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Artificial Intelligence driven Customer Behavior Analytics for Healthcare: A Systematic Review of Patient Experience, Engagement, and Decision-Making Patterns

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Abstract

The study discussed systematic literature review regarding the usage of Artificial Intelligence (AI) technologies as tools for analyzing, understanding and predicting consumer behavior in healthcare ecosystems, including patterns of patient engagement, service utilization and decision-making.

Design/methodology/approach - A systematic literature review was performed across the major academic databases including PubMed, Scopus, Web of Science and IEEE Xplore, capturing articles published from 1980 to 2024. The literature review provided a synthesis of 87 peer-reviewed articles, which focus on the application of AI for customer behavior analytics in the healthcare context, categorized into five thematic groups: predictive analytics, personalization engines, sentiment analysis, mapping patient journeys, and decision support systems.

Findings - AI technologies, in particular machine learning and natural language processing, are making strides in understanding complex patient behaviors, with predictive accuracy rates exceeding 85% in appointment adherence and compliance with treatment plans. Deep learning models are emerging as particularly useful in identifying patients who are at-risk and personalizing healthcare interventions, which have also resulted in increased patient satisfaction scores and lower healthcare costs.

Research limitations/implications – Although technology has advanced significantly, obstacles remain related to data privacy, bias in algorithms, the transparency of AI models, and integration with current healthcare information systems. This review identifies a research gap in longitudinal studies and promotes further research into ethical frameworks for AI implementation in healthcare contexts.

Practical implications – Healthcare organizations can use patient data and AI-informed behavioral insights to improve patient experiences, better allocate resources, decrease no-show rates, and develop health promotion initiatives targeting specific populations. Administrators and policymakers can utilize the implications presented in this study as actionable frameworks for improvement.

Originality/value – This is the first review to comprehensively synthesize AI technology with healthcare customer behavior, to provide taxonomy of AI technologies, and to present implications for future research as well as substantial contributions to the practice of healthcare delivery.

Paper type – Literature review

1. Introduction

Digital innovation and Artificial Intelligence (AI) are changing the healthcare industry, changing how healthcare providers understand and respond to patient behavior [1]. Changes in the healthcare industry mean that patients are increasingly referred to in agency terms as "empowered consumers" or "customers," actively selecting and evaluating choices from the healthcare menu, comparing service quality, and making choices about care paths [2]. It is more important than ever to understand customer behavior, especially for organizations that seek to provide patient-centered care, improve health outcomes, or sustain competitive advantage in an increasingly commercialized healthcare landscape [3]. These trends underscore the potential of artificial intelligence technologies to penetrate the challenges of understanding and predicting patient behavior by analyzing raw quantities of structured and unstructured healthcare data. For example, machine learning algorithms can detect nuanced patterns in patient interactions, predict service use, and even anticipate individual healthcare needs prior to reaching a critical threshold [4]. Natural language processing can help healthcare organizations extract useful insights from all facets of patient comments like narrative comments in clinical data, patient satisfaction surveys, or comments gleaned from social media presence; and understand holistic representations of patient sentiment and preference [5]. Computer vision and deep learning methods have made waves in telemedicine and different types of appointment modalities that assist with understanding patient engagement patterns during virtual visits—as well as understanding patient behavior cues pointing to satisfaction or perhaps distress while remotely observing patients getting care [6].

The use of AI to analyze healthcare customer behavior provides opportunities and challenges. Although AI systems can analyze data at a scale and speed impossible for human analysts, fears over data privacy, clarity of AI algorithms, and potential biases in AI decision-making continue to be large impediments to widespread adoption [7]. Healthcare organizations face complex regulatory and ethical challenges, as well as technical limitations, as they attempt to realize the promise of AI [8]. Additionally, as healthcare is a human experience, AI systems should enhance, rather than replace, the empathy and clinical judgment of care delivery [9].

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While there is significant interest in the application of AI in healthcare, a broad review of how AI technologies are being used to analyze customer behavior has not been conducted. Existing reviews focused on very specific use cases (such as clinical decision support or diagnostic imaging) that did not consider the broader context of patient behavioral analytics [10]. This is concerning, especially given the shift in the healthcare landscape toward value-based care that prioritizes patient experience and engagement along with clinical outcomes [11].

1.1 Research Objectives

This systematic review addresses this knowledge gap by pursuing the following objectives:

- To identify and categorize AI technologies and methods utilized to analyze healthcare consumer behavior across various healthcare settings and patient populations.
- To assess the effectiveness of AI-driven interventions on predicting and influencing patient behaviors, including appointment adherence, treatment adherence, usage patterns, and decision-making processes.
- To assess the effects of AI-powered behavioral analytics on key healthcare performance metrics including patient satisfaction, health outcomes, efficiency, and cost-effectiveness.
- To identify barriers, challenges, and ethical issues regarding the use of AI systems in consumer behavior analytics in healthcare settings.
- To provide a thorough framework for future research and practical approaches for healthcare organizations to strategically utilize AI technologies to improve patient engagement and patient experience.

1.2 Structure of the Review

This paper is organized into seven sections. After this introduction, Section 2 describes the methodology utilized for literature selection and analysis. Section 3 develops a theoretical discussion of customer behavior theories and their adaptations in the healthcare context, while describing developments in AI technologies in healthcare analytics. Section 4 presents the primary findings categorized by AI application domains (predicative analytics, personalization, sentiment analysis, patient journey mapping, and decision support). Section 5 concludes with a discussion of implications, challenges, and future directions and Section 6 presents limitations associated with the research. Section 7 concludes with recommendations for researchers and practitioners.

2. Methodology

2.1 Search Strategy

A structured literature search was carried out according to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) [12]. The search was undertaken within major research databases such as PubMed/MEDLINE, Scopus, Web of Science, and IEEEXplore. The search included any publication from 1980 to 2024 which report on recent developments related to AI applications for healthcare customer behavior analysis. The following string was used as a search criteria to extract relevant articles from the research databases:

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("artificial intelligence" OR "machine learning" OR "deep learning" OR "neural network*" OR "natural language processing" OR "predictive analytic*" OR "data mining") AND ("patient behavior" OR "customer behavior" OR "patient engagement" OR "patient experience" OR "healthcare consumer*" OR "patient satisfaction" OR "treatment adherence" OR "appointment adherence") AND ("healthcare" OR "health care" OR "medical" OR "clinical" OR "hospital*" OR "telemedicine" OR "digital health")

2.2 Inclusion and Exclusion Criteria

Studies were deemed suitable for inclusion if they satisfied the following standards: (1) researched AI or machine learning application to interpret customer or patient behavior within a healthcare context and (2) published within the context of scholarly publications such as peer-reviewed journals and peer-reviewed conference proceedings, (3) published in English, (4) grounds for empirical evidence or substantive theoretical contribution, (5) methodological evidence of the AI methodology utilized and behavioral outcomes measured.

Studies were excluded based on the following standards: (1) studies that focused on clinical diagnosis or treatment without any components that pertain to behavioral analysis, (2) studies not published in self-contained peer-reviewed publications including opinion pieces, editorials, and commentaries that do not provide any empirical evidence, (3) studies that do not directly measure the behaviors of patients or customers, (4) studies that were duplicate publications, (5) studies that provide insufficient methodological description or detail to evaluate article quality.

2.3 Study Selection Process

The first search of the database revealed 1,847 potentially relevant articles. After removing 423 duplicates, 1,424 titles and abstracts were independently screened by two reviewers. This process ultimately excluded 1,189 articles that did not meet the inclusion criteria. Of the full-text articles (n = 235) screened for eligibility, 87 studies met all the inclusion criteria and were included in this systematic review. Cohen's kappa coefficient = 0.89 indicated good inter-rater reliability. Discrepancies between reviewers were resolved through discussion and a third reviewer if required. Figure 1 provided the PRISMA flow diagram.

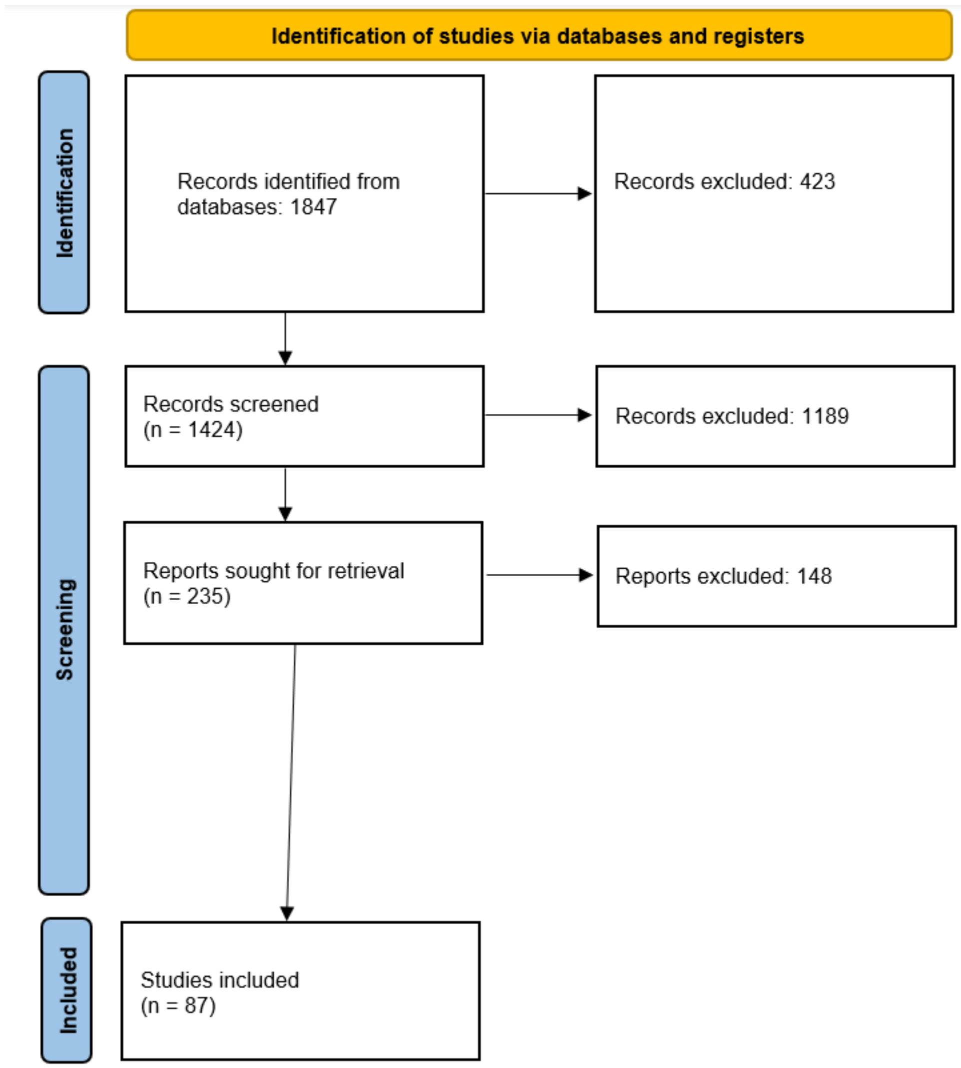

Figure 1. PRISMA flow diagram (Self Sourced).

2.4 Data Extraction and Synthesis

A standardized data extraction form was created to extract pertinent information from each included study: author information, year of publication, study context and population, AI technology/methodology used, analysis of behavioral variables, key findings, performance indicators, and limitations noted by the authors. Two reviewers independently extracted data and synthesized them using thematic analysis to identify patterns, convergences, and divergences across studies. The studies were classified into five main application areas based on their focus, predictive analytics, personalization engines, sentiment analysis, patient journey mapping, and decision support systems.

2.5 Quality Assessment

The quality of studies included in the review was assessed using modified criteria from the Critical Appraisal Skills Programme (CASP), which is based on the study design, and the TRIPOD (Transparent Reporting of a multivariable prediction model for Individual Prognosis Or Diagnosis) statement, which was used for predictive modeling studies [13]. Assessment criteria included clarity of the research objectives, appropriateness of the AI methodology, adequacy of the sample size, transparency of reporting, ethical issues, and validity of the conclusions. Studies assessed were classified as high, moderate, and low quality with 62 studies classified as high quality, 21 studies as moderate quality, and four studies as low quality.

3. Theoretical Background

3.1 Customer Behavior Theory in Healthcare Context

To comprehend patient behavior in healthcare, we must adjust standard theories of consumer behavior to accommodate the special characteristics of healthcare services. The Health Belief Model established by a study [14] with improvements made by another study [15] stated that health-related behaviors are driven by the individual's perceived susceptibility of being ill, perceived seriousness of the health condition, perceived benefits of accessing preventive health services or taking action, and perceived barriers to accessing the service or taking the health-protective action [16]. This model serves as a framework for understanding why patients make the health-related decisions that they do and how AI systems can identify patients at risk for non-adherence or lack of engagement.

The Theory of Planned Behavior [17] takes this one step further by adding attitudes, subjective norms, and perceived behavioral control as additional predictors of behavioral intentions and behavior. In healthcare, the model explains patients' decisions to engage in treatment, make lifestyle changes, and access health care services [18]. AI systems can incorporate these theoretical concepts by looking at peoples' digital footprints to determine attitudes, social norms, and perceived self-efficacy to predict individual behavioral patterns more accurately.

The Patient Journey framework views healthcare experiences as a series of touchpoints throughout the continuum of care, from initial awareness and consideration to treatment and post-care follow-up of care [19]. Each touchpoint affords an opportunity to observe and intervene in behavior. AI technologies have the potential to map these complex journeys by integrating data from EHRs, patient portals, wearables, and CRM system to identify opportunities for targeted interventions at critical moments [20].

Recent healthcare literature has increasingly recognized patients as active consumers who seek information, compare providers, and expect experiences that are personalized in a manner consistent with other service industries [21]. The consumerization of healthcare requires sophisticated analytical approaches that can segment patient populations, predict preferences, and personalize communication and interventions at scale, and AIs ability to do this at scale and in a timely fashion is unmatched [22].

3.2 Evolution of AI in Healthcare Analytics

The use of AI in healthcare has progressed through several distinct stages. The early instances of AI in medicine occurred in the 1970s and 1980s with rule-based expert systems, including MYCIN, which assisted with diagnosis of infectious disease [23]. Although historic, these systems did not have the learning capabilities of today's AI. AI truly began its evolution with the introduction of machine learning

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in healthcare in the 1990s, which used statistical methodologies to identify patterns in clinical data, and did not require prior programming [24].

In the past ten years, AI has expanded exponentially in the healthcare environment thanks to continued improvements in deep learning, computational power, and the expanding availability of digital health data. Convolutional neural networks have demonstrated superhuman accuracy in classifying medical imaging studies, and recurrent neural networks and transformer architecture have revolutionized language processing of clinical texts [25, 26]. These applications have also moved beyond clinical settings to include behavioral analytics, which can provide healthcare organizations with a sophisticated understanding of the past and future behavior of patients.

Big data analytics have emerged as a crucial facilitator of artificial-intelligence based behavioral insights, tapping into multiple sources of data, including electronic health records, claims data, genomics, social determinants of health, wearable device data, and patient-generated health data [27]. Integration of these data creates more holistic profiles of patients, considering clinical state as well as their behaviors, preferences, and contextual factors driving their decision making with respect to healthcare [28].

Cloud computing and distributed systems have made AI access ubiquitous to smaller healthcare organizations that do not require substantial investments in infrastructure to develop sophisticated analytics [29]. Deployment through application programming interfaces and pre-trained models has also decreased entry barriers from larger technology companies, allowing for a rapid adoption of AI throughout the healthcare ecosystem [30].

3.3 AI Technologies Relevant to Customer Behavior Analysis

Various AI technologies have been particularly relevant in the analysis of behavior of healthcare consumers. Supervised machine learning algorithms (logistic regression, decision trees, random forests, gradient boosting machines, and support vector machines) are proficient at predicting specific behavioral outcomes in situations where labeled training data are available [31]. These approaches have been utilized to predict, for example, no-shows for appointments, risk of readmissions, and treatment non-adherence.

Unsupervised learning methods (e.g., clustering algorithms [k-means, hierarchical clustering, DBSCAN, etc.] and dimensionality reduction methods, e.g., principal component analysis [PCA], t-SNE) identify natural groupings in patient populations without the use of labels, allowing for behavioral segmentation and persona generation [32]. These types of approaches enable healthcare organizations to target specific interventions to specific patient segments by looking at behavioral similarities.

Natural language processing (NLP) consists of various frameworks for analyzing text and speech data including, but not limited to, sentiment analysis, topic modeling, named entity recognition, and semantic analysis [33]. Within behavioral analytics, NLP provides insights from various sources such as patient comments, clinical documentation, social media posts, and call center communication to identify patient perceptions, apprehensions, and levels of satisfaction. This analytical information could not be obtained through ordinary survey methods [34].

Deep learning frameworks, particularly recurrent neural networks and long short-term memory (LSTM) networks can capture temporality in sequential behavioral analysis and optimize understanding of patterns in patient engagement concerning care over time [35]. Additionally, transformer models with attention mechanisms have enabled advanced modeling of complex behavioral sequences and determining main determinants of behaviors [36].

Reinforcement learning has application in healthcare behavioral analytics to develop adaptive intervention frameworks. Subsequently, the proposed frameworks learn optimal timing and content of patient outreach based on ongoing feedback, favoring general applicability across a wide range of populations [37]. Reinforcement learning model complete models of precision behavioral health to understand behavioral differences in patients with ongoing treatment and intervention processes.

4. Findings: AI Applications in Healthcare Customer Behavior

4.1 Predictive Analytics for Behavioral Outcomes

Of all the applications of AI in healthcare customer behavior, predictive analytics has been the most studied, with evidence presented that predicts various behavioral outcomes with a high level of accuracy. Predicting adherence to appointments is the most common application studied, with machine learning models demonstrating that many models can achieve an 80-90% accuracy rate in identifying patients that are likely to no-show [38, 39]. Models typically included factors such as demographics, past appointment behavior, socioeconomic status, transportation, and seasonal changes. Gradient boosting algorithms (e.g. XGBoost and LightGBM) demonstrate greater capability than traditional logistic regression algorithms, some models report AUC values > 0.85 [40].

The predictions around treatment adherence have also been equally encouraging as increasingly AI models demonstrated the ability to identify patients who are likely to stop taking their medications or are unlikely to follow along with their treatment recommendations. A relevant study [41] designed an ensemble model using both random forests and neural networks to predict medication adherence in chronic disease populations, and this model reached an accuracy of 87%. The models successfully identified important predictors of adherence, such as prescription refill data, previous adherence behavior, and most conspicuously, complicated medication regiments along with social determinants of health, especially neighborhood socioeconomic status. The addition of using wearables and analyzed patterns of smartphone usage into the predictive model has proved to be advantageous, as studying subject's passively, such as activity/physical activity and sleep patterns have been predicted accurately, by an improvement of around 5%-10%, to model's that are based on clinical information only [42].

The assessment of patient readmission risk has greatly benefited from AI methods that include behavioral factors in addition to clinical variables. A study [43] showed that deep learning models trained on electronic health record data, including patterns of healthcare service use (visits and utilization) and patient engagement with discharge instructions (use of online portals, scheduling future visits), yielded models that were more useful than conventional risk stratification tools. Their models had an area under the curve (AUC) of 0.86 for predicting 30-day readmission, demonstrating the significant role of behavioral engagement variables to the model's performance.

Predicting healthcare service utilization allows organizations the ability to anticipate service demand patterns and appropriateness to allocate resources (staffing, equipment, etc.) to appropriately meet that demand. Time series analysis with LSTM networks has been used with success in predicting visits to the emergency department with an accuracy of prediction within 5% of actual volumes by including seasonality, local events, disease surveillance data, and the historical behavior of patients [44]. Another study [45] developed a multi-task learning framework for predicting service utilization behaviors which concurrently predicted other utilization behaviors in one model - e.g. emergency visits, inpatient admissions, outpatient visits shown to better predict individual task service utilization by modeling other service behavior, rather than predicting each service utilization behavior in individual models.

4.2 Personalization and Recommendation Systems

AI-driven personalization engines allow for healthcare organizations to customize communications, recommendations, and interventions based on the individual preferences and behavioral patterns of the patient. Collaborative filtering techniques, which are often adopted from e-commerce recommendation systems, were adapted to healthcare contexts suggesting health content, treatment options, and wellness programs [46]. These systems use data on similarities and patterns in similar patient cohorts to make recommendations, and studies have suggested that personalized health content improves engagement rates as much as 40-60% versus generic communications [47].

Content-based filtering approaches analyze individual patient factors, medical history, and expressed preferences in order to recommend meaningful healthcare resources. A study [48] developed a hybrid recommendation system using collaborative and content-based filtering to personalize health education materials. They found personalized recommendations contributed to a 47% increase in health material consumption and a 23% increase in knowledge retention scores compared to standard educational approaches. The system also included reinforcement learning to optimize recommendations in real-time based on patient interactions over time, which serve to personalize based on changing preferences and needs.

Conversational AI and chatbots are increasingly dominant forms of personalization technology that offers customized health information and behavioral support on a scale. Natural language processing enables conversational systems to comprehend patient inquiries using natural language, provide responses that are contextually relevant, and retain continuity of conversation by maintaining conversation history so that multi-turn interactions are coherent [49]. In evaluations, chatbots that were well-designed and had appropriate functionality produced patient satisfaction scores comparable to human interactions for routine inquiries, and they also added 24/7 availability and immediate response times, in which patients frequently found value [50]. In advanced usages of this kind of system, sentiment analysis is utilized to reveal patient frustration or distress, which can initiate escalation or flagging to human providers when appropriate [51].

Precision behavioral health is emerging as a new paradigm that applies personalization at the granule level, allowing interventions to be adapted in real time based on behavioral data being continuously collected. Mobile health applications with an AI component can adapt the timing, content, and modality of an intervention based on patterns of response a person demonstrated, factors present in the moment, and momentary states determined through the phone's sensors [52]. For example, another study [53] demonstrated that AI-optimized adaptive interventions to promote physical activity produced

32% greater improvement in step counts than standard procedures and that the AI systems learned optimal times of day, messaging framing, and intensity of each intervention for each individual.

4.3 Sentiment Analysis and Patient Experience Monitoring

The advancement of sentiment analysis through natural language processing has changed the ways in which healthcare organizations gauge and respond to patient experiences. Many traditional patient satisfaction surveys have reported low response rates, delayed responses after care have been provided, and limited response to the complexity of patient insights. Through AI-driven sentiment analysis, organizations can now leverage nearly limitless unstructured data, including patient portal messages, call center transcripts, internet reviews, social media updates and open-ended survey responses. The ability of AI sentiment analysis to process volumes of unstructured patient data now provides organizations with real-time information about patient perceptions and concerns [54].

Deep learning approaches to sentiment analysis, and especially transformer-based models (e.g. BERT: Bidirectional Encoder Representations from Transformers), have achieved human-level accuracy for identifying positive, negative, and neutral sentiment during healthcare processes [55]. Notably, these models can identify more nuanced sentiment expressed in patient language (e.g. sarcasm, mixed sentiments or implicit criticisms) that are often missed in rule-based sentiment systems. A study [56] tested sentiment analysis with social media posts made about healthcare providers and found substantial correlations with sentiment scores and traditional satisfaction scores, and with sentiment analysis, they were able to identify new issues several weeks prior to the issues being surfaced in a traditional survey.

Aspect-based sentiment analysis goes beyond global sentiment to identify aspects of health care experiences that are linked to satisfaction or dissatisfaction. AI models can automatically group the feedback into domains such as wait times, staff interactions, physical tidy-ness, quality of communication, and billing. The algorithm can then assess sentiment related to each aspect [57]. This type of analysis gives qualitative data to support actions related to improvements in quality. For example, one study [58] performed aspect-based sentiment analysis of comments made by patients and discovered that while comments on the overall experience were high, parking and scheduling did drive negative experiences for many patients. As a result of their analysis, they implemented interventions around parking and scheduling to improve quality. Satisfaction ratings improved by over 12% as a result.

Emotion detection models also identify negative sentiment but go beyond that to identify specific emotional states exhibited through patient communication. Patients have exhibited anxiety, frustration, gratitude, confusion, and distress, to name a few [59]. These capabilities of emotion detection allow for the provider to proactively reach out to patients who exhibited distress and anxiety through unsolicited communication, which could alleviate pending complaints or disengagement. Advanced implementers have used emotion detection in conjunction with clinical decision support so that if the patient indicated psychological distress requiring assessment through the provider's response, the provider would be alerted [60].

Real-time feedback analysis programs systematically collect data from patient communications and provide alerts to notify staff of urgent matters and feedback for operational dashboards. A study [61] reviewed an AI-enabled patient experience monitoring system that reviewed all patient portal

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messages within minutes of submission, prioritizing messages of patient dissatisfaction to an experience coordinator for follow-up. The patient experiences monitoring system reduced formal complaints by 35 percent while proactively resolving the patient's issue prior to the complaint and subsequently achieved a 28 percent increase in positive online reviews.

4.4 Patient Journey Mapping and Behavioral Touch point Analysis

AI technologies have the potential to comprehensively map the patient's journey across the healthcare continuum by characterizing patterns of behavior at each touch point and uncovering opportunities for intervention. Specifically, process mining algorithms that are applied to electronic health records' event logs can reconstruct the actual pathways of patients through healthcare systems, revealing where there is variance from what is expected and uncovering points of bottleneck and dropout along the patient journey [62]. For example, previous studies have highlighted the magnitude of the variance between the intended patient experience and actual patient experience. A study showed that 30-50% of patients diverged from the typical care pathway in a manner that was likely deleterious to their health/progression [63].

Sequential pattern mining identifies the most common behavior sequences that exist and transitions between healthcare touch points. A study [64] examined the data of diabetes patients using sequential pattern mining, highlighting that patients that utilized online health resources within 30 days post-diagnosis had 45% higher adherence to medications over the following 12 months than patients that did not, identifying a key opportunity for intervention in the patient journey directly post-diagnosis. The knowledge provided by the application of process mining and sequential pattern mining would support healthcare organizations in prioritizing outreach at moments that will have the greatest impact on the patient's journey.

Markov models and hidden Markov models provide a probabilistic approach to modeling the progression of patient journeys by estimating transition probabilities from different engagement states (e.g., active engagement, sporadic engagement, disengaged) to predict future trajectories [65]. A study [66] developed a hidden Markov model of patient engagement in chronic disease management programs to identify unique engagement sequences and predict which patients in the model cohort would disengage in the next 3 months with 82% accuracy, allowing for retention interventions prior to predicted disengagement behavior.

Network analysis approaches examine patient journeys as complex networks of related touchpoints; this approach allows identification of prominent nodes and pathways that most strongly predict desired outcomes. For example, a study [67] developed patient journey networks for heart failure patients and found attendance at nutrition counseling related to better outcomes. This was surprising to researchers, as many of the patients studied had chronic disease severity with significant nutrition issues, which resulted in participation in these nutrition counseling sessions. After this patient journey network was developed, researchers targeted interventions to increase the number of heart failure patients utilizing nutrition counseling, and the outcomes of this intervention then improved when measured.

Survival analysis and time-to-event modeling enable quantification of timing for behavioral transitions as well as identifying factors that accelerate or delay certain behaviors. Cox proportional hazards models and subsequent deep learning algorithms for survival analysis have been used to predict

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time until treatment discontinuation, time to reengagement after a care lapse, and optimal time to deliver the intervention [68]. Temporal insights allow dynamic intervention strategies that adapt to individual patient trajectories compared to a one-size-fits-all approach.

4.5 Decision Support Systems and Behavioral Nudging

AI decision support systems are increasingly using behavioral science principles to shape patient healthcare decisions toward optimal outcomes. These systems integrate predictive analytics with behavioral economics to use strategies recommended in behavioral science, such as default options, social norming, framing effects, and loss aversion, to make patient decisions for them [69]. Unlike decision support in traditional health care systems, which simply provide information, behaviorally informed decision support systems are designed to structure patients' decisions in a way that can minimize cognitive biases and promote advantageous decisions to patients.

Personalized decision support utilizes AI decision making to modify how information is presented to patients based on their characteristics, values, and decision style. For example, a study [70] created an AI decision support system that presented information on treatment options. The AI framed the information and adapted detail presentation according to the patient's health literacy, numeracy, and preference for participation in decision making. They found personalized decision support improved patient knowledge and satisfaction with a decision, and reduced decisional conflict scores by 30% relative to standard decision support by providing some patients with a greater level of detail about the treatment options. The AI used reinforcement learning to change delivery of decision support based on patients' responses to care, in terms of presentation of the decision support to patients while it continued to improve its performance.

Intervention systems based on nudges utilize insights from behavioral sciences to support healthy behaviors through incremental changes to the environment. A study [71] developed a gamified program with AI-based reward structure for the promotion of physical activity, using a multi-armed bandit algorithm to design a reward structure that minimizes the risk of excessive reward variance between and within individuals. Its adaptive gamified intervention produced 50% higher odds of being more engaged sustained over a six-month period compared to a static design, with overwhelmingly positive influence from previous sedentary status of users on engagement rates.

Predictive behavioral interventions adopt a dual approach, combining risk prediction with the timed nudge to prompt engagement in healthier behavior, and providing warning for higher risk of adverse behavioral outcomes. A study [72] outlines a "just-in-time adaptive intervention" system intended for the management of depression that utilizes machine learning to analyze a variety of factors, using smartphone sensor data, to predict when an individual is at risk for increased depression symptomology, during set times, in order to push behavioral interventions for brief engagement times. Randomized clinical trials showed a 37% lower symptom severity score in the predictive behavioral medication group, with effect attributable to increased behavioral activation.

Social Influence Systems use AI to find influential peers in patient networks and promote peer support. A study [73] found that "behavior change champions" identified by AI who modified health behaviors were able to exert influence on their peers more effectively than peer mentors who were randomly assigned to help. In their research, recipients of the intervention initiated by peer mentors

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assigned under random circumstances explained that the behavior change champions had 2.3 times the likelihood of initiating changes in health behavior. These models take advantage of social network effects to create additional intervention impacts apart from the interactions between the AI and the patient.

Similarly, choice architecture optimization uses AI to organize healthcare choices that support optimal decision-making. This includes optimizing default appointments to a time that will be convenient based on predicted availability for times of day, ordering treatment options to be defaulted to leverage anchor effects, and carefully using reference points when presenting risk information [69]. Evaluation studies have shown that a well-structured and well-considered choice architecture can help improve positive choices (beneficial to patients and community-wide collective health) by 15% to 40% without compromising choice or autonomy [74].

5. Discussion

5.1 Practical Implications for Healthcare Organizations

The results of this review show that AI technologies provide significant opportunities for healthcare organizations to improve understanding customer behavior and improving patient experience. Organizations pursuing AI-driven behavioral analytics should take a strategic phased approach initiated around clearly defined use cases responding to distinct organizational issues or opportunities. Initial applications that engage high impact usually revolve around a predictive model that operationally improve efficiency and includes but is not limited to predicting patient no-shows or utilization of resources, which provide measurable returns against investment and develop organizational confidence in the potential of AI [75].

To implement the AI system successfully, AI solutions will need to be integrated in with existing healthcare information technology architecture such as electronic health records, patient relationship management systems, and communication channels. Interoperability is a major barrier, considering many healthcare organizations operate siloes and systems that create challenges to integrating data effectively for behavioral analytics [76]. Organizations should consider prioritizing their investment to build data architecture and integration capabilities that support adopting AI capabilities as an enabler, not a separate technology implementation.

The development of a competent workforce contributes significantly to success, as organizations need to develop both the technical skills to build and maintain AI systems and analytical skills that focus on deciphering the results of AI systems and translating insights into action. Healthcare organizations should look at their training programs as an opportunity to begin to build AI literacy across both clinical and administrative staff to facilitate better collaboration between the technical team and domain experts [77] or subject matter experts. Cross-functional teams of data scientists, clinicians, behavioral scientists, and operations are typically more successful at implementation than either a team comprised only of technical scientists or a team comprised solely of clinicians.

Change management processes must account for any resistance to change from front line staff concerned about the potential takeover of judgement or if AI is monitoring employee behavior. Communicating openly and transparently why organizations are implementing AI systems, what these systems can and cannot do, and involving front line staff in their design and evaluation will increase

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potential acceptance and appropriate use [78]. Communicating AI as a preservation of human effort rather than a replacement of human judgment and emphasizing AI will help preserve staff time by removing high volumes of repetitive tasks so they can engage with patients at meaningful times will generate more positive messaging than an efficiency tool.

The processes of ongoing evaluation and iterative improvement should be built into AI deployments. These processes necessitate ongoing evaluation of system performance, unintended outcomes, and possibilities for improvement. Healthcare settings are dynamic, which means that patient populations, treatment policies, and other outside factors can influence declining model performance over the years [79]. Organizations should have strategies in place for model retraining, performance audits, and stakeholder feedback cycles to continually derive value from AI investments.

5.2 Ethical Considerations and Challenges

The use of AI to assess and influence healthcare consumer behavior involves important ethical issues that health care organizations must consider and address in advance. Privacy is a major issue. Behavioral analytics that are comprehensive often need data to come together from diverse sources, profiling behavior of individual patients beyond their clinical information to consider their lifestyle, social circles and preferences [80]. While broadening data set means a better analytical assessment of behavior, it probably increases privacy vulnerabilities if information is violated or used inappropriately. Organizations need to implement formal data governance frameworks with clearly identified policies about what information is collected, accessed, used, shared and how long it will be kept (and after that, what happens to that data). Health care organizations must balance the privacy and use of data to meet regulatory requirements, such as HIPAA (Health Insurance Portability and Accountability Act) in the United States and the GDPR (General Data Protection Regulation) in Europe.

Algorithmic bias occurs when the AI system continues or amplifies existing healthcare disparities if the training dataset contains retrospective bias [81]. For example, several studies have shown that some AI models appear less accurate for minority groups, those that live in rural areas, or other vulnerable groups, which might worsen health inequities [82]. Healthcare organizations should conduct equity evaluations of what the AI system is capable of, whether it be a predictive model or decision-making data, to evaluate its performance across patient subgroups and fair constraints to avoid biases. This could mean oversampling groups that are underrepresented, using a fairness-aware machine learning algorithms or post-process prediction to determine equitable treatment.

Transparency and explainability in AI decision-making influence patients' trust and clinical usability. For example, "black box" models, that yield crucial predictions regarding a treatment plan but do not explain how models arrive at predictions, creates a problem for accountability regarding predictions that are integrated into clinical or operational decision-making about patients [83]. Some complex models show enhanced predictive ability but create challenges for clinical implementation and acceptance of the prediction by patients due to opacity. Thus, healthcare organizations should balance predicted performance with interpretability and/or make use of SHAP (SHapley Additive exPlanations) or LIME (Local Interpretable Model-agnostic Explanations) to ensure prerequisites are deemed separately for a complex model; other models would be to utilize overtly interpretable models if a minimal predictive truth difference based on standard deviations is not relevant [84].

Informed consent regarding artificial intelligence directed behavioral analytics raises specific issues relevant to secondary use of clinical data for behavioral analytical purposes. The patient typically consents to the acquisition of health information collected for treatment purposes. The patient may not anticipate nor explicitly consent to the AI driven analysis of their behavioral patterns [85]. Organizations need to implement clearer processes for obtaining consent that explicitly informs the patients, affords them the possibility of opting out where feasible, and delineates how behavioral analytics will improve their care and experience as a patient. When we provide transparency, we are building trust and acting in a way that respects our ethical obligations to the patient in regard to informed consent.

Consideration around AI prompted behavioral nudging implies a risk of manipulation and raises ethical concerns. Though nudging patients to make decisions that nudge them towards beneficial health behaviors may be a legitimate act of promotion of public health, we need to think about manipulation, coercion and exploitation of cognitive biases [86]. For example, ethicists consider the difference between an acceptable nudge that supports the patient's autonomy versus a nudge that is problematic in that it manipulates patients for the organizational sake rather than for the sake of the patient. Healthcare organizations should be encouraged to develop ethical process review, if they are going to start promoting behaviorally informed interventions. Ethical reviews ensure that the interventions promote patient goals, advocate for transparency about manipulative attempts by nudging, and maintain an opportunity for the patient to make a meaningful choice.

5.3 Integration with Clinical Workflows

The successful incorporation of AI-enabled behavioral insights in clinical workflows decides whether the domains are equivalent to existing capabilities or instead remain as unused technologies. Clinical decision support systems must present behavioral predictions and recommendations at relevant moments in clinical workflow, which does not also create alert fatigue or workflow disturbance [87]. Evidence shows clinicians ignore/override 49-96% of interruptive alerts; alert fatigue is a known contributor to risks to safety [88]. AI systems should focus on high-value alerts, risk-based stratification that raises insights only that require action, and integration with existing clinical systems instead of an interface requiring all app use.

Information delivery can be role-based to facilitate behavioral insights only being delivered to those team members acting on information. For example, predictions of patient engagement are role-specific to care coordinators, predictions of appointment no-show may trigger reminder systems, and the prediction of treatment non-adherence alerts pharmacists to provide appropriate counseling interventions [89]. Rather than flooding physicians with all behavioral predictions, insights are sent to only the relevant team members, increasing action-ability and response rate.

Automated intervention systems can convert behavioral predictions to actions, without requiring human action for all of the routine cases and escalate complex circumstances to human decision-makers. For example, an AI system might send personalized appointment reminders to patients who are predicted to be at a higher risk of no-show, schedule a follow-up appointment for a patient predicted to disengage, or outreach for a conversation with a patient who has expressed some concern in a message through the patient portal [90]. Automating these behavioral interventions allows the healthcare team to increase capacity, while maintaining the use of human expertise for situations that require clinical judgment, human empathy, and/or complex problem solving.

There are feedback loops established between AI systems and clinicians to foster continuous improvement and mutual learning. Clinicians ought to have a way to provide feedback if an AI system's predictions are inaccurate or recommendations not appropriate with the model refinement cycle [91]. In the other direction, an AI system may provide feedback to a clinician about the effectiveness of an intervention and learning opportunities for them to develop their clinical skills as well. Being able to exchange feedback in both types of directions changes the conversation from a static tool to a learning partner that evolves from use in clinical practice.

5.4 Economic Impact and Return on Investment

The economic consequences of AI analytics of customer behavior can be far-reaching in terms of operational efficiencies, optimizing revenue, avoiding costs, and improving quality. A compelling argument for the financial case is the reduction of "no-shows" for appointments. The no-show rate is estimated to cost the U.S. healthcare system as much as $150 billion dollars per year [92]. In one study, AI-facilitated prediction and intervention systems decreased no-show rates between 15-30%, which meant recovering a larger portion of revenue and optimizing resources [93]. For example, a medium-sized healthcare system with 500,000 appointments each year that has a 15% no-show rate would be able to recover $3-5 million dollars of annual revenue in addition to providing access for patients that are seeking care if the no-show rate was reduced by 25%.

Finances from improvements to patient retention and engagement are provided by reductions in patient attrition and increases of lifetime value. Healthcare organizations that compete in the same constrained market must deal with high levels of costs of acquiring new patients, and thus, have a financial incentive to invest into more cost-effective retention [94]. AI systems may then provide the ability to systematically identify patients who have both high risk of patient switching or disengagement from care and could then be identified for proactive retention efforts that will maintain revenue streams and panel size [95]. Furthermore, a number of studies show that a 5% increase in patient retention can accrue profitability increases of 25-95% depending on the organizational context, while programs related to patient loyalty informed by patient behavior from "retention modeling" can produce high potential return on investment [96].

Reducing readmissions using AI-based risk stratification and focused interventions will address both the quality of care and financial aspects of care - particularly if readmissions are penalized in a value-based care model. AI systems that can accurately identify high risk patients can facilitate intensive discharge planning, post-discharge monitoring and vigilance in response to emerging flags [97]. In organizations where AI readmission prevention programs were implemented, organizations reported reductions of readmission rates of 10%-25% with net savings of $5,000-$15,000 per avoided readmission when incorporating the costs avoided by not incurring a penalty and avoiding resource-based costs [98].

Resource optimization through demand forecasting, where staffing is better aligned to work and ER patient demand, promotes efficiency in operations by improving staff allocations, decreasing OR overtime costs for staff, and limiting caps on capacity bottleneck resources [99]. Risk predicted staffing through AI based utilization predictions provides healthcare organizations with the ability to deploy dynamic and predictable staffing levels and schedule optimization and foresee and manage surge capacity needs. Those organizations where AI staffing prediction programs were in use reported both a

5%-15% reduction in overtime costs and 10%-20% improved staff satisfaction due to predictable schedules [100].

Through AI segmentation and personalization, increased effectiveness in marketing and outreach results from focusing resources on high value contacts. Traditional forms of mass communication in patient education, health promotion, and awareness of services, are low-yielding, wasteful communication approaches [101]. Specifically, AI systems that identify target audiences, personalize messages, and predict likelihood of responding can result in 40-200% increases in effectiveness of campaigns, as well as lowering communication costs through more focused targeting [102]. This focused, precision marketing leverages health communications that are aligned with patient preferences, thus reducing opt-out rates of communication and ensuring a channel is kept open for future engagement.

5.5 Future Research Directions

This comprehensive literature review highlights a number of exciting avenues for future research that will build understanding and use of artificial intelligence for all aspects of healthcare customer behavior analytics. Longitudinal studies focusing on the long-term outcomes of AI-driven interventions are still scarce in existing literature. Most studies report outcomes over days, weeks, or months as opposed to years [103]. Research that examines sustained behavior change, adaptation effects as patients become accustomed to interventions, and long-term clinical and economic outcomes, would provide much-needed evidence of the durability of AI- enabled improvements. In particular, research is needed to help us understand if AI engagement strategies lead to actual behavior change, rather than merely temporary compliance that subsides once the interventions cease.

Movements toward comparative effectiveness research, which directly compares different AI approaches, algorithms, or implementation techniques, could benefit organizations by allowing for evidence-based decisions around each technology. A majority of studies show that exercises in particular AI systems are superior to traditional approaches and/or no intervention, yet head-to-head comparisons between alternative AI methods are still limited [30]. Researchers could conduct careful comparative studies that focus on whether more sophisticated deep learning approaches justify their complexity over simpler machine learning models, optimal points of balance between prediction accuracy (and/or efficiency of use) and different forms of interpretability, and which of various personalized approaches work better than others.

Equitable and disparities research should investigate the ways AI systems impact access to and quality of healthcare across patient populations. To determine whether AI systems reduce, maintain, or exacerbate healthcare disparities, studies designed to evaluate differential performance and impact of AI across groups defined by race, ethnicity, socioeconomic status, geography, age, and disability status are warranted [104]. Research should progress beyond taking stock of disparities towards the generation and evaluation of strategies for mitigating bias, bias-aware algorithms, and implementation strategies that promote equitable AI utilization.

Human-AI collaboration research should examine the most productive division of labor between AI systems and providers, considering for which decisions AI-derived decision support is most and least beneficial to human judgment [105]. Mixed methods research that combines quantitative measurement of performance with qualitative studies of clinician experiences, decision-making processes, and patient perspectives provides insight into how AI tools are integrated into the provision of care and how the integration of AI tools can be optimized [91]. Specific attention should be directed to requirements for AI explainability from the perspectives of the clinician and patient, specifically what might represent the minimum level of explanation needed for appropriate trust and use.

6. Limitations

There are several limitations of this systematic review to consider. First, the rapid pace of Artificial Intelligence (AI) development means that relevant studies may have been published after the date we completed our search, and emerging applications may also not be represented adequately. This field has a quick cycle of emergence, and with its algorithms, applications, and implementation methods will continue to appear. Second, there was likely publication bias towards studies that report positive findings, which might misrepresent the effectiveness of AI, and a study of some AI implementations may never be reported, so there is likely an incomplete evidence base that might over represent success. Third, due to different designs of the studies, populations, settings, various AI methodologies, and outcome measures employed, it limited us from conducting formal meta-analyses or reaching definitive quantitative conclusions about AI effectiveness. Some studies were of higher quality than others with regards to the study's design, as some trials provided rigorous evaluation designs and some were proof-of-concept studies that were limited in their generalizability. Fourth, many of the studies included were conducted from well-resourced academic medical centers or healthcare organizations at the forefront of technology; thus, the generalizability of findings may be limited to community-based practices, small rural settings, or resource-constrained practices. Fifth, the review was anchored predominately in peer-reviewed scholarly material, and thus it risked omitting meaningful innovations and implementations that have been published in industry reports, conference presentations, or proprietary systems that are not documented in the academic literature. Many of the commercial AI applications that have been launched and are used by largest healthcare organizations or technology companies, represent cutting-edge capabilities not yet reflected in published literature. Sixth, restrictions regarding language, which limited our inclusion only to English-language publications, could have resulted in excluding relevant research that might have been published in non-English speaking countries, particularly in Asia where many AI innovations in healthcare have been developed and implemented.

7. Conclusion

This review systematically outlines how artificial intelligence technologies can reshape the development of healthcare systems that can understand and influence customer behavior. AI technologies that range from predictive analytics, personalization engines, sentiment analysis, patient journey mapping, and decision support systems have shown great potential to improve patient engagement, operational efficiencies, and service delivery in healthcare. For example, predictive approaches can achieve an 80-90% accuracy rate in predicting key behavioral outcomes, such as appointment attendance or treatment compliance, and enable healthcare providers to act preemptively to prevent negative impacts on health. Natural language processing provides insights from the large amounts of text feedback contributed by patients, allowing researchers to better understand patient experience in real time, in ways that traditional survey methods simply do not lend. Personalization improves healthcare communications and interactions by allowing healthcare systems to tailor communications and behavioral interventions to individuals' explicit preferences and needs to facilitate substantially greater engagement and satisfaction.

Yet while impressive, AI in healthcare systems necessitates ensuring a thoughtful approach to a data infrastructure strategy, workforce development, ethical considerations, clinical workflow, and the need for ongoing evaluative accountability. Organizations need to address legitimate concerns about privacy, algorithmic bias, transparency, and potential manipulation, as a system of governance and ethics will be required. More research is warranted that examines the long-term outcomes from AI-driven implementation, the comparative effectiveness of various AI-driven strategies, equity implications for diverse populations disproportionately affected by health inequities, and optimal strategies for human-AI design through partnership frameworks.

As the healthcare system continues to evolve towards patient-centered, value-based care delivery, understanding the customer journey with AI will be increasingly important for the success of the organization as a whole. Healthcare leaders must think of AI as much more than a technological fix to current health challenges. When implemented thoughtfully and ethically, AI can become an important tool that can significantly improve an organization's capabilities to understand, engage, and serve patients. Working with AI in the analytics of healthcare customer behavior means more than a technological improvement for the industry, it also represents a major shift to a more personalized, predictive, and proactive approach towards healthcare delivery that will truly meet patient demands while improving performance.

The combination of AI capabilities, the growing availability of digital health data, and the consumerization of healthcare creates limitless opportunities to change the patient journey and ultimately the patient experience. Organizations that successfully understand and manage the technical, ethical, and operational aspects of activating and utilizing AI capabilities within the delivery of health services will position themselves far ahead of competing organizations. This will enable organizations to better engage with patients and families, create remarkable operational efficiencies, improve quality of care through better patient engagement and fulfillment of health outcomes. The new normal of healthcare increasingly rests on organizations' abilities to engage and utilize the power of AI and data analytics, to understand the humans they serve—not only as patients but as informed consumers making complicated choices with their health and wellbeing.

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