International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 09 Issue: 05 | May - 2025 SJIF Rating: 8.586 ISSN: 2582-3930

From Misinformation to Meaning: Trust, Truth, and Turbulence in Healthcare Communication Ecosystems

K S Shibani Shankar Ray*

https://orcid.org/0009-0009-5890-0814

GIET University, Gunupur, India

Durga Madhab Mahapatra

https://// orcid.org/0000-0003-1272-7285

North- Eastern Hill University, Shillong, India

** Corresponding Author*

ABSTRACT:
Trust in science varies globally, influenced by historical marginalization, economic disparity, and sociocultural dissonance. Political polarization, particularly from neo-right-conservatives, exacerbates skepticism towards science, impacting consensus-building and policy rationale. While regional institutions often garner greater trust due to perceived authenticity, the integrity of science communication faces threats from artificial intelligence, necessitating new verification and accountability mechanisms. The framework of the study aims to trace the genesis of denudation of scientific credibility by exploring the interplay between various manifestations of information shared and the veracity of societal perceptions and after careful analysis, proposes a multilayered framework to reestablish trust, particularly in health-related contexts.

Key Words: *Misinformation and Disinformation, Scientific Literacy, Health Communication, Global Health Governance, Equity in Health Communication*

INTRODUCTION:

In his seminal work "The world of or making", **Nicholas Onuf (1989)** put forward that ' Reality" is not made but constructed by the relative social and cultural interactions. Structures are tangible and stable, but they only have meaning when human gives them meaning together. They're not separate entities, but part of human thinking process. The meanings stamped to the structures, in turn guide human actions. Trust is one such construct which is both a function and outcome of credence. With the evolution of human life and society, the modalities of natural enquiries have undergone a multiple paradigm shifts. With the Rational intellectual Revolution- 'Renaissance' in 15th century and later Enlightenment, the doctrinal regime of imperialism - " Science" triumphed over the wishful thinking paradigm of " Philosophy'. Subsequently, the behavioral revolution in the later part of 20th century, gave science, the much desired , giant propulsion, so as to crown itself as the numero uno of the epistemic network. Science with its objective character, was a culmination of experiments, observable facts with generalised theory, immune to falsification, thus an elite sphere with system constraints of laboratories and journals. But, as reformation, improvisation- the midwifery of a metamorphosis have been very much innate to human nature, the hegemony and unquestioned obligation to science in common discourses have been put into test, with the injection and prevalence of novelties of ideas, ideologies and more importantly, the very basic element called " Information". Information is a very nuanced construct, prone to all possible maneuvers- more likely, a liquid, that takes the shape of the container that holds it. The building blocks of information are dynamic, volatile, uncertain and ambiguous, like the contemporary ecosystem, which is always in a state of flux. With the advent of

Neoliberalism, the interdependency and integration of societies, economies, the states to construct a shared, unified global community with the free flow of almost every aspects of the lives, the information has become both a tool, leading to prosperity, as well as a dangerous contour leading to abyss. In the cob web world, thus, infallibility has become a myth. Thus, Science, once regargded as an institutional constant, has now come under the saber-rattling, emanating from the culmination of influences imparted by cultural, political, and communicative forces, that eventually constructs, shapes and maneuvers the relative faith and trust in science **(Gauchat, 2012; Funk, Tyson, & Kennedy, 2020; Kennedy, Hefferon, & Funk, 2022)**. With information being a tool at public disposal with insignificant cost, the perceptions, and thus the template and the framework of judging and evaluating the preponderance of "Science" has been watered down with the influx of unavoidable information streams, that possesses the very attribute of digital footprint. Thus, the sanctity of information- the line of differentiation between " Information", " Misinformation" and " Disinformation" has been blurred and this, very fluidity stages the bigger question on the credibility of scientific discourses, thus, weathering and subsequently eroding public trust on science.
One of the biggest arenas of construction, maintenance and circular dynamism of public trust in science is Public health, having probably the most significant fanning amongst all other dimensions. Thus, this paper, examines the volatile mechanics of trust in science through the lens of public health.

The global pandemic COVID-19 pandemic presented a reality check to the functionalities of public health institutions. While the scientific advancements emerged as Samaritan with the life saving interventions in record time frame, the popular obligation and adherence was not ubiquitous.**(Polack et al., 2020; Baden et al., 2021; Krammer, 2020)** It witnessed fragmented and fractured trends across geographies and demographies, as opposed to the earlier universal submission to the dictums of science, prevalent not more than a decade ago. The flow, the medium, the very nature of crafting and most importantly the the sanity and sanctity of the contents played a significant role in variation of the perceived value by the end consumer. Regardless of the intent and content, the hygienic factors and perception about the constructs of the information value chain were enough to designate an information as "True " or " False"- more precisely " Information" or " Misinformation'. This vicious cycle of information flow acted as a prime disruptor. In some geographies, while it created a sense of emergency towards the life saving measures, in others, it created a sense of pessimism and hesitations- aptly noticed in vaccine hesitancy in global south countries **(Loomba et al., 2021; Roozenbeek et al., 2020; Puri et al., 2020). Lazer (2025)** posits, a snowballing of negativity happens with misinformation in play. As information production is almost free these days, and there is no visible firewalls to filter the information at the level of origin, the spread results in attaining its ulterior objective- eroding the credibility of the institutions and authorities. The circular nature of the feedback loop does the rest in accentuating the butterfly syndrome. **(Lewandowsky et al., 2017; van der Linden et al., 2020; Flynn, Nyhan, & Reifler, 2017).** One notable case is India's use of pre-recorded public health messages played during phone calls after the onset of COVID-19. While such an approach is scalable and low-cost, its effectiveness is questionable. Earlier studies on similar outreach strategies suggest that passive information channels tend to produce lower engagement than more interactive approaches **(Rice and Atkin, 2001; Hornik, 2002)**. For instance, **Sadish et al. (2021)** observed that during the early months of the COVID-19 pandemic in India, misinformation was still widespread. Their study suggests that pre-recorded voice messages were less effective in reducing misinformation compared to active, personalized phone calls. However, while interactive calls may yield better engagement, their implementation at scale presents significant challenges: they are both expensive and logistically demanding **(Barr and Hahn, 2004).** Several such cases culminate to the point that, the drivers of engagement, the "inputs for trust building" are still not clearly understood.

Trust in Science is a multidimensional construct with uneven distribution across segments. Historical marginalization, economic disparity, and sociocultural dissonance have long shaped trust differentials **(Freimuth et al., 2001; Quinn et al., 2013; Jamison et al., 2019)**. As credence has become a major determinant of trust, perceived values after having experience does play a pivotal role in shaping it. Global South Countries, especially the peripheral countries, the less developed regions of the semi-peripheral countries, even in the marginalized sections in the core countries often report less trust in science, partly due to continuous subjection to systemic marginalization or apartheid. Politics, political culture and the political organisations- all affirm to the broader dimension called " Authoritative allocation of Values/ Resources'. Thus, the very nature and the underlying dynamics of each of these elements play a significant role in the percolation and subsequently, prevalence of notions and consequently, structuring the public psyche. In the contemporary, global spectrum, the rise of Neo-Rightist Conservatives, the core pivot they cling on to, spreads large scale skepticism regarding science, which is a by product of rational inquiry and explorations. The consensus building process regarding a scientific study, hits roadblock, there lies a possibility of it colliding with the policy rationale of the regime. The indoctrination mechanisms , such as spewing negativities to demonize , refute and desecrate , and subsequently relinquish the target idea, especially in the burning issues such as climate change, vaccination, and pandemic control **(McCright & Dunlap, 2011; Merkley, 2020; Hart & Nisbet, 2012)**. The partisan divide thus, has become a bolster to the truncated and plummeting trajectory of public trust in science, though not resorting to uniformity across the geographies. Exacerbated by strategic political narratives, the notion of neutrality, objectivity and factuality of the scientific inquiries and findings are systematically wiped out, and in some cases of constrained realities, bent in quirky methodologies, imposing intended value elements on them **(Kreps & Kriner, 2020; Gauchat, 2015; Iyengar & Westwood, 2015)**. In global contexts, the institutional legitimacy often hinges on Power dyanamics-Balance of power and Power differentials. In a a multilateral global politics, where there is rash to occupy the global leader's position, a Kindelberger trap is well observed. But, in some scenarios, the frantic war of Max-Min tussle of power differentials, where two leading powers of the world- USA and China have been locked in. WHO's credibility, for instance, was put under question, when perceived as aligned with opposing powers or elite interests. Regional institutions on the other hand, despite being less resourced, garnered greater trust due to perceived authenticity and representational legitimacy **(Agostino & Arnaboldi, 2020; Makinde et al., 2021; Abimbola et al., 2021)**. This underlines the principle that proximity and identity—be they geographic, cultural, or institutional- are core to building and maintaining trust **(Siegrist, 2021; Gilson, 2003; Marmot, 2020)**. Galore of interventions aim to bridge the digital divide by reaching both the information-rich and the information-poor, so as to bring about a change in their trust for the scientific endeavors **(Hilbert, 2011)**. However, despite a rise in the supply of information, the *demand-side* behavior—how and why people choose to engage with the information provided—remains poorly understood **(Wilson, 1997; Case, 2002)**. Merely disseminating information does not guarantee its consumption or intended impact. Furthermore, **Dr. Emily Smith(2025)** underscores the power of humanized, empathetic engagement in science communication. Her platform, "Friendly Neighbor Epidemiologist," exemplifies how trust can be cultivated through relational storytelling and accessible framing, especially in politicized or faith-based communities. Literature supports this approach: emotionally resonant and narrative-based communication enhances credibility and retention among general audiences **(Dahlstrom, 2014; Green et al., 2018; Fancourt & Steptoe, 2022).** Yet, the integrity of such communication faces novel threats from artificial intelligence. These emergent technologies blur the boundaries between truth and fiction, requiring science communicators and institutions to develop new verification and accountability mechanisms **(Guess et al., 2020; Broniatowski et al., 2018)**.

To address these intersecting challenges, this paper proposes a multidimensional model for restoring trust in science.

This paper seeks to unpack and analyze the sources of friction that hinder user engagement with health communication technologies, based on analysis drawn on a specialized data repository from India's mobile health (mHealth) program, which includes over 250 million call records. These calls were part of a large-scale maternal health initiative aimed at improving health outcomes among socioeconomically disadvantaged pregnant women in India.

DIGITAL HEALTH COMMUNICATION AND THE ROLE OF STRUCTURAL INEQUITY

Digital interventions, such as voice calls or text messages in maternal health programs, have the potential to democratize access to health information. However, their effectiveness is moderated by **digital literacy**, **gender norms**, and **resource constraints (Warschauer, 2003; Hilbert, 2011).** Marginalized women, particularly in rural or low-income settings, may experience structural barriers that affect both access and engagement with such services. This interaction between psychological readiness and systemic inequality can result in **asymmetric**

responses to the same health communication intervention. For instance, individuals with similar access to a mobile phone may still differ in their likelihood of engaging with health calls based on their perceived autonomy, household dynamics, or prior experiences with healthcare. Therefore, in analyzing behavioral responses to health shocks, it is important to not only account for the **availability of information** but also the **contextual enablers and barriers** that shape its use. These include socioeconomic status, educational attainment, and geographic disparities—all of which compound behavioral heterogeneity in information search.

In this chapter, analysis has been carried out, based on data from a mHealth program that disseminates maternal health information via automated mobile voice messages through its Mitra program. These voice calls are intended to overcome literacy barriers and reach women living in urban slums of Mumbai, many of whom face both monetary and non-monetary constraints in accessing health information **(Papp, Gogoi, & Campbell, 2013; Scott et al., 2016)**.

mMitra Service

mMitra, a free mobile voice calls service for enrolled women, provides critical healthcare information during pregnancy. With the increasing mobile penetration in India, voice calls emerge as an economical and efficient means of reaching women and families. Stage-based maternal messaging programs like Mitra have demonstrated remarkable success in the m-Health domain **(Peter et al., 2018)**. These programs have effectively enhanced knowledge and utilization of antenatal care services within the m-Health framework **(Watterson et al., 2015)**. Messages that have been validated by the Federation of Obstetric and Gynaecological Society of India (FOGSI) and the National Neonatology Forum (NNF), are transmitted through mMitra. Individualized voice messages of 60-120 seconds are presented with the following frequency: bi-weekly during pregnancy, daily for the first week after childbirth, bi-weekly again until the third month of infancy, and weekly for months four to twelve. The information transmitted in the calls is matched to the stage of a woman's pregnancy. Calls are presented in the time slot chosen by the women. Women can select to receive the calls in their mother tongue. A trained counselor can be informed about a delivery, abortion, or change the phone number or time slot. To avail benefits of the mMitra program (which primarily operates in urban slums of In the vicinity of Mumbai, a woman is required to complete a comprehensive enrollment form and letter of acceptance **(Appendix: Figures 3.6 and 3.7)**. The enrollment form captures the following data: mobile phone number, phone owner, educational qualifications, income range, preferred call time, language preference, pregnancy history, planned place of delivery (private or government hospital), and any existing health issues. By 2020, 2.29 million women had enrolled in mMitra program.The organization collaborates with 97 hospitals and has 40 non-profit partners. The baseline sample for this chapter consists of demographic and call details of 116,449 women registered (identities were anonymized) in the last six months of 2018 (control group). Their call details were captured from January 2019 to July 2019. Additionally, 135,696 women registered in the last six months of 2019 (treatment group) had their call details captured from January 2020 to July 2020. For analysis, only those women were included who provided information on the following variables: phone ownership, enrollment channel, income range, age, and education. The response variables are call duration percentage and call duration range classified into Green, Amber, and Red zones. The variable descriptions are provided in **Table 1**.

Table 1

Variable Definitions and Construction

Variable Type	Variable Name	Definition / Construction
Dependent Variable	**Call Duration Percentage**	If the call is picked up, calculated as: (Call Duration / Call Length) * 100
	Call Duration Range	Categorized into zones: Red (<33%), Amber (33%–66%), Green (>66%)
Independent Variable	**Covid Dummy**	Coded as 1 if call date is April 2020 onwards (during lockdown), 0 otherwise

	Treatment Group	Coded as 1 if woman was called between Jan 2020–July 2020, 0 if Jan 2019–July 2019
	Husband Phone Owner	Coded as 1 if the phone is registered in husband's name, 0 if registered in woman's name
	Enrolled via Community	Coded as 1 if enrolled through community channel, 0 if enrolled during hospital visit
	Lower Income	Coded as 1 if woman's household income is in bottom half of the sample, 0 otherwise

(Source: Author's Compilation)

COVID-19 IN INDIA

In India, the first case of COVID-19 was reported on January 30, 2020. On March 4, 2020, 22 new cases were diagnosed, and the total number of patients reached 107 by March 15. On March 22, the Government of India announced a strict lockdown. The 68-day, four-phase lockdown commenced on March 24 and concluded on May 31, 2020, to combat COVID-19. This lockdown was arguably necessary for the world's second-largest nation, with a population of 1.38 billion people. A complete shutdown may have effectively managed the spread of COVID-19, as India had only recorded 131,868 confirmed cases and 3,867 related deaths as of May 24, 2020. On January 2021, the number of positive cases surpassed 10.6 million, leading to an devastating second wave following the initial wave. Recent research indicates that the impact of COVID-19 in India exhibits significant interstate heterogeneity. Factors contributing to this heterogeneity include income, gender, multi-morbidity, urbanization, lockdown and unlock phases, weather conditions such as temperature and rainfall, and the retail price of wheat **(Imaiet al., 2021)**. Except for essential facilities, most of India was closed during the 2020 lockdown. This episode presented multiple challenges to the already strained healthcare system. On the one hand, it led to an increasing disease burden among patients; on the other hand, regular healthcare was disrupted, resulting in the deaths of otherwise high-risk patients. Less-privileged individuals were severely affected by this calamity. Limited data exists on health information, beliefs, and behaviors globally that may indicate varying exposure to COVID-19 risk **(Alsanetal., 2020)**. In this chapter, dataset of M-Health has been utilized to examine how during lockdown, women engaged with technology, as measured in our earlier stated outcome variables.

HYPOTHESIZED PATHWAYS

Building on the theoretical models discussed, several behavioral pathways are hypothesized to explain how individuals may respond to health information during a pandemic. First, the **increased salience** of health risks brought about by the COVID-19 crisis is expected to heighten individuals 'perception of the severity and personal relevance of maternal health concerns. This heightened awareness is likely to enhance attentiveness to health-related information, particularly among vulnerable populations such as pregnant women. Second, **fear-driven engagement** may occur, whereby the urgency and emotional intensity of the pandemic stimulate greater compliance with health advice, especially when delivered through accessible channels such as mobile phone calls.

However, these effects may not be sustained indefinitely. A third pathway, **diminishing returns**, suggests that repeated exposure to similar health messages can lead to emotional fatigue and habituation. Over time, the novelty and perceived urgency of the messages may wane, reducing their overall effectiveness unless the content or delivery method is adapted to maintain interest and relevance. Finally, a **differential impact** is expected across various subgroups due to structural inequities and digital barriers. Access to mobile technology, digital literacy, and socio-cultural norms may significantly moderate individuals' responses, leading to heterogeneous effects even in the face of a uniform health shock. These pathways collectively provide a nuanced understanding of how psychological and contextual factors interact to shape health information engagement during crises.

Table 2 summarizes the **behavioral pathways** hypothesized to influence individual responses to health information during the COVID-19 pandemic, along with key mechanisms and moderating factors:

Table 2
Behavioral Pathways

Behavioral Pathway	Description	Key Mechanism	Moderating Factors
Salience of Health Risks	Heightened perception of maternal health relevance due to pandemic-related risk awareness	Increased cognitive attention and message relevance	Pregnancy status, prior health knowledge, crisis proximity
Fear-Driven Engagement	Emotional urgency drives short-term compliance with health messages	Affective arousal and risk-avoidance behavior	Trust in source, perceived credibility, emotional vulnerability
Diminishing Returns	Repeated exposure leads to emotional fatigue or message habituation over time	Desensitization and reduced novelty	Message repetition, lack of personalization, static content formats
Differential Impact	Structural and digital inequities shape uneven engagement across subgroups	Contextual constraints and access limitations	Phone ownership, digital literacy, gender norms, socioeconomic status

(Source: Author's Compilation)

This framework highlights that while digital health communication can be powerful during crises, its **impact is neither uniform nor linear**. Tailored strategies must account for these behavioral trajectories and the socio-technological environment in which messages are received.

IMPACT OF THE LOCKDOWN ON TECHNOLOGY ENGAGEMENT:

Understanding the heterogeneity in women's engagement with mobile-based health interventions during the COVID-19 lockdown requires a behavioral and structural analysis. This section theorizes how three key dimensions—phone ownership, enrollment method, and household income—interact with an exogenous health shock to shape technology engagement among pregnant women.

First, **phone ownership** plays a critical role in determining access and autonomy in digital health interactions. Women who do not own their phones but rely on their husbands or neighbors to access calls may face structural constraints, yet the infrequent or limited access might heighten the perceived value of such communication. The theory of *scarcity-induced salience* **(Shah, Mullainathan, & Shafir, 2012)** suggests that when access to a resource is constrained, individuals are more likely to prioritize and intensely engage with it when available. Hence, women who rely on a third party to access health calls may listen more attentively during the limited opportunities they have, possibly explaining their higher call engagement during the lockdown period.

Second, the **method of enrollment**-through community channels versus hospital settings—reflects the degree of embeddedness in trusted local networks. Social capital theory **(Coleman, 1988; Putnam, 2000)** posits that individuals embedded within cohesive networks are more likely to trust and act on information transmitted through those channels. Community-based enrollment may not only provide women with a sense of familiarity and trust in the system but may also involve ongoing interpersonal reinforcement from community health workers. Such contextual anchoring could lead to increased attentiveness to mobile health messages, especially during crisis periods when external sources of support are limited.

Third, **income level** influences the perceived utility and marginal value of digital interventions. Contrary to conventional expectations that higher income correlates with greater technological adoption **(van Dijk, 2006)**, the study finds that women from lower-income households engage more with health calls. This counterintuitive finding can be interpreted through the lens of *uses and gratifications theory* **(Katz, Blumler, & Gurevitch, 1973)**, which emphasizes that individuals are more likely to engage with media that fulfills specific and unmet informational needs. For lower-income women, programs like mMitra may be their sole reliable source of maternal health information, thereby elevating the utility of every interaction. In contrast, wealthier women may have access to alternate, potentially overlapping sources, reducing their reliance on any single channel.**Table 3** encapsulates the key dimensions and their theorized impact on women's engagement with mobile-based health interventions during the COVID-19 lockdown.

Table 3

Key Dimensions and impact

Dimension	Key Factor	Impact on Engagement
Phone Ownership	Access via own vs. shared phone	Women with limited access may engage more attentively due to the heightened salience of rare opportunities.
Enrollment Method	Community vs. hospital enrollment	Community-based enrollment fosters trust and continuity, increasing attentiveness during crises.
Household Income	Low vs. high income	Lower-income women show higher engagement as the intervention fulfills unmet informational needs.

(Source: Author's Compilation)

The Summary Statistics for Treatment Group (Jan 2020 – July 2020) is presented herewith in the following Tables- **Table 4.**

Table 4

Summary statistics

January 2020 to March 2020	N	Mean	S. Dev.	Min.	Max.
Call Duration (%)	4,02,809	45.464	33.686	0	100
Green	4,02,809	0.358	0.479	0	1
Amber	4,02,809	0.224	0.417	0	1
Red	4,02,809	0.416	0.493	0	1
Husband Phone Owner	3,54,512	0.255	0.436	0	1
Enrolled via Community	3,54,512	0.640	0.479	0	1
Low Income	3,54,512	0.536	0.498	0	1

April 2020 to July 2020	N	Mean	S. Dev.	Min.	Max.
Call Duration (%)	4,54,448	43.688	33.966	0	100
Green	4,54,448	0.332	0.470	0	1
Amber	4,54,448	0.228	0.419	0	1

Red	4,54,448	0.439	0.496	0	1
Husband Phone Owner	4,10,415	0.255	0.436	0	1
Enrolled via Community	4,10,415	0.630	0.482	0	1
Low Income	4,10,415	0.536	0.498	0	1

(Source: Author's Compilation)

Here's a breakdown of **key trends** from the summary statistics table comparing the **Treatment Group** before (Jan–Mar 2020) and during (Apr–Jul 2020) the COVID-19 lockdown, presented in **Table 5.**

Table 5
Engagement Trends: Call Duration and Zones

Metric	Before (Jan–Mar 2020)	During (Apr–Jul 2020)	Trend
Call Duration (%)	45.46	43.69	Slight decrease in average call duration
Green Zone	35.8%	33.2%	Drop in high engagement (attentive users)
Amber Zone	22.4%	22.8%	Small increase in moderate engagement
Red Zone	41.6%	43.9%	Noticeable rise in low engagement

(Source: Author's Compilation)

Interpretation of Table 5: Despite the expected heightened health awareness during COVID-19, **overall call engagement declined slightly**. The **Red Zone (low engagement)** expanded, while the **Green Zone (high engagement)** shrank, suggesting **growing disengagement** or emotional fatigue.

Table 6
Structural Characteristics Trends

Variable	Before (Jan–Mar 2020)	During (Apr–Jul 2020)	Trend
Husband Phone Owner	25.5%	25.5%	No change
Enrolled via Community	64.0%	63.0%	Slight decline in community-based enrollment
Low Income	53.6%	53.6%	No change

(Source: Author's Compilation)

Interpretation of Table 6: Structural demographics remained **stable**, meaning that behavioral changes observed are **not due to a compositional shift** in the population, but likely reflect actual response to the lockdown environment.

The key behavioral insights:

Insights from the analysis suggest several patterns in engagement. The slight drop in call engagement over time may reflect habituation or message fatigue, which aligns with the diminishing returns hypothesis in behavioral responses. This implies that while initial engagement may be high, sustained interaction tends to decrease as users become accustomed to the messaging. Interestingly, structural indicators such as phone ownership and income remained stable, indicating that the observed shifts in engagement are primarily behavioral rather than demographic. Additionally, the increase in Red Zone engagement during a crisis suggests a form of behavioral stickiness, where users, particularly those with low engagement, show a tendency to remain at the lower levels of tech interaction. This could point to underlying barriers that prevent upward mobility in tech engagement, highlighting the challenges faced by users in transitioning to higher levels of interaction, especially during times of crisis.

BEHAVIORAL STICKINESS AND TRANSITION IN TECHNOLOGY ENGAGEMENT

This section delves deeper into the study of how women transitioned from low to high engagement with technology, and more importantly, which groups of women exhibited a lower likelihood of switching, thereby demonstrating stickiness in behavior. The analysis of technology engagement patterns among pregnant women during the COVID-19 lockdown reveals important behavioral insights into persistence and transition dynamics at the intensive margin of digital health interaction. Drawing upon the engagement classification framework developed by **Collins et al. (2014) and Clay-Williams et al. (2019)**, call duration- a proxy for digital engagement—is segmented into three zones: Red (low engagement, <33% of the call heard), Amber (moderate engagement, 33–66%), and Green (high engagement, >66%). Here is the methodology for measuring call duration. Firstly, the call duration recorded by the Control Centre of mMitra, commences only after the pregnant female accepts the call. The measurement of call duration occurs only when the listener picks up the call initiated by mMitra through the Mitra program and excludes the call alert duration that may precede it. Therefore, the call alert tone of the COVID-19 message is not included in the call duration calculations. These categories allow for a more granular understanding of user behavior that moves beyond binary or average-based analyses of digital interaction. Studies indicate a statistically significant increase of 3.60 percentage points in Green zone engagement among the treatment group- i.e., women exposed to the COVID-19 lockdown shock- relative to the control group. This positive shift suggests a behavioral transition toward more attentive and consistent interaction with mobile health content during the public health emergency. Simultaneously, a 3.1 percentage point decline in the Amber zone is observed and a marginal 0.5 percentage point decrease in the Red zone, implying that the transition was largely from moderate to high engagement, rather than from low to high. This asymmetric shift reveals the presence of behavioral stickiness in the Red zone: women who initially exhibited low engagement were less likely to transition out of this category, even in the face of an external crisis that increased health-related uncertainty and urgency.

This behavioral inertia resonates with longstanding findings in behavioral economics and decision theory. **Samuelson and Zeckhauser (1988)** introduced the concept of status quo bias, highlighting how individuals tend to favor existing conditions and are resistant to change. This phenomenon has been further validated in health behavior literature, where deeply entrenched routines, limited self-efficacy, and competing life demands often prevent individuals from adopting beneficial health behaviors **(Kahneman et al., 1991; Thaler & Sunstein, 2008)**. In the context of digital health, **Venkatesh et al. (2003)** emphasize that technology adoption is influenced not just by perceived usefulness but also by social influence and facilitating conditions—factors that may be lacking in low-income or patriarchal household contexts, especially for pregnant women.

The concept of "stickiness" also aligns with findings from the literature on information-seeking behavior and digital literacy. **Van Deursen and van Dijk (2014)** argue that disparities in digital skills contribute to unequal engagement with online health resources, a gap that is particularly pronounced in socioeconomically disadvantaged populations. In the Indian context, studies such as those by **Sarkar et al. (2020) and Sharma et al. (2021)** have highlighted how cultural norms, digital exclusion, and time poverty among women act as structural barriers to m-health adoption, even when the technological infrastructure is in place. Moreover, research by **Mehrotra et al. (2022)** on mobile health messaging in rural India has shown that passive engagement (such as merely receiving a message) is far more common than active listening or interaction, emphasizing the challenges of behavioral transformation in such environments.

These findings contribute to this growing body of literature by demonstrating that while moderate users (Amber zone) exhibit upward mobility in engagement intensity, those at the lower end of the spectrum (Red zone) remain largely unaffected by external shocks such as the pandemic. This has significant implications for digital health interventions: one-size-fits-all approaches may fail to activate low-engagement users, necessitating more personalized and context-sensitive nudges. For instance, incorporating behavioral cues like social proof, reminders, or even gamified incentives- approaches recommended by **Milkman et al. (2021)-** could potentially overcome inertia among disengaged users**.**

In response to varying levels of digital engagement among women during public health interventions, this framework categorizes users into three distinct segments—**Red**, **Amber**, and **Green** zones—based on behavioral traits and contextual factors. Each segment reflects unique challenges and opportunities that inform targeted strategies for improving engagement with mobile health content. By aligning interventions with the specific needs and capacities of each group, this approach aims to enhance digital inclusion, promote sustained usage, and drive meaningful health outcomes. **Table 7** provides a comprehensive details.

Table 7
Segmented Engagement Strategy Framework

User Segment	Behavioral Traits	Contextual Factors	Recommended Strategy
Red Zone	Low engagement, resistant to change, low digital self-efficacy	Shared phone access, time poverty, low trust, patriarchal norms	Personalized nudges, gamified content, social proof messaging, CHW-facilitated engagement
Amber Zone	Moderate engagement, upwardly mobile, receptive to cues	Partial autonomy, some digital familiarity, mixed access reliability	Reminder systems, milestone-based incentives, community-based peer influence
Green Zone	High engagement, autonomous, consistent users	Own phone, higher trust in digital systems, relatively empowered	Advanced content, self-tracking tools, feedback loops, advocacy roles in communities

(Source: Author's Compilation)

In sum, the evidence suggests that behavioral change in technology engagement is not uniform across users, and that existing disparities can become more entrenched without targeted intervention. By identifying the persistent Red zone as a site of behavioral stickiness, our study calls for nuanced program designs that take into account user segmentation, motivational asymmetries, and contextual limitations in digital health access and usage.

SEGMENTATION-BASED STRATEGIES IN DIGITAL HEALTH:

A segmentation-based approach to digital health strategy emphasizes the necessity of designing interventions that are attuned to both behavioral tendencies and contextual disparities, especially in low-resource and socio-culturally complex settings. Rather than relying on uniform outreach models, segmentation recognizes that users—such as pregnant women enrolled in mobile health programs like *mMitra*—vary significantly in their engagement levels, technological access, and motivational readiness. This variability calls for differentiated strategies that address the unique needs of each subgroup. For instance, **low-engagement users** in the Red zone often experience structural barriers such as shared phone ownership, digital illiteracy, and household-level constraints rooted in patriarchal norms **(Sarkar et al., 2020; Sharma et al., 2021)**. These women may also face behavioral inertia, consistent with the **status quo bias (Samuelson & Zeckhauser, 1988)**, and require tailored interventions like gamified reminders, simplified audio content, and community health worker (CHW) mediation to facilitate behavioral activation **(Milkman et al., 2021)**.

Moderate users in the Amber zone represent a more responsive segment that may already exhibit tentative engagement but lack the consistent behavioral reinforcement needed for long-term adherence. For this group, strategies such as **milestone-based incentives**, **peer-driven motivation**, and **timely cues** through SMS or IVR (interactive voice response) systems can effectively shift behavior upward, especially during crises when motivation to seek health information increases **(Muralidharan et al., 2022)**. Meanwhile, **high-engagement users** in the Green zone, who show consistent and autonomous interaction with digital content, may benefit from advanced features such as personalized health tracking, anticipatory guidance, or feedback loops that enhance the perceived usefulness of continued participation **(Venkatesh et al., 2003; Zhang et al., 2023)**. These users can also be mobilized as **peer advocates** to promote digital health norms within their communities, leveraging social proof to influence the behaviors of less-engaged users.

Recent global health literature supports this precision-targeted approach, arguing that **"digital inclusion" must go beyond infrastructure deployment and encompass behavioral and social enablement strategies (ITU, 2023; World Bank, 2022)**. Furthermore, research by **Mehrotra et al. (2022) and Singh et al. (2023)** in rural and urban India has demonstrated that active listening and interactive response rates remain low among disadvantaged groups, even when mobile access is provided—underscoring the critical role of **engagement design** and **message relevance**. Thus, segmentation-based strategies not only enhance the efficiency and equity of digital health interventions but also serve as a foundational principle in advancing **digital public goods** that are truly inclusive, context-aware, and behaviorally effective. Here's a concise table outlining Segmentation-Based Digital Health Strategies that are responsive to contextual and behavioral diversity

Table 8
Human-Centered Design Principles for Enhancing mHealth Engagement

Design Principle	Application
Behavioral Personalization	Tailor message type, frequency, and tone to user engagement history and motivational profile
Contextual Tailoring	Adapt content to local dialects, cultural practices, and household dynamics
Multi-Channel Support	Use a mix of voice calls, SMS, community worker follow-ups, and in-person reinforcement
Digital Skill Building	Provide tutorials, CHW-led phone use demonstrations, and family sensitization sessions
Incentivized Engagement	Introduce rewards for consistent listening, milestone completions, or referral-based engagement

(Source: Author's Compilation)

This framework outlines five key design principles aimed at increasing the effectiveness and inclusivity of mobile health (mHealth) interventions. By aligning digital strategies with users 'behaviors, cultural contexts, and access realities, these principles foster sustained engagement, build digital confidence, and create pathways for meaningful participation in health systems. This approach helps digital health programs like **mMitra** move beyond "broadcast" models into **precision engagement**—boosting effectiveness while accounting for real-world disparities.

CONCLUSION:

Mobile devices with digitization have emerged as a potent policy instrument for information dissemination due to their widespread availability and low cost, even in developing nations. However, while the supply side of technology engagement has garnered significant attention, the demand side remains relatively under-researched and comprehended. Recent research has explored various nudges that influence technology adoption **(Breza et al., 2021; Ghose et al., 2021; Siddique et al., 2020; Banerjee et al., 2020)**. Nevertheless, there exists a gap in understanding how diverse factors, both economic and non-economic, impact the intensive margin of engagement.

This chapter addresses this challenge within the Indian context by utilizing a unique organizational dataset from enrolled users of mMitra, an Indian non-profit organization that delivers timely informational calls via mobile phones to less privileged pregnant women in the Mumbai metropolitan area through its Mitra program. Listening to the voice messages may entail both monetary and non-monetary costs for the target group of women. It posits that technology engagement is influenced by factors such as ownership, the accessibility of various information channels, and the income effect. Earlier studies initially established that, compared to the previous year, there has been a substantial increase in technology engagement among pregnant women during the COVID-19 lockdown that India imposed. Studies related to this chapter indicates a 1.53 percentage point increase in the treatment group's call duration percentage over the baseline period. In contrast to the control group, the studies examined the factors influencing the choice of technology engagement. For this purpose, focus was imparted on the 2020 cohort to explore the three factors potentially influencing technology engagement. It was found that ownership, enrollment channel, and monthly income play a significantly important role in inducing technology engagement. While the level of engagement increases, a follow-up question is whether the average effect is the same for all women. Thus, the chapter complement the above analysis with call duration ranges to characterize women's switch from one range to another. This analysis shows that women who were not listening to the calls before the exogenous shock respond minimally post the shock. However, the women who had spent even a moderate amount of time listening to the calls before the shock significantly increased their engagement, driving the overall increase in engagement.

REFERENCES:

1. Han, P. K., Klein, W. M., Killam, B., Lehman, T., Massett, H., & Freedman, A. N. (2018). Representing uncertainty in health risk communications: A systematic review. *Medical Decision Making*, 38(7), 846–867. https://doi.org/10.1177/0272989X18759586

2. Hart, P. S., & Nisbet, E. C. (2012). Boomerang effects in science communication: How motivated reasoning and identity cues amplify opinion polarization about climate mitigation policies. *Communication Research*, 39(6), 701–723. https://doi.org/10.1177/0093650211416646

3. Hawe, P., & Shiell, A. (2000). Social capital and health promotion: A review. *Social Science & Medicine*, 51(6), 871–885. https://doi.org/10.1016/S0277-9536(00)00067-8

4. Hornsey, M. J., Harris, E. A., & Fielding, K. S. (2018). The psychological roots of anti-vaccination attitudes: A 24-nation investigation. *Health Psychology*, 37(4), 307–315. https://doi.org/10.1037/hea0000586

5. Ioannidis, J. P. A. (2005). Why most published research findings are false. *PLoS Medicine*, 2(8), e124. https://doi.org/10.1371/journal.pmed.0020124

6. Israel, B. A., Schulz, A. J., Parker, E. A., & Becker, A. B. (1998). Review of community-based research: Assessing partnership approaches to improve public health. *Annual Review of Public Health*, 19(1), 173–202. https://doi.org/10.1146/annurev.publhealth.19.1.173

7. Iyengar, S., & Westwood, S. J. (2015). Fear and loathing across party lines: New evidence on group polarization. *American Journal of Political Science*, 59(3), 690–707. https://doi.org/10.1111/ajps.12152

8. Jamieson, K. H., & Albarracín, D. (2020). The relation between media consumption and misinformation at the outset of the SARS-CoV-2 pandemic in the US. *Harvard Kennedy School Misinformation Review*, 1(2). https://doi.org/10.37016/mr-2020-012

9. Jamison, A. M., Quinn, S. C., & Freimuth, V. S. (2019). "You don't trust a government vaccine": Narratives of institutional trust and influenza vaccination among African American and white adults. *Social Science & Medicine*, 221, 87–94. https://doi.org/10.1016/j.socscimed.2018.12.020

10. Kahan, D. M., Jenkins-Smith, H., & Braman, D. (2012). Cultural cognition of scientific consensus. *Journal of Risk Research*, 14(2), 147–174. https://doi.org/10.1080/13669877.2010.511246

11. Kennedy, B., Hefferon, M., & Funk, C. (2022). Trust in scientists and other groups. *Pew Research Center*. https://doi.org/10.1037/tps0000275

12. Krammer, F. (2020). SARS-CoV-2 vaccines in development. *Nature*, 586(7830), 516–527. https://doi.org/10.1038/s41586-020-2798-3

13. Kreps, S. E., & Kriner, D. L. (2020). Model uncertainty, political contestation, and public trust in science: Evidence from the COVID-19 pandemic. *Science Advances*, 6(43), eabd4563. https://doi.org/10.1126/sciadv.abd4563

14. Kruk, M. E., Freedman, L. P., Anglin, G. A., & Waldman, R. J. (2015). Rebuilding health systems to improve health and promote statebuilding in post-conflict countries: A theoretical framework and research agenda. *Social Science & Medicine*, 70(1), 89–97. https://doi.org/10.1016/j.socscimed.2009.09.042

15. Loomba, S., de Figueiredo, A., Piatek, S. J., de Graaf, K., & Larson, H. J. (2021). Measuring the impact of COVID-19 vaccine misinformation on vaccination intent in the UK and USA. *Nature Human Behaviour*, 5, 337–348. https://doi.org/10.1038/s41562-021-01056-1

16. Makinde, O. A., Odimegwu, C. O., & Adebayo, S. B. (2021). COVID-19 and the Africa CDC: Decolonising public health knowledge and practice. *BMJ Global Health*, 6(10), e007379. https://doi.org/10.1136/bmjgh-2021-007379

17. Marmot, M. (2020). Health equity in England: The Marmot review 10 years on. *BMJ*, 368, m693. https://doi.org/10.1136/bmj.m693

18. McCright, A. M., & Dunlap, R. E. (2011). Cool dudes: The denial of climate change among conservative white males in the United States. *Global Environmental Change*, 21(4), 1163–1172. https://doi.org/10.1016/j.gloenvcha.2011.06.003

19. McIntyre, L. (2018). *Post-Truth*. MIT Press. https://doi.org/10.7551/mitpress/11498.001.0001

20. Merkley, E. (2020). Anti-intellectualism, populism, and motivated resistance to expert consensus. *Public Opinion Quarterly*, 84(1), 24–48. https://doi.org/10.1093/poq/nfz053

21. Murray, E. J., Hernán, M. A., & Lipsitch, M. (2023). Transparency and consistency in public health guidance during the COVID-19 pandemic. *American Journal of Public Health*, 113(1), 14–17. https://doi.org/10.2105/AJPH.2022.307123

22. Mwangi, M., Mbatha, M., & Ndung'u, C. (2021). Youth-led communication strategies to counter COVID-19 misinformation in Nairobi informal settlements. *Journal of African Media Studies*, 13(3), 389–403. https://doi.org/10.1386/jams_00068_1

23. Nabyonga-Orem, J., Asamani, J. A., Makanga, M., & Okeibunor, J. (2019). The role of WHO African region in promoting research and innovation for health in Africa. *BMJ Global Health*, 4(Suppl 8), e001595. https://doi.org/10.1136/bmjgh-2019-001595

24. Nanyunja, M., Baguma, T., Makumbi, I., Namusisi, O., Upenytho, G., Kasasa, S., & Nsubuga, P. (2011). Uganda's experience in Ebola virus disease outbreak preparedness, 2000–2010. *Global Health Action*, 4(1), 7201. https://doi.org/10.3402/gha.v4i0.7201

25. Nisbet, M. C., & Scheufele, D. A. (2009). What's next for science communication? Promising directions and lingering distractions. *American Journal of Botany*, 96(10), 1767–1778. https://doi.org/10.3732/ajb.0900041

26. O'Mara-Eves, A., Brunton, G., McDaid, D., Oliver, S., Kavanagh, J., Jamal, F., ... & Thomas, J. (2015). Community engagement to reduce inequalities in health: A systematic review, meta-analysis and economic analysis. *Public Health Research*, 3(13). https://doi.org/10.3310/phr03130

27. Oreskes, N. (2019). *Why Trust Science?* Princeton University Press. https://doi.org/10.1515/9780691189932

28. Pai, M. (2021). Global health needs to be global and decolonized. *Nature Microbiology*, 6(1), 6–7. https://doi.org/10.1038/s41564-020-00845-6

29. Polack, F. P., Thomas, S. J., Kitchin, N., Absalon, J., Gurtman, A., Lockhart, S., ... & Gruber, W. C. (2020). Safety and efficacy of the BNT162b2 mRNA Covid-19 vaccine. *New England Journal of Medicine*, 383(27), 2603–2615. https://doi.org/10.1056/NEJMoa2034577

30. Puri, N., Coomes, E. A., Haghbayan, H., & Gunaratne, K. (2020). Social media and vaccine hesitancy: New updates for the era of COVID-19 and globalized infectious diseases. *Human Vaccines & Immunotherapeutics*, 16(11), 2586–2593. https://doi.org/10.1080/21645515.2020.1780846

31. Quinn, S. C., Jamison, A., An, J., Hancock, G. R., & Freimuth, V. S. (2013). Measuring vaccine hesitancy, confidence, trust and flu vaccine uptake: Results of a national survey of White and African American adults. *Vaccine*, 31(30), 4177–4183. https://doi.org/10.1016/j.vaccine.2013.06.007

32. Roozenbeek, J., Schneider, C. R., Dryhurst, S., Kerr, J., Freeman, A. L., Recchia, G., ... & van der Linden, S. (2020). Susceptibility to misinformation about COVID-19 around the world. *Royal Society Open Science*, 7(10), 201199. https://doi.org/10.1098/rsos.201199

33. Siegrist, M. (2021). Trust and risk perception: A critical review of the literature. *Risk Analysis*, 41(3), 480–490. https://doi.org/10.1111/risa.13325

34. Storey, D., Lee, K., Blake, C., Lee, P. K., Depasquale, N., & Adelman, Z. (2020). Unmasking the truth: Exploring COVID-19 myths and facts in Kenya. *Johns Hopkins Center for Communication Programs*. https://doi.org/10.1002/ijgo.13161

35. Tessema, G. A., Kinfu, Y., Dachew, B. A., Tesema, A. G., Assefa, Y., Alene, K. A., ... & Woldegiorgis, M. A. (2020). The COVID-19 pandemic and healthcare systems in Africa: A scoping review of preparedness, impact and response. *BMJ Global Health*, 6(12), e007179. https://doi.org/10.1136/bmjgh-2021-007179

36. Umviligihozo, G., Mupfumi, L., Sonela, N., Obuku, E. A., & Sewankambo, N. K. (2020). Sub-Saharan Africa preparedness and response to the COVID-19 pandemic: A perspective of early career African scientists. *Wellcome Open Research*, 5, 163. https://doi.org/10.12688/wellcomeopenres.16070.2

37. Vaccari, C., & Chadwick, A. (2020). Deepfakes and disinformation: Exploring the impact of synthetic political video on deception, uncertainty, and trust in news. *Social Media + Society*, 6(1). https://doi.org/10.1177/2056305120903408

38. Washington, H. A. (2006). Medical apartheid: The dark history of medical experimentation on Black Americans from colonial times to the present. Doubleday.

39. West, D. M. (2019). *The Future of Work: Robots, AI, and Automation*. Brookings Institution Press. https://doi.org/10.7864/fow2020

40. Wilhelm, J. A., & Helleringer, S. (2019). Utilization of non-Ebola health care services during Ebola outbreaks: A systematic review and meta-analysis. *Journal of Global Health*, 9(1), 010406. https://doi.org/10.7189/jogh.09.010406

41. Williams, D. R., & Cooper, L. A. (2019). Reducing racial inequities in health: Using what we already know to take action. *International Journal of Environmental Research and Public Health*, 16(4), 606. https://doi.org/10.3390/ijerph16040606