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A systematic review on the role of emotional regulation and artificial intelligence in consumer engagement

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ABSTRACT

Artificial Intelligence (AI) has transformed consumer interaction, evolving from automation to emotionally attuned engagement. This systematic literature review synthesized 44 studies to understand how AI facilitates consumer engagement through emotion regulation. Following the PRISMA protocol, studies were retrieved from Google Scholar and Scopus and evaluated using quality assessment criteria adapted from Tranfield et al. (2003) and Critical Appraisal Skills Program CASP (2020). The findings reveal that AI techniques, such as sentiment analysis, recommender systems, chatbots, and affective computing, enhance engagement across multiple stages of the customer journey. However, most studies conceptualize AI as a technological enabler rather than a psychological co-regulator of consumer emotions. By integrating the Stimulus-Organism-Response (S-O-R) framework, Gross's (1998) emotional regulation theory and consumer engagement theory. This review reframes AI as an active participant in emotion regulation. This study contributes to the underlying mechanism by guiding organizations toward emotionally intelligent AI design. Future research directions are proposed to strengthen theoretical integration, methodological rigor, and ethical considerations in AI-driven consumer engagement.

Keywords:: Artificial Intelligence, Consumer engagement, Consumer Behaviour, Decision Making, Emotional Regulation, E-commerce, Personalization.
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INTRODUCTION:

Artificial intelligence (AI) has redefined consumer-brand interactions, moving beyond automation to understanding underlying emotions. As consumers increasingly engage with intelligent systems, from chatbots to recommender systems, AI no longer functions merely as a technological tool but as a participant in the emotional and psychological landscape of consumption (Israfilzade & Sadili, 2024; Sheng et al., 2025)

Traditionally, Consumer engagement strategies were grounded in customer relationship management (CRM) systems, which integrated marketing strategies with information technology to manage data, understand customer behaviour, and enable customization (Ledro et al., 2022), however, the introduction of AI has revolutionized CRM by enhancing its core functions, such as enabling targeted marketing campaigns, predicting market trends, and improving customer support through human-like chatbots ((Ledro et al., 2022)**;** (Ledro et al., 2025) while such systems optimize operational efficiency, they often overlook the psychological dimensions of engagement, presenting technology as a mere facilitator of information exchange rather than a co-regulator of human emotions.

Emerging research suggests that AI can function as an emotional co-regulator, as these systems are increasingly being designed to perceive, interpret, and respond to consumers' affective states (Wen et al. 2022)**.** Emerging research suggests that AI can function as an emotional co-regulator, as these systems are increasingly designed to perceive, interpret, and respond to consumers' affective states**.** However, the existing literature largely focuses on technological efficiency, personalization algorithms, and adoption models, with limited empirical or systematic understanding of the psychological mechanisms through which AI enhances emotional connections and prolongs consumer engagement

(Br Perangin-Angin et al., 2024;Davoodi et al., 2025; Sharma et al., 2020). Addressing this gap requires the integration of psychological theories that explain how consumers experience and regulate their emotions during AI-mediated interactions.

Advancing Gross 's (1998) Emotional Regulation Theory, this review conceptualizes AI as an active participant in consumers emotional processes. This theory explains how individuals influence their emotions, when they have them, and how they express them through five regulatory strategies: situation selection, situation modification, attentional deployment, cognitive change, and response modulation. In AI-mediated contexts, these processes occur as consumers interpret system cues such as personalized recommendations or chatbot tone, with AI technologies acting as emotional co-regulators that shape users' affective experiences through personalized and empathic responses.

The integration of Emotional Regulation Theory bridges the gap between marketing and psychology by offering a deeper understanding of how AI fosters engagement not only through operational value, but also through emotional alignment and regulation. In addition, consumer engagement theory (Brodie et al.,2011) situates emotional regulation within the cognitive, affective, and behavioural dimensions of engagement, whereas the stimulus-organism-response (S-O-R) framework positions AI as the stimulus, emotional regulation as the organismic process, and engagement as the behavioural response. Together, these perspectives provide a robust conceptual foundation for examining AI as an emotionally intelligent system that co-creates engagement through both affective and cognitive processes.

Guided by the PRISMA framework, this systematic review studied data from databases such as Google Scholar and Scopus to explore how AI technologies align with emotional regulation processes to enhance consumer engagement. Specifically, this review aims to a) understand the role of Artificial Intelligence in enhancing consumer engagement in digital b) understand how artificial intelligence affects emotional regulation process, and c) identify potential research

gaps and propose future research directions. In doing so, this study responds to the growing need for psychologically grounded frameworks that explain how technology-mediated emotions shape consumer behaviour in the AI age.

Methodology

The study followed the Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) 2020 guidelines to ensure methodological transparency and replicability (Moher et al.,2009; page et al.,2021). This review aims to synthesize the existing literature exploring the role of artificial intelligence (AI) in emotional regulation and consumer engagement.

Search Strategy and Data Sources

A systematic search was conducted across two major databases, Google Scholar and Scopus, to strengthen methodological transparency and enhance the retrieval of multidisciplinary research. The search covered studies published between 2013 and 2015, using Boolean string "Artificial Intelligence" OR "AI" OR "machine learning" OR "deep learning") AND "emotion* regulat*" OR "affective computing" OR "sentiment analysis" OR "emotion* AI" OR "emotion* adapt*" AND "consumer* engag*" OR "customer engag*" OR "user engag*" OR "customer experience" OR "customer interaction" AND "B2C" OR "e-commerce" OR "online shopping." For the systematic review, only studies that were a) peer-reviewed, b) published in English, and c) published between 2013 and 2025 were included. Studies were excluded if they (a) were conference papers, review articles, commentaries, or editorials; (b) lacked full text availability; and (c) focused solely on AI model development without consumer engagement.

Study selection Process

The study identification and screening process followed PRISMA 2020 guidelines to ensure methodological transparency and replicability. A total of 18370 records were identified across two databases Google Scholar and Scopus. 2000 duplicate records were removed by the reference manager and around 15000 records were removed by the automation tool. A total of

188 records were retained for title and abstract screening, and 144 studies were excluded based on the inclusion and exclusion criteria

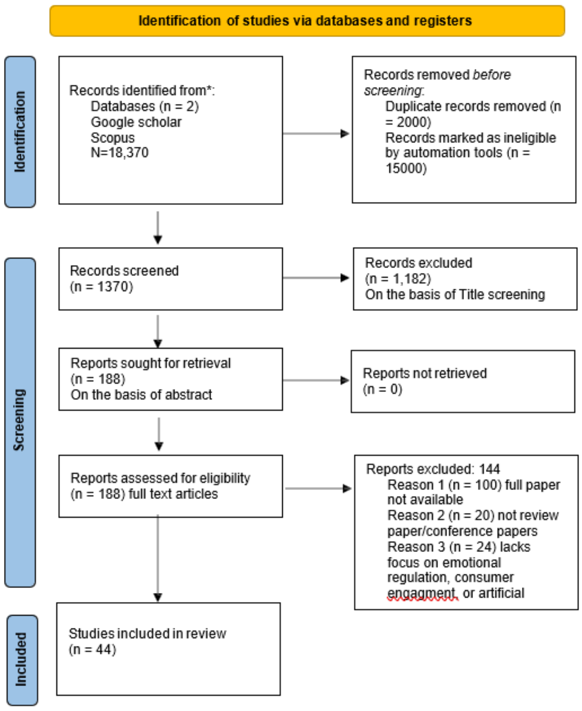

Figure 1 Prisma 2020 flow diagram

Data extraction

Data extraction, as illustrated in figure 1(Page et al., 2021) was guided by a structured table1, figure 2, and figure 3. The extraction framework included the following parameters: aim, methodology, Theoretical Integration, Transparency, Relevance, and quality. Each study was systematically reviewed and coded against these parameters to ensure consistency and comparability. The assessment process involved a screening process, first by title and abstract, followed by a full text-view review, to retain only those studies that met the predefined inclusion and exclusion criteria. This structured approach ensured transparency and minimized subjectivity during the data synthesis.

Quality assessment

To ensure methodological rigor, all 44 studies were evaluated using criteria adapted from Tranfield et al.

(2003) and the Critical Appraisal Skills Program (CASP,2020). The studies were assessed across five parameters: 1) clarity of research objectives,2) methodological rigor,3) theoretical grounding,4) relevance to AI emotion engagement, and 5) reporting transparency. Each study was rated on a 3point scale (high, medium, or low). Of the 44 studies, 33 were rated as high, 10 as moderate, and 1 as low**.** No studies were excluded after quality assessment, as all of them met the minimum inclusion criteria.

The systematic review process yielded 44 studies that provided theoretical and empirical insights into how AI technologies facilitate emotional regulation and consumer engagement. The following section presents a synthesis of these studies and highlights emerging patterns and research gaps.

Results

Table 1 Reviewed studies and its quality assessment on the basis of methodology, relevance and Theoretical integration

Author	Clarity of aim	Methodology Rigot	Theoretical integration	Transparency	Relevance	Quality
. (Adomavicius et al., 2013)	Tests anchoring effects of recommendation system predictions on consumer preferenes	Controlled lab experiment, data collection/analysis, use of statistical model	Behavioral decision theory and psychological anchoring hypothesis	Detailed experimental design across all three studies, controlling variables and providing demographic data	The core focus on the beahvioural impact and design implications of recommender systems in e-commerce	High
(Alghamdi et al., 2025)	Design ENLPPR-ICFFO method to detect and classify sentiment in product ratings	Uses advanced algorithm: CB0W for feature extraction, ELM for classification, ICFFO for hyperparameter turning detailed empirical validation showing metrics	NLP, deep learning method, ELM, metaheuristic optimization	Two amazon datasets, sample sizes (25000;14000),	Accurate data driven sentiment analysis for e-commerce product reviews	High
(Alrefae et al., 2024)	ABSA on Saudi dialect product reviews to enhance customer experience	Manually created and annotated dataset (4000 reviews); tested four Machine learning algorithm (SVM, RF, NB, KNN) with six feature combination (TF-IDF, POS, N-grams)	Employs foundational machine learning algorithm (SVM, NB) and NLP technique (POS TF-IDF)	Acknowledges lack of Arabic datasets; explicitly details manual annotation, cross-reviewing process, and feature combination	Critically highlight the gap in Arabic sentiment analysis, directly aiming to improve customer service in e-commerce	High

(El-Ansari & Beni-Hssane, 2023)	Personlized chatbot enhanced with sentiment analysis for e-commerce customer service	A proof-of-concept system; compared VADER, NB, and SVM performance on Amazon/twitter basis; utilized a BERT-based language model	Personalization technique, and NLP concept	Describe local server hardware configuration and used Amazon twitter datasets	Improving chatbot effectiveness and user satisfaction in e-commerce through sentiment analysis and personalizati on	Medium
(Asante et al., 2023)	Optimize consumer engagement via AI elements (chatbot, image search, recommen der systems, automated after sale service	Used PLS-SEM for complex model estimation; large sample size; rigor validity checks	Explicitly founded on the (stimulus - Organism-Response) paradigm	Detailed demographic profile, translation and pre-testing procedure for survey instrument, specified validation metrics (R^2, Q^2)	Investigate how specific AI elements drive psychological and behavioural engagement in e-commerce	High
(Ashish Suresh Awate, 2024)	Develop deep learning system for sentiment analytic/customer profiling to predict customer churn	Describes methodology steps: data collection, pre-processing, feature extraction (TF-IDF, contextual embeddings like BERT/GPT) and data fusion	Computational linguistics, AI, and data analytics	Notes data privacy challenges, mentions general data sources	Focus on leveraging multi-source data (textual and transactional) for predictive analytic in e-commerce	Medium

(RAJU et al., 2024)	Proposes optimized deep learning model for sentiment analysis to improve e-commerce customer experience	Fejer kernel filtering, fuzzy dictionary-based feature extraction, seahorse Annealing optimization for feature selection, and BERT training, compared performance metrics with SVM, NB, ENN models	Integrates fuzzy logic, metaheuristic optimization, and BERT deep learning architecture	Mentions external datasets (Amazon, Customer Reviews, Kaggle); lists F1-score, accuracy, precision, recall results	Improving sentiment analysis accuracy to enhance personalized recommendation and customer experience in e-commerce	High
(Castillo & Taherdoost, 2023)	Provides general overview of AI's	Review based presents survey	Mentions foundational concepts like ANNs and	Cites external data sources (statista) without detailing	General review of AI adoption and	Low
	9impact on e-business	statistics from external source	ethical/privacy concerns	the internal methodology	benefits in e-commerce	
(Chaldun et al., 2024)	Influencing factors of Indonesian coffee product customer experience using Aspect-based Sentiment analysis	Utilized GPT-3 Davinci model for Zero-shot ABSA; benchmark model accuracy against Senti WordNet dataset; thorough data processing steps detailed	Relies on established social/marketi ng theories for context	Mentions data collection source method (web scrapping); documented F1-score (92.1%) validation metrics. Discusses review row increase due to multiple aspects	Directly applies ABSA using LLMs to extract Customer experience insights for export marketing/bu siness	High
(Chinchanachokchai et al., 2021)	Investigates moderating effects of consumer expertise on performance of user-based collaborative filtering (CF) vs content-based systems	Constructed a specialized "BeerXpert" recommender system; used matrix factorization for CF and TF-IDF for content -based analysis; documented hyperparameter tuning (RMSE); utilized a controlled behavioural experiment	Grounded in recommender system typologies (CF/Content) and consumer behaviour concepts (expertise)	Detailed technical setup of the system architecture, data source, and participant demographics	Focus on optimizing recommender system strategy based on user characteristics in e-commerce	High

(Davoodi et al., 2025)	Propose using ABSA to understand customer satisfactio n by identifying important component of e-commerce platforms	Manually collected and annotated dataset focusing on 14 aspects; tested performance of five deep learning/Machi ne learning models (RoBERTa, DistilBERT, XLNet, LSTM, BERT)	Grounded in customer satisfaction and sentiment analysis concepts, notably linking review sentiment to purchase decisions	Mentions data sources and five e-commerce platforms analysed; details the annotation process by two annotators; mentions open data source availability	Directly addresses customer feedback utilization for e-commerce service improvement	medi um
(Dewi et al., 2024)	Analyse user reviews on shopee and Lazada to compare customer sentiment using Random Forest classifier	Used systematic data collection (manual observation); employed two features' representations (count vectorizer, TF-IDF) with Random Forest; partitioned data 80:20	Application focused, relying on the mechanism of the chosen ML algorithm	Specified data size and platforms	Comparative sentiment analysis to guide platform strategy in e-commerce	medi um
(Perez-Vega et al., 2021)	To enhance the outcomes of online engageme nt behaviours	Using AI systems as Organism to advance theory in management; use of Stimulus – Organism-Response (S-O-R) theory	Relies on S-O-R paradigm engagement behaviours	Clearly defines the purpose of the conceptual model	Proposes that combining uncoslicited online customer engagement data is a better source of input for the AI organism.	High
(Filahi et al., 2025)	Develop Machine learning based sentiment analysis for recommen dation prediction to enhance e-commerce decision making	Compared Logistic Regression Naïve Bayes, SVM, RF, AdaBoosting, GRU and LSTM; utilized Count Vectorizer and TF-IDF; primarily uses Recall as metric due to imbalanced dataset	Anchored in established machine learning and/deep learning techniques and relating them to supply chain logistics and IoT	Identifies Kaggle's "women's E-commerce Clothing Reviews" dataset; meticulously details split ratios and performance metrics (Precision, Recall, F1-score)	Directly linking SA and ML models to core e-commerce functions like personalized recommendat ions and inventory optimization	High
(Hassan et al., 2025)	Investigate moderatin g effect of personaliz ed recommen	Quantitative study using SEM/CFA;	Tests the trust satisfaction loyalty framework and links	Details data collection method and participant demographics; cites validated scales used	Examining how AI personalizati on strategically impacts consumer	High

	dations on trust satisfactio n-loyalty relationshi p in AI	utilized large sample	personalizatio n through social presence theory		relationship and loyalty in e-commerce	
	driven e-commerce					
(He et al., 2022)	Develop fusion sentiment analysis combining textual analysis and machine learning to mine online product experience	Detailed methodology including Fast Text word embedding, dimensionality reduction using PCA, sentiment classification using SVM, and topic extraction using LDA; engineered novel dictionary extension method and weighted calculation for text vector	Grounded in established techniques like SVM, LDA, and PCA; focuses on overcoming limitations of dictionary/machine learning method	Details source amazon reviews, number of collected reviews and specific portioning for training/ testing	Provides actionable insights for product improvement and marketing strategy optimization in e-commerce based on sentiment data	Medium
(Heraz et al., 2024)	Propose advanced forecasting model leveraging emotion gesture correlation to predict returning visitors	Used LightGBM, Extra Trees, Random Forest classifiers; heavily processed unique data types; addressed class imbalance using SMOTE; documented feature selection via Mean decrease in impurity	predictive modelling, utilized adaption of clynes' initial list of emotions tailored to web browsing	Provided detailed data collection process using anonymous visitors ID; explicitly lists all 12 selected generalization test on two e-commerce sites	Predicting user return behaviour and initial engagement based on emotional response in e-commerce	High

(Khrais, 2020)	Lay foundation for universal definition of "explainab ility"	Systematic approach using corpus analysis, word cloud analysis, quantified frequency normalization of	Defines opaque interpretable, and comprehensib le systems; links concepts like predictability,	Details data sources; NIPS and Cognitive Science Society publication from 1900/1987 to 2020	Strategic role of AI and XAI in e-commerce and consumer demand	High
		"explainability "	verifiability, and accuracy			
(Krishna et al., 2025)	Proposes advanced recommen dation framework integrating SA and CF using MLA-EDTANet/ OcOA	Uses novel MLA-EDTCNet architecture, OcOA optimization, and MCGAN for balancing data rigorously t4ested metrics/compa rison with six baselines	Builds explicitly on CF models, metaheuristic optimization data; and addresses AI/ML challenges	Detailed experimental system specs; discusses model performance against baselines; mentions data source	Enhancing e-commerce recommendat ion accuracy/use r satisfaction via hybrid deep learning	High
(Wu & Chi, 2023)	Propose a comprehen sive three tired recommen dation system tailored to different customer journey	Outline use of KNN/SVD(Ma trix factorization) for CF and TF-IDF/K-means for content-based matching; conceptual presentation of implementatio n steps	Concepts of collaborative filtering, content-based systems, and the cold start problem	Identified sources; mentions integration of explanation and transparency	Designing flexible recommendat ion strategies catering to varying business and customer needs in e-commerce	High
(Kunz et al., 2017)	Propose a dynamic strategic value creation framework for data driven customer engageme nt	Conceptual derived from a synthesis of literature and practitioner insight	Grounded in customer engagement theory, Bigdata concepts (Volume, velocity, variety, veracity, value)	Discusses challenges related to data veracity, legal privacy issues, and technical skills	Strategic framework for utilizing bigdata/analy tic to manage customer engagement and value creation	High

(Li et al., 2024)	Develop CNN-SVM sentiment analysis sentiment analysis using keyword generated image for e-	Detailed methodology: Word2Vec-TextRank for key word extraction, integration of stable diffusion generative AI for text -to - image	Relied on established models like CNN, SVM, and NLP method	Mentions details of data collection; shares data sources location; compares performance against five ML/DL	Novel approach to enhance sentiment analysis accuracy by leveraging multi-model data for e-commerce	High
	commerce reviews	conversion hybrid CNN-SVM classification; thoroughly evaluated with multiple metrics				
(Liu-Thompkins et al., 2022)	Investigate the differential effects of artificial empathy-perspective taking vs empathic concern on customer experience	Conducted experiments using two agent types(human/ AI) and two empathy levels(low/hig h); rigorous ANCOVA/MANCOVA tests were performed	Grounded in the core concept of artificial empathy, clearly distinguishing between perspective - taking and empathic concern	Reports manipulation checks for empathy and humanness perception, supporting the experimental design validity	Behavioural exploration of key design factors (empathy) for AI agents in service/marketing	High
(Malik & Bilal, 2024)	Provide a taxonomy of NLP application for online customer reviews and examine emerging methods	Systematic literature review methodology; meticulously defined search query, inclusion/exclusion criteria, and article screening process, analysing 154 publication	Developed five category taxonomy; sentiment analysis, review management, customer experience, user profiling, maketing/reputing	Details research questions, highlights distribution of data sources; discusses limitation and future research direction	Comprehensi ve overview of the state of the art use of NLP in e-commerce	medium
(Marjerison et al., 2022)	Apply the use of gratification (U&G) model to assess consumer acceptance of chatbots in e-commerce	Quantitative survey methodology; primarily focused on psychometric analysis (reliability, correlation, simple regression analysis	Tests conceptual framework derived from the U&G model, incorporating technology,hedonic, and risk dimension	Details sample demographics and survey factors	Investigates consumer behavioral intentions and acceptance towards AI chatbots in e-commerce	High

(Venu Gopalachari et al., 2023)	Develop multi-domain keyword extraction	Using dynamic scraping (Amazon, flipkart, Snapdeal);	Grounded in Aspect based Sentiment Analysis concepts and	Details data sources, methodology (weights, normalization), and	Addresses review quality, cold start problem and	High
	using Word vectors to streamline customer experience	implemented noun adjective pair extraction; integrated proprietary credibility score	word embedding	explicitly addresses data availability	improving review presentation	
(Sharma et al., 2020)	Explore integration of reinforcem ent learning and natural language processing in AI enhanced marketing automation	Outlines a planned methodology including collecting data selecting BERT/GPT models, iterative training, and evaluating using accuracy, precision, recall,F1-score	Integrates two advanced theoretical computational concepts: RL (Markov Decision Processes) and NLP (BERT/GPT) within a marketing automation context	Details planned sample size, clearly mentions method of data collection, explicitly mentions ethical compliance (GDPR) and consent	Revolutionizing customer engagement strategies using advanced AI techniques in marketing	High
(Chioma Susan Nwaimo et al., 2024)	Examine data-driven strategies for enhancing user engageme nt in digital platforms	Review synthesizing reliance on various methods: quantitative analysis (A/B testing, statistical tests like t-tests/chi-square) and qualitative methods (interview/focus)	Grounded in established concepts of user retention, customer loyalty, and predictive analytic	Stresses prioritization of data privacy and ethical considerations, mentioning GDPR principles	Focus on leveraging analytics(especially predictive analytics demonstrated by Netflix/amazon cases) for user retention	medium
(Br Perangin-Angin et al., 2024)	Focus on BERT/GN N application to improve business intelligenc e capabilitie s for customer interaction classificati on and	Achieved high accuracy: BERT 97% classification,9 3% sentiment analysis; GNNs achieved Mean Average Precision (MAP) 0.92, NDCG 0.88;	Explicitly uses BERT (Transformer model) and GNNs (Graph format processing)to model complex customer product relationship	Details inputs (conversational text, transactional data, product information) present quantitative results in structured tables	Directly enhancing core e-commerce Business intelligence functions; automated customer service and personalized recommendat ions)	High

		detailed equations and				
	product recommen dation	rigorous metrics used				
(Thomas & J.R., 2024)	Propose a deep learning based sentiment driven recommen dation system combining SA and CF	Used BERT - GRU model for sentiment analysis; utilized item based CF due to data set sparsity; specified 75:25 data spilt; measured RMSE, accuracy, precision, recall, F1 score	Integrates transformer architecture (BERT) with recurrent networks (GRU) and traditional CF systems	Cites Kaggle datasets; compares metrics against five other DL/ML methodologies	Developing precise, personalized recommendat ion by leveraging sentiment in e-commerce	medi um
(Ruan & Mezei, 2022)	Investigate s when AI chatbots lead to higher customer satisfactio n than HFLEs, considerin g product attribute type	Controlled 2*2 between subjects experiment; manipulated response delay; employed statistical test (MANOVA)	Relies on established concepts like information quality dimensions and hedonic/utilita rian attributes	Presents detailed research design	Directly addresses AI/Human frontline performance in B2C e-commerce	High
(Roy et al., 2024)	Introduce hybrid recommen der system combining content based and item-based CF using cascaded transforme r LLMs	Designed novel CasT5RoBER T model; rigorously compared embeddings; utilizes TF-IDF for content filtering; employs weighted scoring mechanism	Grounded in deep learning LLMs/Transf ormers), collaborative filtering, and sentiment scoring	Identifies dataset; details preprocessing/clean ing steps (HTML tag/stopword removal) provides quantitative comparison tables	Advancing apparel recommendat ion accuracy using multi model data and cascaded LLM architecture	High

(Shan et al., 2025)	Examine customer satisfaction through transformer-based sentiment analysis for improving bilingual e-commerce	Employed transformer models (ELECTRA, BERT) for classification/prediction on Chinese datasets; measured alignment via cohen's Kappa	Relies on deep learning (Transformers, BiLSTM) and NLP concepts (N-grams, VADER)	Uses two Chinese e-commerce datasets; mentions using Google translate API	Focus on utilizing bilingual sentiment analysis to understand customer satisfaction in e-commerce	medium
(Shahbazi et al., 2025)	Cross domain adaptive recommendation system, integrating real behavioural tracking with multi-domain knowledge	Designed CDARS architecture with explainable adaptive learning (EAL) module; quantitative user study across three domains; validated using CTR and NDCG metrics; comprehensive robustness evaluation	Grounded in advanced recommendation theories; cross-domain personalization, knowledge graphs, and real time adaptive learning	Detailed architecture diagram (EAL, Overall CDARS); explicitly details user study demographics and metrics achieved (7.8% CTR improvement over baseline)	Developing high dynamic, explainable, and trustworthy recommendation systems across multiple digital domains	high
(Yi & Liu, 2020)	Propose ML-based approach using MSVM and collaborative/P-P similarity for recommending shops/products based on customer reviews	Used MSVM classifier; employed collaborative filtering (CF) and product-Product (P-P) similarity algorithm; validated using MAE, MSE, and MAPE metrics	Grounded in machine learning (SVM) and recommendation systems (CF/P-P similarity) principles	Mentions states training data volume; details system specs (intel core i7, MATLAB)	Developing a multi-criteria recommendation system focused on customer experience and shop quality prediction	High

(Sidaoui et al., 2020)	Develop and validate novel methodolo gy using AI	Conducted crowdfunded experiment (N=193) using chatbot interviewer; used VADER	Grounded in Consumer engagement framework, addressing the measurement of Consumer	Detailed recruitment process, intercoder reliability, specific algorithm validation	Innovative method for real time customer experience assessment using AI	High
	augmented chatbot interviews for customer experience assessment	SA model; validated model performance through rigorous statistical comparison against manual coding /established scales	engagement feelings (mood, emotion, hedonic value		driven Conversation al agents	
(Sinnasamy & Sjaif, 2022)	Explore sentiment analysis using term-based method and N-gram on amazon product reviews	Employed SVM, NB, DT, KNN classifiers; utilized TF-IDF and N-grams for feature extraction	Focused application relying on traditional machine learning models and VSM concepts	Used amazon electronic category dataset; listed summary performance table	Direct application of Sentiment analysis techniques to extract valuable information from e-commerce reviews	medi um
(Sharma & Paço, 2025)	Investigate moderatin g effect of emotional intelligenc e on relationshi ps between AI usage, AI-PR, and Green Product Awareness (GPA)	Quantitative survey (N=349); employed PLS-SEM/Process macro for path analysis, mediation, and moderation; addressed Common Method Bias using VIF checks	Test hypothesis related to AI-PR, GPA, Green Behavioural Intentions (GBI), and EI	Detailed description of prior and post hoc power assessment, ensuring sample size adequacy; provided reliability/validity metrics	Focus on the intersection of AI, personalizati on, and sustainability /green consumer behaviour in e-commerce	High

(Tamara et al., 2023)	Explore Gen Z customer experience and engageme nt with chatbots in e-commerce	Qualitative research using semi-structured interviews; noted use of triangulation/ member checking for trust worthiness	Mentions foundational theories like innovation theory, trust commitment theory, and flow model for context	Details data collection method (semi structured interviews, direct/remote) and self-as-instrument status	Focus on Genz perception and preference for AI chatbots in the e-commerce customer journey	High
(Truong, 2025)	Investigate individual and interactive effects of gender and culture on customer emotional experience in online textual reviews	Rigorous selection of 6 datasets based on detailed demographic metadata; employed machine learning models (BERT/VADE R derivates) for emotion detection; statistical analysis using ANOVA/MAN OVA)	Ground research in Hofstede's cultural dimensions theory and gender roles, constructing a conceptual model showing effects on Valence, Arousal, Dominance (VAD)	Details the challenging screening process for demographics data across 31 datasets; details covariates and validation procedures used	Crucial for designing inclusive AI tools and personalized marketing strategies based on demographic /cultural emotional differences	High
(Xia & Wang, 2025)	Propose multi-task product recommen der system for cold start and existing users by integrating sales data and user satisfactio n	Designed two models: ranking-based (method 1) and Bias neural collaborative filtering (BNCF) (Method 2); rigorously evaluate3d against baselines (LightGCN, BiasedMF, NCF); performed ablation studies on bias factors	Grounded in Neural Collaborative Filtering (NCF), Bayesian Personalized Ranking (BPR), and incorporating item-level popularity/bia s factors	Used real dataset from Rakuten lchiba; data split ratios; detailed hardware specs mention ethical process for user survey	Addressing the chronic cold start problem and enhancing NCF for personalized e-commerce recommendat ion	High
(Chen et al., 2024)	Review LLMs role in personaliz ation, focusing on conversati onal agents explainabil ity, and tool learning	Survey method; categorization of personalization techniques (recommender systems, personalized assistance); detailed review of LLM application as	Grounded in deep learning (Bert, LLMs) conversational recommendati on theory, and knowledge graph/semanti c representation principles	Detailed tables of LLM approaches/datasets	Comprehensi ve roadmap for adapting state of the art LLMs for personalized recommendat ion e-commerce interaction	High

		knowledge base, content				
		interpreter, and explainer				
(Abdalla et al., 2024)	Develop hybrid AT -IN based CF-BiLSTM model for sentiment prediction and recommen dation	Uses complex hybrid model combining CF,BiLSTM, and a hybrid self-attention mechanism with incentive learning; achieved high accuracy (98.03%) and lowest RMSE (1.19) over LGBM/RNN/ BiLSTM baselines	Integration of CF, deep learning (BiLSTM) self-attention and optimized incentive learning to model sentiments/pre ferences	Specifies datasets used; provides extensive comparative tables of accuracy/MSE/RM SE/precision	Creating a highly precise, sentiment - driven recommende r system for e-commerce platforms	High
(Zhao et al., 2021)	Propose new algorithm (LSIBA-ENN) for sentiment analysis of online product reviews, focusing on feature extraction	Employed novel LTF-MICF term weighting and HM-EWA feature selection; performance assessed using precision, recall, f-measure, accuracy across five weighting schemes and two datasets	Integrates ENN, Bat algorithm optimization, and statistical weighting schemes to handle complex, nuanced, textual data	Mentions explicit two datasets gathered from Amazon; lists comparative metrics in detail	Improving SA accuracy and efficiency for e-commerce review classification	High

Row Labels	**Count of JournalName**
Advances in Nonlinear Variational Inequalities	1
AI & SOCIETY	1
Alexandria Engineering Journal	1
Applied Computational Intelligence and Soft Computing	1
Big Data and Cognitive Computing	1
Cogent Business & Management	1
Complex & Intelligent Systems	1
Computers, Materials & Continua	1
Electronic Commerce Research	2
Electronics	1
Encyclopedia	1
Future Business Journal	1

Future Internet	1
IEEE Access	3
Information Processing & Management	1
Information Systems Research	1
International Journal of Advanced Computer Science & Applications	1
International Journal of Advanced Computer Science and Applications	3
International Journal of AI Advancements	1
International Journal of Electronics and Communication Engineering	1
International Journal of Engineering, Science and Information Technology	1
International Journal of Management & Entrepreneurship Research	1
Journal of Consumer Behaviour	1
Journal of Electronic Commerce Research	1
Journal of Intelligent Systems	1
Journal of Knowledge Learning and Science Technology ISSN: 2959-6386 (online)	1
Journal of Retailing and Consumer Services	2
Journal of Service Management	1
Journal of Services Marketing	1
Journal of the Academy of Marketing Science	1
Journal of Theoretical and Applied Information Technology	1
Jurnal EMBA: Jurnal Riset Ekonomi, Manajemen, Bisnis dan Akuntansi	1
PeerJ Computer Science	1
PLOS One	1
Scientific Reports	1
Sustainability	1
Wireless Personal Communications	1
World Wide Web	1
Grand Total	44

Figure2. Number of paper publication in the Journals

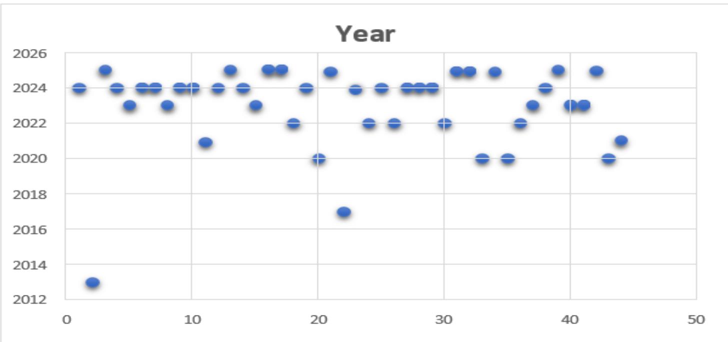

Figure3. Yearly paper publication data

For a comprehensive assessment of publication patterns, figure 2 illustrates that the International Journal of Advanced Computer Science and Applications, IEEE Access and Journal of Retailing and Consumer Services, and electronic commerce research are the primary journals publishing research papers on artificial intelligence (AI) and consumer engagement. This concentration suggests that the topic is attracting growing attention from both interdisciplinary and applied marketing domains. The rise of publication from 2018 onwards and the concentration of number of dots in the 2024 as illustrated in Figure 3 reflects, the maximum number of publications in the year and the advancement of deep learning and affective computing. In addition, there has been a broader conceptual shift from transactional customer relationship management (CRM) to emotionally intelligent consumer engagement, which is reflected in the use of sentiment analysis and affecting computing tools.

A total of 44 studies were reviewed after applying inclusion and exclusion criteria. These studies collectively examine the intersection of artificial intelligence (AI), emotional regulation, and consumer engagement across multiple contexts within the digital environment. Each study was assessed for clarity of aim, methodological rigour, theoretical integration, transparency, relevance, and overall quality (high, medium, or low). Most of the studies were

rated as high for theirs strong methodology and relevance while few of the studies were rated as medium few of them as low. From the table 5 major themes were derived -

Theme 1: AI based sentiment analysis and consumer insights

Studies on this theme explore how AI and NLP techniques (for example, BERT, LSTM, and TF-IDF) were used to analyse consumer sentiment from online reviews and enhance the understanding of customer satisfaction and preferences.

Methodological strengths

High quality studies (e.g., Alghamdi et al., 2025;Filahi et al., 2025; Davoodi et al., 2025)demonstrated methodological rigor by employing large datasets, advanced models, and transparent validation metrics

Theoretical integration

Most studies adopted computational approaches with limited behavioural or emotional regulation framework, highlighting a theoretical gap between affective science and machine learning applications

Key outcomes and contributions

Findings confirm that AI driven sentiment models enhance accuracy in predicting consumer engagement and decision making, but lack insight into underlying emotional regulation mechanism.

Theme 2: AI driven personalization and recommendation Systems

Studies under this theme explored AI recommender systems and hybrid models (CF, NCF, BERT- based, GNN) (Truong, 2025;Chen et al., 2024;Venu Gopalachari et al., 2023).

Methodological rigor

Grounded in decision making theories and personalization logic but rarely in psychological frameworks

Key Outcome

Improved recommendation accuracy, enhanced user satisfaction, but limited exploration of consumer emotion regulation

Quality summary: Majority rated high quality; strong in transparency and experiential rigor **Theme 3: Emotional Regulation and consumer engagement**

Studies under this theme have examined emotional intelligence, empathy, or affective computing in AI interactions(Perez-Vega et al., 2021).

Theoretical grounding: Explicit use of Stimulus Organism and Response (S-O-R), emotional intelligence, or empathy frameworks (e.g., Liu-Thompkins et al., 2022)

Results: Emotional cues embedded in AI enhanced consumer satisfaction, trust, and engagement.

Gap: Gross's emotional regulation strategies can be operationalized in AI consumer interaction studies

Quality summary: Mostly high; experimental designs strong in validity

Theme 4: Conversational Agents and chatbots in Consumer Experience

AI chatbots have been used for customer service, engagement, and real-time feedback (El-Ansari & Beni-Hssane, 2023;Sidaoui et al., 2020).

Methodological patterns: Experiments, proof of concept systems, qualitative interviews.

Key findings: chatbots influence satisfaction, trust and emotional engagement, especially when personalization and empathy are embedded.

Theoretical integration: uses flow theory, Uses &Gratification, S-O-R frameworks; some conceptual gaps persist in emotion measurement.

Quality summary: Mixed (high in experiments, medium in conceptual, or qualitative studies).

Theme 5: Cross-domain, Explainability, Ethical Perspectives

Conceptual frameworks on AI explainability, transparency, and ethical AI for engagement (e.g., Kunz et al., 2017;Chen et al., 2024;Khrais, 2020)

Theoretical contribution: Defines constructs, such as transparency, interpretability, and trust. *Relevance:* Provides groundwork for integration emotional regulation and AI explainability in future empirical designs

Quality: often rated low to medium in quality due to lack of data validation

AI techniques have advanced methodological sophistication, allowing precise consumer modelling and prediction analytics. However, the integration of psychological constructs (such as emotions) remains minimal. Although, there are studies (studies) that have revealed the use of emotional cues embedded in AI enhancing consumer satisfaction, engagement and trust but the operationalization of emotional regulation strategies in AI consumer studies still a gap that needs to be addressed.

DISCUSSION

Building upon the thematic synthesis of 44 studies, this discussion interprets how AI-driven mechanisms, such as sentiment analysis, recommendation systems, and conversational agents, contribute to emotional regulation. The discussion integrates the findings across themes to develop theoretical, methodological, and practical insights

Theme 1: Sentiment Analysis and Consumer Insights

Studies in this theme demonstrate methodological maturity in analyzing consumer sentiment through AI (e.g., BERT, LSTM) but lack psychological interpretation. This supports the need to integrate Gross's (1998) emotional regulation model–understanding how AI-driven sentiment analysis does not just detect emotions but can also facilitate attentional deployment or cognitive reappraisal during online experience.

Theme 2: Personalization and Recommendation Systems

High-quality studies in this cluster show how AI-driven personalization enhances satisfaction and decision quality, aligning with the stimulus-organism-response paradigm. AI functions as a "stimulus" that shapes the consumer's internal states (organism) via adaptive

recommendations, evoking cognitive and affective engagement. However, few studies have examined emotional regulation mechanisms, such as attentional control or situation modification, leaving a gap for future psychological integration.

Theme3: Emotional Regulation and Consumer Engagement

A subset of studies addressing empathy and emotional intelligence bridges the AI and consumer psychology. They showed that affective cues embedded in AI enhance trust, perceived humanness, and sustained interaction-confirming Gross's emotion regulation process in real-time digital contexts. These findings empirically support the theoretical argument that AI acts as a co-regulator of consumer emotions and reinforces engagement.

Theme4: Conversational Agents and chatbots

Chatbot-based studies validated how empathic communication enhances engagement, satisfaction, and trust. This aligns with the consumer engagement theory (Brodie et al., 2011), where emotional resonance deepens cognitive and behavioral participation. However, qualitative studies have emphasized emotional resonance, while quantitative studies still lack validated emotion regulation measures – a methodological gap.

Theme 5: Explainability, Ethics, and Trust

Conceptual papers have highlighted transparency and explainability as emerging themes of emotional engagement. They show that when AI explains its decisions, it fosters trust, an affective state tied to the regulation of uncertainty. The link between explainability and emotional well-being remains underexplored, highlighting the future direction for emotionally responsible AI.

These findings collectively highlight how AI acts as both a stimulus (S-O-R model) and co-regulator (Gross, 1998) of consumer emotions, shaping affective, cognitive, and behavioral engagement responses

Traditionally, the integration of marketing and information technology integration occurred through Customer Relationship Management (CRM) systems designed to strengthen long-term relationship with the key customer segments. These systems are primarily operational-optimizing transactions, automating, communication, and enhancing efficiency (Ledro et al., 2022). However, the emergence of AI has redefined CRM into a more adaptive data-driven system capable of understanding and responding to consumer emotions in real time (Ledro et al., 2022). From the perspective of the stimulus-organism- response (S-O-R) framework ((Mehrabian & Russell, 1974); (Eroglu et al., 2001), such AI mediated interactions serve as stimuli that evoke affective and cognitive responses within the consumer's internal state (the organism). Personalized recommendations, empathic chatbot replies, and sentiment-aware feedback act as environmental cues that trigger consumer appraisal, attention, and emotional arousal.

The Emotional Regulation Model provides a complementary lens to understand the psychological mechanisms underlying these responses (Gross, 1998, 2015). Acting as a stimulus, AI can facilitate situation modification (altering the digital environment to reduce negative effects) and attentional deployment (guiding the focus toward positive or relevant cues). Through Cognitive reappraisal, AI-driven personalization reinterprets product or brand value, reshaping consumers' emotional states and decision-making.

Hence, AI functions not only as a technological tool but also as a co-regulator of consumers' affective experience. It actively participates in the emotional regulation process-identifying, reinforcing, and modulating consumer emotions through adaptive feedback and empathic design. This synthesis aligns with the thematic findings of the review, in which high-quality studies on chatbots and personalization systems demonstrated the ability of AI to perceive and influence affective responses

The integration of these theoretical perspectives reframes AI as an active participant in consumers' emotion-regulation processes. This interpretation deepens our understanding of consumer engagement, suggesting that consumer engagement in the digital environment depends not only on technological functionality but also on the emotional intelligence embedded within AI systems.

Overall, the systematic review achieved its primary objectives by offering a theoretically grounded understanding of how AI technologies facilitate emotional regulation and enhance consumer engagement while identifying the conceptual and methodological directions necessary for advancing this interdisciplinary field.

Theoretical implication

This review uncovers how artificial intelligence (AI) aligns with emotion regulation processes, thereby influencing consumer engagement. This extends the existing theoretical framework in several ways.

First, it extends the Stimulus-Organism-Response (S-O-R) framework by introducing emotion regulation as the missing psychological mechanism that explains how consumers cognitively and emotionally respond to AI stimuli. Second, it reframes consumer engagement not merely as a behavioral outcome, but as a psychological response to AI-mediated emotional regulation. Third, it challenges the technological bias of traditional customer relationship management (CRM) and technology adoption models (Davis, 1989; Venkatesh & Davis, 2000) by incorporating an emotional dimension, thereby bridging marketing technology with psychological theory. Collectively, this review integrates technological emotion and consumer psychology, offering a more holistic understanding of how emotionally intelligent AI systems shape consumer engagement.

Furthermore, the study contributes conceptually by presenting an integrated framework that links (Gross, 1998) the Emotional Regulation Model, the S-O-R paradigm, and Consumer Engagement Theory, providing a new interpretative lens for studying AI-mediated interaction. **Managerial contribution**

Managers and practitioners can leverage these insights to design emotionally attuned AI systems that perceive and respond to consumers' affective cues, thus enhancing trust, empathy, and sustained interactions. Integration emotional regulation processes into AI-driven CRM can help organizations not only improve engagement metrics but also build deeper, long-term relationships with consumers.

The beneficiaries of this work include AI developers, marketing strategists, and CRM practitioners, who can utilize these insights to move beyond surface-level emotional responsiveness toward psychologically informed engagement design. While current AI systems stimulate empathy through sentiment analysis or adaptive messaging, this review highlights the need to understand the underlying psychological mechanisms, specifically how AI co-regulates consumer emotions and sustains engagement. For marketers, effective AI implementation should not only rely on data-driven personalization but should also align with emotional regulation processes, such as attentional focus and cognitive reframing, which shape consumer affect and trust. Organizations can design AI interfaces that are not merely reactive but emotionally intelligent, fostering well-being, satisfaction, and long-term loyalty.

Future research Directions

Advancing Psychological Theory – Theories like Self-determination theory (SDT) (Deci & Ryan, 1985) Appraisal theory of Emotions (Lazarus, 1991) Cognitive Dissonance Theory (Festinger, 1957) Theory of Planned Behaviour (Ajzen,1991), Elaboration Likelihood Model (Petty & Cacioppo, 1986) Social Exchange theory (Blau, 1964) flow theory (Csikszentmihalyi,

1990) Uses and Gratification Theory (Katz et al., 1973), Broaden and Build Theory of positive emotions (Fredrickson, 2001)

Strengthening Methodological Approaches

The reviewed studies were predominantly descriptive or conceptual, with limited empirical validation of emotional or psychological mechanisms. Future research should employ a mixed method approach and an experimental method to test the causal relationships between AI features (e.g., empathy cues, personalization, conversational tone) and emotional regulation outcomes. The integration of affective computing, machine learning, and psychological measures (e.g., trust, satisfaction, and loyalty) can provide deeper insights into human–AI emotional interactions. Combining quantitative behavioural data with qualitative insights from user experience studies will enhance methodological rigor.

Ethical and well-being consideration

As AI becomes increasingly capable of reading and influencing emotions, future research should evaluate the ethical boundaries of emotional engagement. Studies should explore how an AI's emotional attunement affects consumer autonomy, trust, and psychological well-being, addressing concerns about manipulation, privacy, and algorithmic bias. Developing frameworks for responsible emotional AI design can help ensure that emotion regulation mechanisms enhance, rather than exploit, consumer relationships.

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REFERENCES

1. Abdalla, H. B., Gheisari, M., & Awlla, A. H. (2024). Hybrid self-attention BiLSTM and incentive learning-based collaborative filtering for e-commerce recommendation systems. *Electronic Commerce Research*. https://doi.org/10.1007/s10660-024-09888-5

2. Adomavicius, G., Bockstedt, J. C., Curley, S. P., & Zhang, J. (2013). Do Recommender Systems Manipulate Consumer Preferences? A Study of Anchoring Effects. *Information Systems Research*, *24*(4), 956–975. https://doi.org/10.1287/isre.2013.0497
3. Alghamdi, M., Al-shathry, N. I., Said, Y., Beyari, H., Sorour, S., Sattar, K. N. A., Alallah, F. S., & Alshareef, A. (2025). Improved chaotic fruit fly optimization with elman neural network based data-driven approach on product reviews classification. *Alexandria*
4. *Engineering Journal*, *127*, 628–641. https://doi.org/10.1016/j.aej.2025.05.042
5. Alrefae, R., Alqahmi, R., Alduraibi, M., Almatrafi, S., & Alayed, A. (2024). Enhancing Customer Experience Through Arabic Aspect-Based Sentiment Analysis of Saudi Reviews. *International Journal of Advanced Computer Science and Applications*, *15*(7). https://doi.org/10.14569/IJACSA.2024.0150742
6. Asante, I., Jiang, Y., Hossin, M. A., & Luo, X. (2023). OPTIMIZATION OF CONSUMER ENGAGEMENT WITH ARTIFICIAL INTELLIGENCE ELEMENTS ON
7. ELECTRONIC COMMERCE PLATFORMS . *Journal of Electronic Commerce Research* , 7–28.
8. Ashish Suresh Awate, E. al. (2024). Mathematical Modelling and Deep Learning: Innovations in E-Commerce Sentiment Analysis. *Advances in Nonlinear Variational Inequalities*, *27*(1), 52–81. https://doi.org/10.52783/anvi.v27.317
9. Blau, P. M. (1964). Exchange and power in social life. *Wiley*
10. Br Perangin-Angin, S. M., Malem Sembiring, D. J., Surbakti, A. B., & Darmansyah, S. (2024). The Role of Artificial Intelligence in Enhancing Business Intelligence Capabilities for E-Commerce Platforms. *International Journal of Advanced Computer Science & Applications*, *15*(9).
11. Brodie, R. J., Hollebeek, L. D., Jurić, B., & Ilić, A. (2011). Customer Engagement. *Journal of Service Research*, *14*(3), 252–271. https://doi.org/10.1177/1094670511411703
12. Castillo, M. J., & Taherdoost, H. (2023). The Impact of AI Technologies on E-Business.
13. *Encyclopedia*, *3*(1), 107–121. https://doi.org/10.3390/encyclopedia3010009
14. Chaldun, E. R., Yudoko, G., Maryunani, S. R., Kautsar, F. F. K., & Walidayni, C. T. (2024). Influencing factors of Indonesian coffee product customer experience in international market: an aspect-based sentiment analysis with GPT-3 Davinci model. *Cogent Business & Management*, *11*(1), 2429796.
15. Chen, J., Liu, Z., Huang, X., Wu, C., Liu, Q., Jiang, G., Pu, Y., Lei, Y., Chen, X., Wang, X., Zheng, K., Lian, D., & Chen, E. (2024). When large language models meet personalization: perspectives of challenges and opportunities. *World Wide Web*, *27*(4), 42. https://doi.org/10.1007/s11280-024-01276-1
16. Chinchanachokchai, S., Thontirawong, P., & Chinchanachokchai, P. (2021). A tale of two recommender systems: The moderating role of consumer expertise on artificial intelligence based product recommendations. *Journal of Retailing and Consumer*
17. *Services*, *61*, 102528. https://doi.org/10.1016/j.jretconser.2021.102528
18. Chioma Susan Nwaimo, Ayodeji Enoch Adegbola, & Mayokun Daniel Adegbola. (2024).
19. Data-driven strategies for enhancing user engagement in digital platforms. *International Journal of Management & Entrepreneurship Research*, *6*(6), 1854–1868. https://doi.org/10.51594/ijmer.v6i6.1170 Csikszentmihalyi, M. (1990). low: The psychology of optimal experience. *Harper & Row.*
20. Davis, F. D. (1989). Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology. *MIS Quarterly*, *13*(3), 319. https://doi.org/10.2307/249008
21. Davoodi, L., Mezei, J., & Heikkilä, M. (2025). Aspect-based sentiment classification of user reviews to understand customer satisfaction of e-commerce platforms. *Electronic Commerce Research*, 1–43.
22. Deci, E. L., & Ryan, R. M. (1985). ntrinsic motivation and self-determination in human behavior. *Springer.*
23. Dewi, T., Asrianda, A., & Afrillia, Y. (2024). Sentiment Analysis of Customer Satisfaction Towards Shopee and Lazada E-commerce Platform Using the Random Forest Algorithm Classifier. *International Journal of Engineering, Science and Information Technology*, *5*(1), 229–235. https://doi.org/10.52088/ijesty.v5i1.692
24. El-Ansari, A., & Beni-Hssane, A. (2023). Sentiment analysis for personalized chatbots in e-commerce applications. *Wireless Personal Communications*, *129*(3), 1623–1644. https://link.springer.com/article/10.1007/s11277-023-10199-5
25. Eroglu, S. A., Machleit, K. A., & Davis, L. M. (2001). Atmospheric qualities of online retailing. *Journal of Business Research*, *54*(2), 177–184. https://doi.org/10.1016/S0148-2963(99)00087-9
26. Festinger, L. (1957). A theory of cognitive dissonance. *Stanford University Press.*
27. Filahi, Y., Gul, O. M., Elghirani, A., Arican, E., Parlak, I. B., Kadry, S., & Karpouzis, K. (2025). Enhanced E-commerce decision-making through sentiment analysis using machine learning-based approaches and IoT. *PLOS One*, *20*(6), e0326744. https://doi.org/10.1371/journal.pone.0326744
28. Fredrickson, B. L. (2001). The role of positive emotions in positive psychology: The broaden-and-build theory of positive emotions. *American Psychologist*, *56*(3), 218–226. https://doi.org/10.1037/0003-066X.56.3.218

29. Gross, J. J. (1998). The Emerging Field of Emotion Regulation: An Integrative Review.
30. *Review of General Psychology*, *2*(3), 271–299. https://doi.org/10.1037/1089-2680.2.3.271
31. Gross, J. J. (2015). Emotion Regulation: Current Status and Future Prospects. *Psychological Inquiry*, *26*(1), 1–26. https://doi.org/10.1080/1047840X.2014.940781
32. Hassan, N., Abdelraouf, M., & El-Shihy, D. (2025). The moderating role of personalized recommendations in the trust–satisfaction–loyalty relationship: an empirical study of AI-driven e-commerce. *Future Business Journal*, *11*(1), 66. https://doi.org/10.1186/s43093-025-00476-z
33. He, H., Zhou, G., & Zhao, S. (2022). Exploring E-Commerce Product Experience Based on Fusion Sentiment Analysis Method. *IEEE Access*, *10*, 110248–110260. https://doi.org/10.1109/ACCESS.2022.3214752
34. Heraz, A., Sajith, N., & Siddiqi, A. (2024). An Advanced Forecasting Model Leveraging Emotion-Gesture Correlation to Predict Returning Visitors Surpasses Visit Duration as a Predictive Factor. *Applied Computational Intelligence and Soft Computing*, *2024*(1). https://doi.org/10.1155/acis/5539658
35. Israfilzade, K., & Sadili, N. (2024). Beyond interaction: Generative AI in conversational marketing - foundations, developments, and future directions. *JOURNAL OF LIFE ECONOMICS*, *11*(1), 13–29. https://doi.org/10.15637/jlecon.2294 Katz, E. , Blumler, J. G. , & Gurevitch, M. (1973). Uses and gratifications research. *Public Opinion Quarterly*, *37*(4), 509–523.
36. Khrais, L. T. (2020). Role of artificial intelligence in shaping consumer demand in E-commerce. *Future Internet*, *12*(12), 226.
37. Krishna, E. S. P., Ramu, T. B., Chaitanya, R. K., Ram, M. S., Balayesu, N., Gandikota, H. P., & Jagadesh, B. N. (2025). Enhancing E-commerce recommendations with sentiment analysis using MLA-EDTCNet and collaborative filtering. *Scientific Reports*, *15*(1), 6739. https://doi.org/10.1038/s41598-025-91275-7
38. Kunz, W., Aksoy, L., Bart, Y., Heinonen, K., Kabadayi, S., Ordenes, F. V., Sigala, M., Diaz, D., & Theodoulidis, B. (2017). Customer engagement in a Big Data world. *Journal of Services Marketing*, *31*(2), 161–171. https://doi.org/10.1108/JSM-10-2016-0352
39. Lazarus, R. S. (1991). Emotion and adaptation. *Oxford University Press.*
40. Ledro, C., Nosella, A., & Vinelli, A. (2022). Artificial intelligence in customer relationship management: literature review and future research directions. *Journal of Business & Industrial Marketing*, *37*(13), 48–63. https://doi.org/10.1108/JBIM-07-2021-0332
41. Ledro, C., Nosella, A., Vinelli, A., Dalla Pozza, I., & Souverain, T. (2025). Artificial intelligence in customer relationship management: A systematic framework for a successful integration. *Journal of Business Research*, *199*, 115531. https://doi.org/10.1016/j.jbusres.2025.115531
42. Li, J., Huang, Y., Lu, Y., Wang, L., Ren, Y., & Chen, R. (2024). Sentiment Analysis Using E-Commerce Review Keyword-Generated Image with a Hybrid Machine Learning-Based Model. *Computers, Materials & Continua*, *80*(1), 1581–1599. https://doi.org/10.32604/cmc.2024.052666
43. Liu-Thompkins, Y., Okazaki, S., & Li, H. (2022). Artificial empathy in marketing interactions: Bridging the human-AI gap in affective and social customer experience. *Journal of the Academy of Marketing Science*, *50*(6), 1198–1218. link.springer.com/article/10.1007/s11747-022-00892-5
44. Malik, N., & Bilal, M. (2024). Natural language processing for analyzing online customer reviews: a survey, taxonomy, and open research challenges. *PeerJ Computer Science*, *10*, e2203. https://doi.org/10.7717/peerj-cs.2203
45. Marjerison, R. K., Zhang, Y., & Zheng, H. (2022). AI in E-Commerce: Application of the Use and Gratification Model to The Acceptance of Chatbots. *Sustainability*, *14*(21), 14270. https://doi.org/10.3390/su142114270
46. Mehrabian, A., & Russell, J. A. (1974). An approach to environmental psychology. *MIT Press*
47. Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D.,
48. Shamseer, L., Tetzlaff, J. M., Akl, E. A., Brennan, S. E., Chou, R., Glanville, J.,
49. Grimshaw, J. M., Hróbjartsson, A., Lalu, M. M., Li, T., Loder, E. W., Mayo-Wilson, E., McDonald, S., … Moher, D. (2021). The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. *BMJ*, n71. https://doi.org/10.1136/bmj.n71
50. Perez-Vega, R., Kaartemo, V., Lages, C. R., Borghei Razavi, N., & Männistö, J. (2021).
51. Reshaping the contexts of online customer engagement behavior via artificial intelligence: A conceptual framework. *Journal of Business Research*, *129*, 902–910. https://doi.org/10.1016/j.jbusres.2020.11.002
52. Petty, R. E., & Cacioppo, J. T. (1986). Communication and persuasion: Central and peripheral routes to attitude change. *Springer-Verlag*
53. RAJU, B., SRIRAM, M., & GANESAN, V. (2024). Optimized deep learning model for sentimental analysis to improve consumer experience in ecommerce websites. *Journal of Theoretical and Applied Information Technology*, *102*(7), 1–14. https://fringeglobal.com/wp-content/uploads/2024/07/httpsdoi.org10.69996jcai.2024014.pdf
54. Roy, S. S., Kumar, A., & Suresh Kumar, R. (2024). Metadata and Review-Based Hybrid Apparel Recommendation System Using Cascaded Large

Language Models. *IEEE Access*, *12*, 140053–140071. https://doi.org/10.1109/ACCESS.2024.3462793

55. Ruan, Y., & Mezei, J. (2022). When do AI chatbots lead to higher customer satisfaction than human frontline employees in online shopping assistance? Considering product attribute type. *Journal of Retailing and Consumer Services*, *68*, 103059. https://doi.org/10.1016/j.jretconser.2022.103059
56. Shahbazi, Z., Jalali, R., & Shahbazi, Z. (2025). Enhancing Recommendation Systems with Real-Time Adaptive Learning and Multi-Domain Knowledge Graphs. *Big Data and Cognitive Computing*, *9*(5), 124. https://doi.org/10.3390/bdcc9050124
57. Shan, S., Sun, J., & Macawile, R. M. C. (2025). Examining Customer Satisfaction Through Transformer-Based Sentiment Analysis for Improving Bilingual E-Commerce Experiences. *IEEE Access*, *13*, 51027–51041. https://doi.org/10.1109/ACCESS.2025.3551666
58. Sharma, N., & Paço, A. (2025). AI and emotions: enhancing green intentions through personalized recommendations—a mediated moderation analysis. *AI & SOCIETY*, *40*(4), 2821–2838. https://doi.org/10.1007/s00146-024-02031-w Sharma, N., Sharma, D., Singh, R., & Singh, R. (2020). Leveraging Reinforcement Learning and Natural Language Processing in AI-Enhanced Marketing Automation Tools.
59. *International Journal of AI Advancements*, *9*(4).
60. Sheng, M. L., Natalia, N., & Rusfian, E. Z. (2025). AI Chatbot, Human, and In-Between: Examining the Broader Spectrum of Technology-Human Interactions in Driving Customer-Brand Relationships Across Experience and Credence Services. *Psychology & Marketing*, *42*(4), 1051–1071. https://doi.org/10.1002/mar.22165
61. Sidaoui, K., Jaakkola, M., & Burton, J. (2020). AI feel you: customer experience assessment via chatbot interviews. *Journal of Service Management*, *31*(4), 745–766.
62. Sinnasamy, T. a/p, & Sjaif, N. N. A. (2022). Sentiment Analysis using Term based Method for Customers' Reviews in Amazon Product. *International Journal of Advanced Computer Science and Applications*, *13*(7). https://doi.org/10.14569/IJACSA.2022.0130780
63. Tamara, C. A. J., Tumbuan, W. J. F. A., & Gunawan, E. M. (2023). Chatbots in E-Commerce: a Study of Gen Z Customer Experience and Engagement–Friend or Foe? *Jurnal EMBA: Jurnal Riset Ekonomi, Manajemen, Bisnis Dan Akuntansi*, *11*(3), 161–175.
64. Thomas, R., & J.R., J. (2024). Revolutionizing E-Commerce: A Deep Learning-Based Sentiment-Driven Recommendation System. *International Journal of Electronics and Communication Engineering*, *11*(8), 111–122. https://doi.org/10.14445/23488549/IJECE-V11I8P112
65. Truong, V. (2025). Examining Gender and Cultural Influences on Customer Emotions.
66. *Journal of Consumer Behaviour*. https://doi.org/10.1002/cb.70034 Venkatesh, V., & Davis, F. D. (2000). A Theoretical Extension of the Technology Acceptance Model: Four Longitudinal Field Studies. *Management Science*, *46*(2), 186–204. https://doi.org/10.1287/mnsc.46.2.186.11926
67. Venu Gopalachari, M., Gupta, S., Rakesh, S., Jayaram, D., & Venkateswara Rao, P. (2023). Aspect-based sentiment analysis on multi-domain reviews through word embedding. *Journal of Intelligent Systems*, *32*(1). https://doi.org/10.1515/jisys-2023-0001
68. Wen, H., Zhang, L., Sheng, A., Li, M., & Guo, B. (2022). From "Human-to-Human" to "Human-to-Non-human" – Influence Factors of Artificial Intelligence-Enabled Consumer Value Co-creation Behavior. *Frontiers in Psychology*, *13*. https://doi.org/10.3389/fpsyg.2022.863313
69. Wu, K., & Chi, K. (2023). Enhanced e-commerce customer engagement: A comprehensive three-tiered recommendation system. *Journal of Knowledge Learning and Science Technology ISSN: 2959-6386 (Online)*, *2*(3), 348–359.
70. Xia, H., & Wang, Y. (2025). Enhancing Neural Collaborative Filtering for Product Recommendation by Integrating Sales Data and User Satisfaction. *Electronics*, *14*(16), 3165. https://doi.org/10.3390/electronics14163165
71. Yi, S., & Liu, X. (2020). Machine learning based customer sentiment analysis for recommending shoppers, shops based on customers' review. *Complex & Intelligent Systems*, *6*(3), 621–634. https://doi.org/10.1007/s40747-020-00155-2
72. Zhao, H., Liu, Z., Yao, X., & Yang, Q. (2021). A machine learning-based sentiment analysis of online product reviews with a novel term weighting and feature selection approach. *Information Processing & Management*, *58*(5), 102656. https://doi.org/10.1016/j.ipm.2021.102656

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