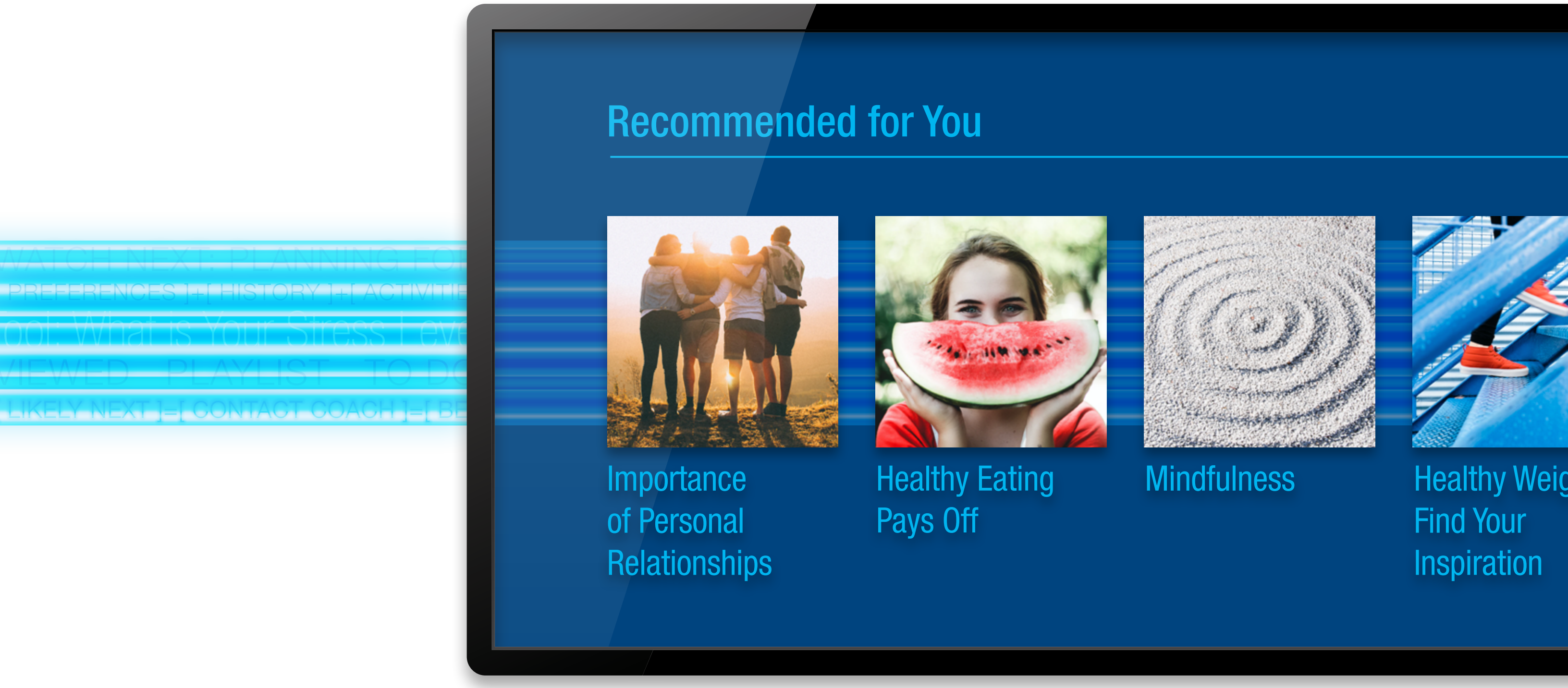
Data Science and the Transformation of Well-Being Engagement Programs

Lessons Learned from Netflix, Amazon, and Google



Onlife HEALTH

Onlife Health

Onlife Health, a GuideWell company, brings end-to-end simplicity to population health and wellness, connecting and integrating people, technology, and benefit design through our user-friendly engagement platform, guiding members on the "next right thing to do" in their healthcare journey. Our unique approach – personalized, supported, connected – drives engagement and delivers value. With its built-in agility, the Onlife platform can be quickly and easily configured and scaled to serve any market, from commercial health insurance to Medicare Advantage and Individual (ACA) lines of business.

Introduction

National retailers such as Netflix, Amazon, and Google continue to revolutionize consumer engagement, applying the tools and methods of data science to create new levels of personalization that transform first-time users into lifelong customers. Equipped with the ever-expanding capabilities of machine learning, algorithms, and artificial intelligence, these retailers can process huge amounts of data to determine consumer preferences and make new recommendations in milliseconds. In short, they've made personalization a powerful marketing strategy, one that is so commonplace that consumers now expect nothing less than an online retail experience that has been specifically tailored to their specific interests and preferences.

This white paper looks at some of the data-science techniques used by Netflix, Amazon and Google and then examines how these same proven, industry-leading models and technologies are being used by Onlife Health to transform the member experience.

Why Personalization Works

Today's consumers live in a world of unending distractions. Content is everywhere, bombarding the consumer around the clock. Every minute, YouTube creators upload 300 hours of video to the platform.[1] On Facebook alone, there are more than four million new posts every minute—250 million new posts every hour.[2] As a result, the average human attention span has decreased to 8.25 seconds,[3] and 55 percent of viewers spend less than 15 seconds on a website.[4]

Despite all this, many people will binge watch a series on Netflix for hours and hours, even days.

How do we explain this? The answer is the power of personalization.

Effective content isn't about who can shout their message the loudest or the most frequently. It's about sparking a connection. It's about presenting content that is relevant, that speaks directly to the consumer and triggers an emotional response. Short attention spans are caused, in part, by the editing function required of the human brain to filter out the overwhelming amount of information that is irrelevant and unimportant to consumers and their purposes. But if the consumer discovers personalized content that matches their specific needs and interests, their attention span increases exponentially. In other words, only personalized content can attract and retain the attention of today's consumers.

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The Power of Personalization in Consumer Engagement

90% **of consumers find personalization very or somewhat appealing.**[5]

74% **of customers feel frustrated when a website is not personalized.**[6]

72% **of consumers say they will only engage with messaging that is personalized.**[7]

Given the power of personalization, let's look at what well-being engagement platforms can learn from three industry leaders and the techniques they use to create a personalized experience that increases consumer engagement and satisfaction.

ONLINE ENTERTAINMENT

Netflix: The Power of Personalized Recommendations

With more than 190 million subscribers, Netflix is the world's largest subscription streaming service.[8] Netflix was one of the pioneers in creating a sophisticated recommendation engine that provides their members with a personalized and highly accurate ranking of viewing options. A recommendation engine is an information filtering system that uses machine-learning algorithms and data analytics to predict consumer behaviors, interests, and preferences in order to make personalized product and purchase suggestions.

Think of Netflix as a giant data-collecting machine gathering information about its subscribers around the clock. Each time a member clicks play, pause, rewind, fast forward, or stops watching altogether, Netflix is gathering data about their preferences. It's also tracking data within the content, such as genre, actors and scenery, as well as a member's viewing history and previous recommendations. By analyzing these terabytes of data and then ranking every title for every member, Netflix serves as the ultimate matchmaker between its subscribers and the content they're watching.

After years of reviewing and improving its recommendation engine, including sponsoring a $1 million contest to improve its algorithm, Netflix estimates that up to 80 percent of its viewer activity today is generated by its recommendation system.[9]

So how does the Netflix recommendation engine work? Let's look at one example of an algorithm they might use by first defining a few terms.

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Matrix: A matrix is a building block of data science. Essentially, it's a grid of numbers arranged in intersecting columns and rows.

Matrix Factorization: Think of matrix factorization as a simple mathematical tool that allows data scientists to break apart matrices into simpler pieces. Put another way, matrix factorization is a method to approximate a larger matrix using two or more smaller matrices. Matrix factorization allows data scientists to discover the latent features that underlie the interactions between Netflix users and their viewing choices.

Latent Features: These are hidden variables or underlying patterns that are not directly observable in the data but can be revealed by machine-learning algorithms. In the case of Netflix, these hidden variables might reflect a title's genre, setting, or lead actor.

Let's now examine how Netflix uses data analytics and algorithms to generate personalized recommendations. Please note that the following example is one of the many techniques employed by Netflix and has been simplified for clarity and demonstration purposes.

We begin with a simple matrix that contains a row for each Netflix user and a column for each Netflix title. A user's row is filled in with a "1" for each title the user has viewed and a "0" for each title not viewed.

Next, we apply a matrix factorization technique to break down the matrix of thousands of tiles and millions of users into two smaller matrices in order to identify the latent features shared by both movies and members. The first matrix we create is a *title matrix*. It contains the same list of titles as the original matrix, but now the rows contain latent features, such as Strong Female Leads, Historical Fiction and Murderous Subplot, instead of users. Each title has a score for each latent feature.

The second matrix we create is a *user matrix*. It provides a score of how strongly each member prefers a specific latent feature. For example, User #2 is more likely to view a title that is Historical Fiction or has Strong Female Leads but is much less likely to view a title with a Murderous Subplot.

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We're now ready to determine the personalized recommendation, in this case, of the movie *The English Game* for User #1. To do this, we first multiply User #'1's score for Strong Female Lead by the *English Game's* score for that same latent feature.

.8 x .2 = .16

We repeat this process for Historical Fiction and Murderous Subplot.

.6 x .9 = .54 **.9 x .2 = .18**

We then add these three products together to determine User #1's personalized recommendation score for *The English Game*.

.16 + .54 + .18 = .88

This score is then compared with thousands of other films to determine its preference ranking for User #1.

Applying Netflix Techniques to the Well-Being Engagement Experience

Just as Netflix can rank all its titles for each member, Onlife Health is working on prioritizing (ranking) the recommended content for each member by analyzing his or her prior behavior and interests. For example, the Explore section of our member portal contains articles, podcasts, videos, and other personalized content. By analyzing what a member has previously viewed in the Explore section, we'll be able to predict what content will be of most interest to that member and then populate the Explore section with that content. As a result, content can be prioritized and rearranged to maximize the likelihood of a member using it.

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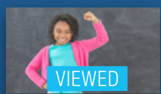
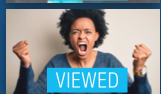
1. *In this example, the member had previously viewed the following content:*

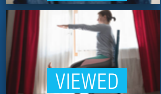
Previously Viewed



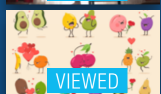
VIEWED
Building Resilience



VIEWED
Common Coping Responses for Stress



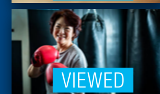
VIEWED
Exercising While Sitting Down



VIEWED
Five Ingredients for Health Eating

VIEWED
Mindful Walking

VIEWED
Planning for a Change that Matters



VIEWED
Stress Busters

VIEWED
Teens: Who Do You See in the Mirror?

VIEWED
Tool: BMI, Waist Size and Health Risks

VIEWED
Tool: What is Your Stress Level

2. *Instead of populating the* ***Explore*** *section with random content, our analysis of this viewing history revealed that the following topics will generate the most interest for the member.*

Explore

Importance of Personal Relationships

Healthy Eating Pays Off

Mindfulness

Healthy Weight: Find Your Inspiration

Health Literacy

Adjustable Gastric Banding Surgery

3. *Within this framework, however, we've found that it's not advisable to make the content static, that is, to always provide the same information in the same order. Dynamically changing the most highly recommended content has proven effective in keeping members interested and coming back to see what's new.*

Explore (TUESDAY)

A B C D E F

vs

Explore (SATURDAY)

G C H A B D

ONLINE SHOPPING

Amazon: Know Your Customer

For Amazon, the world's largest online retailer, the goal is clear:

"Our mission is to be Earth's most customer-centric company… to continually raise the bar of the customer experience by using the internet and technology to help consumers find, discover and buy anything."

—Amazon Mission Statement

That's quite a mission to fulfill considering the fact that Amazon attracts over 130 million customers to its U.S. website alone each month.[10] To create a personalized experience for each of these 130 million customers, Amazon employs a variety of sophisticated data-mining techniques to gain a more precise and in-depth understanding of each customer and his or her purchasing patterns.

For example, a Market Basket Analysis is one of the techniques Amazon might use to determine what items are displayed in its Frequently Bought Together section. Market Basket Analysis uses statistical calculations to determine what combinations of products most frequently occur together in order to provide customers with cross-selling recommendations and promotions that they value. The following is a simplified example of how this technique works.

We start with three shopping carts representing three different consumers. All three consumers bought some combination of backpacks, socks and hiking poles.

By applying an algorithm, we then determine frequent itemsets, which is an item or set of items that appear in a certain number of baskets. For the purposes of our example, we are going to establish a minimum support criterion of .67. In other words, the items must appear in two out of three carts in order to be included in the frequent itemset. *Note: The minimum support criterion used by Amazon would be much smaller.*

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Using the .67 minimum support criterion, the following collections of items qualify as Frequent Item Sets:

- {Backpacks}
- {Poles}
- {Socks}
- {Backpack, Socks}
- {Poles, Socks}

Poles/Backpacks does not qualify as a frequent itemset because this combination appears only in one out of the three shopping carts and therefore, with a support of only 0.33, does not meet our .67 criterion.

To provide additional personalization, Amazon might apply the apriori algorithm to generate association rules. These are rule-based machine-learning results for discovering interesting relations between itemsets like the ones we just identified.

There are a number of metrics used to measure the strength of an association rule. In this case, let's look at the association rule metric called confidence. Given an individual rule, the confidence metric asks the question: *If we see one item or itemset in a given purchase, how confident are we that a second item or itemset will also appear?*

For the purposes of our demonstration, a confidence of 100 percent is required in order for an item(s) to appear in the Frequently Bought Together recommendation. *Note: This is a much higher confidence than Amazon would use.*

Going back to the three carts, we see:

- A backpack purchase is associated with a sock purchase 100 percent of the time because both purchases with a backpack also have socks.
- A hiking poles purchase is associated with a sock purchase 100 percent of the time by similar reasoning.
- A backpack purchase is associated with hiking poles only 50 percent of the time because only one of the two baskets with hiking poles also has a backpack.

After analyzing all this information, we come to two conclusions:

1. When a consumer purchases hiking poles or a backpack, socks <u>should</u> be included as a Frequently Bought Together item.
2. When a person purchases a backpack, hiking poles <u>should not</u> be included as a Frequently Bought Together item.

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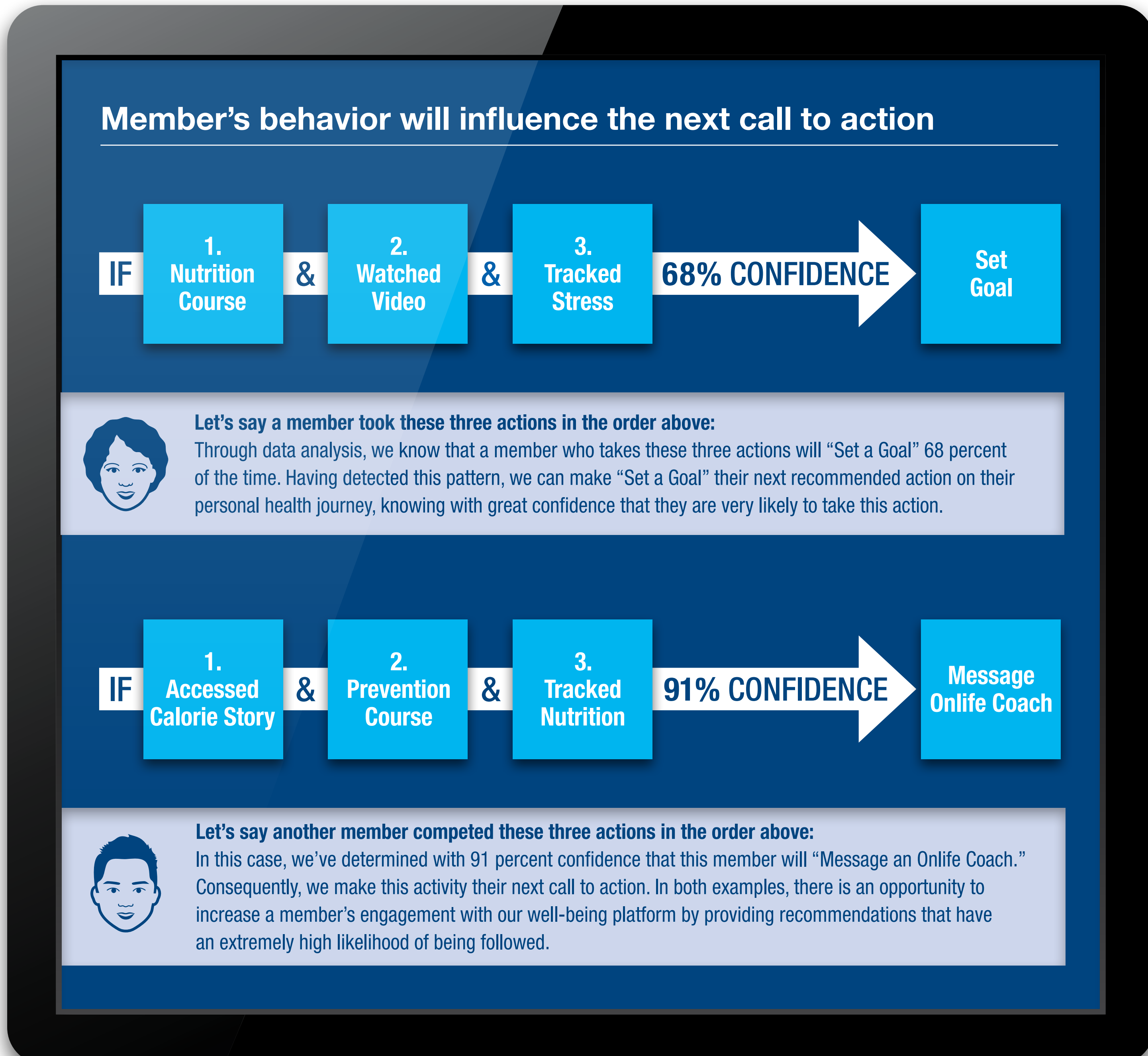
Applying the Market Basket Analysis to the Well-Being Engagement Experience

Using algorithms similar to those employed by Amazon, Onlife Health is exploring ways to predict how likely members are to engage in a new action based on their prior behavior. In this case, instead of making a purchase recommendation, our goal is to provide each member with a recommended next step with a high confidence that they will engage in this activity.



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SEARCH ENGINE

Google: The Power of Predictive Texting

More than 70 percent of the world's search requests are handled by Google, the American online search engine founded in 1998.[11] Today, Google offers more than 50 products and services, from email to online document creation. To improve the user experience in its search, mobile, app, translation and other services, Google uses natural language processing (NLP) to create personalized language models. NLP is a combination of machine learning and linguistics that uses artificial intelligence to analyze human language and gain insights about improving communication.

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In the following example, we'll show how an NLP model is used to analyze a person's messaging history, especially word-usage patterns, in order to predict the next word a person will use in texting. As a result, Google can create a personalized language model based on an individual's messaging history.

NLP represents unstructured free text data (words) as structured data (numbers) in a tabular form. The simplest form of "turning words into numbers" is an algorithm called Bag-of-Words. The algorithm converts free text to a matrix in which the columns correspond to the words used and the rows show how many times each word is used in a given message or document.

For the purposes of this simple demonstration, let's say that a person texts the following:

"Will do. You have a good day at work and a good trip."

In order to numerically encode this message, we begin by counting the number of times each word is used in the phrase.

In the "real world," the entire collection of thousands of words from a person's texting history, called the Corpus, would be used in the process. Additionally, common words like "a" and "the" are usually removed during pre-processing because of their lack of meaning. We now have a single encoded text message.

In the next step, we would start with a baseline English language model and tweak it to be more personalized by using the encoded text message. A baseline English language model is a pretrained statistical model (many are available to the public), created by Google and other tech companies, that has analyzed an extremely large corpus of English language documents to determine the probability distributions for sequences of words. A neural network or another machine learning model is then used to update and refine the baseline English language model to generate the final model to predict the next best word.

Because the final model includes the baseline English language model, which has analyzed an entire universe of users, it's robust enough to make a recommendation no matter what the word is. Because the baseline model has been adjusted slightly using an individual's messages, it is also highly personalized for a particular texter and may recommend a different "next word" based on their own unique texting history,

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Coaches use recommended phrases to increase member response.

Coaches who used the suggested phrases during our trial had a member response rate of **37%** compared to **22%** for those who did not use the suggested phrases.

My name is _______ and I'm one of the coaches with our wellness program. It's nice to meet you!

Thanks for taking the time to add a new fitness goal!

If you don't mind me asking, what makes this goal important to you?

CASE STUDY

Application of NLP to Improve Member Engagement

Onlife used natural language processing and machine learning in a recent pilot study to identify phrases that were more likely to motivate members to reply to a message sent by a coach. Health coaches incorporated recommended preferred phrases that were associated with a higher and/or quicker response rate into their conversation with members.

The pilot study targeted members who had signed up for a new goal but had not responded to a coach's outreach after seven days. We asked participating coaches to work in the phrases recommended by NLP when they sent a second "cold" outreach via secure message.

The results: Participating coaches had a 37 percent response rate compared to only 22 percent for non-participating coaches, an increase of 15 points that helps build better rapport and help members achieve their desired outcomes.

Because of these positive results, Onlife Health is coaching communication on a much larger scale in order to increase member engagement.

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What's Next in Personalization

Like technology in general, the science of personalization is rapidly changing. Here are three technologies that are changing the member experience.

Conversational Chatbots Currently, predictive texting anticipates the next word in a text message. In the near future, whole phrases and even sentences will be predicted by an automated chatbot.

Geolocation Also known as Location Intelligence, geolocation first appeared in 2014 and has been growing steadily in both its capabilities and importance as a marketing tool. Geolocation communicates with customers through messaging that is based on a person's location.

Geofencing This technology allows marketers to send messages to smartphone users within a defined geographic area. For example, when shoppers arrive at a retail center or mall, they receive targeted ads from the stores located in the retail center.

Key Takeaways

Intelligent personalization efforts are critical to capture the attention of today's increasingly distracted consumers.

Almost every successful retail UI or portal today regularly uses machine learning for the organization and placement of information that is useful, relevant and desired by the consumer.

Machine learning and data analytics can drive member engagement for well-being platforms by dynamically updating and revising content, recommendations, challenges, and other engagement touchpoints in order to match and meet the specific personalized needs and interests of each member.

Well-being platforms that invest in the science of personalization will significantly increase member engagement and gain a strong competitive advantage.

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Endnotes

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