The Design and Testing of a Personalized Health Engagement Platform

A Case Study in Relationship-centered Innovation

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***Abstract*—Engagement remains a primary challenge to the adoption and success of public health interventions. Digital tools offer unprecedented capability to reach individuals where they live, even in underserved communities; however, lack of engagement is a persistent barrier to their effectiveness. Prior efforts at intervention and solution design attempt to employ a human-centered approach to address this challenge but have lacked the ability to use large data sets to both inform content and drive precision delivery of that content. Additionally, evaluation of the impact of these solutions takes a long time, hampering ability to test and tweak content and delivery strategies to achieve better engagement along the way. GoodLife Media's solution is a data-driven health participant engagement platform with dashboards for real-time monitoring of performance. This paper provides an overview of the GoodLife solution, the relationship-focused approach taken to its design, and the outcomes and learnings from the study of initial implementation.**

Keywords-health engagement; health communication; machine learning; human-centered design; innovation.

I. INTRODUCTION

Engagement remains a primary challenge to the adoption and success of public health interventions [1]. Research cites lack of personalization as a barrier to user engagement with digital health tools [2]. Prior efforts at intervention and solution design attempt to employ a human-centered approach to address this challenge but have lacked the ability to use large data sets to both inform content and drive precision delivery of that content [3][4]. Additionally, evaluation of the impact of these solutions takes a long time, hampering ability to test and tweak content and delivery strategies to achieve better engagement along the way.

Human-Centered Design as a best practice has at its core a focus on the patient's needs, motivations, and lifestyle [3][4]. The challenge remains exactly how to deliver solutions that yield the high rates of participant engagement necessary to deliver an intervention's intended results. Designed to address this challenge, the GoodLife Media™ (GLM) platform is a precision communication solution powered by a novel card sorting game designed to collect end users' behavior, motivation and lifestyle data. It was developed by The McClennan Group [5], an innovation agency that creates digital health products and marketing programs for corporate clients such as IBM, AARP, Humana, Gilead, Vanguard, Blue Cross Blue Shield Carefirst, Partners in Primary Care, among others.

This paper outlines each component of the GoodLife solution, featuring the relationship-focused approach that drove the design of the platform and content strategy (Section II). Following is a brief description of the initial implementation of the platform presented as a case study (Section III) along with the evaluation of the platform's impact on average closure of care gaps for older adults receiving Medicare benefits (Medicare is a federally-funded program in the U.S. that provides health insurance coverage to individuals who are age 65 and over, and some people under age 65 with certain disabilities, including people with severe, end-stage kidney disease. Medicare Advantage refers to Medicare-approved health insurance plans from a private company providing health and drug coverage to the Medicare population) from a top five U.S. payor. We conclude (Section IV) by discussing future plans to adapt the platform to serve individuals from historically underserved communities.

II. GOODLIFE MEDIA SOLUTION

The GoodLife Solution aims to engage users while prompting and enabling them to take specific health-related actions. The solution consists of four major components: (1) engaging, data-driven personalized content fueled by a (2) behavioral science-informed strategy that leverages the engaging power of relationships, (3) bi-directional, omni-channel communication infrastructure, and (4) a comprehensive dashboard allowing for understanding of program progress on a variety of levels, identification of specific areas for intervention or shift in strategy, and design and testing of targeted campaigns aimed at specific participant segments or tasks.

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A. Data-driven personalized content

The key to solving the personalization challenge lies in collecting hard-to-get datasets, including data on individual-level motivation & lifestyle. To accomplish this, we created a first of its kind card sorting game designed to collect hard to get non-clinical data in a fun and engaging way. It enjoys 86.5% completion rates, and it is the initial primary driver of the solution's personalized experiences. This device-agnostic card sorting game collects patients' behavior, lifestyle, and motivation with that challenge in mind, delivering as a result a Purpose Statement sentence consisting of their Talents, Passions, Impacts, Values, and Goals along with a compelling collage reflecting the output of the activity. As the target audience for the initial application of the solution was Medicare Advantage participants, the card sort activity was initially conceived in collaboration with colleagues at AARP's Life Reimagined Institute [6].

In our hypothesis, the benefit of using a card sorting activity in a health context points to theories of intrinsic motivation, which is central to one's engagement in and maintenance of health. Research has shown that tapping into patients' intrinsic motivation (acting for the inherent enjoyment of the activity involved) is the most autonomous form of motivation [7]. When the desired behavior is not inherently enjoyable (e.g. embarking on a restrictive diet), one may still be autonomously motivated through integrated regulation (i.e., acting in line with one's own goals and values).

B. Evidence-based behavioral science inspired content strategy

At its core, the GoodLife solution strategy is built upon evidence- both clinical evidence regarding healthful behavior as well as behavioral and social science principles proven to engage and impact the way that people conceptualize and address health-related issues. GoodLife's extensive Health Content Library contains a series of sequential communications designed to educate recipients around basic health-related topics (e.g. importance of blood pressure awareness) and principles of health management (e.g. annual wellness exams). Communications pathways are designed to be experienced as asynchronous, ongoing dialogues as one might enjoy with a trusted friend or care provider. The personalization as well as relationship focus of content are key to the GoodLife solution's content strategy.

To increase the impact of these dialogues, Health Content Library material is infused with behavioral economics inspired "nudges" based on the BASIC toolkit strategy for developing behaviorally informed interventions. Developed by the Organization for Economic Co-operation and Development (OECD), an international organization that works to build better policies for better lives, BASIC consists of four principles (Attention, Belief Formation, Choice, Determination) derived from the behavioral and social sciences—including psychology, cognitive sciences, and group behavior—to provide adopters with a step-by-step process for analyzing a problem and building strategic solutions [8]. Combining the power of analytics to personalize content and target the most prominent and costliest care gaps using behavioral economics enables us to increase our impact on member behavior in the areas that matter most to their health and well-being. Our systematic approach to developing and implementing these strategies allows us to monitor, test, and tweak tactics based on their success.

C. Bi-directional, omni-channel communication infrastructure

We used dynamic segments, generated by applying machine learning techniques to participant data, to drive communication plans in various ways (see Section III for details on techniques used). Firstly, dynamic clusters correlate directly to tone determined most likely to resonate with that segment. And each cluster is further segmented by conditions and healthcare gaps which drive overall content, subject lines, and call-to-action statements. Additionally, tones are constantly enhanced by how users respond to the communications. For example, if during our communications with a particular member we perceive a Social Determinants Of Health (SDOH) barrier, messages will shift to conform to their reality. As a result, we produced 108 communication streams with bilateral capabilities, i.e., the ability to collect information from users along the way.

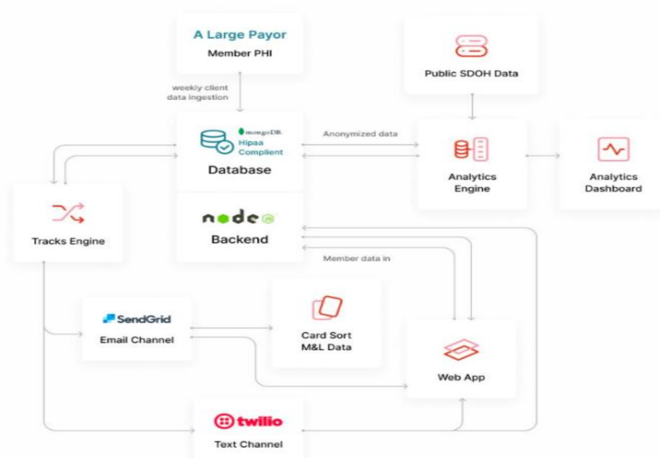

Figure 1. GoodLife Solution Infrastructure

GoodLife's communication infrastructure is illustrated here (see Figure 1) and includes:

- SDOH data curated from public databases.
- An analytics engine designed to power our real-time Analytics Dashboard
- Member Personal Health Information (PHI), provided by the large payor every week and including claims data allowing us to measure gap closures.
- A Health Insurance Portability and Accountability Act of 1996 (HIPAA)-compliant database designed to

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hold member PHI as well as the communication streams and card sorting data [9].

- SendGrid and Twilio implementations designed to maximize the deliverability of content by allowing for participants to seamlessly receive communications via text and/or email.
- A web application that provides users with a responsive experience, no app download needed.

As the participant experiences progress, we keep our stream of communication conversational by allowing them to provide us with self-reported data, including their personal goals, barriers, distractions, reasons for missed appointments, etc. Communication streams are built with trust and reciprocity at their core so that over time participants come to view communications from GoodLife as relevant and valuable- making clear there is "payoff" for every data point shared in line with that participants goals and values. We utilize simple, accessible language, avoiding jargon to ensure content is approachable and understandable at first read. Our range of strategically motivated formats is continuously evolving and includes:

- HIPAA-compliant bidirectional/conversational SMS (supports conversational tone).
- Talking Clinician Videos (authority or subject matter experts build credibility and trust).
- Storytelling/Animated Videos (supports understanding ideas in new ways)
- Cartoons/Webtoons (promotes relatability and playfulness)
- Emojis, Memojis (animation with authentic voices to make content easily digestible
- Stickers (supports peer to peer dissemination of simple calls to action)

We are constantly adding new formats as they are invented and tested. They are carefully selected based on project goals, the cohort's literacy level, age, call-to-action, and culture/language.

Figure 2: Real time dashboards illustrating participant program enrollment, status, and measure compliance

D. Real-time dashboards

Precision-communication demands increased rigor in measurements of results. The custom-built, real-time analytics dashboard delivers intelligence around key performance indicators and allows our partners to adapt and change direction as needed. The analytics dashboard can be accessed by a variety of users with various permissions levels and was designed to be standalone or integrated with our partner's system.

This first dashboard (right) image illustrates an overview of the population of the data, focusing on compliance for several healthcare measures. All the visuals are controlled by interactive filters that enable focus on specific groups within the population. This second dashboard image (left) features statistics around the different communications and activities, indicating how successful each campaign was in closing gaps. Other dashboards show detailed information regarding email delivery (e.g. sent, received, read) trended by date.

III. CASE STUDY: GOODLIFE APPLIED TO OLDER ADULT HEALTH ENGAGEMENT

In its first implementation, GLM partnered with a top five U.S. payor to apply the GoodLife solution to a group of older adult Medicare participants who were provided the opportunity to opt into communications from GoodLife as part of their regular benefits and communications from their payor.

Utilizing the latest data science techniques, including silhouette analysis and K-means [10], we created dynamic participant segments infused with insights generated from 101.9MM data points from 80 thousand members. These techniques were chosen for their ability to best utilize the card sort data to generate clusters that informed how participants would be segmented for targeted communications. K-means is a centroid-based clustering algorithm that identifies groups of program participants with common characteristics; Silhouette Analysis measures the distances between clusters, allowing us to divide participants into segments with the least amount of feature overlap between individuals in different clusters.

Using these techniques to combine card sorting output with payor provided SDOH and clinical data, we were able to generate insights on members' psychological drivers, preferences, attitude formation, and decision-making approach. Using this data-driven approach to communication and messaging, the GoodLife Solution delivered a personalized participant journey to 1000+ participants that directly addresses key challenges for public health programs: 1) relevance in messaging; 2) ability to address a broad range of psychosocial (i.e., depression), structural (i.e., transport), clinic-based (i.e., no access, waiting times, etc.), and other barriers (i.e., stigma and others, alone or in combination).

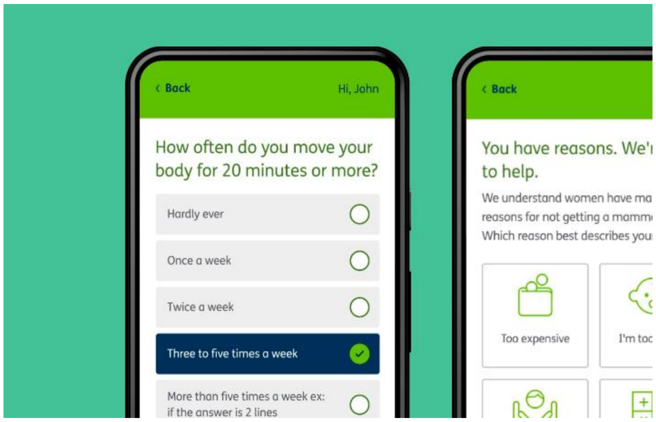

Figure 3: Example Communication

Evaluating Impact

To evaluate the impact of the program, two groups were set up: "test" group (exposed to standard Payor communications & GLM personalized content) and a lookalike "control" group (exposed only to Payor communications). Comparing these two groups provides insight into how effective the program is. To increase confidence in the ability to compare the two groups, additional analysis was performed to confirm the level of similarity between them.

To verify the effectiveness of our program, we designed a test to measure the higher gap closure rates among program participants. The gap closure rates for the test and control groups were compared for each measure, calculating the delta between each. The delta was then applied to the total group size for each measure to find the incremental gap closures, or the number of gaps closed in the test group due to the increased closure rates.

Our test results show both that there was an increase in gap closures among program participants and the increase in gap closures was statistically significant (at $p<0.05$) for 6 out of the 9 gaps. An average reduction in gaps of care of 9.4% was observed. In the case of breast cancer screening the reduction was more than 25% (26.89%). Chi-square analysis indicated that test and control groups were highly alike regarding their healthcare needs, further confirming findings of program effectiveness.

IV. CONCLUSION

This initial case study illustrates how, through s relationship-focused approach to design, along with data- and evidence-based development, the GoodLife Solution provides the foundation for a comprehensive program to reach, engage, educate, and sustain engagement of participants in their health behavior. In the future, applications of the GoodLife Solution will be applied as an engagement solution for members of historically underserved communities. The relationship-focus of the GoodLife solution, along with its modular infrastructure and tailorable content provides a strong foundation from which to build community and individual level engagement strategies.

REFERENCES

[1] S. O'Connor, P. Hanlon, and C. O'Donnel, "Understanding Factors affecting patient and public engagement and recruitment to digital health inventions: a systematic review of qualitative studies," BMC Med Inform Decis Mak, vol. 16, 2016, doi: 10.1186/s12911-016-0359-3

[2] C. Lyles, R. Watchter, and U. Sarkar, "Focusing on Digital Health Equality," JAMA, vol. 326, pp. 1795-1796, 2021, doi:10.1001/jama.2021.18459

[3] P. Koen, "Lean Startup in Large Enterprises Using Human-Centered Design Thinking: A New Approach for Developing Transformational and Disruptive Innovations," Howe School Research Paper, Jan 2015, doi:10.2139/ssrn.2556187

[4] T. Schulte and S. Bohnet-Joschko, "How can Big Data Analytics Support People-Centered and Integrated Health Services: A Scoping Review," Int J Integr Care, vol 16, June 2022, doi: 10.5334/ijic.5543.

[5] McClennan Group, [online] www.mcclennangroup.com [accessed October, 2022]

[6] AARP Life Reimagined Institute, [online] www.aarp.org/about-aarp/life-reimagined/ [accessed October, 2022]

[7] E. Deci, and R. Ryan, "Self-determination theory," in Handbook of theories of social psychology, P. Van Lange, A. Kruglanski, and & E. Higgins, Eds. New York: Sage Publications Ltd., pp. 416-436, 2012, doi:10.4135/9781446249215.n21

[8] OECD, "Tools and Ethics for Applied Behavioral Insights: The BASIC Toolkit," Paris: OECD Publishing, 2019, doi: 10.1787/9ea76a8f-en.

[9] HIPAA, [online] www.hhs.gov/hipaa/index.html [accessed October, 2022]

[10] D. Sharma, K. Thulasiraman, D. Wu, and J. Jiang, "Power Network Equivalents: A Network Science Based K-Means Clustering Method Integrated with Silhouette Analysis," Studies in Computational Intelligence, vol 689, C Cherifi, H. Cherifi, M. Karsai, and M. Musolesi, Eds. New York: Springer International Publishing, pp. 78-89, 2017, doi: 10.1007/978-3-319-72150-7_7