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Exploring the Role of Community Engagement and Big Data Analytic Capacity on Community Participation in Health Interventions: Mediating Effects of Organizational Agility

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Abstract: **Enhancing community engagement and participation in public health interventions is crucial for addressing societal health challenges. Consequently, various measures are being implemented to foster better collaboration between community members and public health experts, aiming for societal improvement. Presently, big data analytics emerges as a pivotal tool for enhancing community engagement and participation in public health interventions, especially considering the diverse nature of modern communities. This research investigated the impact of big data analytics capability on community engagement and participation in public health interventions, with organizational agility as a mediator. Smart PLS was utilized to analyze the data employing a structural equation model. The findings indicate that big data analytics capability positively influences community engagement, community participation in public health interventions, and the agility of community health professionals. Furthermore, it was revealed that organizational agility positively contributes to community engagement and participation in public health interventions. It also mediates the connections between big data analytics capability, community engagement, and community participation in public health interventions. The study underscores the pivotal role of big data analytics capability in fostering community engagement and participation, both critical elements of health promotion. Recommendations include governments in developing countries assisting in establishing big data infrastructure and facilitating the storage of quality data necessary for analysis, as these endeavors are often financially burdensome for individuals. Public health institutions should also organize training sessions for personnel on big data analytics and incentivize individuals to enhance their understanding of this field.**

Keywords: **community engagement, big data analytics, community participation, organizational agility, cosmopolitan.**

1. INTRODUCTION

In recent years, the intersection of community engagement, big data analytics, and health interventions has emerged as a critical focal point in understanding and improving public health outcomes (1). Big data analytics is becoming influential in gathering the needed data on population and demographic specifics within communities (2). With the emergence of big data analytics at the community level, community engagement and participation in public health intervention have improved as public health workers have a more defined target population to whom community participatory activities are directed due to the availability of factual data about people within the communities (2)(3).

As societies navigate the complexities of healthcare delivery, the need to actively involve communities and harness the potential is being made more accessible through the building of data systems that demonstrate community characteristics

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just at the click of a baton, and this makes big data analytics a vital component in community engagement and participatory in public health intervention(4)(5). Big Data Analytics capacity refers to an organization's ability to effectively and efficiently process, analyze, and derive insights from large volumes of data. It involves the infrastructure, tools, technologies, and expertise required to manage and make sense of massive datasets (5)(6). Big data analytic capacity has appeared in diverse research about how it influences firms' decisions by lowering the gaps between predictions and actual occurrence, as data-based decision-making is becoming a significant resource for firms' operations (7).

In the field of public health, society is becoming more diverse and complex due to the growth of urbanization, making communities more cosmopolitan (8). Targeting and reaching out to the right population with health interventions is vital in making good use of scarce health resources and reducing time wastage; hence, community engagement, which refers to the more inclusive process of involving the community in decision-making, planning, and problem-solving is vital in building relationships, collaboration, and communication between community members and external entities such as public health institutions for health promotion and education activities (9)(10). Big data analytic capacity appeared critical in all community engagement steps to achieve the above. The use of big data for community engagement and participation in public intervention was pervasive during the outbreak of the COVID-19 pandemic from 2020 to 2023, enabling countries that have big data systems being able to control the spread of the COVID-19 virus more effectively than others(11) (4). For example, big data analytics was the backbone of contact tracing in China. Big data helps trace the path of infected people and the people they come in contact with; it also helps identify populations at risk and how to channel specific health interventions to particular populations (12).

Community engagement drives community participation in public health intervention as advocacy groups have encouraged walking with targeted communities through the decision-making processes. However, studies still show that community participation needs to yield the needed results as several public health interventions collapse before scaling up or hardly meet the targets set by donors (13)(13). The use of big data analytics in the community to influence community participation in public health intervention is likely to boost the outcomes of interventions and increase the achievement of donors' targets, as record keeping and dealing with the right people in the population could be boosted by big data analytic capacity of public health organizations(13) (14).

Community participation in public health interventions implies a more direct and hands-on involvement of community members in specific activities or projects. It often focuses on active participation, contribution, and shared responsibilities in the implementation of initiatives (15); big data analytics serve as the needed resources in changing the face of community participation by enabling firms to identify and apply specific participatory strategies to particular groups through building concrete knowledge about their targeted population through information provided in extensive data systems(16).

With communities becoming more complex and cosmopolitan, public health organizations need to be flexible in adopting multiple strategies to achieve effective community engagement and participation; hence, the variable of organizational agility is becoming relevant in public health research in addressing dynamism in the population(17)(18). Big data creates room for firms to be agile as it is easier to explore the dynamics of communities in big data systems (19)(18).

Integrating community engagement into health interventions recognizes the inherent value of community perspectives, local knowledge, and collaborative decision-making in shaping effective and culturally sensitive health programs (20). Simultaneously, the era of big data presents unparalleled opportunities to leverage vast datasets for informed decision-making and enhanced healthcare strategies(21)(11). This study aims to bridge these two realms by investigating how community engagement and utilizing big data analytics collectively influence community participation in health interventions. Moreover, by introducing the mediating role of organizational agility, the research seeks to unravel the mechanisms through which adaptable and responsive organizational structures facilitate or hinder the translation of community engagement and big data analytics into meaningful community participation in health initiatives.

Understanding these relationships is crucial for advancing academic knowledge and informing policymakers, healthcare practitioners, and community leaders on effective strategies to design and implement health interventions that resonate with communities' diverse needs and contexts.

2. HYPOTHESES DEVELOPMENT

2.1 Effects of Big Data Capacity on Organizational Agility in Handing Public Health Interventions.

Agility generally refers to the ability of an individual, organization, or system to adapt quickly and effectively to changing circumstances or environments (11) (22)(23). It involves being flexible, responsive, and able to make rapid adjustments to navigate uncertainties, capitalize on opportunities, or address challenges, which is hence vital in public health intervention implementation (14). The big data analytics capacity of firms and organizational agility are mutually reinforcing as big data analytics provides the necessary information for agile decision-making and adaptation, while organizational agility creates an environment that maximizes the value derived from big data analytics(11)(24). Together, they form a synergistic relationship that positions organizations to thrive in dynamic and cosmopolitan environments (25). Based on the above, most studies have established that big data analytics positively affects organizational agility (26).

The relationship between firms' big data analytics capacity and organizational agility is intricate and dynamic, with each influencing and reinforcing the other in various ways (25). In health promotion activities, the big data analytics capacity helps gather, process, and analyze vast amounts of data from multiple sources to make informed decisions from such data; the organization needs to be agile to access timely and relevant information, enhancing the organization's agility. Decision-makers can quickly respond to changes in the community, which is certain to influence the achievement of international goals (27).

Other studies that established a relationship between big data capacity and agility of organizations stated that the two variables work together to enhance innovation in organizational performance (11). Equally, in public health programs, big data analytics may provide the information needed for innovation (3). In this case, the organization's agility level has the chance to speed up the adoption of innovation to maximize the outcomes of health intervention (27). The positive effects of big data analytics on organizational agility can be deduced from the ability of big data to enable the analysis of community data to gain insights into customer behavior, preferences, and needs of community people (28). In contrast, organizational agility will help to use the insights to tailor public health interventions by developing distinct strategies to meet the evolving health needs of communities and enhance their participation in public health programs. Based on this, the hypothesis below was developed.

1. *Big data analytic capacity has positive effects on organizational agility.*

2.2 Effects of Big Data Capacity on Community Engagement and Participation in Public Health Interventions.

The effects of big data analytic capacity on community engagement and community participation in public health interventions are significant and transformative (Kaur et al., 2018; Francis et al., 2022). Leveraging data analytics in community initiatives can lead to more targeted, responsive, and impactful engagement strategies, ultimately creating a more empowered and involved community (29)(30). The effects of big data analytic capacity on community engagement and participation reflect the transformative influence that advanced data analytics can have on how communities interact, participate, and collaborate, as research findings have emphasized that big data analytics enable organizations to derive meaningful insights from large and diverse datasets (2) (31).

This information can be used to make informed decisions, allowing community leaders and organizations to tailor engagement strategies based on a data-driven understanding of community needs and preferences (32); by so doing, different community segments are identified, and public health interventions are directed toward them (33). Big data analytics empower community organizers to customize communication and outreach efforts by analyzing demographic, behavioral, and contextual data, and community engagement strategies can be personalized to resonate with specific groups, fostering more effective communication and participation (34). The insight from big data analytics helps reduce public health intervention expenditure as specific information is channeled to the right target (27).

Other studies provide the circumstances that big data analytics may influence community engagement and participation in public health interventions positively, as big data analytics facilitate the identification of trends, patterns, and emerging public health issues within a community(14)(4). This insight helps community leaders proactively address concerns, anticipate needs, and design targeted engagement initiatives that align with the community's dynamics(15) (35). Through data-driven campaigns and information dissemination, big data analytic capacity contributes to raising community awareness as timely and relevant information about health, social services, or local events can be shared, promoting a more engaged and well-informed community (26)(17). This is vital in community engagement and leads to improved community participation (29).

Though many studies have not been done about the effects of big data analytics capacity on community engagement and participation, studies in similar fields show that big data analytics assist in efficiently allocating resources based on identified community health intervention needs (36). By understanding where resources are most impactful, public health organizations will likely optimize their efforts and resources, fostering a more engaged community that perceives tangible benefits from interventions(37)(38). Feedback is vital to the sustenance of public health interventions and gains from big data analytic capacity when investigating the benefits of big data analytics to community engagement and participation in public health interventions. Big data analytic capacity enables the establishment of feedback loops within the community(39) (30). Continuous monitoring and evaluation of engagement initiatives allow for adaptive strategies, responding to community feedback, and ensuring that engagement efforts evolve in line with changing community dynamics. Based on the above explanation, the following hypotheses are developed.

2. *Big data analytic capacity has positive effects on community engagement*
3. *Big data analytic capacity positively affects community participation in public health interventions.*
4. *Community engagement positively affects community participation in public health interventions.*

2.3 Direct and Indirect Effects of Organizational Agility on Community Engagement and Community Participation in Public Health Interventions.

Organizational agility is a pivotal characteristic denoting an organization's adeptness in responding promptly and adapting to dynamic environmental changes (40). Its implications for public health interventions extend far beyond mere operational efficiency, significantly influencing community engagement and participation. The multifaceted impact of organizational agility on public health initiatives is underscored by its role in fostering responsiveness, adaptability, collaboration, effective communication, resource optimization, and crisis management(41). These attributes collectively contribute to the development of more productive and sustainable public health interventions that resonate with the diverse needs and preferences of communities (17).

The prominence of agility in organizational operations is particularly evident in the realm of health delivery, as exemplified by health workers and systems adapting swiftly during the COVID-19 pandemic (41). Public health education and promotion dynamically adjusted to the evolving demands of the health situation, showcasing the imperative role of agility in meeting the diverse needs of society (42)(43) . The agility of health workers directly influences their ability to effectively engage and cater to the varied segments of the population, thereby shaping community participation in health interventions (44).

Critical to community engagement processes, organizational agility is indispensable in managing the expectations of diverse groups during various stages of public health interventions(17)(10). In economically disadvantaged communities, past challenges stemmed from intervention implementors being ill-equipped or inadequately communicating with the target population, and in culturally diverse communities, organizational agility acts as a potent tool for navigating through different feelings, attitudes, and expectations of community members, fostering a more inclusive and responsive approach (43).

Despite the widespread recognition of agility in operational contexts, its application in the public health domain still needs to be explored (17). While public health professionals employ strategies such as segmentation, targeting, and the innovation diffusion theory, which involves tailoring messages and materials to individuals at different life cycle stages, the explicit consideration of organizational agility is often lacking (10) (26). However, it is evident that the adaptability of organizations to changes inherently exists in the implementation of public health interventions, even if not explicitly acknowledged (4).

In the intricate landscape of community engagement, the strategies employed vary based on the hierarchical leadership of the community and its unique settings (45). Organizational agility becomes a linchpin in overcoming complex issues within communities, facilitating the smooth implementation of community projects (46). This study aims to bring attention to the vital role of organizational agility in public health operations, especially during outbreaks and emergency scenarios, emphasizing the need for greater focus on this dimension.

The positive influence of organizational agility on community engagement and participation in public health interventions is underscored by its role in resource allocation to diverse communities (24). It empowers public health experts to gain a deeper understanding of their communities, fostering more targeted and effective interventions (14). Drawing parallels with big data analytics, organizational agility emerges as a mediating force, influencing the relationships between the analytical capacity of organizations and various subjects (1). The expectation is that organizational agility will similarly mediate relationships between big data analytics capacity, community engagement, and community participation in public health interventions, further highlighting its integral role in shaping successful outcomes in the public health landscape (47)(24) (48). The connectivities between variables are alson show in figure 1.

H5: Organizational agility has a positive influence on community engagement in public health interventions

H6: Organizational agility positively influences community participation in public health interventions.

H7: Organizational agility mediates the relationship between the capacity of firms to use big data analytics and community engagement for public health interventions.

H8: Organizational agility mediates the relationship between firms' big data analytics capacity and community participation in public health interventions.

Insert Figure 1 Here

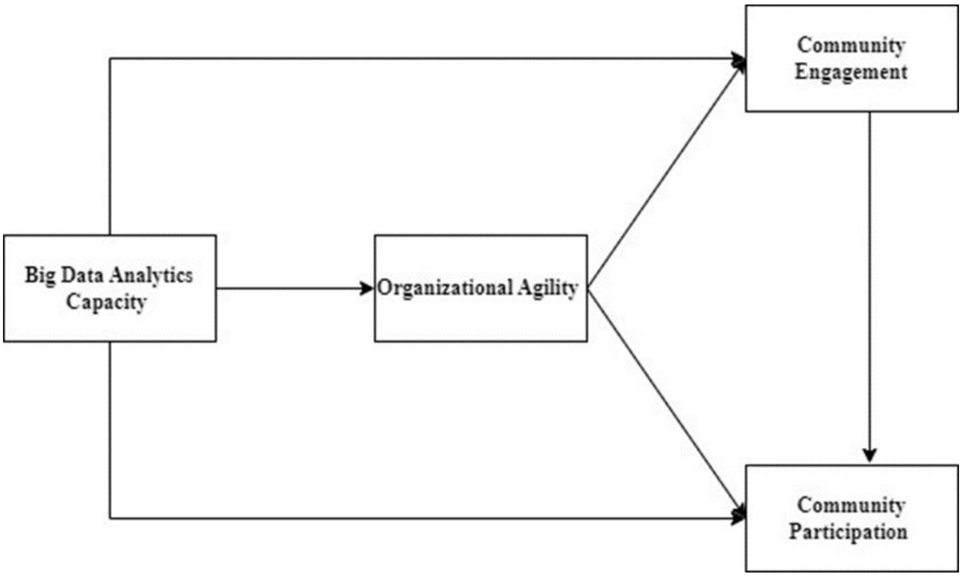

Figure1: Conceptual framework

3. RESEARCH METHOD

In order to assess our proposed research model, data were collected from public health workers in seven districts within the greater Accra region of Ghana. Employing a cross-sectional study approach, questionnaires were disseminated to public health professionals, and a cover letter was accompanied by clarifying the study's objectives, assuring respondent confidentiality, and soliciting voluntary participation. Acknowledging that public health professionals primarily focus on community engagement and implementing public health interventions (Xie et al., 2019), a stratified sampling method was utilized to ensure a representative sample from each district. Specifically, public health professionals were categorized into seven strata based on their respective districts. Subsequently, purposive sampling targeted individuals with at least three years of experience, regular involvement in community activities, and comprehensive knowledge of big data analytics operations. Only those meeting these criteria were invited to participate, thus ensuring clarity and minimizing ambiguity in the study.

3.1. Measures

Public health professionals indicated their level of agreement with each statement on a 5-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). Questionnaires assessing big data analytic capacity were adapted from (48)(49), comprising seven items (Cronbach's alpha 0.885)out of the seven questions . Sample items included 'Our enterprise uses BDA purchasing analytics for purchasing.' Questionnaires evaluating organizational agility were adapted from (50) consisting of six items (Cronbach's alpha 0.891), with a sample item, 'Recognizing dynamic environmental transition.' Questionnaires for measuring community engagement were adapted from (18)featuring four items (Cronbach's alpha 0.908), including a sample item, 'We can see public announcements from the government for household solid waste recycling around our living community.' Finally, questionnaires for assessing community participation were adapted from (35), comprising seven items, with a Cronbach's alpha of 0.814, and a sample item, 'Participating in the preparation of city strategies.' All tools were adapted to suit the research objectives since these tools were not directly designed for this particular study.

3.2 Data analysis

We utilized Smart PLS-Graph software (version 03.00 Build 1058) to analyze data and test hypotheses. Previous research suggests that PLS analysis involves two key components: calculating the measurement model and conducting predictive analysis Hair et al.,(2017) (51) .The measurement model calculation assesses the constructs used in the study, revealing relationships between observable variables and theoretical or hidden concepts, including item reliability, construct reliability, AVE, and discriminant validity. The second component, causal predictive analysis, examines relationships among constructs to test the consistency of suggested causal interactions with existing data. Latent model mechanisms were employed to analyze connections between constructs and their indicators, assuming the hidden variable as the indicator source.

4. RESULTS

4.1 Demographic Characteristics of Respondents

A total of 426 questionnaires were distributed, with 413 returned. Upon careful review, seven incomplete or improperly filled questionnaires were excluded, resulting in 406 questionnaires being deemed usable for the study. The majority of respondents (90.14%) identified as female. Regarding education, 72.15% held a diploma in nursing, while others possessed degrees or master's degrees in various nursing programs. Regarding work experience, the majority (50.24%) had been employed as community health professionals for 3 to 6 years, with the remaining portion having worked for over seven years; details are shown in Table 1.

Table 1. Demographic Characteristics of Respondents.

Variable	Frequency	Percentages	Accumulative percentage
Gender			
Female	384	90.14	90.14
Male	42	9.86	100
Age			
23-30	254	59.62	59.62
31-40	152	35.68	95.3
Above 41	20	4.68	100
Education			
Diploma	307	72.15	72.15
Degree	91	21.36	93.51
Postgraduate	28	6.57	100
Duration			
3-6	214	50.24	50.24
7-10	184	43.19	93.43
Above 10	28	6.57	100

4.2 Data Validity and Reliability Test

From table 2, the study aimed to operationalize four constructs, BDAC, OA, CE, and CP, as first-order reflective constructs, evaluating individual item reliability (see Table 2). Results indicate that indicators exceeded the recommended threshold of 0.7 for factor loadings Carmines & Zeller, (1979) (52), leading to removing items with low loadings and retaining those with high loadings.

For example, BDAC comprised seven items, with six showing strong loadings and one displaying a low loading, which was subsequently excluded. Similarly, OA consisted of 5 items, with four demonstrating strong loadings and one with poor loading, also removed. Conversely, CE contained five items, all exhibiting solid loadings, and was retained, as did CP, which had four items, all loading well and retained. Results in the same table strongly supports the reliability of the four constructs. Both Cronbach's alpha, composite reliability and average veriance extracted values exceed Nunnally's recommended threshold of 0.7 . According to the rule of thumb, AVE should surpass 0.5, indicating that at least 50% of the dimensions' variance is explained (52). Ashown in the same table, data of all four constructs of the model met all data quality thresholds (53).

Table 1: Measurement Model.

Constructs	Code	Factor loading	CA	CR	AVE
Big Data Analytics Capacity	BDAC1	0.750	0.847	0.888	0.570
	BDAC 2	0.745			
	BDAC 3	0.846			
	BDAC 4	0.740			
	BDAC 6	0.783			
	BDAC 7	0.652			
Organizational Agility	OA1	0.699	0.778	0.848	0.528
	OA 2	0.722			
	OA 3	0.707			
	OA 4	0.759			
	OA 5	0.744			
Community Engagement	CE1	0.844	0.855	0.895	0.632
	CE 2	0.722			
	CE 3	0.755			
	CE 4	0.641			
	CE 5	0.636			
Community Participation	CP1	0.830	0.868	0.909	0.715
	CP 2	0.848			
	CP 3	0.843			
	CP 4	0.861			

4.3 Assessing Common Method Variance (CMV)

Data for all constructs were collected from a single source, namely various public health professionals from different districts, using a self-administered questionnaire. This setup may have introduced common-method variance. To address this, researchers took several steps. Firstly, they ensured respondents' anonymity and confidentiality, encouraging honest and sincere responses. Additionally, pilot testing of the questionnaires with scholars and practitioners improved the content validity of the constructs, reducing ambiguities. Harman's one-factor test was also applied to all items, following recommendations by Podsakoff et al. (2012) (25). The unrotated factor analysis yielded four distinct factors, explaining 68.2% of the total variance, with the first factor accounting for 32.5%. This analysis revealed no dominant factor or significant variance attributed to any single factor, indicating minimal concern regarding common method variance and validating the measurements.

4.4 Descriptive Statistics and Correlation Matrix

Results from table 3, suggest that each construct has a perfect positive correlation with itself, which is expected. Additionally, there are positive correlations between the constructs, with varying strengths. BDAC shows a moderate positive correlation with OA, CE, and CP. OA shows a similar pattern of correlation with the other constructs. CE and CP demonstrate weaker correlations with the other constructs, with CP showing the strongest correlation with CE. Overall, these findings provide insights into the relationships between the constructs and their levels of association within the dataset.

Table 3: Descriptive Statistics and Correlation Matrix

Constructs	Mean	Standard Deviation	BDAC	OA	CE	CP
B DAC	3.824	1.113	1			
OG	4.235	0.940	0.574	1		
CE	4.017	1.148	0.429	0.337	1	
CP	3.685	1.312	0.329	0.319	0.507	1

Key: BDAC = Big Data Analytic Capacity; OA = Organizational Agility; CE = Community Engagement; CP = Community Participation

4.5 Testing Hypotheses.

From tabl4, hypothesis testing was conducted to assess the effects of big data analytic capacity on organizational agility, community engagement, and community participation in public health interventions. Structural equation modeling was employed using SMART PLS software version 03.00 Build 1058 for data analysis and hypothesis testing. PLS was chosen due to its suitability for predictive purposes and its effectiveness in theory development (Hair et al., 2017). Additionally, key statistical measures such as means, standard deviations, Cronbach's alpha, composite reliability, and average variance extracted were considered (refer to Table 2 and 3), with the results of hypothesis testing presented in Table 4.

Hypothesis 1 proposed a positive relationship between big data analytics capacity and organizational agility (b= 0.380; SD =0.031; P = 0.000) in implementing public health interventions. Hypothesis 2 suggested that big data analytic capacity positively influences community engagement (b= 0.083; SD =0.029; P = 0.005) in public health interventions. Similarly, hypothesis 3 posited a positive relationship between big data analytics capacity and community participation (b= 0.559; SD =0.021; P = 0.000) in public health interventions.

In hypothesis 4, it was found that organizational agility positively affects community engagement (b= 0.097; SD =0.027; P = 0.000) in public health interventions. Hypothesis 5 revealed that organizational agility positively influences community participation (b= 0.382; SD =0.030; P = 0.000) in public health interventions. Hypothesis 6 demonstrated a positive relationship between community engagement and community participation (b= 0.414; SD =0.025; P = 0.000) in public health interventions.

Furthermore, hypotheses 7 and 8 investigated the mediating role of organizational agility in the relationship between firms' big data analytic capacity and the implementation of public health interventions. The results showed that organizational agility mediates the relationship between big data analytic capacity and community engagement (b= 0.558; SD = 0.015; P = 0.000), as well as between big data analytics capacity and community participation (b= 0.445; SD = 0.016; P = 0.000) in public health interventions. All hypotheses were supported.

Table 4: Hypotheses Testing

Construct	Path Coefficient	Standard Deviation	T Statistics	P Values	Decision
BDAC -> OA	0.380	0.031	12.282	0.000	Supported
BDAC -> CE	0.083	0.029	2.804	0.005	Supported
BDAC -> CP	0.559	0.021	26.282	0.000	Supported
OA -> CE	0.097	0.027	3.615	0.000	Supported
OA -> CP	0.382	0.030	12.793	0.000	Supported
CE -> CP	0.414	0.025	16.319	0.000	Supported
		Mediating Effects			
BDAC -> OA -> MP	0.558	0.015	7.116	0.000	Supported
BDAC -> OA -> OP	0.445	0.016	6.230	0.000	Supported

Key: BDAC = Big Data Analytic Capacity; OA = Organizational Agility; CE = Community Engagement; CP = Community Participation

4.6 Model Fitness

Table 5 presents fitness indices for the model. The X²/df ratio is 1.673, below the recommended threshold of 3, indicating a reasonable fit between the model and the data. The Normed Fit Index (NFI) is 0.890, surpassing the commonly accepted threshold of 0.90, indicating a good fit. The Standardized Root Mean Square Residual (SRMR) is 0.050, within the acceptable range (ideally below 0.08), suggesting a reasonable fit between the model and the observed data. The Root Mean Square Error of Approximation (RMSEA) is 0.042, falling below the recommended threshold of 0.05, indicating a close fit of the model to the data. Additionally, the Comparative Fit Index (CFI) is 0.967, exceeding the desired threshold of 0.90, suggesting a good fit between the model and the data. Overall, these fitness indices indicate that the model adequately fits the observed data, supporting the plausibility of the hypothesized relationships between variables (Hosen et al., 2024; Cheung et al., 2022).

Table 5: Model Fitness Results

Measure	X^2	Df	X2/df	NFI	SRMR	Rmsea	CFI
Estimate	2014.736	1204.342	1.673	0.890	0.050	0.042	0.967

5. DISCUSSION

The rise of big data as a novel asset in organizational management and operations is revolutionizing decision-making processes by moving away from generalizations and toward targeted actions aimed at relevant groups (54). Big data has become indispensable across various domains of human activity, notably playing a pivotal role in public health decision-making, particularly evident during the COVID-19 pandemic (55). As public health initiatives increasingly prioritize community involvement, the concept of community engagement and participation remains enduringly pertinent (56)(57). Focusing big data analytics on community engagement and participation in public health interventions signifies a shift away from mass generalization towards tailored interventions for those in need, thereby optimizing resource allocation (58)(3).

The study investigated the impact of big data analytics capacity on the implementation of public health interventions. It found a positive correlation between big data analytics capacity and community engagement and participation in such interventions. These findings echo prior research emphasizing the transformative role of big data analytics in healthcare delivery (59)(11). Such studies highlight how big data analytics facilitates informed decision-making in hospitals by accurately categorizing and forecasting the medical requirements of diverse population segments (60). Consequently, in public health, community health workers can proactively prepare to meet the specific needs of targeted populations (61).

While discussions surrounding big data analytics in public health operations in developing nations may be less prevalent, the positive impact of such analytics on community engagement and participation in public health interventions can be attributed to the wealth of information stored within big data platforms about various communities (3). The detailed insights provided by big data facilitate health promotion efforts by enabling public health professionals to accurately segment and target specific population groups with appropriate communication and interventions (62). As communities become increasingly diverse, traditional generalizations in public health activities are becoming less effective (63) (26). Big data analytics plays a crucial role in identifying distinct population segments and directing interventions accordingly, thereby reducing the inefficiencies associated with misdirected efforts, which lead to the wastage of resources and time (61).

Moreover, the study indicated that the capacity for big data analytics within organizations influences the agility of public health entities in engaging with their communities. While the correlation between big data analytics capacity and organizational agility in the realm of public health may be relatively new, similar effects have been observed across various fields of study (64)(14). In the context of health promotion activities, big data furnishes public health professionals with precise information that enhances their adaptability to dynamic situations in their daily operations (3). For instance, during emergencies, big data informs agility by providing insights into the size and demographics of affected populations, allowing public health organizations to respond promptly and effectively to specific needs at critical times (63). This proactive approach reduces trial-and-error approaches in community engagement and participation, thereby enhancing overall effectiveness (27).

Additional findings from the study indicate a positive relationship between organizational agility and community engagement and participation in public health interventions. Across various fields, examinations of organizational agility in firms' operations have predominantly yielded favorable outcomes (26). Agility enhances the capacity of public health institutions to adapt to societal changes (14). Public health professionals are acquiring diverse skills through education and engagement with social media, enabling them to collaborate with increasingly cosmopolitan communities effectively (6)(65).

Studies reveal that factors such as climate change prompt population migrations between communities, underscoring the importance of public health professionals' agility in addressing the needs of diverse community segments to facilitate their participation in interventions (66) (67). Furthermore, research suggests that organizational agility contributes to improved community engagement and participation in public health interventions by enabling professionals to address segments of communities that were previously overlooked (17). As public health professionals' skill sets are honed to cater to the specific needs of even the smallest community groups, agility becomes instrumental in making interventions accessible to all segments of the community (25).

The study found that organizational agility plays a crucial role in amplifying community engagement and participation in public health interventions. Specifically, it acts as a positive mediator between the capacity for big data analytics and these community-oriented outcomes. This suggests that organizations capable of swiftly adapting to changing circumstances and leveraging big data effectively are more likely to foster meaningful engagement and participation from the community in public health initiatives (68). In simpler terms, being nimble and able to quickly respond to changes, combined with utilizing big data effectively, leads to better involvement from the community in public health efforts.

6. CONCLUSION AND RECOMMENDATIONS

Recent studies are shedding light on the valuable role of big data analytics in enhancing the operational efficiency of firms across various sectors. Similarly, in the realm of healthcare delivery, the capacity for big data analytics is revolutionizing health services by providing critical population data for accurate projections. This study reaffirms that a robust capacity for big data analytics positively impacts community engagement, community participation in public health interventions, and the overall agility of public health organizations in executing health promotion activities. Furthermore, it highlights the reciprocal relationship between the agility of public health institutions and professionals and community engagement and participation in public health interventions.

These findings, coupled with those of previous studies, underscore the imperative for healthcare institutions to invest in robust big data platforms and gather comprehensive data on the demographics and other pertinent variables within their target populations. Given the potential cost implications of data collection and storage, governmental support in providing infrastructure for big data initiatives and regular updates on population data is paramount. Moreover, training programs in data analytics should be implemented for public health workers to enhance their capacity for making data-informed decisions when engaging communities in health promotion activities.

Lastly, management within public health institutions should incentivize employees to develop proficiency in big data analytics and community engagement skills. This could be achieved through the establishment of reward systems for individuals who demonstrate a commitment to mastering these areas, ultimately enhancing their agility in responding to emergencies and addressing the diverse needs of the population.

Declaration

The authors declare that there are no conflicts of interest associated with the writing of this article, which is solely for academic purposes.

Ethical Aproval and Consent of Participate for Publication.

Since this research did not entail any experimental procedures or the collection of personal/identifiable data, it was exempt from review by the ethics committee in accordance with our institution's guidelines. Nonetheless, the study procedures adhered to the Ethical Code of Conduct outlined by the American Psychological Association (APA). Informed consent was obtained from all participants involved in the study. Participation in the survey was voluntary, and participants had the option to withdraw at any time. All respondents participated in the study of their own volition. Furthermore, the study adhered to the principles of the Declaration of Helsinki, and participants provided written informed consent. A professor from Jiangsu University supervised this research project, and the Institutional Review Board of Jiangsu University approved the study.

Availability of Data And Material

As per the agreement between the authors and respondents, the data will not be made public. However, data will be shared upon reasonable request. It is important to note that this is primary data collected from respondents specifically for the study. Research ethics mandate that such data be securely maintained for the purpose of the study, and therefore it can only be accessed upon reasonable request.

Competing Interest

The authors declare that there are no competing interests.

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Authors Contribution

All authors contributed equally to the conduct of this study

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