for understanding the role of AIA capability in patient care. The findings suggest that these capabilities are relevant and essential in enhancing patient-centered care, thus validating the extension of BDAC theory into healthcare contexts.

Moreover, this study reinforces the idea that the successful integration of AIA capability into healthcare systems is not solely dependent on technological investments but also requires the development of specific organizational capabilities, as suggested by previous research (Wang et al., 2018b; Wang & Hajli, 2017). The evidence that AIA capability positively influences patient-centered care across various aspects, including effective communication, empathy, and involvement in care, supports the notion that AIA in healthcare can lead to improved healthcare organizational performance, particularly in terms of patient satisfaction and outcomes.

Finally, the study contributes to the understanding of patient-centered care by integrating patient-reported measures to assess the impact of AIA capability. This approach underscores the importance of incorporating the patient's voice in evaluating healthcare interventions, thus aligning with the growing emphasis on patient-centeredness in healthcare research and practice (Tzelepis et al., 2015).

While our findings highlight the positive role of AIA in enhancing patient-centered care, it is also important to recognize the potential negative consequences of healthcare datafication. Without strong governance, health data collected by wearables may be vulnerable to misuse by various actors, including cybercriminals or insurance companies (Ewoh & Vartiainen, 2024; Newell & Marabelli, 2015). This risk highlights the need for research on robust data governance frameworks to strike a balance between the benefits of connected health and the risks of surveillance and exploitation (Chatterjee & Sarker, 2024).

6.2. Implications for Practice

This research is particularly relevant for healthcare policymakers, administrators, and practitioners in LMICs. The findings suggest that investing in developing AIA capability within healthcare organizations can significantly improve patient-centered care, even in resource-constrained environments. It highlights the potential for wearable health devices and AIA to bridge gaps in healthcare delivery in regions where traditional healthcare infrastructure is lacking. For healthcare providers, the results underscore the importance of focusing on the specific AIA capabilities identified in this study: traceability, analytical capability, speed to decision, predictive capability, and interoperability. By enhancing these capabilities, healthcare organizations can improve the quality of patient care, particularly in terms of communication, empathy, and patient involvement – crucial aspects of patient-centered care. This research also provides valuable insights into the design and implementation of healthcare technologies in LMICs. Given the positive impact of AIA capability on patient-centered care, healthcare organizations in these regions should consider integrating wearable devices with advanced AI analytics to enhance patient care. However, the findings caution against overreliance on eHealth literacy as a moderating factor, suggesting that more organization-facing factors, such as healthcare provider workload, organizational readiness, and trust in AIA technologies, or cultural norms surrounding patient autonomy, may be critical in effectively deploying this technological capability.

Additionally, given the modest income levels and health expenditures reported by participants, implementation of AIA-enabled wearable programs in LMICs should assess economic feasibility and cost-effectiveness. Tailored financial models, such as subsidized access, public-private partnerships, or community-based financing mechanisms, could improve affordability and uptake. Investigating these dimensions will ensure that solutions are both impactful and financially accessible to the populations they serve.

6.3. Limitations and Future Research

As with all research, some limitations also present opportunities for future research. First, this study relies on self-reported data, which may be subject to biases such as social desirability or recall bias. Although we took evidence-based measures to address such biases, participants may have overstated their eHealth literacy or experiences with patient-centered care, potentially skewing the results. Future research could incorporate more objective measures, such as usage data from wearable devices or third-party assessments of healthcare provider interactions, to complement self-reported data and provide a more comprehensive understanding when possible. Additionally, we acknowledge that the survey items used to measure analytics capability did not explicitly capture prescriptive analytics. Future research should adapt and extend these scales to incorporate prescriptive AI functionalities more thoroughly.

Second, this study focuses on two countries (i.e., Cameroon and Ghana), which, while providing valuable insights into these specific contexts, limit the generalizability of the findings. Healthcare systems, cultural attitudes toward health, and levels of digital infrastructure vary significantly across countries, particularly in the Global South. Future research could consider expanding the geographic scope to include a more diverse range of countries within and beyond sub-Saharan Africa to assess whether the observed relationships hold in different contexts and identify region-specific factors that may influence the effectiveness of AIA capability and eHealth literacy in enhancing patient-centered care.

Third, the cross-sectional design of the study limits the ability to establish causality over time, necessitating further longitudinal validation. This study is also subject to potential biases related to the digital divide and demographic disparities between the national samples. As participation required internet access and ownership of wearable devices, individuals in Cameroon and Ghana with limited connectivity, lower digital literacy, or economic constraints may be underrepresented, particularly in rural or marginalized communities. This introduces a sampling bias in the results, favoring more technically literate, urban populations.

Fourth, consumer wearable devices, such as smartwatches, are not medical-grade instruments, and their accuracy is lower than that of technologies used in clinical settings, which are more extensively calibrated. Although medical-grade alternatives exist, they are often too costly for average users in LMICs. Our study, therefore, focuses on the preventative health potential of consumer devices, which can provide anecdotal evidence on well-being.

7. Conclusion

This study highlights the transformative potential of wearables, combined with the AIA capability of healthcare systems, in enhancing patient-centered care perceptions. It predicts that AIA capability, bolstered by data from wearable devices, can significantly improve perceptions of patient-centered care, including effective communication, empathy, and patient involvement in their care. The findings reveal that while AIA capability integrated with wearable data has the potential to positively influence these aspects of healthcare, the extent of its impact differs between countries. Thus, this research contributes to the existing literature by providing empirical evidence from two Sub-Saharan African countries, highlighting the potential challenges and opportunities of integrating smart wearables and AI capabilities into healthcare systems in LMICs. The comparative analysis between Cameroon and Ghana offers valuable insights into how regional differences can impact the adoption and effectiveness of such endeavors, which is particularly relevant for policymakers, healthcare providers, and technology developers seeking to leverage these technologies to enhance healthcare services. As wearables and AI integrate into healthcare, we hope this study inspires future research on the effective global implementation of these innovations, ensuring they enhance patient care and improve health outcomes across diverse regions and contexts.

8. Declarations

Ethics approval and consent to participate

- Not applicable

Consent for publication

- All authors have read and approved the final manuscript, giving their consent for publication.

Availability of data and material

- Available upon request

Competing interests

- None to declare

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- Not applicable

Authors' contributions

- Ransome Bawack: Conceptualization, Methodology, Formal Analysis, Investigation, Writing – Original Draft.

- Denis Dennehy: Conceptualization, Editing, Supervision, Project Administration.
- Caleb Amankwaa Kumi: Investigation, Data Collection, Data Curation, Data Analysis.
- Will Boutchouang: Investigation, Data Collection, Data Curation, Data Analysis.

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