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Chapter 8: Improving customer engagement through behavior-driven artificial intelligence recommendations and interactive platforms

8.1. Introduction

Customer engagement has become a priority of firms but defining it, identifying, and measuring its drivers, and testing financial consequences, is still a work in progress. Engagement relates to the behavioral dimension of the service relationship, beyond satisfaction, and depends on customer motivation, based on affective and cognitive commitment to an activity. However, little has been done to provide deeper insights into the determinants of the customer motivation to engage in service interactions. Social media has boosted digitalization, transforming traditional unidirectional communication into a bidirectional dynamic between suppliers and consumers creating new opportunities for organizations to partner with customers. Recognizing and understanding the values customers pursue when engaging is an important challenge for suppliers. A deeper understanding of these customer values is believed to facilitate the supply of adequate tools and communication means, allowing organizations to influence customer engagement behaviors, and increase the value of the service relationship for both parties (Adomavicius & Tuzhilin, 2005; Chen et al., 2015; Kaptein & Parvinen, 2015).

Prior research examining motives, values, or drivers, of engagement has suggested a variety of behavioral dimensions and focus, focusing on specific social media-related or brand-centered behavior. However, these drivers have not been tested in a comprehensive model. If organizations expect customer participation, commitment, and connection with the organization while cooperating to achieve service outcomes, these values should be at least similar, if not identical. In this paper, we investigate the motivations of customer engagement behaviors with organizations on social media. We start by analyzing the motives for customer engagement behaviors on social media to establish a parsimonious set of values proposed, the initial personalized value model.

Following the initial model, we test empirically the model with a sample of users of a social media platform centered on user-generated visual content. Finally, we discuss the results and their implications (Wang et al., 2002; Zhang et al., 2019).

8.1.1. Contextualizing the Importance of Customer Engagement

Today, the key to success in fast-paced competitive environments is customer engagement. Customer engagement is the level of a customer's emotional, psychological and physical investment in their relationship with a brand. Engaged customers are loyal, spend more, and help brands grow through word-of-mouth. Therefore, building customer engagement is paramount to profitability, especially for service industries where interactions are integral to the value proposition. While traditional customer relationship management systems only manage and drive customer engagement through touchpoints in a one-to-many manner, today's omni-channel services include many different dependent interactions in a one-to-one manner. Consequently, customer interactions generate massive amounts of transactional data, which organizations can leverage to address the gaps left by traditional CRM practices. Business activity data is generated from ongoing customer interactions during service delivery, and reveals the behavioral context for these actions and decisions. In addition to insights from business activity data, customer and service insights from organizational data can help organizations respond to their customers in context to improve outcomes.

Fig 8 . 1 : Customer Engagement and AI-driven

Given the richness of information in business activity data, organizations can utilize customer behavioral data, including service insights and service cues, for understanding customers, refining service delivery, and managing engagement. Further, recent advances in AI, including machine learning and natural language processing, enable organizations to unlock the potential of business activity data. However, the question remains, what should organizations do with the insights from behavioral data? Since customer engagement is driven by services, the answer needs to focus on managing services. Consequently, we propose to employ AI-driven recommendations for choreographing services in the context of customer engagement. Such recommendations improve existing and future services by addressing current customer interaction challenges, enhancing services for maximizing present engagement, or influencing customers to drive future engagement through recommendations. Furthermore, enabling services as interactive platforms enables feedback-driven co-creation with customers.

8.2. Exploring Customer Engagement Dynamics

While the term customer engagement (CE) is widely used in the scholarly and managerial domains, papers that explore its definition, dimensions, components, or drivers can be counted on the fingers of one hand. CE space is described as a change-oriented experience that enables co-value through participative value creation processes. From a more social interaction perspective, CE is viewed as a motivationally driven state and proposes affective, cognitive, and behavioral dimensions of engagement. B2B research differentiates CE from customer experience (CX) and other customer relationship benchmarks and proposes an involvement-based CE definition that is an important pre-condition for achieving positive outcomes of inter-firm relationships. CE is labeled as a momentary construct and mechanistically linked to emotions, experience, and outcomes. CE consumes resources and is characterized by escalation and de-escalation, as is the customer relationship itself, which might be on a higher or lower involvement level.

Despite the fact that research has made some fruitful contributions in examining customer engagement, much needs to be done to advance our knowledge in this area. The CE literature is considered "relatively disperse and early stage" and urges researchers to relook definitions of CE, as it is "significantly under-theorized, poorly differentiated from other constructs in the social media domain, and in need of providing a deeper understanding of the engagement process." The overarching objective of this paper is to deepen our understanding of the ongoing CE process and to clarify especially the pre-countries of CE, the interlinkages between CE and related constructs, and the CE outcomes in a B2B context. B2B customer engagement is conceptually illustrated as part of the customer relationship life cycle.

8.2.1. Significance and Core Concepts

Customer engagement is growing as a key priority for organizations and their customers as they navigate increasingly uncertain ambidextrous work and learning environments driven by forces such as new technology, the pandemic, climate change, and hybrid labor models. These new environments create new, sometimes conflicting customer preferences related to company interactions across the pre/post-purchase and cognitive/emotional engagement spectrum, while simultaneously increasing customer desire for products that best fulfill their unique functional and emotional needs. Aligning with these customer desire and preference trends improves customer satisfaction, increasing purchase intent and ultimately profitability. However, many organizations, especially those historically dependent on physical customer engagement channels, struggle to discover optimal customer engagement management strategies that take full advantage of the current work-learn-play paradigm transition towards availability of new technology and hybrid engagement and interactive platform models.

The broad range of dimensions and variables impacting customer engagement across multiple interaction channels and touchpoints, and the lower degree of artifact control afforded organizations for many of those channels and touchpoints, make management of the customer engagement model complex. Not only can negative interactions with one customer engagement model partner affect performance of the entire model, paving the way for widespread infection from one dissatisfied customer, those potential negative interactions can arise anytime through multiple organization-uncontrolled channels. Furthermore, those potential negative interactions can lead to decreased engagement throughout the customer journey rather than increased engagement, the goal of many organizations that have instituted customer satisfaction programs reliant on tracking of multiple customer satisfaction metrics.

8.2.2. Key Drivers of Customer Engagement

The understanding of customer engagement is evolving. In the early 2000s, engagement was still primarily understood as a means of customer acquisition that would lead to conversion and revenue, whereby the P2P connection of an engaged customer was seen as mere word-of-mouth power. The P2P connection was important but not sufficient to turn customer engagement into a self-reinforcing mechanism. Only when customers invested in their personal relationship with the brand could engagement in fact be transformed into revenues for the firm, along the dimensions of customer value and spending potential, customer loyalty, and customer profitability over the lifetime horizon. Based on these ideas and more than a decade of empirical testing across a variety of fields, the Customer Engagement Cycle Framework was developed.

More recently, researchers are proposing an even broader understanding of customer engagement. In particular, these scholars are combining the understanding of customer engagement as a brand relationship with the earlier views on customer engagement as a wealth-generating co-creation process, whereby brand engagement is seen as one factor among many to engage customers as co-creators. According to this view, brands should not only seek to engage their customers but also empower them to engage with one another and choose reserves to identify and leverage brand advocates. In these models, customer-to-brand engagement is the foundation of all brand-consumer interactions rather than a stage within a joint activity pattern. Although these findings are progressing the understanding of customer engagement, empirical support is still limited.

8.3. Behavior-Driven AI: An Overview

1. What is Behavior-Driven AI?

Behavior-Driven AI is built on the premise that to adapt to changing environments, AI technology has to learn not only from the past but from the moment. Aspects of Behavioral AI allow businesses to, among other things, capture real-time data through preliminary event analysis, anticipate behavior to optimize the customer experience, and provide recommendations to assist decision-making. In the process, customers engage deeper with a brand, through processes that are more efficient and restore their trust in brands again. In addition to instant recommendations, Behavior-Driven AI opens doors to real-time warning systems to prevent churn or automated actions offering incentives to dissuade customers from leaving.

Behavior-Driven AI focuses on using a combination of behavioral AI technologies surrounding question-answer chatbots, behavior modeling to predispose decisions, predictive and prescriptive data analytics to shine the light at the end of dark tunnels, and sentiment and tone of voice analysis as a guiding compass during times of confusion. Unlike traditional recommendation engines, Behavioral AI is not a shift in technologies; rather, it is a closed-loop approach to continuously optimize those recommendations based on customer interactions with the brand over time, using Behavioral AI technologies. A recommendation for a particular group may not be valid for specific individuals.

2. Technologies Behind Behavior-Driven AI

Behavior-Driven AI also goes beyond traditional recommendation engines that provide recommendations based on real-time psychographic profiles, rather than a user account history blended with a user-household profile. By augmenting traditional recommendation engines with behavioral AI algorithms, brands can predict and dictate chaotic patterns better and turn customer engagement during dark moments into action.

Traditional engines are good at recommending popular products for a particular profile; Behavior-Driven AI augments the speed, accuracy, and value of these recommendations through a closed loop system for continuous optimization. Implementing a closed-loop model for traditional recommendation strategies, using machine learning-based creative controls, email shape and segmentation suggestions increases clickthrough rates up to six times.

8.3.1. What is Behavior-Driven AI?

At several levels, Beh-D AI primarily focuses on activation: pushing users towards actions that can convey positive signals in terms of meaning and significance. For instance, if a shopper, after browsing dozens of leather jackets online, adds one in his cart but leaves it there for days or weeks, the online store would step in with an engaging notification or ask him if it helps to close on the buy. In a nutshell, the AI would send a signal to the shopper that his behavior is being actively monitored and that the need (in this case, nudge) to buy the jacket is not solely a matter of urgency but also a condition of transaction pricing.

From a marketplace perspective, it is crucial to know which signals to both monitor and react to, so that a predictable behavioral profile can be created for each user. Analysis of a customer's shopping and payment history, frequency of interactions, responses to promotions, and views can all convey some level of intent. These profiled levels of intent can flexibly and situationally influence how and to what extent ads, push notifications, and patronizing messages from loyal or potential brands should be adjusted for specific customers, or even groups of customers. While still at the exploratory level, group grouping is important in order to reduce the amount of required data and thus ease the burden on the algorithms at work in order to create behavioral profiles.

Enablings of Beh-D AI can be seen as an iterative refinement of more conventional models and monitor behavioral changes over time in the light of marketing actions taken, which in turn leads to behavioral-induced changes in input and output variables. With advanced details, aggregate models join high-frequency observational data from personalized services with time-delayed pricing and placement instruments to determine the models underlying the dynamic interaction of offers on consumer-level demand.

8.3.2. Technologies Behind Behavior-Driven AI

We offer here a brief overview of the information technology stack that enables behavior-driven AI. Please note that many components contained in the listed stack are de-facto standards. Some of them, mainly at the edges of the stack, are our selections, however, we do not claim originality in the choice of the most particulars, which is the consequence of its evolutionary nature throughout multiple independent events. Instead, we pay tribute to our predecessors who built the foundations of the stack. The history of these technologies can be traced back several decades and we only select the milestones that are related in some way to behavior-driven AI. The BDAI stack is built around a large number of discipline-centered components that continuously change model and concerns. The bottom of the stack is built on blockchain-enabled decentralized digital ledgers and accountable smart contracts that have consolidated during the final phases of Web3 emergence. Moving up the stack, we rely on multi-agent systems and social-electricity networks creating a wide range of digital portfolios including avatars and conversational systems. These components empower the automated direct control and supervision of user-layer algorithms dedicated to interest affinity identification and monitoring based on deterministic behavioral transition models learned through data-based system identification. The semantic-enrichment layer relies on a combination of NLP systems, large language models, and commonsense knowledge bases in the space of expert systems, semantic webs, and goal-driven chatbots. The personalized storytelling layer uses graphical story reconstruction systems. The services at the top of the stack bridge user and business needs with curated behavioral and experience recommendations and interactive narrative-design services as building blocks.

8.4. The Role of AI Recommendations in Customer Engagement

1. Personalization Techniques

80% of the interviewed consumers indicated being more inclined to do business with a company that provides personalized experiences. However, developing a personalization strategy at the level of creating tailor-made experiences for customers is complex and requires sophisticated tools. Our view is that AI can be the graphic engine that drives customer experience interaction throughout the customer life cycle. In this chapter, we outline some possible paths for introducing AI into the personalization strategy of customer relationships and CRM, followed by a detailed analysis of the potential of recommendations in improving customer engagement based on two successful case studies we have developed for a high-end retailer.

The major role of AI is to develop engagement techniques that can impact every single relationship action of the company with its customers through recommendations. Whether it concerns the proposal of products or services available in a catalog, or that of activities for the demand generation process, the objective is always the same, namely, to ease and help customers in making their purchases, by eliminating the overload of too many options to choose from. In particular, our proposal is to develop personalized messages to support customers' purchase decisions and the proactive promotion of products in which customers could be interested. With this focus, two main streams of applications based on some common methodologies can be identified: product recommendation engines and predictive analytics capabilities.

2. Predictive Analytics

Predictive analytics first began to be incorporated into websites and mobile apps by leading e-commerce operators and have become customary functionalities also in other sectors like media services with the recommendation engines developed by various platforms. Today, companies all across industries invest significant effort in capabilities designed to predict customer behavior or intent by deploying increasingly accurate models able to detect and filter the least probable behaviors from a big set of possible ones, based on the analysis of features associated with a more favorable outcome.

While exploratory analysis of customer behavior helped identify how different categories can be headed in different cyclical directions and how those purchase pyramids can evolve based on changes in state variables or actions on the parts of the companies themselves, AI has allowed us to move from a holistic analysis that only highlights the collective effect of these interactions, to granular-level predictive solutions that provide a concrete and positive long-term profitability impact by influencing single customer and activity-specific interactions.

8.4.1. Personalization Techniques

During the last few years, the Internet has been flooded with platforms where customers can ask, interact, and get feedback on many products and characteristics, experiences, and company reliability. The amount of information created is priceless, but the level of knowledge extraction is not yet close to optimizing communication with customers. The assistance of machine learning techniques can and will help with this, by making this process efficient and saving customers time. In addition, processing unstructured data, such as e-mail communications, chat transcripts, and online reviews, is a very promising area of development. It is expected that the competition among on-line retailing companies will increase their efforts to attract customers and keep them happy, which will lead to further innovations in machine learning technologies applied to this field. In particular, elastic computing clusters will become even more efficient for real-time applications associated with personalized communications.

Such tools, composed of recommendation keys and directly related to potentially relevant entities and features, can be further applied to several recommendation scenarios, linking and enhancing the classical approaches for collaborative filtering or content-based filtering. The notion of human-in-the-loop recommendation is becoming more accepted, in which recommender systems display a set of suggestions to users, but offer the chance to interactively modify the claims with the help of some recommendation keys. The intuition is that the additional effort from the user will allow personalized recommendations, which will be more relevant than the classical ones. Negative a priori knowledge can be passed to the recommendation system, based on interactive feedback, as the user can indicate which items within a displayed list do not appeal. Functionally, it corresponds to an interactive filtering interface, which can efficiently hone in on user preferences and help improve user experience.

8.4.2. Predictive Analytics

Customers are bombarded with huge amounts of information and choices at any given moment. Every platform fights for their attention, striving to be at the forefront of their thoughts. The challenge culminates when a customer is not positively engaged or enticed by any brand either intentionally or unintentionally, making the brand's position insignificant at that very moment. The best digital marketers do not wait until customers browse their homepage or social media profiles. They harness the power of predictive analytics for proactive engagement. They predict when and what users want to know, wear, eat, read, or learn at any moment in any place and communicate with them accordingly. Predictive personalization engages users and entices them to indulge with the brand, ensuring that they are not lost in the overwhelming expanse of information.

When customers think about a brand, they are assessing value and pondering whether it provides the best answer for their need at that moment. The better the forecast, the stronger the motivation for the user to use the brand's service or purchase its freemium/service. Predictive personalization does not close the room for a click without having to select an outfit color for a product category. Rather, it decorates the whole room with a digital screen showcasing the options and variations of outfits embellished with the brand's pick. However, predictive personalization is not only limited to e-commerce. It extends to different sites, different sectors, and several different label-named sites. Predictive personalization and analytics anticipates your customer's next steps and consolidates those outcomes, providing an appropriate answer on the forefront just when he/she is inquiring about it. By leveraging predictive analytics tools and implementing them correctly, businesses will see a dramatic difference in the results.

8.5. Interactive Platforms: Enhancing User Experience

Improving user experience for B2B customers has become increasingly important for companies and organizations, as a means of meeting high expectations on the part of customers, segmented offerings, supported decision processes, with the goal of achieving optimum fit and affinity with specific needs of diverse customer groups.

Organizations in virtually all areas of business are expanding their offerings into digital spheres, in the process further accentuating customers' links to the organizations by providing web-based and mobile services and enabling and incentivizing interactions with the organization via these virtual portals. Customers come to expect more from these digital interfaces, indeed, tasking the organizations with providing more value through higher functions and increasingly complex interactions to stimulate deeper commitment through higher levels of engagement. We observe an emerging imperative in the business domain to improve customer engagement through the design and management of interactive digital environments that enhance customers' business processes and individual user experiences. Interactive platforms utilize various online interactive features. Some of these enable customers to engage with the company or organization through access to information and communication, while others provide instrumentation and connectivity to collect and analyze data streams related to tasking functions. A third set of interactive features refers to transactions that take place directly involving the company's offering, such as e-commerce. The functional principle is to introduce some kind of intelligent automation or advanced integration of functionalities that improve user experience and operational efficiency, thus stimulating and optimizing user interactions. These various types of interaction should be viewed as parts of a continuum. Early development of web and mobile-based platforms centered on the design of user interfaces to facilitate the efficient collection and presentation of relevant data and information.

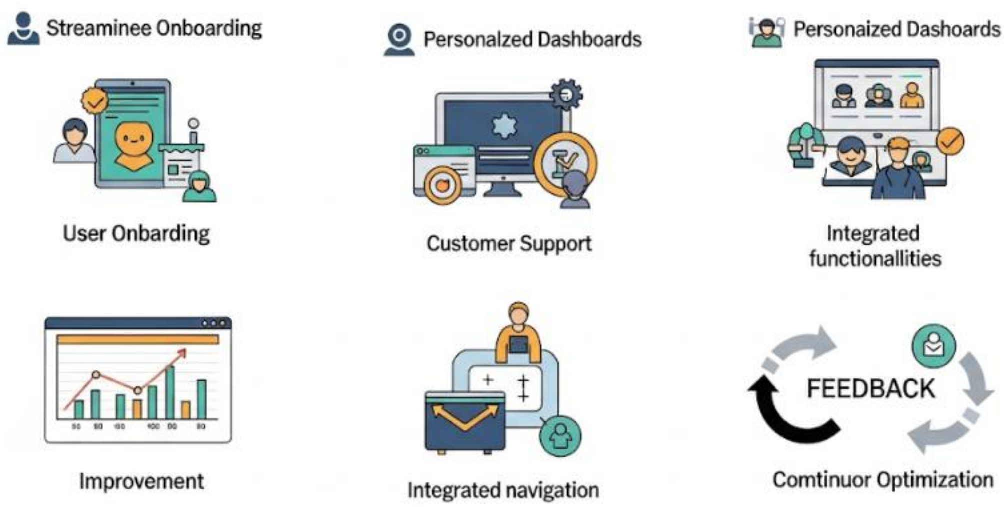

Fig 8 . 2 : Improving User Experience for B2B Customers

8.5.1. Types of Interactive Platforms

Interactive platforms are tools and services that allow users to actively engage with the data and customizable areas of user interest and select the preferences and values that match their needs while interacting with the data or other participants. User activity on the interactive platform modifies the data that can be displayed and the relevant parameters, so that subsequent recommendations become more relevant and useful. The specific characteristics of the recommendation provide the motivation, attractiveness, and rationale to engage users to provide their feedback along the recommendation interaction cycle. Cleverly designed interaction self-learning platforms are able to intelligently generate actionable consumer engagement and dialogue through personalized experiences that increase conversion and build loyalty. In this context, different types of interactive platforms exist, usually classified based on the extent of user engagement. Collaborative filtering relies on the entry of ratings and opinions that stimulate peer exchange on products of a similar type or category. Content-based filtering asks users to provide attributes and preferences concerning product types, with the aim of eliciting satisfaction. Contextual information such as follower or affinity interests influences the engagement on easy interfaces where a simple click can reveal the richness of selection. Customizable interfaces engage a community of users interested in very specific products between different categories. Interactive chatbots and agents are programmed for a strict dialogue interaction, aiming at achieving goals that are set by the platform developer, such as answering queries, booking hotels, ordering food, planning a journey. These platforms are mainly used in customer service, although they can be used also to facilitate commerce.

8.5.2. User Interface Design Principles

Once a decision is made to employ interaction for a system, the next step is to design the user interface to facilitate the engagement. User interface design is focused on enabling people to employ a system effectively and enjoyably. The user interface is the part of the machine with which the user interacts, it provides the means for the user to communicate with the system. Of course, a design that fulfills just this role is not sufficient. A user interface should also leave the user happy and eager to use the system again. For recommendation systems, this requirement has the added burden that the user interface needs to give the user access to the recommendations, present the output of the recommendation system, allow the user to evaluate these outputs and provide feedback to the recommendation engine. Given the importance of UI and the human-computer interaction design guidelines that have been proposed, it is surprising that such principles are not more widely employed in the design of recommender systems.

So, some fundamental design principles are required when defining a more task-centered and user-centered approach to UI recommendations. The interface for interactive recommender systems is a critical aspect of the user-system interaction pipeline. One way to understand user interaction with recommender systems is to briefly consider other areas of human-computer interaction. User experience strongly guides the design of many other interactive computer-based systems. We rely on expert design guidelines from the fields of graphic design, usability research, user cognition, etc., to ensure that information systems in general and recommender systems in particular are effective and easy to use. There has been much research on Graphical User Interface design and supporting principles. Those design principles describing the user interface also have become useful to generic user interface design guidelines and to more specific domains/geographical design guidelines for input and interaction design guidelines with visual displays and the mapping of controls to desirable maneuvers.

8.6. Integrating AI Recommendations with Interactive Platforms

Providing users with recommendations tailored to their preferences is a fundamental first step to increasing their engagement and ultimately attracting their attention and keeping them connected for much of their time. Typically, this is achieved with item-based collaborative filtering, utilizing similar users' preference patterns to make suggestions about unexplored or yet-unrated products. However, this initial recommendation is delivered during the Discover phase, remote from the users' usual interaction with the platform. To increase the level of engagement, companies have implemented their content throughout the service with other entertainment products, suggesting sequences of items to be engaged with. One way to make the transition smoother is for the algorithm to become a part of the interface where these users come in contact with the product, providing recommendations in parallel with the website search and browse functionalities.

By that token, researchers have proposed several methods to explore areas like picture cropping, highlighting salient areas, or even guiding the user gaze to improve the viewing experience. Ways have also been proposed to integrate recommendation algorithms into the interface directly through stickers left in the movie thumbnails, promoting items to be engaged with over others, among others. Rather than exploring the cinema database depthwise through genre links or others, or even the breadth with a provider browsing step, by implanting the recommendation service into the items with higher expected reward, dynamically updating them every time the users clicked on a thumbnail and making their assistance visible, a better generalization, especially during the early stages of the user interaction, is possible.

It has famously stated that their only competitor is user time. But to take these services to the next level, stricter limitations should be posed to recommended content. Following the way social media implemented engagement faster than VOD for example, these companies could take advantage of user behavioral data to bring a deep learning approach to the level of users' experience, creating an interactive hybrid platform. Users should be able to interact with the interactive recommendation service through a set of commands, tutorials, or even allowing them to create browsing paths themselves, in charge of transferring the user between episodic content, movies, and even related extras, while dynamically learning where to take them based on user viewing history across the different domains.

8.6.1. Case Studies of Successful Integration

Recommender systems offer efficient sorting and filtering tools to organize the results of an otherwise overwhelming search space. Retailers began using algorithms to guide customers to products associated with higher sales conversion rates in an effort to reduce choice overload, without the personal investment of a sales person. Proactive strategies can further guide customers toward better-fit products, suggesting something that customer did not originally request but would likely find useful. Recommender systems also open the door to serendipitous discovery, ushering in new products that customers might never have otherwise found. With the right degree of accuracy and diversity, recommender systems can add huge value to the overall shopping experience. As recommender systems have matured with dramatic leaps in sales revenue and usability through data-driven machine learning methods, particularly deep learning, there has been a parallel growth in engagement through interactive platforms across all domains, especially travel, entertainment, and dining. Only in the last few years has research started to focus on the integration of recommender systems with interactive recommendation platforms, in the domain of travel in particular. A few travel case studies highlight and draw connections to the key research directions in this space. Travel recommender systems have a few special twists that make them interesting and also introduce additional challenges in creating effective integrated recommendation platforms.

8.6.2. Challenges and Solutions

What challenges do researchers and practitioners face when they incorporate AI recommendations in interactive systems? They find that explaining exactly how recommendation and action datasets are constructed is important for trust building. They see that engagement and feedback are often very mundane, employing button clicks, where it seems that creative ways to elicit and curate complex feedback should be attempted. Users often struggle with understanding the purpose of a recommendation, preferring that additional context also be provided. Users have a varied threshold for recommendation intrusion, wanting a balance between targeted and general recommendations, between retelling a pattern they may already understand, and surfacing an emergent aspect of digital life. Computationally, others have observed several technical challenges with online feedback from interactive systems. User noise creates poor signals for learning user models. User feedback may not correspond to the implicit reward signal that learning algorithms seek to optimize. Automated mechanisms must be built for robust detection of trust signals that give hope of addressing these challenges. Trustworthy methods must help avoid those situations where the difficulty of labeling user experience as helpful or not helpful about a recommendation contrasts with the importance of correcting the model of how to generalize user feedback across context. Finally, often these systems will be tasked with multi-objective learning, such as either classifying an action signal as something that requires a recommendation, or not, or predicting the click-through rate or next-activity action that might follow in just a way that captures the complication of temporal discounting long after an interaction has occurred.

8.7. Measuring Customer Engagement

In order to quantify the value of the work carried out on customer engagement and assess the effects generated by the investments made, it is necessary to define a series of Performance Indicators able to measure the impact of the customer engagement strategy. Defining the Key Performance Indicators is a necessary step to create an effective customer engagement strategy and it is essential to measure. Furthermore, measuring allows you to understand your business better, allows for appropriate control actions and then to manage the levers well. KPIs should be kept to a limited number to avoid excessive complexity in the evaluation, but at the same time, they must give answers to different information needs. The evaluation of the defined KPIs must be periodic and carried out in a timely manner.

A thorough review of the literature on the subject allows us to focus on some important indicators of business performance and others that can be more associated with customer engagement. Furthermore, the mass of information generated today thanks to the digital has given birth to a series of more complex analysis and control systems. Among the traditional indicators that are more statistically correlated with business performance, there are studies that identify dimensions such as Satisfaction and Trust, which in turn recurs on the drivers of customer engagement such as Interaction and Use. From a quantitative point of view, this path expresses a link with traditionally used indicators such as Sales Volume and Customer Loyalty. In the era of Big Data, the preparation of suitable Interaction systems allows for more sophisticated analyzes. You can explore the correlation between messages in your social media feed, likes, and marketing spend with Customer Engagement; Predict engagement using time-series analysis and predict future interactions; Group potential clients into clusters based on their activity on your site.

8.7.1. Key Performance Indicators (KPIs)

Key performance indicators (KPIs) are critical business measurements; they act as valuable sources of information, enabling organizations to make informed decisions about product development and customer engagement practices. KPIs measure customer engagement and interaction, capturing shifts in customer sentiment and identifying what drives customer satisfaction. KPIs are critical for assessing whether or not an organization is meeting business objectives. Businesses can experience ups and downs and identify risks using KPIs.

Identifying, assessing, and analyzing measurable goals is the key to identifying and using effective KPIs. However, this task is a major aspect facing business owners and marketers alike. The primary issue is that not all performance objectives can be translated into KPIs; hence, choosing an unusual, differentiated, achievable, relevant, and time-bound indicator is critical. It is essential to remain open-minded throughout the KPI selection process and avoid “defaulting” to the KPIs that an organization might typically use for benchmarking. The commercial level of customer engagement differs per industry, company, and department. Determining prior commercial objectives allows businesses to identify their own level of customer engagement. The existing fast pace of customer interaction and sentiment analysis further complicates the need for KPI exploration and selection. Furthermore, customer engagement strategies may define an organization's overall performance level and the potential performance levels of each channel interaction.

8.7.2. Tools for Measurement

Google Analytics is a popular tool for measuring web page success. It began as a tool to measure the number of page views each page received but has morphed into a more advanced and powerful tool. However, it is discontinuing Universal Analytics in 2023 and switching over to GA4, its new version. Among other enhancements, GA4 offers better tracking of online and offline interactions. Although GA4 provides more tools to measure customer activity, you still need to interpret its tools’ results. Conversions in GA are a measure of success on your web pages but not necessarily customer engagement. GA4 counts interaction events as conversions and features some automatic conversions along with any you have specifically defined as conversions. Events allow you to measure almost any action visitors take while on a page, be it video play, outbound link click, file download, etc. Among the assignment of event values, use destination page, no. of pages per session, time on site, and bounce rate. These latter metrics serving as KPI traffic signals of user interest and interaction can also provide pointers to engagement. Explore these on a page and/or site visitation basis for indications of a page visitor engagement level. No. of pages per session and time on site metrics can indicate customer engagement, and a high bounce rate can indicate disengagement. A visitor who only visits your landing page during their entire session will bounce from your site.

GA Analytics is only one example of web page tracking and measuring tools available today. Other popular tools include Adobe, Matomo, Woopra, HubSpot, and Clicky, each with its own features that can be more aligned for your website needs. If you are entering the online shopping business for the first time, research these tools to find which best fits your needs. You may also want to utilize more than one service in order to reach a broader perspective on engagement with your website or app. Aside from using a company such as GA Analytics, which specializes in web tracking and performance analysis, you could outsource your analysis to an inbound marketing agency and let them do the heavy lifting for you. For ongoing ecommerce website building and maintenance, utilizing a marketing agency may be a prudent choice.

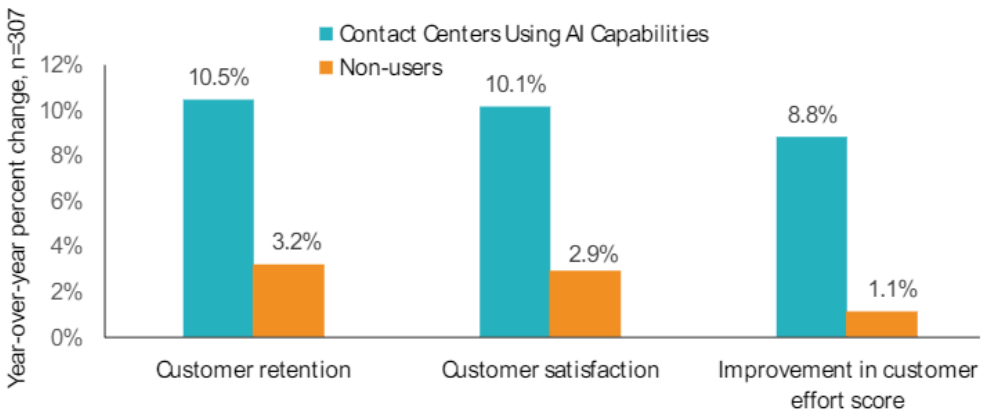

Fig 8 . 3 : AI in Customer Experience (CX)

8.8. Conclusion

This chapter offered insights and guidance to both researchers and practitioners focused on the intersection of customer engagement and AI technology. As we have established, customer engagement is a process, not an event. Successful management of customer engagement must consider phase-appropriate strategies and tactics. These must be integrated across all relevant customer behaviors, positive and negative, at all relevant touchpoints where customers and brands interact across the enterprise journey. We hope this chapter provides an accessible, actionable synthesis of existing wisdom and available resources while complementing it with our take on where customer engagement is and where it's going next. Looking ahead, we see application and integration challenges for many organizations as they seek to harness behavioral science insights to close the loop on learn, influence, and activate. The stakes are high; platforms, company infrastructures, and budgets are in place. Enhancements to existing touchpoints come next. In addition, there are clear opportunities to build and fund entirely new forms of engagement, which are frequently experimental today and thus may orbit an enterprise's internal walls. Product sampling initiatives at scale and unbranded customer experiences are two examples that are being created or funded by enterprising organizations seeking a high ROI on new customer growth. Some of this expansion is being fostered through advanced, agency-like consultancy services that are tightly integrated into the offering or use equivalent fee-for-service models in B2B markets where organizational word-of-mouth is crucial and needs nurturing and support.

8.8.1. Final Thoughts on the Future of Customer Engagement and AI Integration

Through the interaction of our product algorithm on an interactive, no-code website editing platform, we hope to provide businesses with a clearer understanding of their customers through no active engagement methods. Guide customers to arrive at the solution that both solves their problem the fastest, but also engages them. Through this no-code platform, your marketing efforts will be aimed in the direction of the customers' desires. Customers' emotional responses are crucial to determining how much they value your brand. Products or branding that create an emotional experience for consumers are likely to elicit far greater levels of customer engagement. Emotionally engaged consumers buy 2.5 times more and are 3 times more likely to recommend a brand than highly satisfied consumers. Brands that create lasting relationships with their consumers by understanding their deeper, emotional motivations for raving about the brands they love. Through a constant interaction, that is unseen in offline interactions, while not wasting any resources, companies will be able to take full advantage of the various elements of their customers' profiles.

While personalization is not new, deep-level, behavior-driven personalization has complicated many aspects due to the growing interest in protecting the customers' data privacy. As companies look to be more transparent and leave it to consumers to approve what data they exchange for what benefit, the need for new unique ways to use this behavior-share ledger present new opportunities. We have always imagined technology as a tool to save us more time; they let us focus on the truly human interactions. Creating powerful connections with people will stimulate the growth we are all looking for, both on a customer level while speeding up a company's flywheel.

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