ARTIFICIAL INTELLIGENCE IN CONSUMER BEHAVIOUR: A SYSTEMATIC LITERATURE REVIEW OF EMPIRICAL RESEARCH PAPERS PUBLISHED IN MARKETING JOURNALS (2000-2021)

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ABSTRACT

This study is a synthesis of empirical literature on AI in consumer behaviour and aims to provide actionable insights for academicians and practitioners and potential directions for research. The perspective adopted for this study is the consumer behaviour school of thought. A content analysis on 64 empirical papers published in high quality indexed marketing journals were reviewed to inductive derive themes and sub themes for the systematic literature review. A thematic analysis approach was adopted to classify studies into specific topics and evaluate the AI applications in consumer behaviour, marketing decision making and adoption and implementation of AI in consumer behaviour. Recommendations are proposed to for future trends and challenges.

Keywords: Machine Learning, Natural Language Processing, Thematic Analysis, Content Analysis, AI Enabled Devices, IT Adoption.

INTRODUCTION

AI (Artificial Intelligence) is normally defined as "machines which react to stimulation in accordance with traditional responses from humans (contemplation, judgment, and intention) (Shubhendu and Vijay, 2013). Such software systems have qualities of intentionality, intelligence, and adaptability Ahmed et al. (2020).

Sales of AI and Machine Learning (ML) is expected to rise from \$1.4 Trillion to \$2.6 Trillion in next three years as per McKinsey Global Institute and investment in AI systems is forecasted to grow to \$77.6 billion in 2022 (IDC, 2019). A survey conducted on early AI adopters concluded that the top objectives of industry of AI use were marketing-oriented: value addition to existing products and services, creating new products and services, and growing relationships with customers (Davenport et al., 2021) Andrew (2017). As per McKinsey analysis of 400 advanced use cases, AI can contribute most to the domain of marketing and use of AI in marketing increased by 84% in 2020. According to Marketing Leadership Benchmark Report, the technologies most likely to impact marketing in next five years are AI, ML, marketing & advertising technologies, voice/chat/digital assistants and mobile technologies & applications (Drift's, 2020).

Marketing practitioners are investing in AI for customer segmentation, advertising, social media marketing and customer experience and engagement according to a recent study by Advertiser Perceptions (Marketing Charts, 2021). Marketers are adopting AI and ML to automate repetitive and standardized tasks (Drift and Marketing Artificial Intelligence Institute, State of Marketing AI Report, 2021) and AI-powered tools are being used for dynamic pricing,

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merchandize optimization, product information management, shelf optimization, visual search , image tagging/create unique content(context aware advertising, neuro marketing, content generation, mobile marketing, e-mail marketing, video commerce and personalized marketing campaigns(recommender systems and social analytics, (https://research.aimultiple.com/marketing-ai/).

Companies like Disney are adopting AI modelling techniques and ML algorithms, to fine-tune and optimize its media mix model (https://www.tableau.com/best-marketing-dashboards). Starbucks is aiming to create real time personalization experience through predictive analytics and ML, while Alibaba's retail store in Hong Kong "*Fashion AI*" is enhancing the fashion retail experience through AI by using intelligent garment tags and smart mirrors for assisted shopping. Unilever has AI data centres globally to generate insights and act on insights from social listening, CRM, and traditional marketing research. In June 2019, Amazon launched Amazon Personalize, to provide accessibility of Amazon.com's ML technology to AWS customers that delivers up to 50% better recommendations across categories i.e., books, movies, music, and news articles while eBay uses Brand Language Optimization to enhance e-mail Marketing and AI-powered customer experience platform Phrasee to boost its marketing Arasu et al. (2020)

Review studies on AI applications in consumer behaviour (CB) are still at a nascent stage and various scholars have called for further research on specific applications (Martínez-L´opez and Casillas, 2013). The review articles on CB and AI include book chapters, conference papers, opinion based, conceptual and review papers in their sampling frame thus exposing the results to potential bias and subjectivity. They are focussed on specific themes i.e. AI-based CRMs in B2B digital marketing (Saura, 2021), personal selling and sales management (Syam and Sharma, 2018), exploration of AI resolutions which meet marketing needs (Worakamol Wisetsri, 2021), threats and opportunities developing from sales digitalization technologies Singh et al. (2019); ML, word of-mouth, social media and sentiment analysis (Feng, Cai Mitsu, 2020) and impact of Internet research and business-to business technology on research fields (Kumar, 2020).

The conceptual review articles i.e. ML in marketing research (Ma Sun, 2020); integration of AI to organizational strategy (Borges, 2020), implementation of AI (Davenport, 2020); strategic marketing planning Huang et al. (2021) intend to develop a theoretical framework for practitioners and academia while historical review papers (Vlacic, 2021; Mustak, 2020) have maedp the pattern of evolution of AI in marketing over time. Thematic review paper by Kopalle, 2021 evaluates the impact of AI on marketing through the global lens of the dimensions of human–machine interaction and automated analysis of text, audio, images, and video. Bibliometric, scientometric, topical modelling and network analysis based review papers (Feng Cui Mitsui, 2020; Worakamol Wisetsri, 2020; Kumar et al., 2020; Verma, 2021; Mustak, Mekhail, 2020; Schiessl, D, 2020) extract the emergent key concepts and research themes by using algorithmic techniques like Latent Dirichlet Allocation (LDA) (Loureiro et al. 2020;Verma et al., 2021); Multiple correspondence analysis (Vlaˇci´c, 2021) and software like Vosviewer (Chintalapati and Pandey, 2021;Syam and Sharma, 2021) Florez-Lopez & Ramon-Jeronimo (2009).

Till date however a unified consensual framework on applications of AI in consumer behaviour is not reached (Ma, Sun, 2020). The importance of AI is established in marketing practice and research, but debate on whether AI will replace humans still prevails Huang et al. (2021); Malone 2018).

This study aims to enrich the existing body of knowledge in the field of consumer behaviour and marketing implications of AI through synthesis of empirical literature on AI in consumer behaviour in high quality indexed and relevant publications from perspective of the consumer behaviour school of thought (Shaw, 2005). This study is grounded in consumer behaviour school of management thought which draws from theoretical perspectives in behavioural and social

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sciences.

The current study uses (1) a content analysis approach to inductively derive themes and sub themes from empirical studies in the marketing literature and (2) a thematic analysis approach similar to the ones used by Loureiro et al.,2018 and Cortez et al.,2018 to synthesize the findings.

A review of literature on empirical studies from marketing journals with focus on consumer behaviour was not accessible despite exponential growth of AI and its applications in various marketing functions,. Therefore, to address this gap in literature, the following research question (RQ) is proposed Cui et al. (2006):

RQ1. What are the applications and uses of AI-based techniques and methods in consumer behaviour and marketing?

Objectives

1. Identify the main themes and research issues on AI techniques and methods in consumer behaviour using content analysis.
2. Identify future research directions for empirical research on applications of AI tools and methods to consumer behaviour.

To achieve these objectives, this study adopts a systematic review of the literature methodology. The results are categorized thematically based on consumer behaviour school of thought.

LITERATURE REVIEW

Machine learning tasks and methods A specified dataset is processed by AI machine learning algorithms with a specific objective.

1. Supervised learning: A training dataset consisting of independent (X) and dependent (Y) variables is employed for learning and developing a prediction function, Y = f(X) which is referred as regression/classification if the output is a numeric/categorical variable. The main focus is learning a function with maximum predictive accuracy when testing with a different dataset. Models are trained with training dataset and validated with testing dataset and evaluated for out of sample performance (e.g. Hartmann, Heitmann, Schamp, & Netzer, 2019).The Bayes classifier chooses the class that maximizes the posterior probability and is widely used, particularly in text mining. Support-vector machine (SVM) is a maximum margin classifier (Cortes & Vapnik, 1995; Vapnik, 1998) that establishes a linear hyper plane in the input space between the two classes that maximizes the margin of error. Structured SVM further addresses the problems involving multiple dependent variables (Tsochantaridis, Joachims, Hofmann, & Altun, 2005). SVM can also be used for regression tasks, for which it is known as support-vector regression (Drucker, Burges, Kaufman, Smola, & Vapnik, 1997). In decision tree method (Quinlan, 1986), input dataset is successively split into subsets. Artificial neural networks (ANN) are derived from biological neural networks in animal brains (Lippmann, 1987).
2. Unsupervised learning: In unsupervised learning, the output variables are undefined/unknown and the training dataset consists of input variables, while the output variables are either undefined. The objective is to uncover hidden patterns from the data. In clustering, the input data points are assigned to multiple groups to maximize between group differences. In dimensionality reduction tasks, high dimensional data are transformed to lower dimensional data without loss of information. In unsupervised feature learning or representation learning, key features are extracted from input data to be used as input for further analysis.
3. Semi-supervised learning and transfer learning: In a semi-supervised learning task (Zhu, 2005), output for a part of the data is known and training dataset for which output is not known is used to improve learning through for example label propagation by leveraging an existing model trained with a different dataset or different purpose(Pan& Yang, 2009). Transfer learning is used for leveraging existing knowledge such as for image analysis by updating a trained dataset by using the images from the research project (Dzyabura, El Kihal, Hauser, & Ibragimov, 2019; Hartmann, Heitmann, et al., 2019).

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4. Active learning: Limited data instances are available and algorithm acquires new and most important training instances to enhance predictive accuracy (Cohn, Ghahramani, & Jordan, 1996; Lewis & Gale, 1994).
5. Reinforcement learning: The learning agent optimizes the objective function by interacting with the environment, and feedback mechanism (Sutton & Barto, 2018). It's similar to Markov decision process (MDP), wherein forward-looking behaviours are determined using dynamic programming models.

METHODOLOGY

The articles selected for review were extracted from indexed online databases (Scopus, World of Science) and leading marketing journals listed in the 2018 Chartered Association of Business Schools Journal Guide (ABS guide) (https://charteredabs.org/ academic-journal-guide-2018/). WoS and influential journals like Management Science, MIS Quarterly, and Computers in Human Behaviour Boulton (2018). Scopus and Web of Science (WoS) are the two most reputed bibliometric databases. Both Scopus and Web of Science (WoS) databases were employed to search for relevant literature. According to Yong-Hak, 2013, Scopus has broader coverage, and it includes more than 20,000 peer-reviewed journals from different publishers (Fahimnia et al., 2015).

Defining Keywords Search Strategy

Search was conducted with the key words "*artificial intelligence*" , "*artificial-intelligence*" "*artificial-intelligence+Consumer behavior*","machine learning+Consumer behaviour) and type of document: "*empirical*" in Title, key words and abstract. Synonyms used for artificial intelligence like machine learning, deep learning, natural language processing, etc., were employed with boolean operators like "*OR*" , "*AND*" to get the intersection set of papers on consumer behaviour and AI. To refine initial results, inclusion and exclusion criteria were used. Only empirical articles published in marketing journals were considered for this study as they represent "*certified knowledge*" (Ramos-Rodríguez and Ruiz-Navarro, 2004). Conference papers, book chapters, commentaries, erratum etc., were excluded from the study Chintagunta et al. (2016).

Data Analysis Plan

Two researchers analysed the extracted papers for inter-rater validity. Data analysis is structured in three stages:

Stage 1: data analysis focused on identifying the most relevant articles in the research domain.

Stage 2: analyses used content analysis to inductively derive the relevant themes and sub themes based on the consumer behaviour school of marketing thought. Thus, themes and sub-themes represent the core ideas, arguments and conceptual linking of expressions on which an article's research questions, constructs, concepts and/or measurements are based (Thorpe et al. 2005). Drawing on these principles, themes were inductively derived from our holistic understanding of each article (Jones et al. 2011) as shown in Figure 1 Cui & Curry (2005) Shen et al. (2020).

Stage 3: Analysis focused on categorization of the articles using a systematic analysis approach and full text screening process: validity, reliability, credibility, and integrity (Moher, et al, 2009; Nill & Schibrowsky, 2007) by adopting the quality criteria of Macpherson and Holt, 2007 into the themes, sub themes and future research directions of AI in Consumer behaviour.

625 articles were initially extracted. After excluding conference papers, book chapters,

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conceptual papers and articles published in computer science, information systems and engineering journals and topics related to machine learning algorithms, Natural language processing tools, but not linked with consumer behaviour or its marketing applications, 416 articles were excluded . Based on evaluation of abstracts, 111 articles were excluded as they were unrelated or vaguely related to the theme of this paper. 64 empirical articles were selected for further review Table 1. They were systematically evaluated following full text screening process. Two academic scholars independently evaluated the art and categorized the papers according to identified themes and sub themes for the topic "*AI in consumer behaviour*". The researchers degree of agreement was evaluated with Cohen's Kappa coefficient >0.85 Table 2 and Figure 1.

Table 1
SUMMARY OF ARTICLES PUBLISHED IN MARKETING JOURNALS ON THE THEME

Journal Name	Authors	No of art
Journal of Business Research	McLean, G. et al. , 2021, Hasan et al. 2020, Rodgers et al. 2021, Albrecht et al. 2021	4
Computers in Human behaviour	Kim, S. & Choudhury, A, 2021, Canziani and MacSween, 2021, Rhee et al., 2020, Youn and Jin, 2021, Lv et al., 2021, Ameen et al, 2021.	6
Industrial Marketing Management.	Albert Orriols-Puig, et al., 2013, Arno De Caigny, 2021, Wilson et al., 2019, Kushwaha et al., 2021, Aydin et al., 2020, Wang & Wang (2020),Shen, C., et al, 2019, Bag et al, 2020, Mikalef et al, 2020, Francisco J. Martínez-López et al., 2009	10
International Journal of Advertising	Wu L., et al. 2021, Kim J., et al., 2021	2
International Journal of Research in Marketing	Vermeer (2019), Katja, G., et al, 2021	2
Psychology and Marketing	Cui, Yuanyuan & van Esch, Patrick. (2022), Moriuchi, Emi. (2021). Tassiello, V, 2021, Belanche, D, 2021,Balakrishnan, J and Dwivedi, YK, 2021, Kim et al., 2021, Moriuchi, E. ,2019,	7
Marketing Science	Cui, D and Curry, D, 2005, Ghose, A., et al., 2012, Timoshenko & Hauser (2019), Netzer at al., 2012	4
Journal of Consumer Marketing	Dhaoui et al. (2017)	1
International Journal of Information Management	Chatterjee & Kar (2020) , Mishra, A., et al. , 2021,Qian Hu et al., 2021	3
Journal of Emerging Trends in Marketing and Management	Adrian, M., et al., 2018	1
Journal of Interactive Marketing,	Pamuksuz et al. (2021), Pagani et al., 2019	2
Technological Forecasting and Social Change,	Capatina et al. (2020), Sohrabpour,V et al., 2021	2
Social Science Computer Review	Raquel Florez-Lopez, 2009	1
International Journal of Bank Marketing	Riikkinen, Mikko et al., 2018	1
International Journal of Retail & Distribution Management,	Chopra (2019)	1

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International Marketing Review	Deng, G. et al. , 2020	1
Telemedicine and e-Health	Huang et al. (2021)	1
Technology in Society	Jung, S.H and Jeong,Y. J., 2020	1
Procedia - Social and Behavioral Sciences	Stalidis, G, et al. , 2015	1
International Journal of Hospitality Management	Kwok et al. (2020)	1
international Journal of forecasting	Yongdae An, et al., 2020	1
Journal of Destination Marketing & Management	Penagos-Londono G. et al., 2021, Grundner and Neuhofer, 2021	2
Journal of Digital Contents Society	Park et al. (2018)	1
Journal of Cleaner Production	Bj€orn Frank, 2021	1
Journal of Retailing and Consumer Services,	Atieh, P. , 2021,Chinchanachokchai et al., 2021; Pantano and Lizzi, 2021, Dolega et al., 2021	4
Journal of Business & Industrial Marketing,	Hall et al., 2021	1
Journal of Service Management	Flavián, C. et al., 2021	1
Journal of Management Science and Engineering	Jian and Hua, 2020	1

Table 2
YEAR OF PUBLICATIONS

Year	No of publications
2005	1
2015	2
2012	2
2009	3
2013	1
2006	1
2018	4
2019	8
2020	15
2021	25
2022	2

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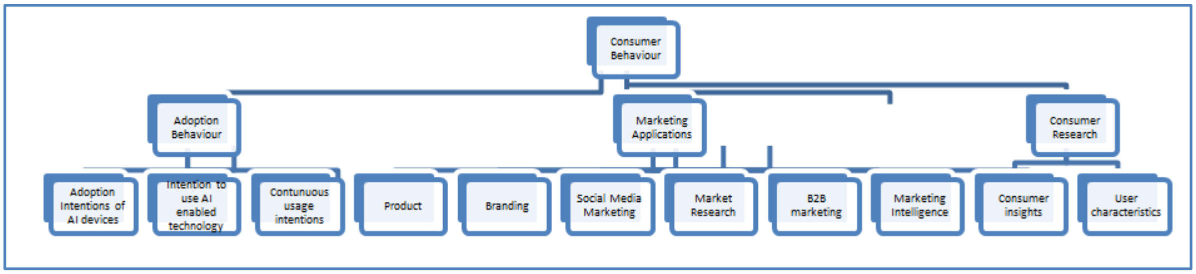

FIGURE 1
THEMES AND SUBTHEMES INDUCTIVELY DERIVED FOR THE STUDY

RESULTS AND DISCUSSION

The themes and subthemes (Figure 1) and results are summarized in Tables 1 and 2. The maximum articles related to AI in consumer behaviour were published in Industrial Marketing Management though the publications are scattered across various journals (28) as shown in Table1. Upsurges in publications are observed from 2018 onwards (Table 2). Though most of the art for this study are from marketing related journals, some art are from associated journals like Marketing Science which are multi-disciplinary in scope. The themes re inductively derived from the selected art (Figure 1). The thematic structure is as follows Lucas et al. (2007):

Consumer research (consumer insights, user characteristics, and market segmentation variables), 2.Adoption and usage intentions (Adoption intentions of AI tools and AI enabled devices, continuous usage intentions of AI enabled artefacts), 3. Marketing Applications (Product, Customer experience, market research, Branding, Social media Marketing, B2B marketing, Marketing Intelligence, Forecasting).

Consumer Insights

Open vocabulary approaches such as LSA, LDA, and k means analysis are used for insights into consumer perceptions related to product positioning (Lee and Bradlow 2011), mapping market structures (Netzer et al. 2012), identifying trending topics from consumer reviews (Lee et al., 2020, Tirunillai and Tellis 2014; Buschken and Allenby 2016), and measuring the relationship of consumer sentiments to other variables. Sentiment analysis and text mining analysis techniques applied to UGC (user generated content) and deep learning techniques like SVM, convolutional neural network been found to be significantly better than traditional ML methods. ML techniques like Natural Language processing (NLP) for text based content analysis have higher reliability, validity and efficiency than manual and computer aided approaches (Lee et al, 2020). Supervised ML techniques i.e. SVM and N-gram approaches (which takes characters -letters, space, or symbols) as the basic unit in the algorithm) were found to offer better accuracy than the Naïve Bayes approach for sentiment analysis of online reviews in travel blogs (Qiang Ye et al., 2009). Netzer et.al., 2012 combined a text mining approach with semantic network analysis tools to convert the user-generated content to perceptual market structures and consumers' associative network for multiple brands Tsao et al. (2019). Ghose et al. (2012) applied a random coefficients-based structural model to design a hotel ranking system based on consumer utility gain from each hotel estimated from distribution of consumer preferences.

User Characteristics

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A study on how users' characteristics and information processing affect the performance of recommender systems showed that expert consumers prefer user-based collaborative filtering systems, whereas there is no difference between the two systems among novice consumers (Chinchanachokchai et al.,2021) Quantum (2017).

Market Segmentation Criteria

Review shows a shift towards Bayesian models and machine learning paradigms (decision trees, artificial neural networks, genetic algorithms (Kim et al., 2005) for selection of most relevant segmentation criteria and market segmentation Penagos-Londoño et al. (2021).

Pitt ,2020 research generated insights into how NLP analysis, automated text analysis and correspondence analysis can be used to reveal four distinct clusters of art collectors based on their "*Big Five*" personality traits and how these types talk about their possessions. Raquel Florez-Lopez et al., 2009 study established that univariate decision trees using CART model (both univariate and oblique variants), using the Gini splitting rule and a pruning technique provided superior results as compared to traditional statistical techniques for direct marketing to large insurance marketing companies for maximizing account final profit, accounting performance, and minimizing opportunity costs. Penagos-Londono G. et al. (2021) applied a metaheuristic (genetic algorithm) to select most applicable variables of perceived sustainability and trustworthiness for segmentation of 438 tourists from Chile and Ecuador aged over 17 years.

Intention to Use AI Tools

Inductive research and empirical studies using technology adoption theories (UTAUT2) have been preferred to evaluate antecedents of intention to use AI tools. Chopra (2019) determined that Indian shoppers are motivated to use and adopt AI tools, (Chatbots, Voice Assistants, Augmented reality) which are easy to use (expectancy), competent in performance (instrumentality) and create satisfaction, trust and rewarding experience (valence). Huang et al. (2021) empirically proved that habit followed by personal Innovativeness, network externality (NE), and performance expectancy (PE) were predicted intention to use intelligence-powered weight loss and health management application (UTAUT 2).

Consumer adoption intentions of Voice Assistants/Digital Voice Assistants/AI enabled CRM/SVA/voice-activated smart home devices (SHDs)/Analytical AI.

The role of social traits of the conversational agent on human computer interaction and impact of atmospherics on consumer retail experience are being increasingly explored. (Rodgers et al, 2021) provided evidence of effect of artificial intelligence-driven music biometrics induced emotion on retail buying behaviour for utilitarian-type customers in a high-involvement AI purchase condition. Flavian et al., 2021 empirically established that customer' technological optimism increases and insecurity decreases their intention to use robo-advisors. Atieh, 2021 identified seven voice assistant personality traits (VAP) of three commonly used mobile applications (Brett et al., 2020). Belanche et al. (2019) experimental studies proved that perceived competence of the robot has positive influence on utilitarian expectations (i.e., functional and monetary value), while influence of perceived warmth on relational expectations (i.e., emotional value) is higher users with lower social interaction needs. Adoption of AI generated information depends on the preciseness of the information format leading to higher evaluations and behavioural intentions (Kim et al., 2021).

Mishra et al., 2021 empirically determined that playfulness and escapism positively

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influence hedonic attitude while anthropomorphism, visual appeal, and social presence influences utilitarian attitude, SVA (smart voice assistant) usage and WOM (word of mouth) recommendations. Hassan, 2021 proved the positive effect of consumer trust, interaction, and novelty value and negative effect of perceived risk on brand loyalty for AI supported devices. Effort expectation (EE) impact on consumers' usage experience of the VA is higher for information- gathering activities, whereas performance expectation impact on usage experience is higher for task- completion purposes (Moriuchi, Emi., 2021). Involvement level of the users and their psychological condition of power was found to meditate their willingness to purchase low involvement products through VA (Tassiello et al., 2021). Chatterjee & Kar (2020) empirically validated the effect of perceived usefulness and perceived ease of use on behavioural intention of the employees to adopt an AI integrated CRM system in organizations Duan et al. (2019).

Continuous usage intentions of AI artefacts or autonomous agents (Intelligent personal assistants-IPAs) is a function of situational factors (anthropomorphism -van Pinxteren et al., 2019),(trust -Chattaraman, et al, 2019),(parasocial relationships -Han & Yang, 2018),(benefits-McLean & Osei-Frimpong, 2019) and artificial autonomy or human-likeness perceptions of IPAs (i.e., displaying competence and warmth), (Shen Hu et al., 2021).

MARKETING APPLICATIONS

Product

Focus of research on product design and recommendation has changed from technological focus on algorithms (Bonhard & Sasse, 2006; Sinha & Swearingen, 2001) to social and psychological aspects (Chen & Lee, 2008; Sher & Lee, 2009). Rhee and Choi, 2020 experimental research showed that both personalization (that a reflected individual preference for product attributes) and social role of voice agent contributed to positive attitude towards the product. Qian hu, 2021 research on AI artefacts design empirically validated the impact of artificial autonomy and its downstream consequences on human behaviour. Riikkinen, Mikko, 2018 uncovered how insurance Chabot’s support customers’ value creation through illustrative case examples.

Customer Experience (CX)

Amen et al., 2021 revealed the mediating effects of trust and perceived sacrifice and the direct effect of relationship commitment on AI-enabled customer experience (CX) on users of a beauty brand. CX of AI enabled Chabot in B2B organizations is impacted by the overall design of the system, user’s ability and trust towards the brand and system (Khushwaha et al.2021).

Market Research

Cui et al, 2006 developed and tested a predictive model with integrated customer lifetime, transaction and RFM (recency, frequency, monetary value) variables of consumer response to direct marketing using Bayesian Networks. SVM model predicted outcomes in emerging environments in marketing, such as automated modelling, mass-produced models, intelligent software agents, and data mining (Cui and Curry, 2005). Netzer et al, 2012 combined text-mining approach with semantic network analysis to derive competitive landscape insights and market structure from user generated content (UGC).

Branding

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Culotta and Cutler (2016) automated data analytics tool predicted brand perceptions from Twitter while machine-learned text-analysis approach of Pamuksuz et al. (2021) detected brand personality from user generated content in social media. Voice Assistant's AI attributes of social presence, perceived intelligence, social attraction, and technology attributes, utilitarian benefits influence consumer brand usage intention though it has no impact on purchase intentions (Mclean et al., 2021). Youn and Jin, 2021 in their study established that the relationship type with a Chabot (friend vs. competent assistant) affected CRM-related outcomes.

Social Media Marketing

Combination of classification based methods based on lexicon of weighted words (Bolat and O'Sullivan, 2017) and machine learning or supervised learning approach to sentiment analysis used in marketing research (Pathak and Pathak-Shelat, 2017) were demonstrated to have better performance for analysing social media conversations Dhaoui et al. (2017) ; Shen, C. et al. ,2019 applied text mining approach known as two-tier concept-linking analysis to extract cognitive patterns in Twitter posts to infer hidden social media marketing strategies of competitors

ML supervised and unsupervised methods (LDA, text based classification algorithms) were found to be more effective than sentiment analysis in detecting and responding to eWOM in context of web care and social media monitoring (Vemeer et al., 2019) ; deep learning ML methods as more accurate in to predict the social media engagement level for start-up firms as a proxy for their social media marketing activity effectiveness(Jung and Jeong, 2020; Capatina et al. (2020), exploratory study on correlations between the experience in the field of SMM and the level of knowledge regarding the applicability of Machine Learning (ML) in SMM . Wu et al., (2021) applied topic modelling and sentiment analysis to identify the most salient topics on AI in advertising in social media and found that AI-powered marketing tools" was most positive topic and the most negative topic was "*AI's involvement in social media campaigns*."

Service failure: Lv et al., 2020 in their research established that cuteness of AI Assistant has positive impact on customer tolerance of service failure through the mediating constructs (tenderness and performance expectancy) and boundary (failure severity and time pressure) of the cuteness effect Brill et al. (2019).

B2B marketing: Mikalef et al., 2020 established that AI can be applied for customer insights, aligning process with customer needs and developing new services in B2B marketing. Aydin et al, 2021 provided evidence of use of AI to detect crisis related to events from e-mail communication for B2B marketing decision making. The uplift logit leaf model enables better B2B customer retention predictive performance with interpretability (Arno De Caigny et al., 2021). ANN (Artificial neural networks) models have better predictive ability for classification problems (when the outcome variable is binary and sample size is small (Dale et al., 2019). Hybrid particle swarm optimization (PSO) approach (biology inspired optimization framework) cab is used to design an optimal industrial product line (Tsafarakis et al., 2013).

Marketing Intelligence systems: Genetic Fuzzy Systems and knowledge discovery in databases (KDD) method can be applied for consumer behaviour modelling (Francisco J. Martínez-López and Jorge Casillas, 2009). Unsupervised ML techniques and KDD approach of Fuzzy-CSar can be applied to solve unstructured marketing/business problems using marketing databases (Albert Orriols-Puig et al., 2013)

Forecasting; ML approaches i.e RF and SVM outperform time series methods (e.g., ARIMA, exponential smoothing, etc.) for forecasting of call centre arrivals of an online (Albrecht et al., 2021). Non -linear ML methods like ANNs and GP are superior to linear statistical methods of forecasting. Sohrabpour et al., 2021 demonstrated application of causal GP to predict the effect

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of input variables marketing and packaging, production costs, exchange rate, discounts and unit prices on export sales. Albrecht et al., 2021 demonstrated that ML models have better prediction accuracy and practicability and RF algorithm is superior method to predict intra-daily call centre arrivals' based on online retailer's customer support and complaints queue datasets Table 3 and Table 4.

Table 3
MAPPING OF AI TOOLS AND TECHNIQUES WITH CONSUMER BEHAVIOUR AND MARKETING APPLICATIONS

AI techniques and tools	Consumer behaviour and marketing applications
Sentiment analysis, text mining analysis techniques and deep learning techniques like SVM, CNN	Market and competitive structure analysis; generate perceptual market structures
ML supervised and unsupervised methods (LDA, text based classification algorithms)	SMM, Social media listening,
Bayesian models, NLP and ML paradigms (decision trees, artificial neural networks, genetic algorithms)	Market Segmentation
Automated data analytics tool, machine-learned text-analysis approach	Predicting brand perceptions and detecting brand personality
ML approaches ie RF algorithms, tree-based models, KNN algorithm, SVM and non-linear methods (GP, ANN)	Forecasting for example of call centre arrivals
Bayesian Networks (BNs) learned with EP	Modelling consumer response to direct marketing
Genetic Fuzzy Systems, and knowledge discovery in databases (KDD)	Consumer modelling and solving of unstructured marketing/business problems by analysis of marketing databases
Hybrid particle swarm optimization (PSO) approach (biology inspired optimization framework) ANN models	Designing optimal product line

Table 4
ANTECEDENTS OF CONSUMER ADOPTION AND USAGE OF AI TOOLS AND TECHNIQUES

Consumer behaviour	Antecedents
Consumer adoption of IT tools and devices	Consumer characteristics (for exp., anthropomorphic tendencies, personality, user experience, age, habit, personal innovativeness), Psychological perceptions (attitude-utilitarian vs. hedonic, effort expectation, performance expectations, involvement level of user, utilitarian and relational expectations, perceived level of similarity with the tool, social interaction needs), Attributes of the AI enabled device (for exp., anthropomorphism, social traits, flow experience, type of relationship-virtual friend vs. virtual assistant) Situational factors (trust, anthropomorphism, Para social relationships, network externalities and environment of interaction (atmospherics of the retail store).
Continuous usage intentions of AI artefacts (IPAs)	(Anthropomorphism -van Pinxteren et al., 2019), (trust -Chattaraman, Kwon, Gilbert, & Ross, 2019),(parasocial relationships -Han & Yang, 2018),(benefits-McLean & Osei-Frimpong, 2019) and artificial autonomy of IPAs or human-likeness perceptions of IPAs (i.e., displaying competence and warmth), (Shen Hu et al., 2021).

CONCLUSIONS

Research on AI and its applications in consumer behaviour have been focussed at the technical level of AI, emphasizing customer acceptance and satisfaction evaluation (Murphy et al., 2017). Various technology-adoption theories have been used to explain why customers adopt AI,

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such as the technology acceptance model and the unified theory of acceptance and use of technology (UTAUT; Lu et al., 2019). AI technology characteristics and customer environment influence customers' willingness to use AI mediated by customers' expectations of the technical performance and capability of AI services (Ruyter et al., 2005; Fritz et al., 2016; Lu et al., 2021).

AI techniques have better reliability, validity and predictive accuracy than traditional statistical techniques. Sentiment analysis, text mining analysis techniques and deep learning techniques like SVM, CNN (convolutional neural networks) have better efficiency and accuracy than traditional machine-learning methods for content analysis of UGC and online reviews to generate perceptual market structures and consumers' associative network for multiple brands. Marketing scales developed by combining traditional marketing scales with textual and semantic analysis yield better insights into theoretical constructs.

There is a shift towards Bayesian models, NLP and ML paradigms (decision trees, ANN, and genetic algorithms) for market segmentation. NLP analysis, automated text analysis and correspondence analysis can be used to apply most relevant criteria for market segmentation.

Functional, social and relational elements of AI enabled intelligent devices drive their adoption. Some of the factors influencing adoption of IT tools and devices are consumer characteristics (for exp., anthropomorphic tendencies, personality, user experience, age, habit, personal innovativeness), psychological perceptions (attitude-utilitarian vs. hedonic, effort expectation, performance expectations, involvement level of user, utilitarian and relational expectations, perceived level of similarity with the tool, social interaction needs), attributes of the AI enabled device (for exp., anthropomorphism, social traits, flow experience, type of relationship-virtual friend vs. virtual assistant). Situational factors (trust, anthropomorphism, Para social relationships, network externalities and environment of interaction (atmospherics of the retail store).

Social and psychological aspects of AI enabled products are now the focus of design and development research. Artificial autonomy and human likeness are major factors driving adoption and usage of AI devices and tools.

Bayesian Networks (BNs) learned with EP for market research is effective in modelling consumer response to direct marketing. Text mining approach combined with semantic network analysis can be used to derive insights into market structures and competitive environment from UGC.

AI can be used to generate insights, predict and influence consumer brand related behavioural and psychological outcomes. Brand perceptions can be predicted and brand personality can be detected through AI tools (automated data analytics tool, machine-learned text-analysis approach) from UGC in social media. VA attributes (social presence, perceived intelligence, social attraction, technology and utilitarian benefits) influence brand usage intentions. Type of relationship with Chabot (friend vs. assistant) and brand personality perceptions influence trust, relationship, satisfaction and visit intentions of Chabot users.

ML supervised and unsupervised methods (LDA, text based classification algorithms) enable social listening, identifying salient topics on social media, and predicting social media engagement level for start-up firms and implementation of SMM strategies more effectively.

AI can be applied for crisis detection, predictive modelling (using ANN methods) and product line optimization in B2B marketing. Unsupervised ML techniques and KDD approach can be used for solving unstructured business/marketing problems by analysis of databases. ML approaches i.e. random forest algorithms (RF), tree-based models, k-nearest neighbour (KNN) algorithm, support vector machines(SVM) and non-linear methods (GP, ANN) are superior to linear statistical methods of forecasting. Customer experience with AI enabled devices (Chabot) and tools can be enhanced through overall design of system, user's ability and trust towards the

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brand.

Theoretical Implications

The review paper provides empirical support for the application of socio-psychological and consumer behaviour theories for predicting adoption and usage of AI enabled devices and tools. This study contributes towards the development of a unified theory of AI applications for consumer behaviour by integrating the empirical results of applications of AI tools and methods to consumer behaviour. By mapping the AI tools and techniques to consumer behaviour and marketing decisions, this study attempts to provide an empirically grounded framework (Table 3 and Table 4) for further research and theory development in this domain.

Managerial Implications

A framework for practitioners (Tables 3 and 4) is developed based on results of empirical research into AI applications in consumer behaviour. Practitioners can apply the findings from this study in design and development of AI enabled devices and for enhanced adoption and usage of AI tools.

Future Research Directions

Future research in AI applications in consumer behaviour can be oriented towards development of a unified theory of adoption of AI enabled tools, devices and techniques. With advancements in AI devices and tools, traditional theories of consumer decision making may not be fully applicable and further research is required towards development of an integrated model of consumer behaviour which incorporates empirical findings from various theories applied to this domain. The dominance of ML methods and techniques in this arena is evident. Most research on AI in consumer behaviour can be classified as narrow or weak AI based on its capabilities as it performs defined tasks intelligently but does not perform any task as efficiently as humans (general AI).

The domain of AI applications researched in Consumer behaviour is restricted to specific applications and functionalities as discussed in the article. However, the scope of consumer behaviour is not fully addressed as various tasks and functions are still un researched for example consumer decision making models, impulsive behaviour, obsessive behaviour which could generate insights into specialized fields of enquiry. Based on the segmentation-targeting-positioning and 4P model (Kotler, 1999), research into AI application in brand and product positioning, Pricing, Promotion, Place and Product are limited and scarce. AI can be applied for pricing optimization, dynamic pricing, price discrimination and channel management decisions which have not received adequate attention of scholars.

The theoretical frameworks used for studies on Adoption and usage of AI are limited by the dominance of technology adoption, consumer behaviour and socio-psychology theories which are limited by their generalizability. Studies which incorporate theoretical frameworks from Computer-human interaction for example flow theory (Csikszentmihalyi, 1997), Technology task Fit theory (Goodhue, D.L., Thompson, R.L, 1995), motivational theories of adoption and learning theories for example Social Cognitive Theory (SCT, bandura, 1986), Activity network theory (Burt, 1982), diffusion of innovation theory (Rogers, 1962) could provide further insights into adoption and usage of AI by consumers.

Limitations

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This review study is limited by the findings of the articles selected and may not cover the universe of empirical findings in this field. The themes and sub themes are inductively derived and hence have some subjectivity which may be biased by the knowledge and experience of the academic scholars who categorized the findings. However, this study provides a framework for future research into AI in consumer behaviour by compiling and synthesizing the research till date.

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