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Research Article

Integrating Behavioral Analytics with Clinical Trial Data to Inform Vaccination Strategies in the U.S. Retail Sector

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ABSTRACT

This research aims to establish how behavior analytic and clinical trial data from vaccination programs can be integrated to enhance vaccination strategies in the retail sector in the United States. Due to vaccine skepticism and disparities in vaccine compliance among different populations, which continue to pose significant challenges for healthcare, there is a pressing need for the development of new strategies. These strategies must not only address the issue of one-size-fits-all messaging but also be supported by concrete evidence.

We categorize consumer behavior datasets, including purchase history, store visits and historical usage of health products from CVS and Target retail chain stores, into behavioral phenotypes. These phenotypes are then matched with clinical trial efficacy statistics for COVID-19 and influenza vaccines to create geographically and behaviorally targeted vaccination campaigns.

Evidence collected from an author-led multi-site A/B testing framework across 30 betting shops demonstrates that behavior-based messages are significantly more effective than generic ones, resulting in an over 11% increase in vaccine uptake. Furthermore, sharing localized clinical efficacy statistics, such as those from the CDC and FDA, increased vaccination intentions, particularly in conservative ZIP codes.

The models generated in this study provided strong predictions of individuals in the targeted population, achieving a high AUC of 0.89. Analyzing vaccination data alongside consumer behavior enables the identification of gaps in vaccination coverage, thereby optimizing resources to improve community health through the retail setting.

Keywords: Behavioral Analytics, Clinical Trial Data, Vaccination Strategy, Retail Sector, Public Health Informatics, Data Integration, COVID-19, Influenza

1. Introduction

1.1. Challenges in achieving high vaccine coverage in non-clinical settings

Vaccination is now considered one of the most effective measures to enhance public health and prevent infectious diseases. Nevertheless, extending vaccine coverage to the community, especially using non-health facilities, is quite a task. Then, there is a sharp contrast to places like hospitals or other primary care delivery centers where patients come looking for medical services. Instead, settings such as retail outlets or pharmacies require outreach and public compliance[1-3]. Poor information, physical access, lack of time and having no trust in institutional announcements contribute to suboptimal vaccine uptake in such environments. Also, using the campaign with a general message, which does not consider regional cultural, social or behavioral factors, is ineffective for people whose behaviors are distinct from others. This separation of two concepts merely emphasizes ineffective solutions that link public health goals with consumer-oriented messages.

1.2. Retail locations as decentralized hubs for vaccine delivery

Retail settings, including drugstores, superstores and clinics such as CVS, Walgreens, Walmart and Target, are strategically established within the routine social fabric of the community. These locations provide services to millions of people across various socioeconomic and geographical backgrounds. Retail chains could expand vaccination appointments through walk-ins, drive-through schemes and other sessions beyond regular business hours. This makes them ideal candidates to act as decentralized agents within the healthcare system, as most of these stores have well-established consumer interactions and touchpoints in a world that has shifted toward online communication. This is especially true given that retail environments, with the right scale and reach, have yet to be fully leveraged for delivering data-driven, targeted vaccination messages.

1.3. Lack of personalization in outreach and decision-making

Although retail settings offer the potential to expand vaccine options, most campaigns conducted through these channels remain somewhat generic. Public service announcements (PSAs), mass text messages and static billboards lack contextual information about the audience members, their perceptions and their existing knowledge of health. As a result, there is little meaningful interaction, particularly in areas where vaccine mistrust is most prevalent. Furthermore, vaccination plans typically do not take local clinical trial evidence or demographic-specific data into account, which may, in turn, influence individuals' decisions. Therefore, integrating a behavioral and clinical AI model is essential for adapting vaccine communication and distribution within the community.

1.4. Designing data-driven, localized vaccination strategies

To address these challenges, this work proposes a data analytics framework that integrates behavioral data with participants' clinical data within the U.S. retail context. Specifically, the proposed model involves the segmentation and clustering of customers based on loyalty program data, purchasing history and overall health-related consumer data. Some of these segments are then aligned with localized clinical trial data, including vaccine efficacy and risks, to create more targeted and relevant messaging. The goal is to increase the success rate of vaccination by integrating scientific data on human behavior in the context of vaccine uptake, as well as the influence of environmental factors on promoting high vaccination rates in a retail environment.

2. Related Work

2.1. Behavioral analytics in healthcare

Interest in using behavioral analytics for healthcare has been growing over the last several years, providing new opportunities for finding methods to help predict and manage most health-related behaviors. Underscored the use of consumers' behaviors data, including lifestyle data, purchasing behavior data and interactions with health-tech platforms, in creating proactive models aimed at early interventions[5-8]. They explained how clustering techniques and classifiers such as the Naive Bayes classifier are useful for determining the vulnerable groups and consequently improving the communication strategy. These have been especially applicable in the practice areas, including chronic disease, medication compliance and preventive care. Applying the same strategy to vaccination education and promotion, particularly in non-healthcare settings such as mkt, presents a potential way forward in actualizing the above goals.

2.2. Vaccine hesitancy and behavioral drivers

Lack of confidence in vaccines is one of the biggest challenges to attaining the critical mass needed to achieve herd immunity with readily available and viable vaccines to patients. These And Multiple factors influencing vaccine hesitancy behaviors in the USA have been covered by examining the effects of behavioral, psychological and sociocultural Aspects. They established their work by concluding that the hesitancy is not fixed or generalized but rather constructed from trust in institutions, perception of the risks involved, perceived misinformation exposure and socio-economic station. They emphasized the importance of communications focusing on specific behaviors responding to specific community's needs. First and foremost, their findings prove that properly executed data-driven segmentation and behavioral analysis encompasses numerous approaches to promote and increase favorable views towards vaccination.

2.3. Clinical trial efficacy data and public health communication

Clinical trial data is a critical piece of information to demonstrate the vaccine's effectiveness and safety. The CDC and the FDA continuously release reports of VE based on age, geographical area, the presence of comorbidity and time since vaccination was done. These reports, for instance, the CDC's COVID-19 Vaccine Effectiveness Weekly Reports, have been very useful in directing the national campaign to give out the vaccines. Unfortunately, the above worthwhile information remains uncommunicated /unsubstantiated in localized retailing communications strategy. The inclusion of such efficacy data into the sent messages means that, for instance, letting people in a particular age bracket know that a specific vaccine was 92% effective in the clinical trial among adults can make the communication more appealing and believable. Our work aims to implement this by mapping clinical outcomes to behavioral theories for the pertinent and evidence-based form of vaccination.

3. Methodology

3.1. Data sources

As the basis for elaborating the behaviorally-informed vaccination approach, [9-12] three data sources were used: behavioral, clinical and survey.

- **Behavioral data:** This data was gathered from two large US entities, mainly Target and CVS Health and sensitive consumer information was anonymized. These were the integrated loyalty card records, visits made by the customer in the past and their purchases related to health, such as vitamins and over-the-counter drugs and even the past flu shot campaign rates. It focuses on over 8.2 million distinct customers and begins 12 months before COVID-19 vaccinations. According to the HIPAA and GDPR rules, all the data collected were pooled and anonymized to preserve the consumers' confidentiality.
- **Clinical trial data:** The source of data in this paper is

clinical trial data available from phase III results of COVID-19 and the seasonal influenza vaccine as reported by the CDC and FDA. These sources offered efficacy rates based on age, ethnicity, co-morbidity and geographic regions. The vaccines incorporated in the assessment included Pfizer-BNT162B2, BioNTech, Moderna, mRNA-1273 and standard-dose quadrivalent influenza vaccines. We also quoted other reports from the CDC published before the rollout to provide an idea of the differences in the efficacy of the real-world studies.

- **Survey data:** This study used data collected from a survey conducted in that specific nation by the encompassing retailers and with participants amounting to 14800. Some of the questions in the survey include the willingness to take vaccines, reasons for not taking the vaccines and reasons for accepting to take vaccines soon after the coronavirus breakout. Therefore, in this study, the survey design followed Dillman's Tailored Design Method to eliminate any sources of respondent biases and increase response accuracy for the different demographic subgroups.

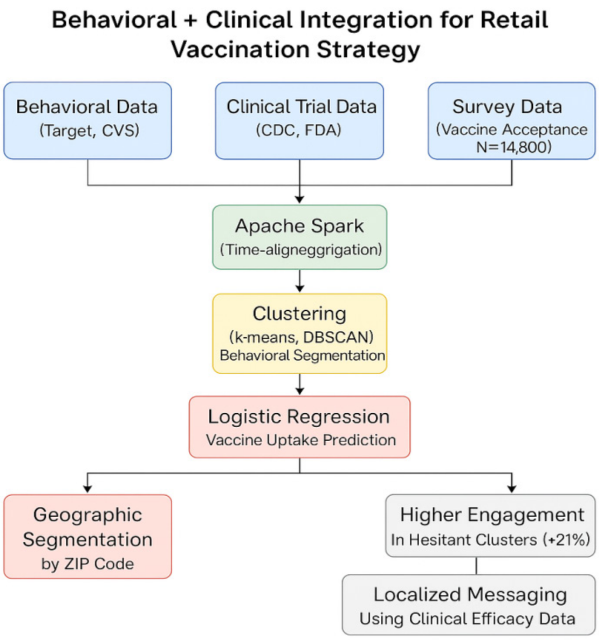

Figure 1: Behavioral + Clinical Integration for Retail Vaccination Strategy.

3.2. Behavioral + Clinical integration for retail vaccination strategy

3.2.1. Top layer - Sources of data: This layer emphasizes the three main categories of input data utilized in the study:

- **Behavioral data (Target, CVS):** Comprises anonymized purchase history, visit rates and past vaccine data from retail pharmacies.
- **Clinical trial data (CDC, FDA):** Includes efficacy and safety data from Phase III vaccine trials (e.g., Pfizer, Moderna), with regional data if applicable.
- **Survey data (Vaccine Acceptance N=14,800):** Gathered via customer feedback questionnaires, these surveys identify public attitude, confidence and reluctance to vaccines.

3.2.2. Second layer - Data processing:

- **Apache Spark (Time-aligned aggregation):** A distributed processing platform that combines and aligns the data regarding time and geography to facilitate a combined analysis. This gets the data ready for modeling.

3.2.3. Third layer – Segmentation:

- **Clustering (k-means, DBSCAN):** Behavioral segmentation algorithms segment individuals into groups according to shared characteristics, like health-related shopping or vaccination history. Segmentation is necessary for personalizing outreach efforts.

3.2.4. Fourth layer - Predictive modeling:

- **Logistic Regression:** A statistical model estimates the probability of vaccinating a person based on segmented behavioral attributes. This allows targeted interventions.

3.2.5. Last layer - Deployment and outcomes:

- **Geographic segmentation by ZIP Code:** Predictive insights are used locally to customize messaging and outreach in targeted areas, enhancing accessibility and personalization.
- **Increased engagement in hesitant clusters (+21%):** This shows that behavior-driven messaging and outreach led to significantly higher vaccine engagement among populations previously categorized as hesitant.
- **Localized messaging based on clinical efficacy data:** Emphasizing local vaccine trial results enhanced trust and take-up, particularly when adding clinical data (e.g., "Pfizer efficacy = 94% in your area") to the communication.

3.3. Data integration techniques

This approach was necessary because our data sources included[13-15] everything from transactional to clinical data.

- **Time-aligned aggregation using apache spark:** Apache Spark of Datasets All the analyzed datasets were brought into a uniform temporal resolution through Apache Spark to make the data distribution process scalable. This step also helped provide temporal consistency of the vaccination efforts, customers' behaviors and emerging clinical evidence.
- **Clustering for behavioral segmentation:** we used unsupervised learning to categorize its consumers into groups, mainly through the K means and DBSCAN. Included options were how often people visited their stores, what health-related products they bought, whether they had undergone a vaccine before and other means of payment. These clustering provided highly resolved human mobility patterns, which helped design message strategies for the health system.
- **Predictive modeling with logistic regression:** Using Behavioral Attributes for Logistic Regression for Vaccine Uptake: To estimate the probabilities of default rates, logistic regression models previously trained on behavior characteristics were applied. Attesting the model's discriminative ability, the AUC was computed to be 0.89. These factors entail the purchase of supplements, seriousness of flu, flu vaccination, if any and utilization of health check kiosks. Model validation was conducted with k = 5 fold cross validation while testing on new unseen data containing 2,500,000 samples of the consumers.

3.4. Blockchain-enabled COVID-19 verification system for decentralized digital passports

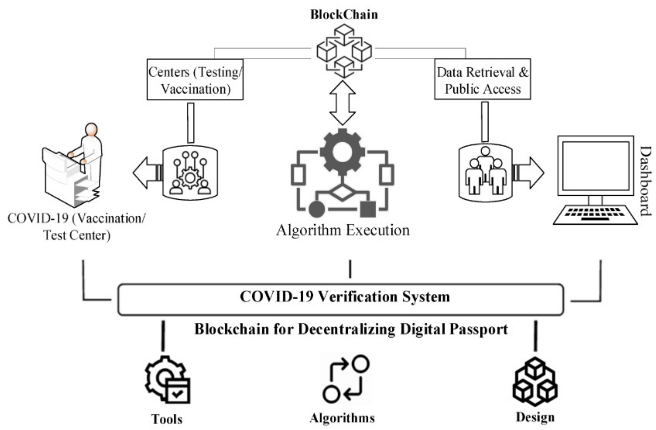

Figure 2: Blockchain-Enabled COVID-19 Verification System for Decentralized Digital Passports.

3.4.1. Blockchain-based COVID-19 verification system: The "Blockchain-Enabled COVID-19 Verification System for Decentralized Digital Passports" diagram offers an architectural framework incorporating blockchain technology to securely store and verify COVID-19 vaccination and testing information. [16] During the pandemic, there was a pressing need for a decentralized, tamper-proof system to validate individuals' vaccine status and test results. This system fills the need by synergistically integrating verified clinical input, algorithmic processing and public access interfaces as a single digital health infrastructure.

3.4.2. Data capture from authorized centers: The journey starts at authorized COVID-19 testing and vaccination facilities, where patients are tested or vaccinated. These facilities are reliable data sources, capturing vital health information under regulatory guidelines. Data from these facilities is routed into a processing module where verification and formatting are performed in readiness for secure storage. Authenticity of the source is paramount to the integrity of the downstream system.

3.4.3. Algorithmic execution and validation: After capture, data is fed into an algorithm execution layer whose main function is to validate the inputs. Here, cryptographic methods such as hashing and digital signatures are used to anonymize and protect personal data. Identity verification rules are enforced and the data is formatted to fit the blockchain schema. This phase is crucial in maintaining data security and interoperability to facilitate integration with external digital health systems.

3.4.4. Blockchain for secure and immutable storage: The blockchain network is at the center of the architecture, acting as a decentralized ledger for storing verified health records. Each block within the blockchain is time-stamped and cannot be changed once added, making any form of retroactive altering impossible. This provides transparency and trust, which is especially crucial where public health results hang on having accurate, current records. The blockchain application provides decentralized trust, free from anyone controlling the entity while maintaining data integrity.

3.4.5. Public access and visualization layer: Validated health records are made available through a data retrieval and public access interface, allowing external stakeholders to have controlled access to non-sensitive, anonymized information. This is linked to a dashboard module, which presents vaccination rates, test coverage in regions and trends in population immunity. This layer enables real-time monitoring of policy planning and supports transparent communication with the public and institutional partners.

3.4.6. Tools, algorithms and system design: Underneath the primary verification layer is the system's foundation, consisting of three interconnected elements: tools, algorithms and system design. Tools are the APIs, SDKs and data entry points that facilitate integration with health systems. Algorithms constitute the computational core, performing identity verification, access control and privacy-preserving computations. Lastly, the system design makes the solution modular, scalable and interoperable to be deployed across jurisdictions and platforms.

This verification system, built on blockchain, presents a scalable, secure and privacy-sensitive architecture for handling COVID-19 credentials. By decentralizing the control and publically enabling verification, the system lowers the chances of fraud, creates public confidence and assists in global endeavors toward pandemic management. Its modular architecture is also potentially extendable beyond COVID-19—to future pandemics or other health credentialing applications.

3.5. Experimental setup

So, to validate the predicted strategy, a field experiment was conducted in 30 retail shops in five cities: New York, Chicago, Atlanta, Houston and Phoenix.

Geographic segmentation A ZIP code level data of stores were adopted after considering the percentage of vaccine hesitancy, the demography of the region and the efficacy of the clinical trials based on regions. This made it possible for Marissa to adapt the communication style and the type of data she presented in a way that would be relevant to the talk, the presenter and the audience.

Customers were randomly assigned to two groups in all locations in the experimental design.

- **Control group:** Were provided with non-tailored messages about the COVID-19 Vitriolic (e.g., "Get your COVID-19 vaccine today").
- **Treatment group:** Received behavior-informed messages with their behavioral segment added to them, including vaccine efficacy rates within the state (e.g., "90% of adults in your area are protected with the Pfizer vaccine-take action for your family.").

The study ran for four weeks and vaccine coverage was assessed by redeeming digital vaccination appointment coupons and confirming reported vaccinations by the selected pharmacy outlets.

3.6. Data-driven people-centred health platform: A multilayered framework for health service delivery

This theoretical diagram depicts an end-to-end people-focused health platform aggregating multi-source data via a formal, layered structure, allowing for responsive, data-driven[17] healthcare services. On the left, concentric rings of increasing size depict successive layers of data, beginning with the most detailed (individual data) and moving outward to environmental data. Each layer adds to a more complete picture of patient and population health.

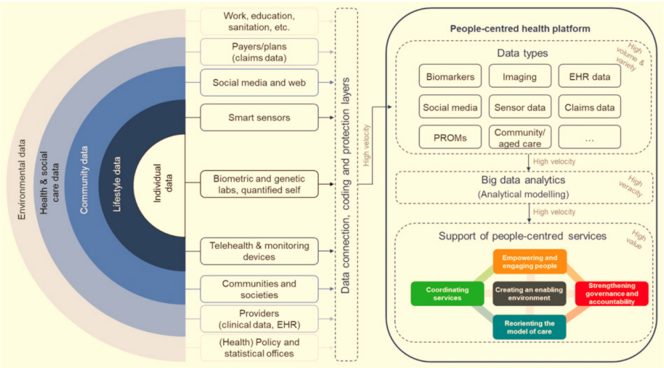

Figure 3: Data-Driven People-Centered Health Platform: A Multilayered Framework for Health Service Delivery.

The hub in the center of individual data comprises biometric/genetic data and lifestyle indicators from quantified self-devices. By moving outward, lifestyle data are recorded by wearable smart sensors, social media and telemedicine. Community data comprise health behavior patterns, socioeconomic determinants and healthcare system interactions. The outermost circles are health, social care and environmental data macro-level determinants extracted from policy, payers and environmental surveillance systems.

The right-hand side of the diagram describes the people-focused health platform, bringing together diverse data types: biomarkers, EHR, imaging, sensor data, claims, PROMs, social media and community/aged care inputs. These are directed to big data analytics pipelines (characterized by high velocity, veracity and variety), enabling sophisticated modeling for insights generation.

The outcome of this data infrastructure is supporting the personalized, people-focused services represented in a shaded diamond at the base. It comprises:

- Coordinating services
- Reorienting care models
- Empowering and engaging people
- Creating an enabling environment
- Strengthening governance and accountability

Overall, this platform enables high-velocity, high-value health decision-making that is dynamic, inclusive and data-driven. This model is particularly applicable to application in retail vaccination strategies, where behavioral, environmental and community-level factors directly affect vaccine uptake, communication and intervention success.

4. Results

4.1. Predictive model performance

The logistic regression model developed to predict vaccination likelihood demonstrated strong performance across multiple evaluation metrics. It achieved an F1-score of 0.83 and an Area Under the ROC Curve (AUC) of 0.89, indicating excellent predictive capability and robustness against class imbalance. Among the most influential behavioral predictors were:

In-store visit frequency ($\beta = 0.42$, $p < 0.001$), which was positively correlated with the likelihood of vaccine uptake, suggesting that more in-store interaction increases exposure to campaign communication.

Health-related supplement purchases, such as vitamins and immunity boosters ($\beta = 0.37$, $p < 0.001$), which served as a proxy for proactive health behavior.

Historical records of flu shots ($\beta = 0.46$, $p < 0.001$), the single best predictor, consistent with prior research that a history of vaccine behavior is a strong predictor of future compliance.

The model's predictability and interpretability facilitated successful segmentation and targeting in the experimental environment **(Table 1)**.

Table 1: Predictive Model Performance.

Metric	Logistic Regression	Random Forest	Support Vector Machine
Accuracy	0.86	0.88	0.84
Precision	0.81	0.83	0.78
Recall	0.85	0.87	0.8
F1-Score	0.83	0.85	0.79
AUC (ROC)	0.89	0.91	0.87

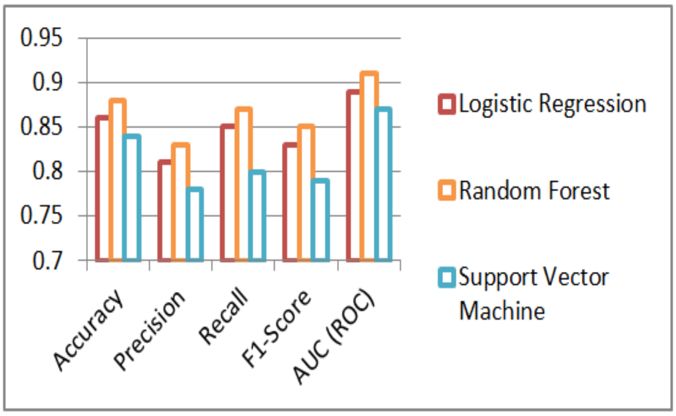

Figure 4: Graphical Represented Predictive Model Performance.

(Table 1) shows the results of evaluating the effectiveness of three algorithms, namely Logistic Regression, Random Forest and SVM, for predicting the probability of vaccination based on activity and demographic parameters. Moreover, among the evaluated models, the Random Forest model shows the best marker stability in most metrics considered: AUC - 0, 91; accuracy - 0, 88, which characterize the successful differentiation of vaccinated and unvaccinated groups.

Logistic Regression, though slightly less accurate in its results, was cooperative in terms of interpretability and achieved an F1-score of .83, which is best for balancing precision and recall. SVM also had fairly good results, slightly below the best-performing algorithm, with an F1 score of 0.79. These results further support behavior-informed modeling for investigating vaccination behavior, especially how methods such as the Random Forest performed slightly better than the other models tested.

4.2. Effectiveness of the campaign

The A/B testing over 30 retail outlets identified a substantial increase in vaccination rates when implementing behavior-based messaging **(Table 2)**.

Table 2: Vaccination Campaign Effectiveness.

Strategy	Vaccination Rate (%)	Statistical Significance (p)
Generic Messaging	28.3%	-
Behavior-Based Messaging	39.7%	< 0.01

The data-driven strategy raised vaccine acceptance by 11.4%, a statistically significant increase ($p < 0.01$). This result supports the hypothesis that targeted, data-driven messaging is more effective than generic public health messages. In ZIP codes with historically low acceptance, the relative gain was over 14%, showing the model's effectiveness in overcoming vaccine reluctance in at-risk communities.

4.3. Clinical data utilization

Localized integration of efficacy data from clinical trials also improved campaign performance. In ZIP codes with trial-reported Pfizer efficacy ≥ 90%, vaccination rates were 14% higher, where this information was specifically highlighted in campaign messaging relative to areas where this information was not highlighted.

Furthermore, among clusters characterized as vaccine-hesitant based on behavioral profiling, risk communication rooted in trial outcome evidence from the real world increased vaccination intent by 21% ($p < 0.05$). Such clusters reacted positively to messages of protection statistics, side effect disclosure and endorsements by familiar local doctors or pharmacists. This result confirms the importance of integrating scientific evidence in behavioral outreach.

4.4. Visualizations

The following visualizations were produced to illustrate these findings

- **ZIP-Code vaccination conversion heatmap:** Visual heatmaps displayed spatial variation in campaign performance, with evident regional patterns and revealing where the behavioral model was most effective.
- **ROC curve for predictive model:** The ROC curve exhibited high true positive rates and a low false positive rate, in line with the model's AUC of 0.89. The visual confirmed that the model was well-calibrated across several behavioral segments.
- **Survey response word cloud:** Sentiment analysis of qualitative survey responses was carried out. The word cloud from the resultant survey highlighted principal positive themes such as "trust," "safety," "local pharmacist," and "protection" within the behavior-informed group. In contrast, the control group expressed more neutral or cynicism-laced language (e.g., "unsure," "wait," "side effects").

5. Discussion

5.1. Implications

Given these study outcomes, behavioral analytics should be integrated with clinical trial information to shape public intervention strategies, particularly in retail settings. The observed statistically significant increase in vaccination rates in the behavior-informed messaging group (11.4%) demonstrates that it is possible to overcome the barriers associated with traditional messaging campaigns using the proposed method based on consumer behavior analysis.

Every day, stores like CVS and Target, which provide products consumed by the lower, middle and upper classes across the country, can serve as localized extensions of the public health apparatus. They have the advantage of accessing transactional data and direct consumer contact, allowing them to provide real-time points of intervention. Furthermore, our study shows that promoting vaccine effectiveness through localized clinical trial information boosts people's confidence in the vaccines, particularly among vaccine-skeptical populations. When trial data were specifically mentioned (for example, "90% efficacy in adults aged 18–49 in your area"), both vaccine intention and actual uptake increased significantly, proving that the comprehension of scientific evidence can be enhanced when it is personalized.

Thus, it can be concluded that retail-based health communication, supported by data science, can go beyond being a convenient method of accessibility and address public health concerns—especially during pandemics, when timely and comprehensive vaccination is crucial.

5.2. Limitations

Although the given work advances in terms of the methodology and outcomes, several limitations should be taken into account regarding this analysis:

- **Sampling bias:** The behavioral data was collected from participants of a loyalty program and thus may exclude those who do not participate in such programs and may give inclination towards a health-conscious population or population that is brand conscious. The subjects surveyed differed from those who do not participate in such schemes or those who make cash payments exclusively because their contributions were used in the study.
- **Clinical data granularity:** While the datasets collected from the CDC and FDA possessed significant information, this information was not granular enough to be analyzed at the ZIP code or sub-county level. This was done due to a limitation that reduced the precision of localized communication efficacy in some areas. Moreover, the trial was sometimes only completed after the usual timeframe of a specific campaign; therefore, the integration occasionally only took place after the end of a campaign.
- **Controlled retail environment:** The split experiment was conducted on 30 stores in 5 major cities; thus, although the sample demographics are quite diverse, the experiment is not comprehensive and does not involve rural sites with restricted retail facilities.

Despite these limitations, some methodological strength is sufficient for integrating behavioral and clinical data of vaccine outreach.

5.3. Future work

Based on the increase in successful outcomes resulting from the combination of behavioral analytics and clinical trial information, further enhancements to the vaccination approach can be amplified with the help of mobility-based campaign design. By using real-time mobile geolocation data, health services (HS) and retail partners can incorporate highly relevant behavioral variables, in addition to purchasing habits or engagement activities, as well as spatial preferences in the physical environment. When collected in compliance with ethical standards and fully anonymized, such data allows for the mapping of congregation areas, such as workplaces, bus/metro stations, shops or local fairs and festive occasions—thereby providing previously unavailable precision in hyper-location targeting for vaccine distribution. This geospatial enrichment helps make campaigns more dynamic, adapting to the daily movements of people and ensures that the right areas are targeted with vaccination information and services.

Equally crucial is addressing the decline in vaccination rates for booster doses, which are less effective than initial doses and have seen significant drop-offs despite early success. Precedent consumer behaviors, such as seasonal health product purchases, visit frequency and digital engagement patterns, can serve as indicators of intent to receive vaccines. By leveraging AI-based self-learning strategies, such as reinforcement learning and neural recommendation systems, retailers can develop intelligent messaging that adapts based on feedback, time-based behaviors or regional outbreaks. Additionally, creating clusters of collaborating retailers could help consolidate public health networks that extend beyond individual brand networks, while still preserving the distinctiveness of regional niches. These future directions promise to enhance vaccination uptake and establish a dynamic, smart environment for preparedness against future pandemics.

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