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TOPICAL REVIEW

Artificial Intelligence and Behavioral Economics: A Bibliographic Analysis of Research Field

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ABSTRACT Behavioral economics and artificial intelligence (AI) have been two rapidly growing fields of research over the past few years. While behavioral economics aims to combine concepts from psychology, sociology, and neuroscience with classical economic thoughts to understand human decision-making processes in the complex economic environment, AI on the other hand, focuses on creating intelligent machines that can mimic human cognitive abilities such as learning, problem-solving, decision-making, and language understanding. The intersection of these two fields has led to thrilling research theories and practical applications. This study provides a bibliometric analysis of the literature on AI and behavioral economics to gain insight into research trends in this field. We conducted this bibliometric analysis using the Web of Science database on articles published between 2012 and 2022 that were related to AI and behavioral economics. VOSviewer and Bibliometrix R package were utilized to identify influential authors, journals, institutions, and countries in the field. Network analysis was also performed to identify the main research themes and their interrelationships. The analysis revealed that the number of publications on AI and behavioral economics has been increasing steadily over the past decade. We found that most studies focused on customer and consumer behavior, including topics such as decision-making under uncertainty, neuroeconomics, and behavioral game theory, combined mainly with machine learning and deep learning techniques. We also identified several emerging themes, including the use of AI in nudging and prospect theory in behavioral finance, as well as undeveloped themes such as AI-driven behavioral macroeconomics. The findings suggests that there is a need for more interdisciplinary collaboration between researchers in behavioral economics and AI. We also suggest that future research on AI and behavioral economics further consider the ethical implications of using AI and behavioral insights in decision-making. This study can serve as a valuable resource for researchers interested in AI and behavioral economics.

INDEX TERMS Artificial intelligence, behavioral economics, behavioral finance, consumer behavior, investor behavior, decision making, neuroeconomics, machine learning, bibliometric analysis.

I. INTRODUCTION

Behavioral economics is a subfield of economics that examines the decision-making processes of individuals and groups and how they affect economic outcomes. It is an interdisciplinary field that combines elements of psychology, sociology, neuroscience, and economics to provide a more complete understanding of human behavior in the marketplace [1]. It differs from classical economics, which assumes that individuals are rational and always make decisions that maximize their utility. In contrast, behavioral economics acknowledges that people frequently behave irrationally and that a variety of factors, including emotions, social norms, and cognitive biases, can influence their decisions (cite:

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kai1979prospect). Behavioral economics does not annihilate the classical economic models but rather adds another layer of complexity when those models do not seem to hold true, especially when rationality is bounded by limits on information, time, and uncertainty. The origins of behavioral economics can be traced back to Adam Smith's seminal work, "The Theory of Moral Sentiments" in which he argued that human behavior was determined by the struggle between the "passions" and the "impartial spectator". [2]. However, it wasn't until the mid-20th century, when John Maynard Keynes developed the concept of "animal spirits" [3] that behavioral economics began to take shape. Despite this early work, behavioral economics faced limitations and was not widely accepted until the 1970s. In fact, many of the early pioneers of behavioral economics came from the field of psychology, such as Daniel Kahneman, a Nobel laureate in economics, and Amos Tversky. Their work on prospect theory and decision-making under risk and uncertainty [4] provided important insights into the ways in which psychological factors can impact economic behavior.

Artificial Intelligence (AI) technology has come a long way since its inception in the 1950s by John McCarthy, Marvin Minsky, and Frank Rosenblatt among others [5]. Recent advancements in machine learning, natural language processing (NLP), and computer vision have enabled AI to make significant breakthroughs in numerous scientific domains. In economics, AI has been used to develop predictive models [6], automate data analysis [7], and aid decision-making processes [8]. The application of AI in behavioral economics is still in its early stages, especially given its interdisciplinary nature, making it sit at the crossroads of several disciplines, including computer science, mathematics, psychology, and economics. However, significant progress has been made in recent years with the integration of AI into sub-fields such as finance, so-called behavioral finance [9], and advertising [10]. Researchers have developed algorithms that can predict consumer behavior [11], forecast stock market trends [12], and even identify and mitigate human biases [13]. Additionally, AI has been used to create behavioral simulations [14] that can provide insights into how various economic, regulatory, and behavioral factors might impact consumers and organizations in a market. The development of AI technologies has opened up new opportunities for behavioral economists, allowing them to analyze and understand complex economic systems in new and innovative ways. The potential applications of AI in behavioral economics are vast and varied, and the future of the field is undoubtedly thrilling and promising.

To the best of the author's knowledge, no bibliometric analysis of research articles on artificial intelligence (AI) in the behavioral economics field has been published. In this article, we will focus on the recent advancements in AI and behavioral economics during the last decade, exploring the ways in which AI is transforming the field and what the future of AI in behavioral economics looks like. To do so, we start by establishing the theoretical background in section II, followed by section III in which we define the bibliometric approach to analyze the first step, then we select a set of bibliometric tools and techniques to address questions regarding the overall trends in the artificial intelligence and behavioral economics field, section IV presents the analysis results, while section V discusses the key findings and suggestions. By doing so, we hope to contribute to the ongoing efforts to expand the role of AI in behavioral economics and to identify areas for future research.

II. THEORETICAL BACKGROUND

A. FROM CLASSIC TO BEHAVIORAL ECONOMICS

Although the psychological aspects of the economic decision-making process were known to the scientific community, interest in behavioral economics was limited as the classical economists believed that including psychological factors in the economic decision-making process would make the models too complex and difficult to solve. Additionally, it was assumed that any irrational behavior would be smoothed out by market forces and competition; therefore, traditional economic theory assumes that individuals are rational and self-interested beings who make decisions based solely on maximizing their own utility. As Richard H. Thaler points out [15], this assumption is known as the Homo economicus or economic man model, and it's more of an idealistic model or a normative theory that does not always hold in real life, which means it prescribes how people should behave rather than describing how actual humans (Homo Sapiens) behave, whose choice making is influenced by a variety of psychological factors, such as emotions, biases, heuristics, or mental shortcuts.

One example illustrating this assumption in comparison to actual behavior is the marginal-cost pricing principal [16], which is a pricing strategy where a good or service is priced at the marginal cost of producing one additional unit of the good or service. In classical economics, this principle is seen as an efficient pricing mechanism that leads to allocative efficiency. Behavioral economics, on the other hand, argues that by assuming that individuals make rational decisions and have perfect information in a competitive market, this principal isn't always consistent with the actual economic behavior; in fact, consumers may be more responsive to certain types of pricing strategies, such as bundling [17], than to marginal-cost pricing, as consumers can have a difficult time understanding the marginal cost of a product and may be more influenced by the overall price of a bundle.

Several factors prevented the development of behavioral economics at an early stage, including the reluctance of mainstream economists to adopt behavioral economics due to the lack of available data on decision-making behavior and the need for empirical evidence of the bonded rationality [18] before shifting from a well-established economic theory. Also, behavioral economics relied heavily on experimental methods and required interdisciplinary collaboration with other social scientists, such as psychologists and neuroscientists, which was not a common practice until recently. However, the rise of behavioral economics was mainly a response to the successive failures of traditional economic models in predicting and explaining many economic events like economic and financial crises over the last half-century, including the financial bobbles. Especially when steady advances in the experimental economics and psychology fields led to a greater understanding of how people actually behave in economic situations, including decision-making processes. Therefore, behavioral economics has provided an alternative framework and gained recognition as a sub-field within economics that can help explain why individuals and institutions make decisions that can lead to economic instability. As a result, there has been a growing interest in interdisciplinary research, greater availability of data, and increased institutional support for behavioral economics and the application of its insights to economic and financial decision-making, as highlighted by [19].

B. SUB-FIELDS OF BEHAVIORAL ECONOMICS

To identify other behavioral economic subfields, we use the JEL classification codes (Journal of Economic Literature), which are a system used to categorize economic research papers and cover a wide range of subfields in economics [20]. Based on the JEL codes descriptions, we identify several subfields that are relevant in behavioral economics, which are:

- Behavioral finance: Even though finance is a subset of economics, it is commonly considered a separate discipline because, even though both finance and economics deal with the allocation of scarce resources, finance has a more practical focus, as it is concerned with the application of economic principles to financial decision-making. Consequently, we can identify behavioral finance as a major subfield of behavioral economics, as it focuses specifically on the study of financial markets and financial assets in light of the psychological influences and biases that affect the financial decision-making process and investors' behavior, which can be the source for the explanation of market anomalies. It can be linked to JEL codes G11 G22 G41 D81.
- Decision-making under uncertainty: This subfield focuses on how people make decisions, including decision-making under risk and uncertainty, which involves the factors that influence their choices, such as cognitive biases, heuristics, emotions, and self-control. It can be linked to JEL codes D03 D64 D81 D83 D84 D91 Z13.
- Behavioral macroeconomics: Behavioral macroeconomics is a field of study that combines macroeconomic theories and models with insights from behavioral economics to better understand how individuals and groups make decisions in a macroeconomic context. Its main focus is to examine how human biases and heuristics affect macroeconomic phenomena such as economic growth, unemployment, inflation, monetary policy, and business cycles. It can be linked to JEL codes E31 E32 E61 E71.
- Behavioral game theory: Behavioral game theory uses game theory models to study how individuals and groups make decisions in strategic situations and how they interact with one another. It incorporates insights from psychology and sociology to explore how factors such as social norms, emotions, and cognitive biases influence decision-making in games. It can be linked to JEL codes C70 C78.
- Experimental economics: Experimental economics uses laboratory experiments to test economic theories and hypotheses. It is particularly interested in exploring how individuals and groups make decisions in controlled environments and how their behavior may differ from theoretical predictions. Experimental economics often draws on insights from psychology and other social sciences to design experiments that can shed light on economic behavior. It can be linked to JEL codes C90 C91 C92 C93.
- Neuroeconomics: Neuroeconomics is an interdisciplinary field that seeks to understand how the brain processes economic decision-making. It combines insights from neuroscience, psychology, and economics to study how the brain mediates economic behavior, and how economic behavior in turn affects the brain. It can be linked to JEL code D87.
- Health, Education, and Welfare: This subfield of behavioral economics examines how individual and household behavior and choices affect outcomes related to health, education, and welfare. It explores how behavioral biases and social norms affect decision-making related to these outcomes and how policy interventions can be designed to promote healthier behavior. Examples of research topics in this area include studies on substance abuse and addiction as related to economic behavior, the impact of financial incentives on preventive care, and the role of information and nudges in promoting educational attainment. It can be linked to JEL codes I12 I2 I3 I18 H51.
- Marketing and Advertising: Marketing has always been centered on understanding and targeting consumers based on their behaviors, preferences, and actions, so behavioral marketing can be characterized as an instance of pleonasm. Incorporating behavioral science aims at integrating marketing ideas into a uniform behavioral framework. This approach employs data and analytics to gain insights into consumer behavior and develop more effective, personalized marketing campaigns to drive conversions and sales. It can be linked to JEL codes D12 M31 M37.
- Sustainability and Energy Consumption : Sustainability and energy consumption refers to the study of how individuals make decisions that affect the environment and the natural resources that support human well-being. It mainly focuses on the underlying behavioral drivers

of environmental degradation, such as overconsumption, waste, and pollution, especially in the energy sector, and aims to identify effective strategies to promote more sustainable behavior. This may include designing incentives that nudge individuals to adopt environmentally-friendly behaviors, such as recycling, reducing energy consumption, or using public transportation. It can be linked to JEL codes Q41 Q47 Q48 Q52.

These subfields and codes may be used to classify academic research related to behavioral economics, but it's important to note that other subfields may be relevant depending on the specific focus of the research, considering the interdisciplinary nature of the behavioral economics field and its merging trend.

C. ARTIFICIAL INTELLIGENCE AND BEHAVIORAL ECONOMICS

The artificial intelligence field has evolved from the early experiments of Turing and Shannon in the 1950s to the current applications of Watson [21] and GPT-3 [22] in the 2020s. Along the way, it has benefited from the advances in AI methodologies (e.g., neural networks, machine learning), computational tools (e.g., cloud computing, GPUs), and data sources (e.g., web, social media), as well as insights from neurosciences [23] that enabled AI systems to learn from data without explicit rules or human intervention.

The advancements in AI techniques have had a significant impact on multiple domains and industries, transforming the way we work and live. AI techniques such as machine learning and natural language processing are used to analyze vast amounts of data and extract valuable insights and opportunities for businesses to improve their operations and profitability.

In behavioral economics, artificial intelligence can be used to enhance and further develop the field in many ways [24]. However, whereas a number of obstacles hampered the development of behavioral economics up until recently, the applications of artificial intelligence in behavioral economics face more complex and ongoing challenges, among which we can mention:

- Data availability and quality: AI techniques, especially machine learning algorithms, require vast amounts of data to train and learn from, and the quality of the data plays a significant role in their accuracy. However, in behavioral economics, collecting high-quality data on human behavior is often difficult and expensive.
- Complexity of human behavior: AI methods are based on mathematical models that can learn from data and perform tasks such as classification, regression, clustering, etc. However, these methods may not be able to capture or model the complexity and diversity of human and social systems that exhibit emergent behavior and self-organization [25] that are not easily predictable or reducible to simple rules or equations, leading to inaccurate predictions.
- Overfitting and generalization: AI algorithms can sometimes overfit to the specific data they are trained on, leading to poor performance on new and unseen data. In behavioral economics, where human behavior can be highly variable and context-dependent, generalizing insights from one context to another can be challenging.
- Lack of interdisciplinary collaboration: AI algorithms are general-purpose methods and require domain-specific knowledge to apply them effectively to a particular field. In behavioral economics, this means that domain experts need to collaborate closely with AI researchers to develop effective applications.
- Ethical concerns: The use of AI in behavioral economics raises ethical concerns around privacy, bias, and the potential for unintended consequences. As such, any development of AI applications in this field must be done with careful consideration of these issues.

Several solutions have been used to overcome the impediments to the development of AI and machine learning applications in the field of behavioral economics. These include improving data quality [26], enhancing feature engineering [27], developing more robust algorithms [28], fostering interdisciplinary collaboration [29], and incorporating ethical considerations' [30]. What makes it worth to further try to take up this challenge is the common background and shared foundation in psychology and neuroscience between behavioral economics and artificial intelligence. This symbiotic relationship provides a holistic approach to understanding human decision-making processes and enhancing the capabilities of AI systems. As a consequence, the actual state of the art in AI applications in behavioral economics is swiftly evolving, and the intersection of these two fields has led to numerous research questions and practical applications, with new advancements being made on a regular basis. In this mindset, this study intends to conduct a bibliometric analysis for which the methodology is discussed.

III. METHODOLOGY

In this paper, a bibliometric analysis is performed, which is a scientific software-assisted statistical method that employs quantitative tools for the analysis and interpretation of bibliometric and bibliographic information. The bibliometric approach differs from systematic literature reviews in the use of quantitative methods to analyze and summarize the characteristics of a body of literatures [31] and [32]. In particular, as shown in Figure 1 we adapted the [33] process for bibliometric analysis as follows:

Phase 1: Planning the bibliometric analysis process.

Phase 2: Conducting the bibliometric analysis process.

Phase 3: Reporting results and Discussing insights.

A. AIM AND SCOPE DEFINITION

This study aims to examine research growth trends, collaboration ties, and influences within the global scientific community and then provide researchers with a comprehensive overview of current and future research on artificial

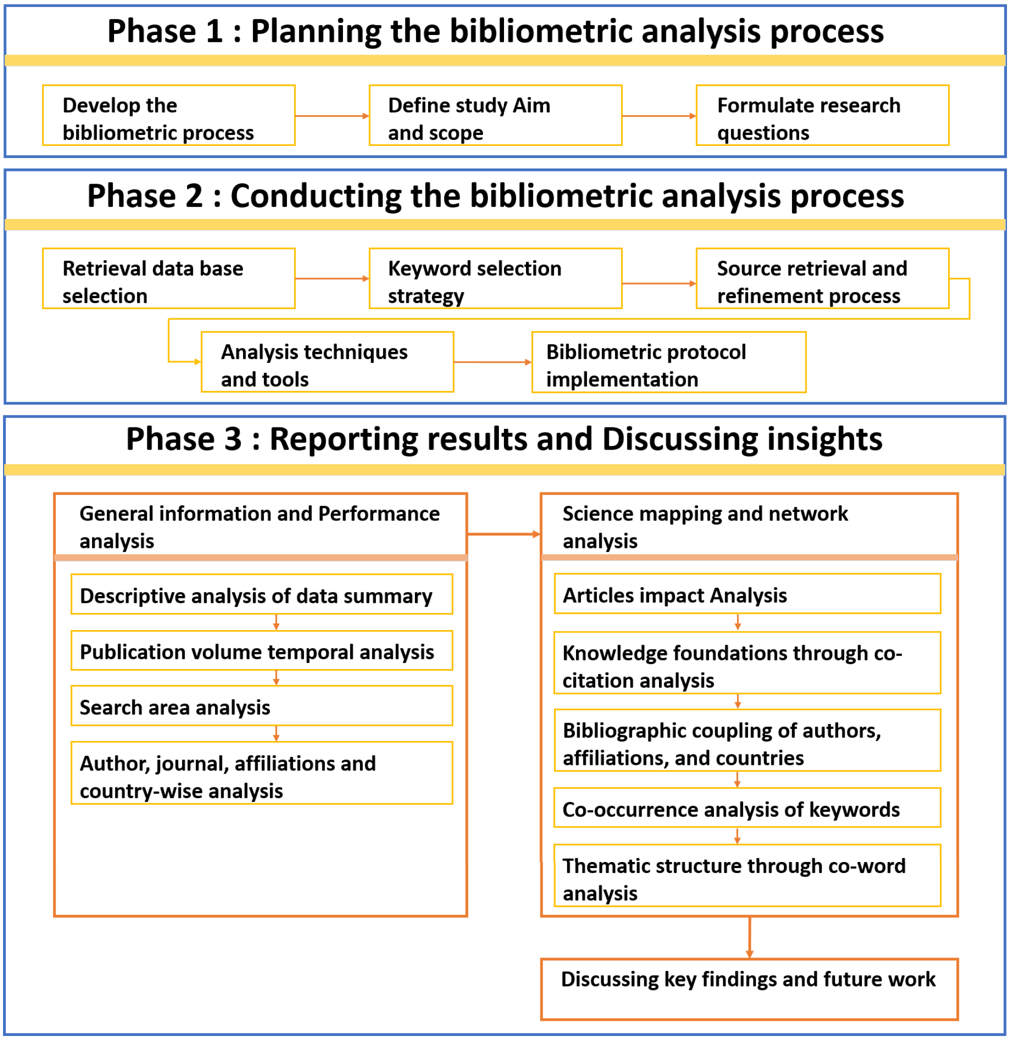

FIGURE 1. **Bibliometric analysis workflow.**

intelligence and behavioral economics-related issues through the following questions:

- How has the research conducted on "Artificial intelligence and behavioral economics" evolved over time?
- What are the most productive and influential universities, journals, and researchers?
- Which countries and universities collaborate on the behavioral economics field spectrum?
- What are the Knowledge foundations of "Artificial intelligence and behavioral economics"?
- Within the literature, what are the current and emerging trends related to "Artificial intelligence and behavioral economics"?
- What are the potential future directions for the "Artificial intelligence and behavioral economics" research field?

The scope of the review is significantly large, as both AI and behavioral economics are multidisciplinary sciences intersecting at the edge of thriving fields like computer science, mathematics, psychology, or economics.

B. DATA COLLECTION

1) RETRIEVAL DATA BASE

The Web of Science (WoS) core collection was used as the retrieval database. WoS is one of the most widely used scientific citation index databases [34], we chose WoS considering it has strong coverage and offers high-quality data due to its stringent journal and article selection processes in comparison to other popular index databases such as Scopus, which covers more journals but has a lower impact and is limited to recent articles [35]. It also provides a user-friendly interface and advanced search features, enabling researchers to find and retrieve relevant article samples.

2) KEYWORD SELECTION STRATEGY

First, as a main subtopic of economy, we added the finance term to the initial query (#0), as described in Table 1, on the WoS core collection including SCI-EXPANDED, SSCI, AHCI, CPSI-S, CPCI-SSH and ESCI indexes, the search query was initiated on the topic (TS) of the indexed articles including the title, abstract, author keywords, and Keywords Plus. resulting in 6461 documents (Figure 2). but when combined with "artificial Intelligence" term, the retrieved records were limited. Therefore, we expanded our keyword set with additional terms relating to behavioral economics and did the same for AI-relevant techniques. The resulting query terms were then grouped by topic as shown in Table 1.

TABLE 1. Initial and final Search keywords.

No.	Main topic	Keywords
#0	behavioral economics	"behavioral economics" OR "Behavioral finance"
#1	behavioral economics	"behavio$ral economics" OR "behavio$ral finance" OR "consumer* behavio$r*" OR "customer* behavio$r*" OR "investor* behavio$r*"
#2	Artificial Intelligence	"artificial Intelligence" OR "machine learning" OR "learning system" OR "neural network" OR "deep learning" OR "support vector machine" OR "decision tree" OR "supervised learning" OR "unsupervised learning" OR "random forest" OR "natural language processing" OR "reinforcement learning" OR "text processing" OR "AI"

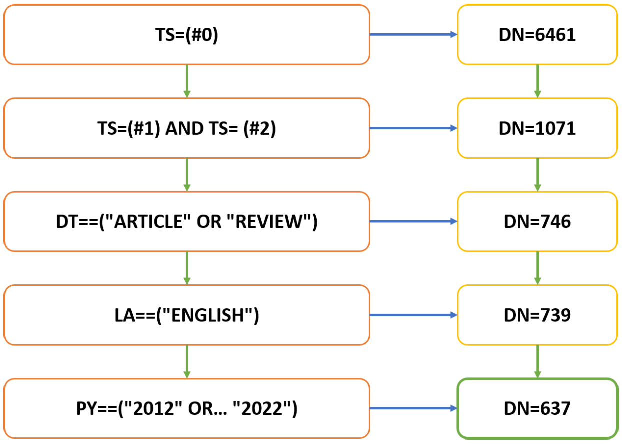

FIGURE 2. Search query refinements and results flow note(s): TS=topic, DT=document type, LA=language, PY=publication year, DN=documents number, date of retrieval: 18 February 2023.

3) SOURCE RETRIEVAL AND REFINEMENT PROCESS

Following the preparation of the query terms (#1 and #2), a search was conducted based on the TOPIC criteria, as given in Figure 2, yielding 1071 results.

Several refinements to the search query were made in order to gather the most pertinent articles and reviews for our research. We restricted the findings to journal papers and reviews published in English, yielding 739 documents, and then we restricted the time span of the publications to 2012–2022. This was based on the fact that, prior to 2012, there were just a handful of studies on AI and the behavioral economics field. The final result comprised 637 documents, which will serve as a sample for our study.

C. ANALYSIS TECHNIQUES AND TOOLS

To conduct our bibliometric approach for analyzing publications, we employed various techniques to address our formulated questions about the AI and behavioral economics field. After evaluating several options to meet our needs in investigating bibliometric data, we selected two tools commonly used in similar studies: the Bibliometrix/Biblioshiny R package and VOSviewer software. This section starts by introducing the two chosen tools, followed by a description of the bibliometric techniques utilized with each one.

- Bibliometrix/Biblioshiny: Bibliometrix is an R package [36] that provides a set of tools for quantitative research in bibliometrics and scientometrics. It allows users to analyze and visualize bibliographic data, including scientific publications, authors, journals, keywords, and citations. Biblioshiny is a web-based interface for Bibliometrix that allows users to access the package's functions through a graphical user interface (GUI). It provides an ergonomic environment for loading, cleaning, analyzing, and visualizing bibliometric data. The main features of Bibliometrix and its web interface, Biblioshiny, include: Evaluating the research performance of individuals, institutions, and countries by analyzing the impact and productivity of their publications. Providing a comprehensive analysis of publications, including metrics such as citation counts, h-index, and g-index, can help researchers evaluate the impact of their work. Identifying research trends and topics by analyzing the frequency of keywords and the co-occurrence of terms in publications. Mapping research collaborations by analyzing the co-authorship networks of publications.
- VOSviewer: VOSviewer is a software tool [37] that enables users to analyze bibliometric data and generate customizable and interactive visualizations that help researchers gain insights into patterns and trends in scientific research. The software is designed to visualize bibliometric networks, which consist of nodes representing publications or other research items, and edges representing relationships between those items. The primary uses of VOSviewer are to generate maps of research fields, identify clusters of related research, and visualize co-authorship networks. It can also be used to perform citation analysis, analyze the impact of individual publications, and identify key and emerging research topics.

Both software are freely available to researchers, including a user-friendly interface, provide a transparent and reproducible analysis of publications, and allow users to customize their visualizations by adjusting the layout and data configuration, enabling researchers to easily upload their data, analyze, visualize, and share their findings.

To implement the bibliometric protocol, we use the following techniques:

- Citation and publication analysis: The Bibliometrix package is used to conduct citation and publication analysis by analyzing metrics such as Total publications, Total citations, Average Citations, h-index, g-index, and m-index of authors, journals, affiliations, countries, and articles.
- Co-authorship analysis: VOSviewer is used for co-authorship analysis to gain insights into the collaboration patterns between authors, affiliations, and countries.
- Co-citation analysis: Bibliometrix is used to conduct co-citation analysis by analyzing the co-citation patterns of cited references.
- Bibliographic coupling analysis: VOSviewer is used to conduct bibliographic coupling analysis by analyzing the bibliographic coupling patterns of authors, affiliations, and countries.
- Co-occurrence analysis: VOSviewer is used to conduct co-occurrence analysis by analyzing the co-occurrence patterns of keywords and generating co-occurrence networks and clusters.
- Bibliographic clustering/co-word analysis: Bibliometrix is used to identify the main topics or themes within the set of documents under study by applying a clustering algorithm, performing co-word analysis, and generating a two-dimensional thematic map of themes.

IV. RESULTS

A. GENERAL INFORMATION AND PERFORMANCE ANALYSIS

1) DESCRIPTIVE ANALYSIS OF DATA SUMMARY

As reported in Table 2, produced using biblioshiny package, there are a total of 637 documents from 373 active sources over a ten-year period of publication activity, with an average of 13,88 citations and 34193 references to preceding publications.

There were a total of 1997 authors, with 3,38 authors per document, and only 61 (9.5%) single-authored documents. A collaboration index of 3.38 represents a significant collaboration score, with international co-authorships accounting for 30.61% in the research area of artificial intelligence applications in behavioral economics. The number of Keywords Plus generated by using word appearance frequency analysis techniques is 1352, while the total number of keywords chosen by authors is 2218.

2) PUBLICATION VOLUME TEMPORAL ANALYSIS

Figure 3 captures and plots the annual scientific production combined with citation trend (measured in terms of average total citations per article) over a 10-year period from 2012 to 2022 in order to provide insights on the evolution of scholarly papers in the AI and Behavioral economics field of study. Until 2017, the annual production ranged from 12 to 21, with an average of 15 publications per year. Over the last five years, productivity has seen an exponential and sustainable increase, with 34 articles published in 2018, 56 articles published in 2019, 87 articles published in 2020, and 167 articles published in 2021, followed by 196 articles published in 2022. This production growth rate indicates a rising interest in the research of AI applications in behavioral economics.

TABLE 2. Overview of retrieved records.

Description	Results
Timespan	2012:2022
Sources (Journals, Books)	373
Documents	637
Annual Growth Rate %	35,13
Document Average Age	3,02
Average citations per doc	13,88
References	34193
Document contents	
Keywords Plus (ID)	1352
Author's Keywords (DE)	2218
Authors	
Authors	1997
Authors of single-authored docs	61
Documents per Author	0,31
Single-authored docs	62
Co-Authors per Doc	3,38
International co-authorships %	30,61
Collaboration Index	3,36

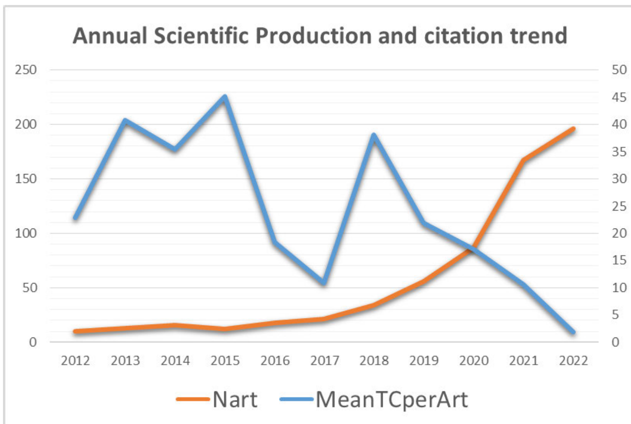

FIGURE 3. Annual scientific production and citation trend. note(s): NArt = number of publications, MeanTCperArt = average total citations per article.

Based on the average number of total citations per article, citation-wise analysis was conducted, and the year 2015 was found to have the highest average total citations per article, with approximately 45 citations per article, followed by 2013 with 40 citations per article, and 2018 with 38 citations per article. Based on citations, the results indicate that valuable research on AI applications in behavioral economics was published during these years.

3) RESEARCH AREA ANALYSIS

As emphasized by Figure 4, Business Economics and Computer Science are the most prevalent research areas, with a total of 383 articles (199 for Business Economics and 184 for Computer Science), representing more than 60% (383/637) of

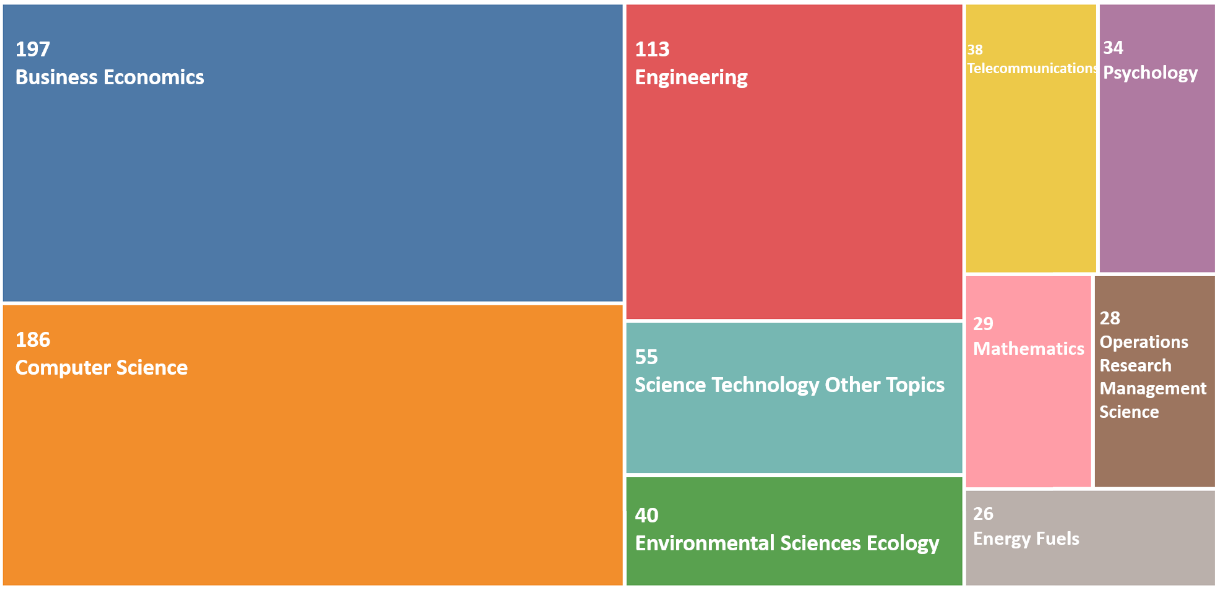

FIGURE 4. Top 10 research areas. source(s): Web of Science.

articles in our study, followed by Engineering (115 articles), Science Technology Other Topics (55 articles), Environmental Sciences Ecology (40 articles), Telecommunication (38 articles), and Psychology (35 articles). Other areas with less contribution to AI and Behavioral Economics include Operations Research Management Science, Mathematics, and Energy Fuels. This does not necessarily indicate less relevance to the AI applications in Behavioral Economics, as we already mentioned, both AI and Behavioral Economics are interdisciplinary sciences by nature, which makes it more convenient to classify related articles in research areas with a broader scope.

TABLE 3. Most Relevant Authors by publications and citations note(s): h_index=The highest number of an author's publications with at least that many citations, g_index=The highest number g such that the top g articles received a minimum of g^2 citations collectively, m_index=The h-index divided by the number of active years of an author, TC=Total citations, TP=Total publications, PY_start=Starting year of an author publication.

Auther	h_index	g_index	m_index	TC	TP	PY_start
PANTANO E	5	6	1	133	6	2019
KIM J	5	6	0,833	60	6	2018
KUMAR S	3	5	1	90	5	2021
LI B	3	4	0,6	42	4	2019
KUMAR P	3	3	0,75	23	3	2020
WANG ZY	3	3	0,6	51	3	2019
DENNIS C	3	3	0,6	49	3	2019
LIU X	2	4	0,25	91	4	2016
DHIR A	2	3	0,667	106	3	2021
WANG Y	2	3	0,4	458	3	2019
ZHANG Y	1	3	0,333	11	4	2021
WANG HX	1	2	0,2	4	3	2019

4) AUTHOR-WISE ANALYSIS

Considering the high degree of collaboration, we conducted an author-wise analysis of the most prolific authors (at least 3 publications) in AI and Behavioral Economics research based on the multiple metrics as presented in Table 3. Based on both the h-index and g-index measures, Pantano Eleonora (abbreviated as PANTANO E) ranks as the most influential author in AI and Behavioral Economics research, with an h-index of 5 and a g-index of 6 (133 citations for 6 publications starting in 2019), followed by Kim Jina (abbreviated as KIM J) with an h-index of 5 and a g-index of 6 (60 citations for 6 publications starting in 2018). However, when considering m-index, taking the number of active years into account, we discover that, along with Eleonora Pantano, who maintains the first position, Kumar Satish (KUMAR S) comes in as the second-most influential author with a m-index of 1 (90 citations for 5 publications starting in 2021).

To examine the prominent author's influence over time, we display the findings of a year-wise analysis of the scientific production activity of the top 12 authors in Figure 5. This figure reveals that LIU X was the earliest to begin working in the field, from 2016 to 2022, which makes her the longest active author with 8 years of activity, followed by KIM J with the second-longest period of activity in the field from 2018 until 2022. Kumar S and DHIR A are the most recent researchers to engage in this field beginning in 2021, yet Kumar S has the highest production per year (4 papers in 2022), while WANG Y has the highest citations per year (91.0).

5) JOURNAL-WISE ANALYSIS

In a similar manner, an impact analysis of the most productive journals (at least 7 publications) is conducted using several metrics, including h-index, g-index, and m-index, as shown in Table 4. Based on the h-index measure, "JOURNAL

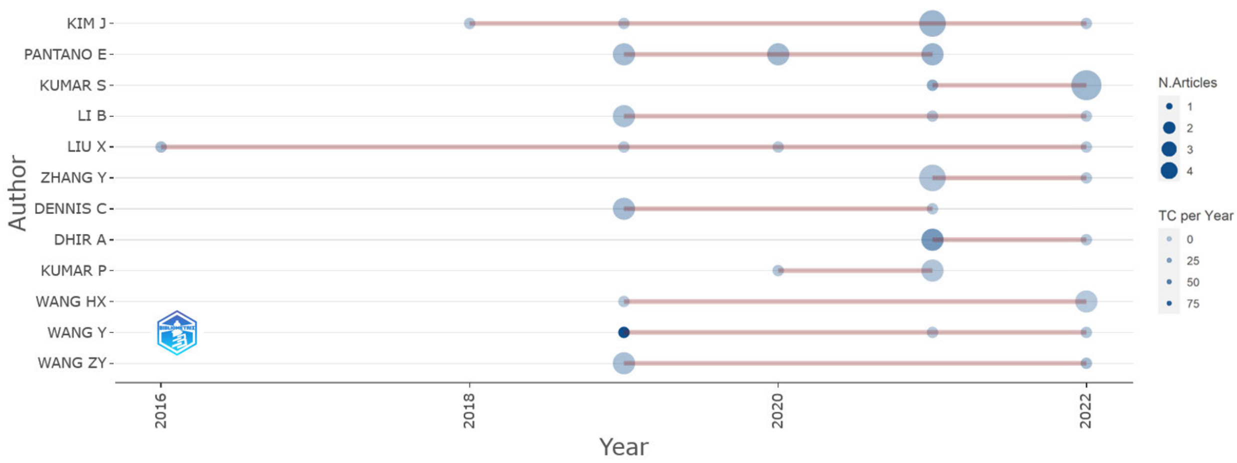

FIGURE 5. Most relevant authors production over time.

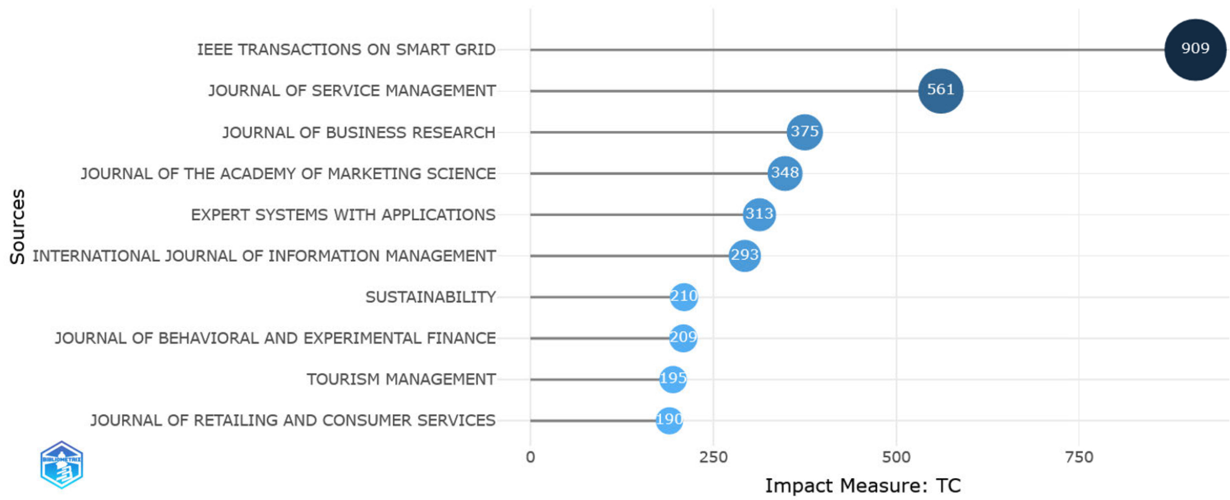

FIGURE 6. Most relevant journals by total citations.

TABLE 4. Most Relevant journals by publications and citations note(s): h_index=The highest number of a journal's publications with at least that many citations, g_index=The highest number g such that the top g articles received a minimum of g^2 citations collectively, m_index=The h-index divided by the number of active years, TC=Total citations, TP=Total publications, PY_start=Publication starting year.

Journal	h_index	g_index	m_index	TC	TP	PY_start
JOURNAL OF RETAILING AND CONSUMER SERVICES	8	9	1.600	190	9	2019
IEEE ACCESS	7	13	1.400	185	19	2019
JOURNAL OF BUSINESS RESEARCH	7	12	0.700	375	12	2014
JOURNAL OF BEHAVIORAL AND EXPERIMENTAL FINANCE	6	6	1.500	209	6	2020
SUSTAINABILITY	6	14	1.000	210	21	2018
ENERGIES	6	10	1.000	119	13	2018
IEEE TRANSACTIONS ON SMART GRID	6	7	0.667	909	7	2015
EXPERT SYSTEMS WITH APPLICATIONS	6	12	0.500	313	12	2012
JOURNAL OF BIG DATA	5	9	1.000	90	9	2019
COMPUTERS IN HUMAN BEHAVIOR	5	7	0.833	164	7	2018

OF RETAILING AND CONSUMER SERVICES'' with an h-index of 8 appears to be the most influential journal in the AI and Behavioral Economics field. The same goes when measuring the m-index with a value of 1.6 since 2019 is its publication starting year, followed by ''JOURNAL OF BUSINESS RESEARCH'' and ''IEEE ACCESS'' with

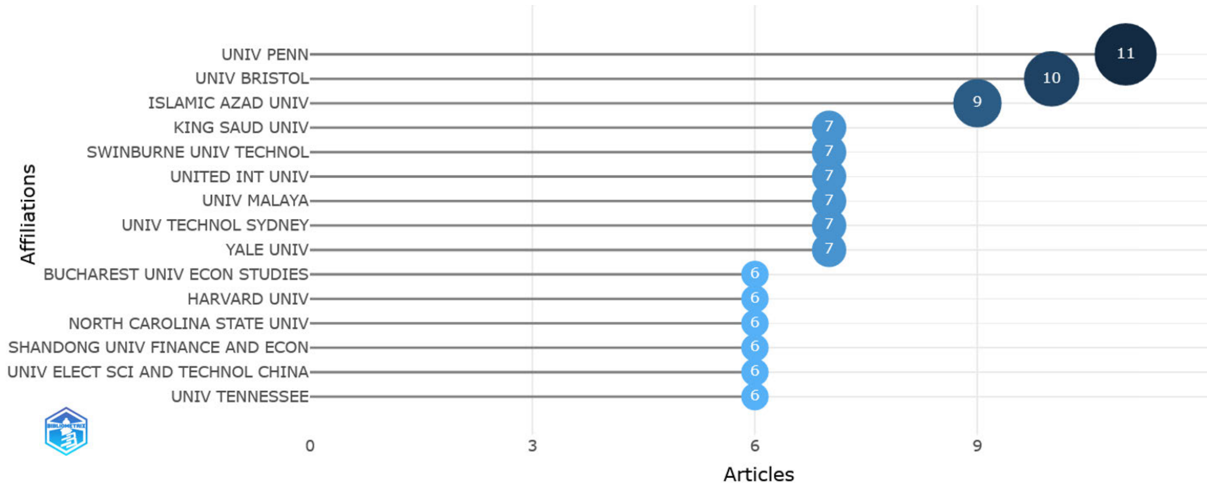

FIGURE 7. Most relevant affiliations by publication.

TABLE 5. Most relevant countries by scientific contributions and citations note(s): TP=Total publications, TC=Total citations, MeanCperArt=Average Article Citations.

Country	TP	TC	MeanCperArt
USA	288	1153	12.40
CHINA	226	1446	12.80
INDIA	123	301	5.90
UNITED KINGDOM	110	839	19.51
SPAIN	50	337	15.32
AUSTRALIA	49	209	13.06
SOUTH KOREA	43	169	8.05
MALAYSIA	35	267	24.27
TURKEY	34	100	7.69
IRAN	33	61	3.81

an h-index of 7 each and an m-index of 1.4 for the last, then IEEE TRANSACTIONS ON SMART GRID, EXPERT SYSTEMS WITH APPLICATIONS, SUSTAINABILITY and ENERGIES each having an h-index of 6. However, when considering g-index giving more weight to highly-cited papers, we find that SUSTAINABILITY is the most influential journal, with a g-index of 14 (210 citations for 21 publications starting in 2018), followed by IEEE ACCESS with a g-index of 13, then JOURNAL OF BUSINESS RESEARCH and EXPERT SYSTEMS WITH APPLICATIONS, both having a g-index of 12.

To further highlight highly-cited publications, we plotted Figure 6, in which the analysis of journals impact based on Total Citations revealed that IEEE TRANSACTIONS ON SMART GRID is the most influential journal with a total of 903 citations, followed by JOURNAL OF SERVICE MANAGEMENT as the second-most influential journal (561 TC), then JOURNAL OF BUSINESS RESEARCH, JOURNAL OF THE ACADEMY OF MARKETING SCIENCE and EXPERT SYSTEMS WITH APPLICATIONS with 375, 348, and 313 TC, respectively. This result underlines the multidisciplinary nature of the AI and Behavioral Economics research field as we observe interdisciplinary journals along with specialized journals across several fields, including Energy, business, psychology, marketing, and computer science.

6) AFFILIATION-WISE ANALYSIS

In Figure 7, the affiliation-wise analysis reveals that *University of Pennsylvania*, *University of Bristol* and *Islamic Azad University* are the most productive affiliations/organizations in terms of total number of publications, with 11, 10, and 9 publications, respectively, *King Saud University*, *Swinburne University of Technology*, *United International University*, *University Malaya*, *University of Technology Sydney* and *Yale University* have contributed 7 articles each, followed by *Bucharest University of Economic Studies*, *Harvard University*, *North Carolina State University*, *Shandong University of Finance and Economics*, *University of Electronic Science* and *Technology of China* and *University of Tennessee* with 6 articles of each.

7) COUNTRY-WISE ANALYSIS

Figure 8 illustrates the impact of countries in the fields of AI and Behavioral Economics. China (1.446 citations), the United States (1,153 citations), the United Kingdom (839 citations), and Singapore (627 citations) are the most influential countries in terms of total citations, followed by the Netherlands, Finland, and Spain. Other less influential countries include India, Ecuador, and Malaysia.

To further analyze country productivity, Table 5 reveals that the United States and China are the most prolific countries, with 288 and 226 total publications, respectively. Australia, South Korea, Turkey, and Iran, despite having fewer citations, are also among the most productive countries. Accordingly, we relied on the corresponding authors for additional evidence concerning the countries' productivity. The prevalence of the most active countries based on the corresponding authors is depicted in Figure 9, along with

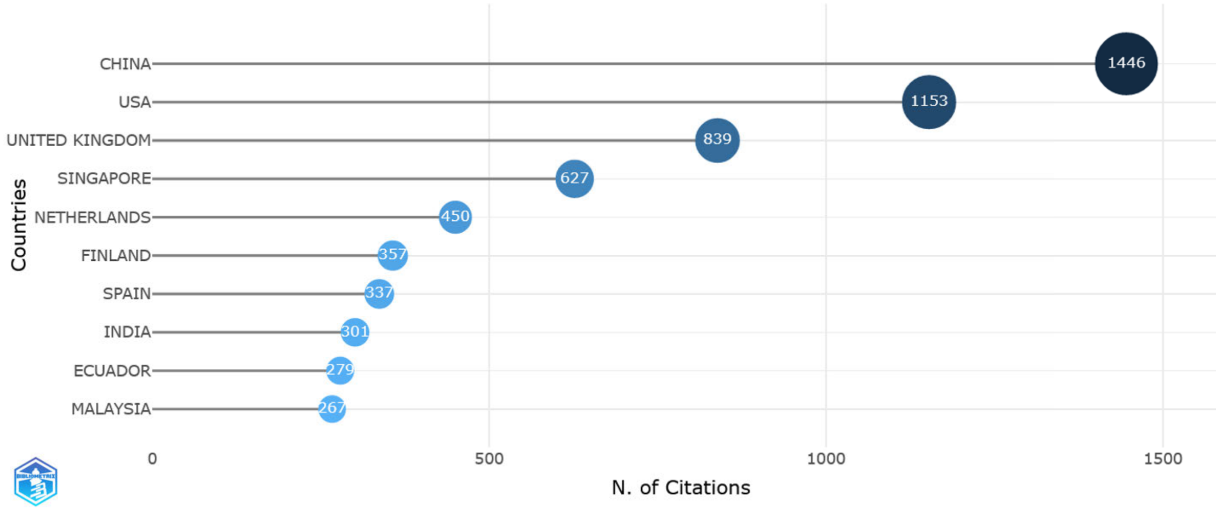

FIGURE 8. Most Cited Countries.

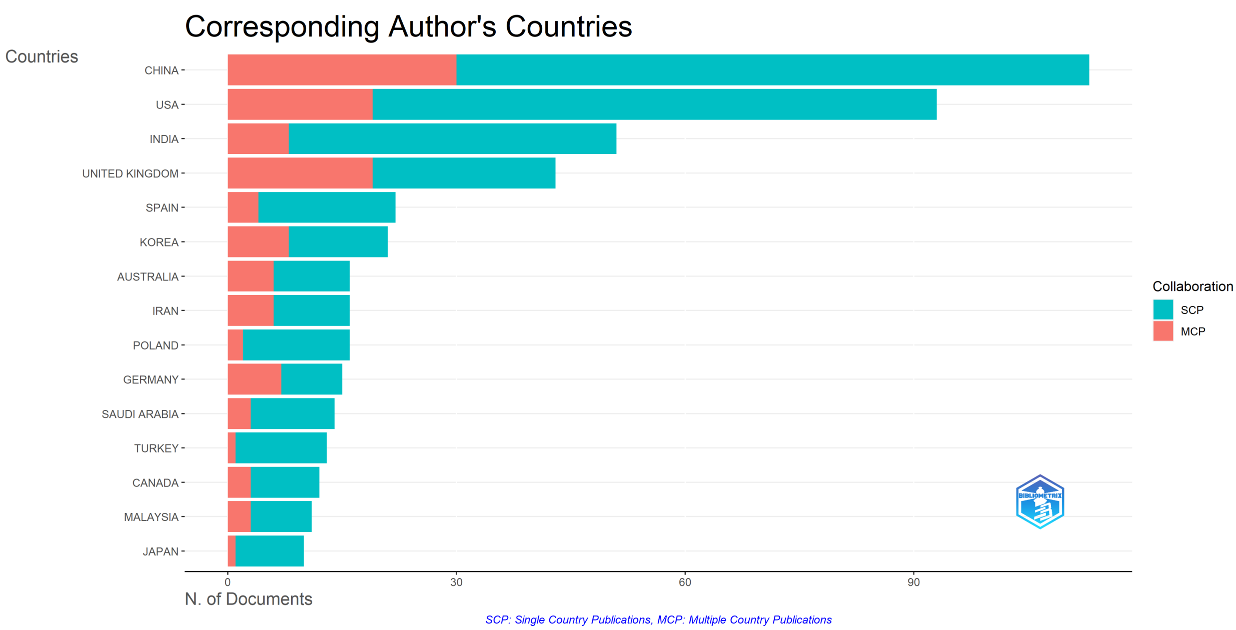

FIGURE 9. Country production based on the corresponding authors. note(s): MCP=Multiple country publications, SCP=Single country publications.

the ratios of multiple country publications (MCP) and single country publications (SCP).

B. SCIENCE MAPPING AND NETWORK ANALYSIS

1) ARTICLES IMPACT ANALYSIS

The total citations metric is best for emphasizing highly cited articles when conducting publication impact analysis. In Figure 10 we clearly distinguish the prominence of the article *Brave new world: service robots in the frontline* [38] published by *Journal of Service Management* in 2018, with 559 citations as the highest total citations for a single article. It highlights both the benefits of service robots, such as increased efficiency, cost savings, and improved customer experience, as well as the related challenges and risks, such as ethical concerns, job displacement, and the need for human oversight.

With 455 citations, the second article was *Review of Smart Meter Data Analytics: Applications, Methodologies, and Challenges* [38] published in 2019 by *IEEE Transactions on Smart Grid*. This article provides a comprehensive overview of the current state of smart meter data analytics, and its various applications and methodologies, such as load forecasting, customer segmentation, and demand response, which include optimizing consumption by changing consumer behavior.

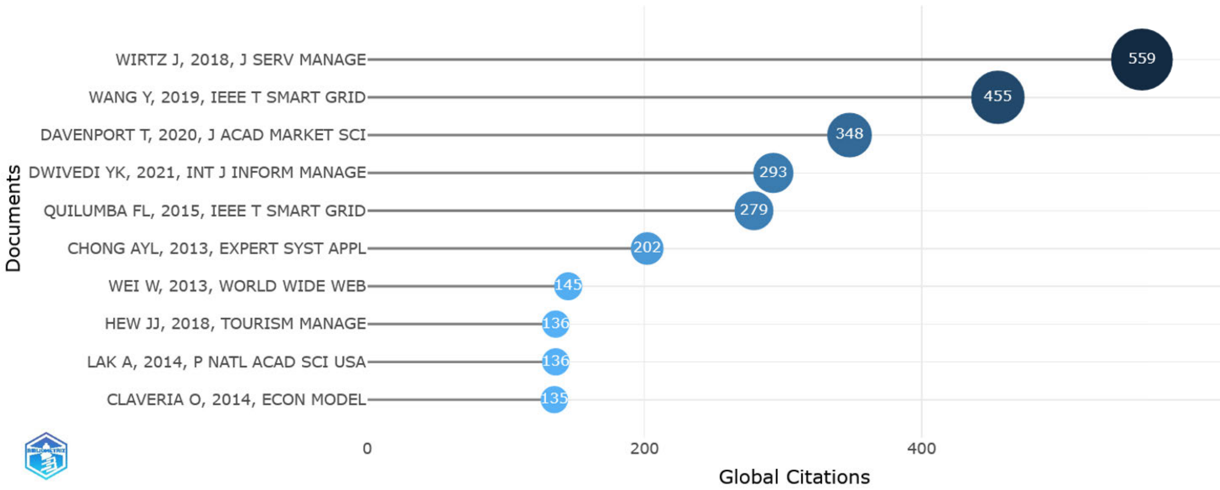

FIGURE 10. Most cited articles.

The third most cited article is *How artificial intelligence will change the future of marketing* [39] published by *Journal of the Academy of Marketing Science* in 2019 with 348 citations. According to the article, AI has the potential to transform marketing and provide significant benefits to both marketers and consumers, as it can help marketers identify patterns in customer behavior and improve the customer experience by providing personalized recommendations, but it must be used responsibly and ethically to avoid potential pitfalls such as manipulation.

Published in 2021 by *Journal of the Academy of Marketing Science volume*, the paper *Setting the future of digital and social media marketing research: Perspectives and research propositions* [40] holds the fourth position with 293 citations. Overall, the paper provides a comprehensive overview of the key research areas and opportunities for future research in digital and social media marketing, highlighting the importance of understanding the complex interactions between consumers, marketers, and digital technologies, including artificial intelligence and augmented reality.

The fifth article with the most impact (279 citations) is *Using Smart Meter Data to Improve the Accuracy of Intraday Load Forecasting Considering Customer Behavior Similarities* [41] published by *IEEE Transactions on Smart Grid* in 2021. The article aims to improve the accuracy of intraday load forecasting by considering customer behavior similarities while using a machine learning algorithm.

The paper *Predicting m-commerce adoption determinants: A neural network approach* [42] of Alain Yee-Loong Chong, published by *Expert Systems with Applications* in 2013, stands in sixth place among the most cited articles with 202 citations. The article provides insights into the determinants of m-commerce adoption decisions and demonstrates the usefulness of a neural network approach for predicting these determinants by using a non-linear and non-compensatory model and incorporating additional constructs such as perceived value, trust, personal innovativeness, and perceived enjoyment.

The paper published by *World Wide Web* in 2013 *Effective detection of sophisticated online banking fraud on extremely imbalanced data* [43] ranked seventh as the most impactful publication, having 145 total citations. In this article, the author proposes a machine learning-based approach for detecting sophisticated online banking fraud on extremely imbalanced data. The authors highlight that current fraud detection methods are often inadequate, as fraudsters are constantly evolving their tactics and behavior to evade detection, then propose an approach that uses several machine learning techniques to identify previously unknown fraud patterns.

In the 8th position, we find the article *Mobile social tourism shopping: A dual-stage analysis of a multi-mediation model* [44] published by *Tourism Management* in 2018 with a total citation count of 136. The article explores the relationship between mobile shopping, social media, tourism, and shopping behavior. Using dual-stage analysis with PLS-SEM (Partial least squares structural equation modeling) and Artificial Neural Network (ANN), the study suggests that there is a complex interplay between these factors, which may be useful for marketers who are looking to target tourists through mobile and social media channels.

Holding the 9th position, with 136 citations as well, the research article *Dopamine prediction error responses integrate subjective value from different reward dimensions* [45] published by *Proceedings of the National Academy of Sciences* in 2014 comes last among the most cited articles. The article investigates how dopamine neurons integrate subjective value from different reward dimensions in the brain, and provides important insights into the neural mechanisms underlying reward processing in the brain, with potential applications in the development of more biologically inspired reinforcement learning algorithms.

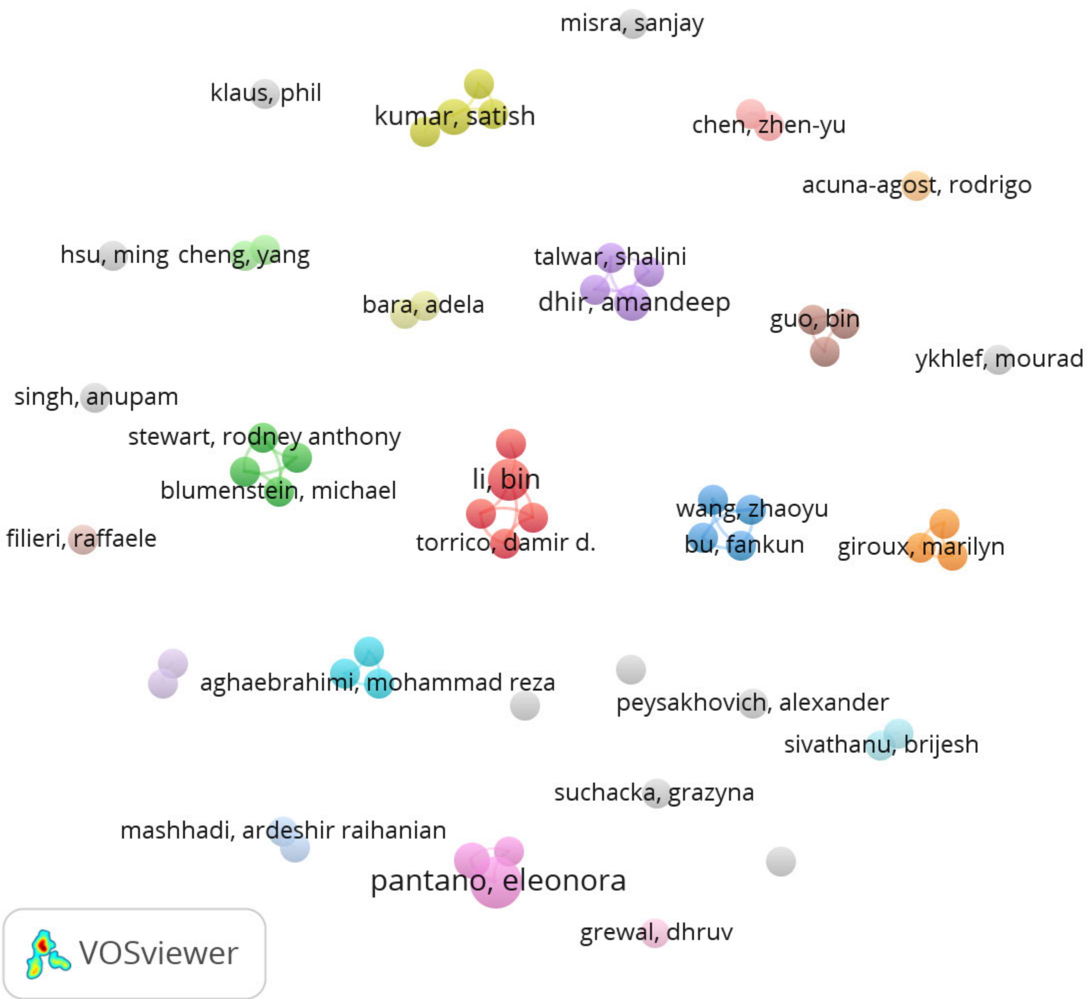

FIGURE 11. Co-authorship network visualization of relevant authors.

Finally, the article *Forecasting tourism demand to Catalonia: Neural networks vs. time series models* [46] published by *Economic Modelling* in 2014, which has 135 citations, compares the performance of neural network models with traditional time series models in predicting tourism demand in the Catalonia region of Spain. It also finds that economic factors, such as exchange rates and GDP growth, have the strongest impact on tourism demand in Catalonia. The authors conclude that neural network models offer a promising approach to forecasting tourism demand and can help policymakers and businesses make better decisions.

Overall, these articles cover various topics, including smart meter data analytics and load forecasting, the potential and impact of artificial intelligence, service robots, social media, and mobile technology adoption on marketing and service industries such as tourism, detecting online banking fraud, and investigating the neural mechanisms underlying reward processing in the brain. The articles use various approaches, including machine learning algorithms, neural network models, and dual-stage analysis with PLS-SEM and Artificial Neural Networks, to provide insights into complex interactions between consumers, marketers, and digital technologies. The articles also highlight the importance of using AI responsibly and ethically to avoid potential pitfalls such as manipulation.

2) SCIENTIFIC COLLABORATION NETWORK

Figure 11 shows the co-authorship network of authors who published at least 2 co-authored papers cited at least 10 times (58 authors). The illustration reveals an underdeveloped network of collaboration between co-authors in the scientific literature. This low co-authorship urges the formation of more interdisciplinary research collaborations in this field. As we already mentioned, considering the nature of behavioral economics knowledge, domain-specific scientists such as economists, psychologists, and neuroscientists, along with general-purpose computer scientists, must collaborate to generate new ideas, solutions, and research directions for AI applications in behavioral economics.

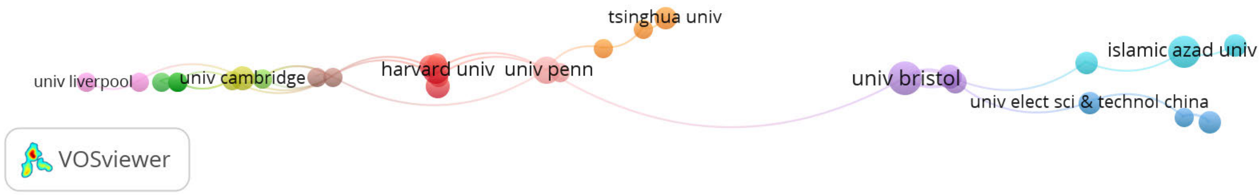

FIGURE 12. Co-authorship network visualization of relevant affiliations.

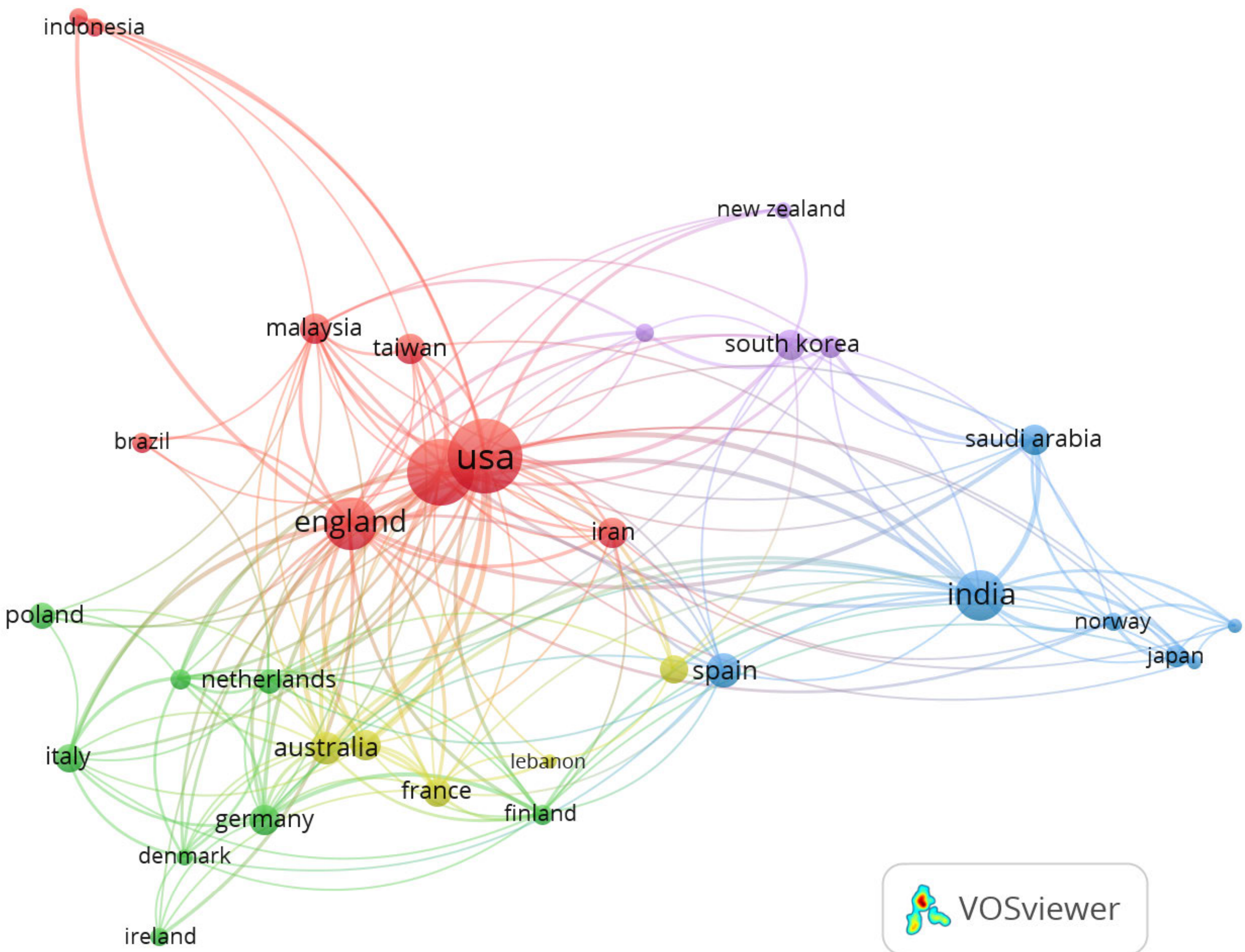

FIGURE 13. Co-authorship network visualization of relevant countries.

Figure 12 depicts the co-authorship network of the author's affiliated institutions. From the 66 selected affiliations (at least 3 publications with at least 10 citations), the largest set of connected affiliations consists of 32 nodes. One striking observation is that most institution collaborations are within the same country, which can be related to geographic proximity.

Concerning the author's affiliation countries collaboration network, Figure 13 displays 33 countries (out of 34 with at least 5 publications with at least 50 citations) arranged in 5 clusters. The red cluster contains 9 countries, including the United States, China, and the United Kingdom, serving as a hub for co-authorship publications in the field of artificial intelligence and behavioral economics.

3) KNOWLEDGE FOUNDATIONS THROUGH CO-CITATION ANALYSIS

Co-citation analysis [56] is appropriate for defining the research knowledge foundations (Intellectual structure), which is a list of papers with the highest co-citation indicators

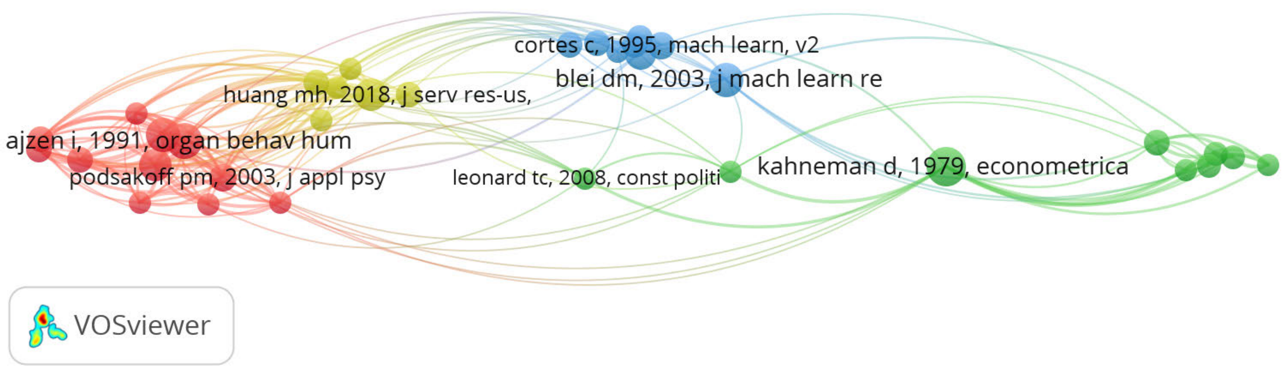

FIGURE 14. References Co-citation network notes: threshold of 10 co-citation.

TABLE 6. Knowledge foundation clusters of AI in behavioral economics through Co-citation analysis.

Cluster	Theme	Authors	References titles
1	Behavioral research and Technology acceptance	Fronell and Larcker [47] Davis [48] Ajzen [49]	Evaluating Structural Equation Models with Unobservable Variables and Measurement Error. Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology. The theory of planned behavior.
2	Machine Learning	Breiman [50] Cortes and Vapnik [51] Blei et al. [52]	Random Forests. Support-Vector Networks. Latent Dirichlet Allocation.
3	Psychology and financial Decision-making	Kai-Ineman and Tversky [4] Bollen et al. [12] Baker and Wurgler [53]	Prospect Theory: An Analysis of Decision under Risk. Twitter's mood predicts the stock market. Investor sentiment and the cross-section of stock returns.
4	AI and customer behavioral	Huang and Rust [54] Wirtz et al. [55] Davenport et al. [39]	Artificial Intelligence in Service. Brave new world: service robots in the frontline. How artificial intelligence will change the future of marketing.

among the citing publications. As illustrated in Figure 14, co-citation analysis of co-cited references (38 documents having at least 10 co-citations each) reveals that AI research in behavioral economics draws upon existing research from four foundational research clusters. In Table 6 we identify the main themes in each foundation cluster by spotlighting the 3 most co-cited references in each one as follows:

a: CLUSTER 1: BEHAVIORAL RESEARCH AND TECHNOLOGY ACCEPTANCE (RED NODES)

Fred D. Davis's article *Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology* published in 1989 [48] puts an emphasis on the factors that influence the acceptance of information technology by users. Specifically, the article explores the relationship between users' perceptions of the usefulness and ease of use of technology and their acceptance and adoption of that technology. The article *The theory of planned behavior* written by Icek Ajzen and published in 1991 [49] deals with the theory of planned behavior (TPB), a theoretical framework for understanding and predicting human behavior. It explains how various kinds of behavioral intentions can be accurately predicted on the basis of three main components of the TPB: attitudes toward the behavior, subjective norms, and perceived behavioral control. The article *Evaluating Structural Equation Models with Unobservable Variables and Measurement Error*, authored by Claes Fornell and David F. Larcker and published in 1981 [47], focuses primarily on the statistical and methodological aspects of structural equation modeling (SEM), which is used to analyze relationships between unobservable variables (i.e., latent variables) and observable indicators. The article provides recommendations for addressing measurement errors and other issues that may arise when working with SEMs.

Examining these articles, we observe that this cluster encompasses two foundational themes. Specifically, behavioral research, which is the study of human behavior and the factors that influence it, and technology acceptance, which explores the factors that influence user acceptance of information technology.

b: CLUSTER 2: MACHINE LEARNING (BLUE NODES)

The article *Latent Dirichlet Allocation* of David M. Blei published in 2003 [52] introduces and explains the Latent Dirichlet Allocation (LDA) model, a generative probabilistic model for text data, and its applications in the field of natural language processing. Leo Breiman's article *Random Forests* published in 2001 [50] develops and describes the Random Forest algorithm, which is a machine learning method for classification and regression tasks. The 1995 article

Support-Vector Networks by Corinna Cortes and Vladimir Vapnik [51], discusses the SVMs or support-vector networks approach to classification and regression analysis. The authors also discuss their mathematical basis as well as their practical applications in areas such as image recognition and text classification.

Reviewing these articles reveals that this cluster includes machine learning as a foundational theme, showcasing a variety of supervised and unsupervised learning algorithms and their applications to solve various types of data analysis problems, such as classification, regression, feature selection, and topic modeling.

c: CLUSTER 3: DECISION-MAKING IN FINANCE (GREEN NODES)

The article *Prospect Theory: An Analysis of Decision under Risk* of Daniel Kahneman and Amos Tversky in 1979 [4] is the most co-cited reference by publications under study. Its main focus is the critique of the traditional economic model, which assumes that individuals make choices based on the expected value of outcomes. And the development of an alternative model of decision-making under risk called ''prospect theory''. The main topic of the article *Twitter mood predicts the stock market* by Johan Bollen [12] in 2011 is the potential of using the collective mood on social media as a predictor for changes in the stock market. The article discusses how changes in the collective mood of Twitter users, as measured by a system called the Google Profile of mood states (GPOMS), can be used to predict changes in the stock market with a high degree of accuracy. The article *Investor sentiment and the cross-section of stock returns* by Malcolm Baker and Jeffrey Wurgler published in 2006 [53] investigates the relationship between investor sentiment and the cross-section of stock returns. The article explores various factors that may influence investor sentiment and its impact on stock returns.

The assessment of these cluster's articles uncovers decision-making in finance as a foundational theme, emphasizing prospect theory as a prominent descriptive model of psychological factors influencing people's decision-making under conditions of uncertainty and its application in finance by exploring the underlined psychological concepts that may influence investors sentiment and stock market behavior.

d: CLUSTER 4: AI AND CUSTOMER BEHAVIOR (YELLOW NODES)

The article *Artificial Intelligence in Service* by Ming-Hui Huang and Roland T. Rust [54] discusses the impact of artificial intelligence (AI) on the service industry. The authors explore how AI can be used to improve customer experiences and increase efficiency for service providers, as well as the potential challenges and limitations of AI in service, including ethical and privacy concerns. Jochen Wirtz's article *Brave new world: service robots in the frontline* published in 2018 [55] explores the use of service robots in various industries, including healthcare and hospitality, and highlights their potential benefits and challenges. The authors discuss the role of service robots in enhancing customer experiences and improving service quality, while also considering the potential impact of service robots on job displacement and the future of work. The article *How artificial intelligence will change the future of marketing* authored by Thomas Davenport in 2020 [39], aims to provide insights into how AI can transform the future of marketing and how companies can effectively leverage this technology to improve various aspects of marketing, including customer segmentation, targeting, personalization, and pricing.

Through the review of the articles in this cluster, AI and customer behavior are revealed as foundational themes, which study how artificial intelligence-powered technologies such as service robots are influencing consumer behavior in different service industries. It also raises questions regarding ethical and privacy concerns around AI technologies.

Overall, these overarching foundational clusters represent the knowledge foundations of AI and ML research in behavioral economics.

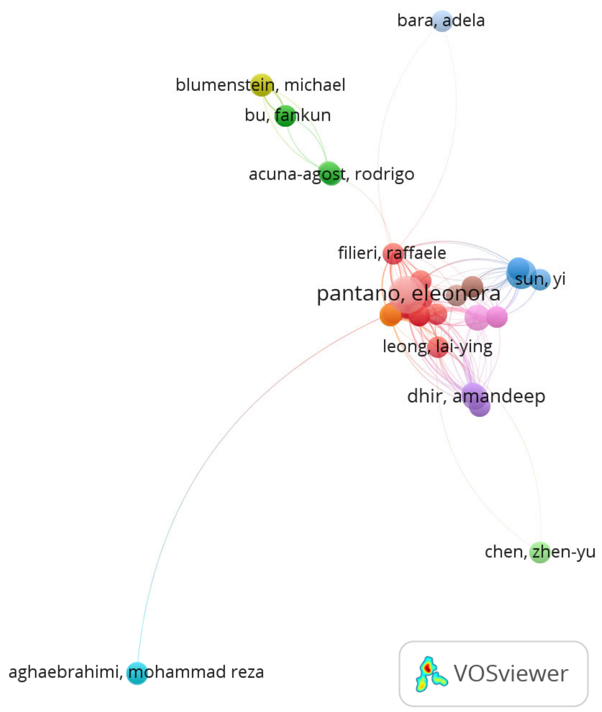

FIGURE 15. **Bibliographic coupling of authors. notes: minimum publication threshold of 2 documents and 10 citations.**

4) BIBLIOGRAPHIC COUPLING OF AUTHORS, AFFILIATIONS, AND COUNTRIES

While co-citation is essentially a forward-looking perspective, bibliographic coupling is retrospective, Bibliographic coupling uses the number of references shared by two documents as a measure of the similarity [57]. The strength of

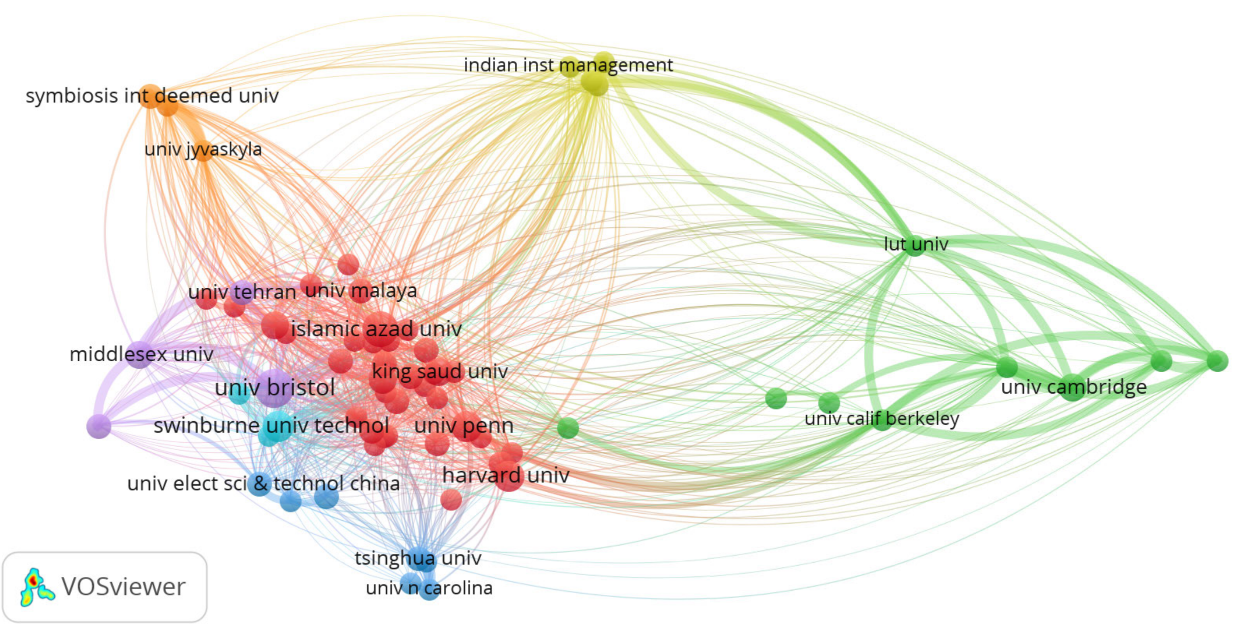

FIGURE 16. Bibliographic coupling of affiliations. notes: minimum publication threshold of 3 documents and 10 citations.

the bibliographic coupling is determined by the total number of references or citations of other third documents that they share, and it indicates the strength of their ties in terms of shared fields of focus. Figure 15 displays the bibliographic coupling of authors publishing in behavioral economics and AI.

The largest cluster (red) of coupled authors is represented by cheng yang, jiang hua, pillai rajasshrie, sivathanu brijesh, ameen nisreen, and filieri raffaele. Their shared topic of research is the relationship between AI and consumer behavior in various contexts, specifically as it pertains to how AI-powered chatbots, robotics, and augmented reality impact consumer behavior and emotions in the context of hospitality and tourism, digital and social media marketing, and customer-brand relationships.

The second-largest cluster (green) is mainly driven by bu fankun, dehghanpour kaveh, wang zhaoyu, yuan yuxuan, suchacka grazyna, and acuna-agost rodrigo, Rodrigo. The common research topic among those authors is the application of data-driven and AI-based approaches to areas such as e-customer behavior and pricing optimization. More specifically, these articles address issues related to data collection, analysis, and modeling using AI and machine learning techniques.

The blue cluster consists of authors who tend to research consumer behavior and decision-making, specifically consumer attitudes toward food products.

The purple cluster is comprised of authors whose study focuses on the application of psychology and AI to better understand and predict the financial decision-making processes of humans using behavioral theories such as decision avoidance.

The illustrated network of bibliographic coupling of authors confirms the need for expanded interdisciplinary research collaboration in this field, most especially to unlock the full potential of data-driven AI technologies in behavioral economics-related research.

The bibliographic coupling of author affiliations in Figure 16 illustrates a network of coupling between universities engaged in AI and behavioral economics studies. We can observe seven relatively distinguishable clusters, with the largest cluster (red) linking 36 universities. We note that the most productive and influential universities in AI and behavioral economics (Figure 7) also appear to be influential in bibliographic coupling.

Figure 17 presents the bibliographic coupling of countries with existing contributions in the field of AI and behavioral economics. Bibliographic coupling of countries occurs when publications from two countries reference publications from a third country. This figure suggests that the USA, China, and the UK have a central influence in the field. However, the figure also illustrates frequent coupling among other countries such as India, South Korea, and Saudi Arabia.

5) CO-OCCURRENCE ANALYSIS OF KEYWORDS

To conduct an accurate topical analysis, we first preprocessed the data prior to conducting the keyword co-occurrence analysis. We used the VOSviewer thesaurus file [58] to

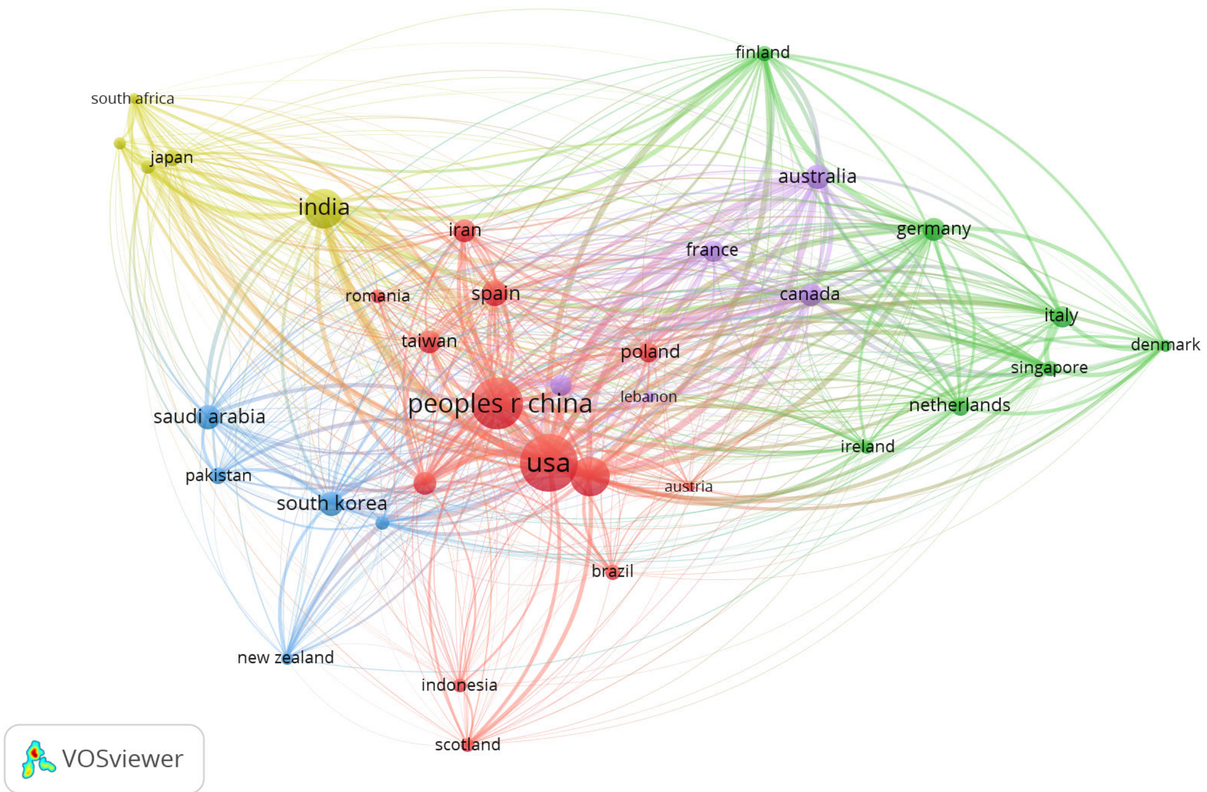

FIGURE 17. Bibliographic coupling of countries. notes: minimum publication threshold of 4 documents and 50 citations.

TABLE 7. Cluster's keywords. notes: Ordered by weight(Occurrences).

Cluster	Keywords
Red	consumer behavior, artificial intelligence, impact, artificial neural network, intentions, adoption, satisfaction, trust, attitudes, internet, acceptance, consumer, experience, online, reviews, determinants, framework, customer satisfaction, information technology, covid-19, word-of-mouth, loyalty, perceived risk, purchase intention, user acceptance, bibliometric analysis, innovation, quality, service robots, blockchain, business, hospitality, mobile commerce, planned behavior, robotics, behavioral intention, commerce, service quality, antecedents, anthropomorphism, online consumer behavior, perceived value, beliefs, customer engagement, customer loyalty, digitalization, ewom, mobile banking, perceived usefulness, sales, structural equation modeling, tam, technology acceptance, tourism, transformation
Green	machine learning, big data, neural network, behavior, e-commerce, deep learning, algorithm, classification, management, customer behavior, prediction, decision tree, support vector machine, data mining, churn prediction, segmentation, customer, big data analytics, analytics, clustering, data analytics, demand, services, patterns, selection, energy consumption, retention, cluster analysis, crm, regression, design, telecommunication, random forest, demand response, machine, lstm, smart grid, convolutional neural network, rfm, business intelligence, education, customer segmentation, motivation, attention, retail, load forecasting, support, predictive analytics, relationship management, data science, k-means clustering, smart meters, feature extraction, online shopping
Blue	behavioral economics, decision making, reinforcement learning, emotion, optimization, decision, personality, preferences, electroencephalogram eeg, bias, choice, forecast, human-computer interaction, neuromarketing, brain, economics, feature selection, nudge, psychology, recognition, recommender systems, cost, dynamics, memory, prospect-theory, consumer neuroscience, emotion recognition, energy, games, growth, neuroeconomics, prefrontal cortex, signals, simulation, traits
Yellow	social media, consumption, perceptions, price, sustainability, brand, knowledge, marketing, perspective, strategies, product, purchase, communication, food, competition, responses, topic modeling, engagement, power, chatbots, consumer decision making, fraud detection, opportunities, students, supply chain management, willingness
Purple	risk, behavioral finance, performance, sentiment analysis, market, investor sentiment, natural language processing, returns, time series analysis, sentiment, stock market, media, news, volatility, cross-section, ethics, investment, text mining, twitter, digital marketing, financial markets, unsupervised learning

clean the data by merging plural terms to their singular form (e.g. "customer" and "customers"), correcting spelling differences (e.g. "behavior" and "behaviour"), and combining abbreviated terms with full terms (e.g. "artificial intelligence" and "AI"). We removed general terms (e.g. "time" and "future") and obtained 192 keywords from the filtering of keywords with less than five occurrences before proceeding to the keyword co-occurrence analysis. In Figure 18 the overview displays five thematic clusters that underpin the knowledge structure of AI research in behavioral economics, while the Table 7 reflects the keywords affiliated with each of these clusters, sorted by their number of occurrence. We inferred these clusters' main topics and a brief description mainly from keyword semantics, and we present these findings below.

- Red cluster: Customer Behavior and Technology Adoption topics
  Based on the keyword analysis, it appears that the main issues addressed in this cluster (55 items) include using artificial intelligence techniques to predict customer behavior and intentions, building trust, enhancing the online customer experience, reducing perceived risk, and driving customer engagement, trust, and loyalty. Additionally, in businesses and industries like banking, hospitality, and tourism, AI-driven technologies such as service robots and anthropomorphic technology are used to leverage online reviews, e-WOM, and other customer feedback to gain insights into the customer experience and satisfaction, reducing perceived risk and improving user acceptance and adoption of new technologies.
- Green cluster: Consumer Behavior and Energy consumption topics
  The keyword network in this cluster (54 items) points out that encompassed topics focus on using data-driven approaches to understand consumer motivation, identify consumer behavior patterns, and predict customer demand, retention, or churn. Various AI techniques are commonly used: machine learning, deep learning, classification, big data analytics, data mining, decision trees (DT), clustering, convolutional neural networks (CNN), regression, long short-term memory (LSTM), feature extraction, and support vector machines. One particular issue addressed in this topic includes identifying patterns in energy demand and consumption, improving load forecasting and management, and optimizing energy services. Examples of AI-powered applications in this industry include smart meters and demand response systems.
- Blue cluster: Decision Making and Neuroeconomics topics
  The keyword analysis in this cluster (35 items) implies that the involved topics cover the use of AI techniques combined with neuroscience to assist in decision-making by incorporating insights from the study of psychological, cognitive, and emotional factors that influence people's decision-making processes. Emotion recognition and personality analysis are integrated into AI models such as reinforcement learning (RL) algorithms to better understand how individual differences influence decision-making. In the context of neuroeconomics, electroencephalograms (EEG) and other neural signals are used to gain insight into brain processes underlying decision-making. Concepts like Prospect theory and Nudge are incorporated into optimization and recommender systems to suggest personalized interventions that improve an individual's decision-making.
- Yellow cluster: Marketing topics
  This cluster's keywords (26 items) suggest that the comprised topics deal with the analysis of consumer behavior and consumption patterns. AI is used to analyze consumer preferences and engagement through the use of social media data to enhance brand perception, develop effective marketing strategies, and improve supply chain management's sustainability. Techniques for natural language processing, such as topic modeling, are used to identify patterns and trends in data, which can be used to improve product design and marketing strategies.
- Purple cluster: Behavioral finance topics
  In this cluster (22 items), keyword-related topics seem to focus on using artificial intelligence applications in behavioral finance to analyze investor sentiment in financial markets. The main issue is understanding how the emotions and sentiments of investors impact stock market performance and decision-making, along with factors such as volatility, risk, and returns. The techniques used include sentiment analysis, natural language processing, text mining, time series analysis, and unsupervised learning. Twitter and the news media are key data sources for analysis in this context.

Overall, as illustrated by the clusters entanglement in Figure 18, these topics are not exhaustive, and many techniques and issues overlap across different domains of AI and behavioral economics.

The overlay visualization in Figure 19, which depicts the temporal distribution of the previously identified clusters keywords between 2018 and 2021, is an additional illustration to consider. In this illustration, the keywords' colors range from blue (the earliest) to green and yellow (most recent). Examining the evolution of AI and behavioral economics research sub-fields through keywords and capitalizing on the keyword co-occurrence analysis of Figure 18 reveals that the newest keywords are associated with the technology adoption topic (Red cluster), followed by the behavioral finance and Investment topic (Purple cluster), while the earliest keywords are associated with the consumer and customer behavior topics (Green and Red clusters). However, further analysis reveals a tendency in the artificial intelligence approach and techniques applied across the sub-fields of behavioral economics toward deep learning and natural language processing techniques.

6) THEMATIC STRUCTURE THROUGH CO-WORD ANALYSIS

To further analyze the thematic structure and evolution in the AI and behavioral economics research field, and to confirm our previous insights from the co-occurrence analysis, we used co-word analysis of the author's keywords (number of words = 200, minimum frequency = 7) and we plotted a thematic map in Figure 20 using two dimensions. The first is density, or the measure of the internal strength of the network, which indicates the degree of development of

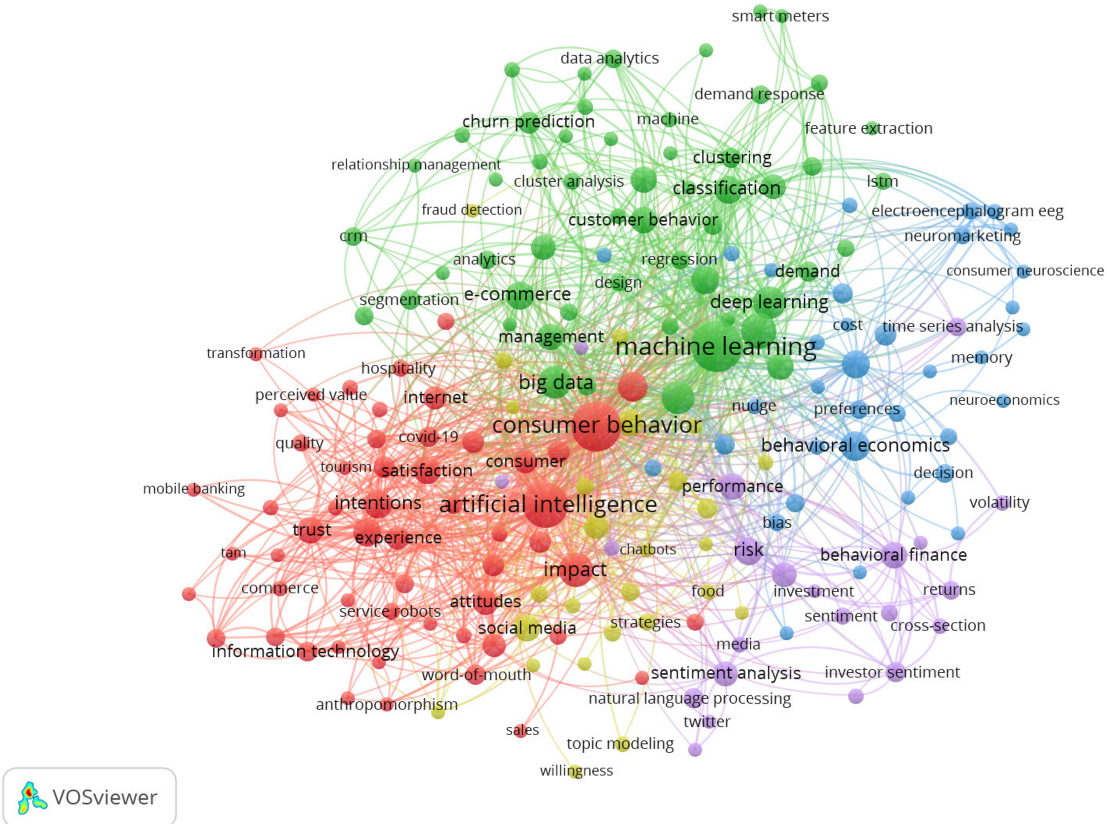

FIGURE 18. Network visualization of keyword co-occurrence. note(s): -Each node in a network represents a keyword. -The size of the node shows the keyword occurrence,. -The link between the nodes represents the co-occurrence between keywords. -The thickness of the link indicates the occurrence of co-occurrences between keywords. - Each color represents a cluster (theme), in which the nodes (topics) and links (relationships) explain the cluster's coverage of nodes and the links between the nodes manifesting under that cluster.

the themes as measured by the internal associations among the keywords. The second is centrality, or the measure of the strength of external ties to other networks, which indicates the relevance of the themes in the development of the entire research field as measured by the external associations between the keywords [59]. The size of a cluster is defined by the frequency of the keywords it contains, which is impacted by the number of linked documents. The labels on a cluster correspond to the most prevalent keywords. The dataset was sanitized before conducting the co-word analysis by removing generic keywords and merging keywords with spelling variants and acronyms.

The visual representation of the keyword clusters identifies the main research themes, structured in four quadrants used to track the evolution and mutual influence of the research themes:

- Upper-Right: motor themes with high density and centrality. These are highly developed themes that are central to the overall structure of the research field.
- Lower-Right: basic themes with low density and high centrality. These are transversal and general themes that are important for the research field but are still not well developed.
- Upper-Left: niche themes with high density and low centrality. These are well-developed and highly specialized themes, but marginal in the overall field.
- Lower-Left: emerging/declining themes with low density and centrality; this mainly comprises emerging or declining themes that are underdeveloped and poorly tied with other themes.

The analysis corroborates the findings of the co-occurrence network of keywords in Figure 18. To further evaluate the theme content, for each quadrant, clusters with a significant number of affected papers are screened, and the findings are presented as follows: We start with the motor themes quadrant, where we examine the 2 identified clusters, followed by the basic themes quadrant with 2 observed clusters, one of which is positioned at the junction between 2 quadrants, then we continue with 1 prevalent cluster in the niche themes quadrant, and finally the emerging/declining themes quadrant with one noticeable cluster.

a: CLUSTER 1: BEHAVIORAL ECONOMICS

As a motor theme, we may claim that this theme encompasses the core studies related to behavioral economics and AI by exploring how AI techniques such as reinforcement

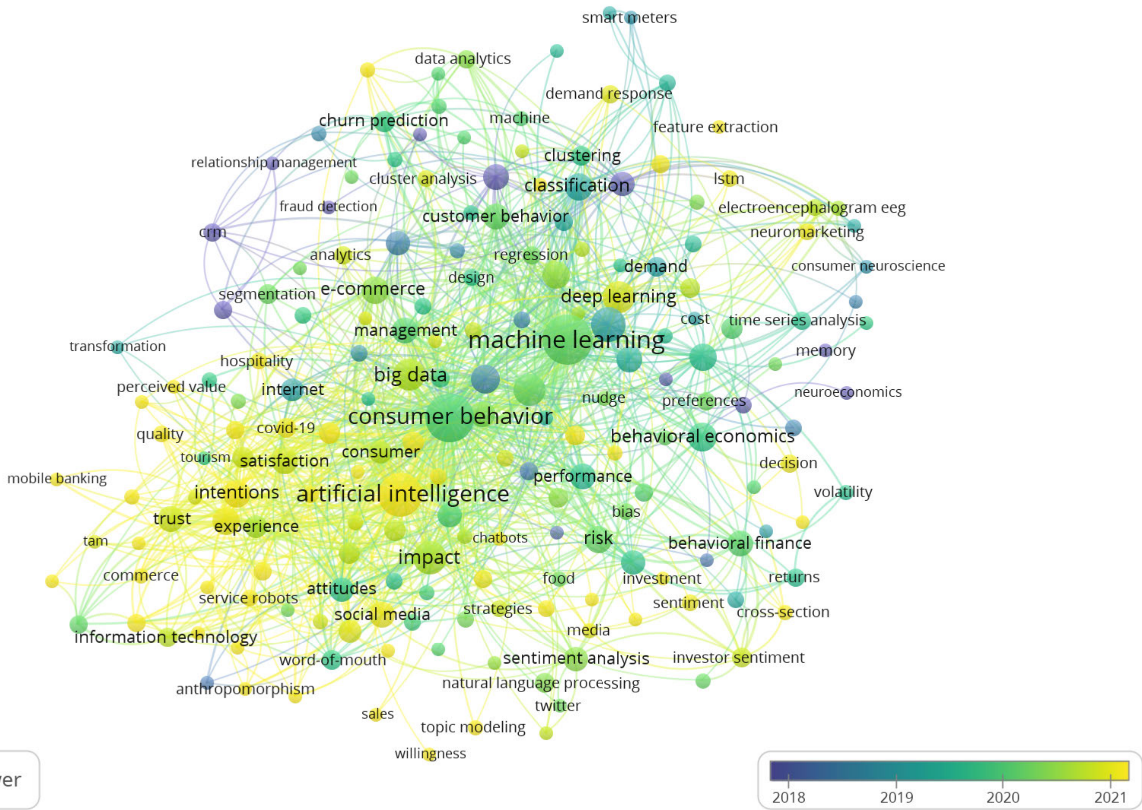

FIGURE 19. Overlay visualization of keywords based on the average frequency of occurrence between 2018 and 2021.

learning can be applied along with psychological and cognitive concepts such as nudge or prospect theory to various areas of economics, including economic games [60], behavior change [61] and social interaction [62]. Some studies discuss how subtle nudges can influence consumer behavior, often without the consumer's knowledge, and how cognitive biases can affect decision-making in the presence of these nudges [63]. Other articles investigate how machine learning techniques, such as SVM and feature selection, can be applied to neuromarketing research to gain insights into consumer behavior and preferences [64], examine how AI and artificial neural networks can help improve our understanding of decision-making processes in the context of neuroeconomics [65], the use of inverse reinforcement learning (IRL) to explain user behavior on YouTube [66], and the use of prospect theory and hybrid machine learning, which combines traditional econometric models with machine learning algorithms to analyze the impact of macroeconomic factors such as inflation and economic growth on exchange rates [67].

b: CLUSTER 2: SMART GRID

Also identified as a motor theme, here we depict studies focusing mainly on the application of deep learning techniques in various aspects of the energy sector, including studies on optimal dynamic pricing for an electricity retailer in the price-responsive environment of a smart grid [68], profit maximization for an electricity retailer [69], and enhancing sustainable smart grids using a hybrid classification approach [70]. Other studies discuss the use of deep learning models like convolutional neural networks in analyzing consumer behavior and predicting customer choices [71], the development of a deep hybrid learning model that can predict customer repurchase behavior [72] and decision tree models for efficient customer behavior learning and prediction of campaign participation [73].

c: CLUSTER 3: CUSTOMER BEHAVIORAL

Mainly positioned as a basic theme, it encloses studies that use predictive analytics, data mining, clustering, and classification techniques to analyze and understand customer behavior, personalize tariff plans [74], predict customer engagement behavior in response to marketing posts [75] and incorporate opinion mining and sentiment analysis in advertising strategies [76]. They also apply machine learning models to identify patterns and insights from large datasets in the electricity [77] and water consumption [78] industries. The theme studies highlight the importance of using AI techniques to improve customer satisfaction and loyalty [79], reduce customer churn in the telecom industry [80], and optimize pricing and tariff plans [81].

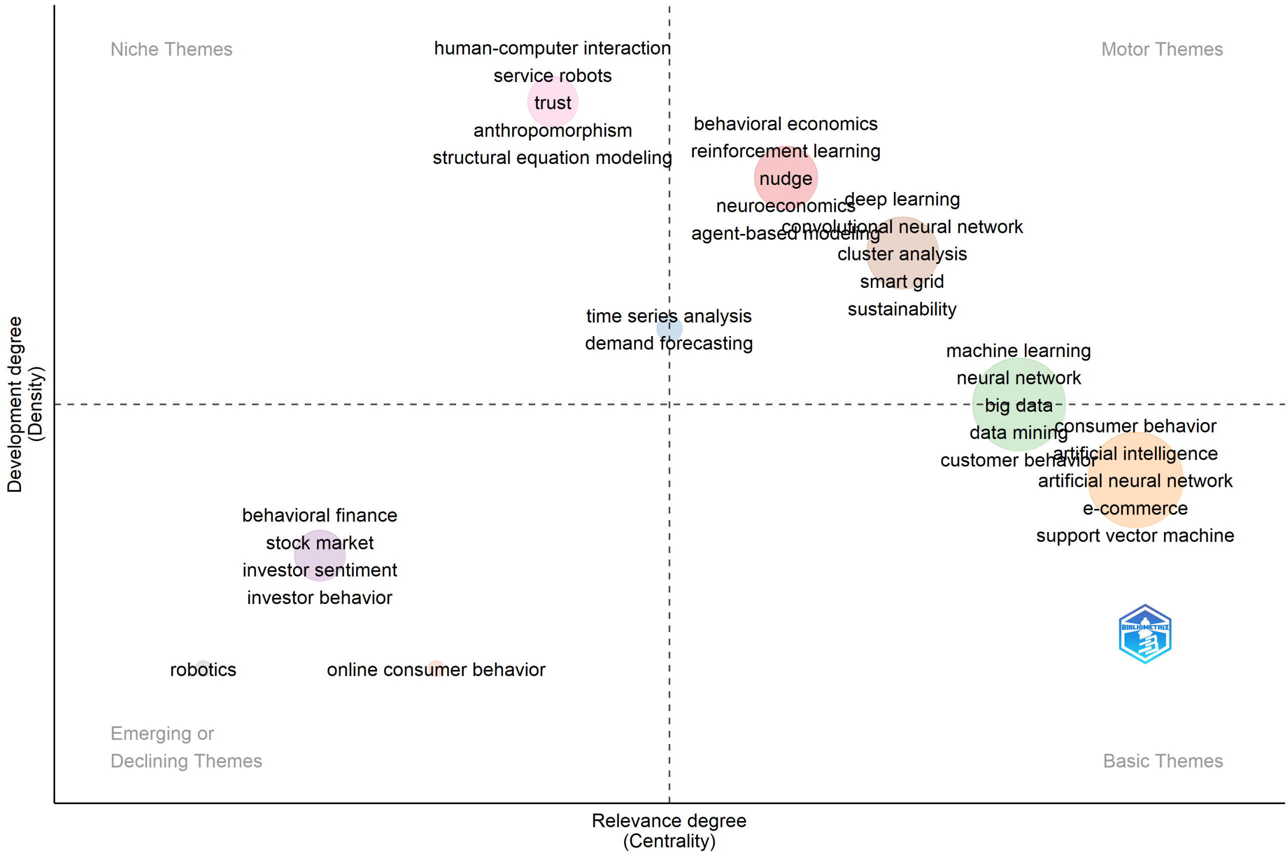

FIGURE 20. Thematic Map through co-word analysis.

d: CLUSTER 4: CONSUMER BEHAVIORAL

As a basic theme, it involves research topics that pertain to the use of machine learning and data analytics in various behavioral economics-related topics. These studies use AI techniques to classify consumer behavior [82], use latent Dirichlet allocation (LDA) to identify and analyze topics related to sustainable consumption behavior during the pandemic [83], evaluate the effectiveness of machine learning algorithms, particularly Support Vector Machines (SVM), for predicting consumer behavior and identifying its key influencing factors [84], examine the impact of risk averseness and emotional stability in e-commerce environment using machine learning models such as random forest [85], develop a blockchain-based framework for eSports using a combination of the theory of planned behavior (TPB) and machine learning [86], and use brain-computer interfaces (BCI) and electroencephalography (EEG) signals to predict consumers' choices in the context of neuromarketing [87]. Overall, the theme-related studies highlight the importance of using machine learning techniques to understand and predict consumer behavior in various contexts.

e: CLUSTER 5: HUMAN-COMPUTER INTERACTION

Primarily a niche theme, its study's fundamental focus is the adoption and acceptance of artificial intelligence and Service Robots in the service industry, specifically in hospitality [88], tourism [89], and restaurants [90]. The studies explore various factors that affect consumer trust, acceptance, and intention to use AI devices and service robots, such as perceived psychological anthropomorphic characteristics [91], trust, and perceived risk [92]. Some studies examine the impact of socialness [93] and number presentation detail [93] on consumer trust and acceptance of AI recommendations; others suggest the use of AI techniques such as the hybrid PLS-ANN approach, which provides a useful framework for analyzing the adoption of technologies such as proximity mobile payment services [94]; and others explore the impact of trust and customizability in conversational agents on health engagement [95]. Additionally, studies explore the relationship between social media marketing and consumer purchase behavior using a combination of structural equation modeling (SEM) and unsupervised machine learning approaches [96].

f: CLUSTER 6: BEHAVIORAL FINANCE

To determine if this theme is emerging or declining, we take a look at the previous overlay network map 19, which indicates an emerging trend for keywords such as behavioral finance and investor sentiment, validating the theme's emerging nature. The main scope of the scientific articles in this theme is the intersection between behavioral finance and AI techniques and algorithms, to analyze and predict market trends and investor behavior. The specific topics include measuring investor sentiment using machine learning and news photos [97], using sentiment analysis and options volume to anticipate future returns [98], examining differences in investors' behavior across different financial markets [99], analyzing the relationship between social moods and the stock market [100], using artificial neural networks to examine behavioral biases in retail investors during the pandemic [101], bankruptcy modeling using neural trace [102], media sentiment and international asset prices, accounting for unadjusted news sentiment for asset pricing [103] and applications of AI in commercial banks for behavioral finance.

Overall, AI applications in behavioral economics studies appear to be primarily focused on consumer and customer behavior, whereas investor behavior studies seem currently underdeveloped; nevertheless, they reflect an emerging trend alongside the behavioral finance sub-field broadly. The development of the field is mainly driven by sectors such as e-commerce, finance, energy, and telecommunications industries. In addition, unless we see increased interest in interdisciplinary collaborations in the future, human-computer interaction, and service robot studies are presently marginal in the development of the field.

V. DISCUSSION

To address the research questions previously formulated, the key findings from the bibliometric analysis, including the research performance analysis key results, insights from current and emerging trends, as well as potential future directions are discussed.

A. KEY FINDINGS FROM THE RESEARCH PERFORMANCE ANALYSIS

Based on bibliometric data, we present the key findings of the research performance analysis as follows:

- **Global Publication performances**: A total of 637 articles were published by 1997 authors in 373 journals between 2012 and 2022. 2022 was the most prolific year, with 196 articles. Business Economics and Computer Science are the most prevalent research areas, with a total of 383 articles.
- **Key Authors**: The key authors by a number of publications, as well as h-index, g-index, and m-index, are PANTANO E, KIM J, and KUMAR S, from year-wise analysis, LIU X shows himself as the longest active author in the field (since 2016), Kumar S has the highest production per year (4 papers in 2022), and WANG Y has the highest citations per year (91.0).
- **Key Journals**: The most relevant journals in terms of productivity and impact are the Journal of Retailing and Consumer Services, Journal of Business Research, IEEE Access, IEEE Transactions on Smart Grid, Expert Systems with Applications, Sustainability, Energies, Computers in Human Behavior, the Journal of Big Data, Applied Sciences-Basel, and Frontiers in Psychology.
- **Key Affiliations/Universities**: The most productive as well as bibliographically coupled affiliations are found to be the University of Pennsylvania, University of Bristol, Islamic Azad University, King Saud University, Swinburne University of Technology, United International University, University Malaya, University of Technology Sydney, Yale University, Bucharest University of Economic Studies, Harvard University, North Carolina State University, Shandong University of Finance and Economics, University of Electronic Science and Technology of China and University of Tennessee.
- **Key Countries**: The most productive, influential, and collaborating countries in the field of AI and behavioral economics are found to be the USA, China, India, the United Kingdom, Singapore, Spain, Australia, South Korea, Malaysia, Turkey, Iran, Ecuador, Netherlands, Finland. In terms of bibliographic coupling, the USA, China, and the United Kingdom have a central influence in the field, followed by India, South Korea, and Saudi Arabia.
- **Key Articles**: The most notable articles based on total citation are Wirtz et al. [55], Wang et al. [38], Davenport et al. [39], Dwivedi et al. [40], Quilumba et al. [41], Chong [42], Wei et al. [43], Hew et al. [44], Lak et al. [45] and Claveria and Torra [46].

B. KEY FINDINGS FOR THE SCIENCE MAPPING AND NETWORK ANALYSIS

Building on the behavioral economics subfields discovered in the theoretical background section and through the bibliometric analysis findings in the previous section, including the knowledge foundation discovered through co-citation analysis and the body of knowledge depicted through co-occurrence analysis and co-word's thematic structure (current research), as summarized in Table 8, we provide our concluding thoughts on the current landscape and suggestions for future direction in the artificial intelligence and behavioral economics research field as follows:

1) CURRENT LANDSCAPE

- Research on psychology such as Prospect Theory [4], Theory of Planned Behavior [49], AI, machine learning techniques such as Latent Dirichlet Allocation [52], Random Forests [50] and Support Vector Networks [51] applied to financial decision-making [12], [53], customer behavioral, service industry [54], [55] and technology acceptance [48] related topics are the main knowledge foundations for the AI and behavioral economics research field.
- The intersection of AI and behavioral economics predominantly focuses on consumer and customer

TABLE 8. Summary of bibliometric analysis of thematic evolution.

JEL code based subfields	Co-citation analysis (knowledge foundations)	Co-occurrence analysis of keywords (current research)	Thematic structure through co-word analysis (current research)
Themes • Behavioral finance • Decision-making under uncertainty • Behavioral Macroeconomics • Behavioral game theory • Experimental economics • Neuroeconomics • Health, Education and Welfare • Marketing and Advertising • Sustainability and Consumer behavior	*Themes* Cluster 1: • Behavioral research • Technology acceptance Cluster 2: • Machine Learning Cluster 3: • Psychology and financial Decision-making Cluster 4: • AI impact on customer behavior	*Themes* Red cluster (55 items): • Customer Behavior • Technology Adoption Green cluster (54 items): • Consumer Behavior • Energy consumption Blue cluster (35 items): • Decision Making • Neuroeconomics Yellow cluster (26 items): • Marketing Purple cluster (22 items): • Behavioral finance	*Themes* Motor themes: • Behavioral economics, nudge, neuroeconomics, • Smart Grid, sustainability Basic themes: • Customer behavioral • Consumer behavioral and e-commerce Niche themes: • Human-computer interaction, service robots, trust Emerging themes: • Behavioral finance, stock market, investor sentiment
	Used techniques ML, classification, regression, feature selection, topic modeling, NLP, LDA, SVM, Random Forests	*Used techniques* ML, Feature Extraction, Regression, Classification, Decision Tree, SVM, NLP, Sentiment Analysis, Text Mining, Topic Modeling, Big Data analytics, Data Mining, Clustering, Time Series Analysis, DL, AAL, LSTM, CNN and Reinforcement learning	*Used techniques* ML, Feature Selection, Classification, NLP, LDA, Data Analytics, Predictive Analytics, Data Mining, Clustering, DL, CNN, SVM, RL, IRL, BCI, hybrid ML, Hybrid PLS-ANN and Blockchain
	Sectors Finance, marketing, healthcare, hospitality	*Sectors* Energy, finance, marketing, banking, hospitality, and tourism	*Sectors* Energy, electricity and water, finance, marketing, telecom, e-commerce, hospitality, tourism, restaurants, healthcare

behavior and less on investor behavior, employing mainly ML, ANN, data mining, and NLP techniques. Various customer and consumer-centric topics have been examined including neuromarketing and neuroeconomics research. Applied techniques include SVM and feature selection to gain valuable insights into consumer preferences and behavior [64], artificial neural networks to enhance the understanding of economic decision-making processes [65], and data mining algorithms to personalize tariff plans and forecast customer engagement behavior [74], [75].

- On the other hand, behavioral finance-related topics, especially investor behavioral and stock market studies, are on the rise. This trend is prominently driven by applications of NLP, text mining, and sentiment analysis techniques, as evidenced by studies focusing on measuring investor sentiment through news photos [97], employing sentiment analysis for anticipating future returns [98], and analyzing the impact of media sentiment and social moods on the stock market [100] and international equity prices [104].
- AI and behavioral economics core studies are driven by decision-making under uncertainty, neuroeconomics, and behavioral game theory-related concepts such as nudge, prospect theory, cognitive biases, and bounded rationality combined with deep learning [105] and reinforcement learning [106] techniques. This synergy between AI techniques and psychological concepts such as nudge or prospect theory empowers researchers to explore diverse economic domains, including economic games [60], behavior change [61] and social interactions [62].
- Energy, finance, marketing, telecommunications, and hospitality emerge as the main sectors where the intersection of behavioral economics and AI techniques has found substantial application. This tendency is evident in studies focusing on optimizing sustainable smart grids through deep learning models [70], analyzing investor sentiment and stock market performance using sentiment analysis and neural networks in finance [97], [100], predicting consumer behavior and preferences in marketing [82], [83], reducing customer churn in the telecommunications industry [80], and enhancing customer trust and acceptance of AI devices in the hospitality sector [88], [91].
- Behavioral economics research is actively moving towards more use of advanced deep learning techniques, specifically CNN and LSTM models. This transition is particularly prominent in sustainability and energy-related studies. For instance, researchers employ CNN for predicting choices in the context of sustainable consumption [83], and utilize LSTM models for optimizing dynamic pricing in the electricity sector within smart grids [68].
- Research on ML and NLP applications in marketing and advertising has reached a mature stage, as evidenced by comprehensive studies exploring the integration of ML algorithms, particularly SVM, for predicting consumer behavior and identifying influencing factors in e-commerce environments [84]. Additionally, the incorporation of NLP techniques in advertising strategies has been extensively explored, with studies employing opinion mining and sentiment analysis to enhance marketing efforts [76].

- Human-computer interaction is a particular field related to marketing where studies focus on the impact of AI technologies rather than their application to consumer behavior. Notably, studies investigating technology acceptance and adoption, such as the impact of AI-driven chatbots on consumer interactions [96], as well as the integration of service robots in hospitality, tourism, and restaurant industries [88], [89], [90], have garnered significant attention.
- Studies on macroeconomics and experimental economics are scant, with some first studies such as the use of prospect theory and hybrid machine learning, which combine traditional econometric models with machine learning algorithms to analyze the impact of macroeconomic factors such as inflation and economic growth on exchange rates [67].

Broadly speaking, while studies of AI in behavioral economics indicate a steadily increasing interest in investor behavior, the field is still largely focused on consumer and customer behavior. This is partly due to the fact that available data on investor behavior is often limited to a smaller number of individuals or institutions, making it more difficult to develop accurate models that can explain and forecast their behavior.

2) SUGGESTIONS FOR FUTURE DIRECTION

- Giving greater attention to AI applications in behavioral macroeconomics, including monetary policy and fiscal policy, would help policymakers make more informed decisions about economic policy, financial regulations, and other key issues.
- Greater interactions between experimental economics and AI-related studies can lead to higher data quality, more accurate and insightful research, and help inform economic policy decisions in a more data-driven and effective way.
- New advanced AI models, including hybrid machine learning, ensembles, and explainable AI models, can provide more predictive power and transparency in behavioral economics studies, particularly in behavioral macroeconomics and finance.
- More inter-disciplinary research both in emerging (behavioral finance) and developing themes (marketing and advertising).
- More emphasis on ethical and privacy concerns in AI and behavioral economics research.

Overall, AI has the potential to revolutionize the way we understand human behavior, therefore, more interdisciplinary research studies on AI and Behavioral economics related issues are needed for several reasons, including to improve the accuracy and efficiency of data analysis using more complex approaches and to develop more transparent and explainable AI models, particularly within behavioral finance and behavioral macroeconomics related studies where, as previously mentioned, advanced AI tools are needed for better understanding and modeling of investors and market behavior, and to push forward more topics such as institutions decision-making, corporate ethical responsibility, and regulatory policy.

Moreover, every technological advancement, including AI and behavioral economics, carries inherent challenges alongside its potential. Therefore, it is essential to address these issues diligently. Ethical considerations, the prevalence of algorithmic biases, the potential dehumanization of decision-making processes, job displacement concerns, and regulatory intricacies all demand deep examination. To effectively overcome these challenges and ensure that the integration's benefits are harnessed while safeguarding individuals and society at large, a full engagement of experts spanning AI, behavioral economics, ethics, and policy-making is required.

Even though our study exhibits some consistent results and offers significant insights, it also has some limitations. The data sample was initially restricted to the Web of Science database; using different databases could yield a larger sample. Second, we composed a specific set of keywords to finalize our data retrieval request, and we adopted a specific bibliometric analysis approach, which can be enhanced to produce distinct insights from different metrics. Further, the extraction period could be modified to disclose varying publication tendencies.

Finally, Bibliometric analysis, as demonstrated in this study, provides a quantitative assessment of the scholarly literature, illuminating patterns of publication, citation, and collaboration within the specific field of AI and behavioral economics. However, it is important to acknowledge the limitations associated with this methodology. While our bibliometric analysis has offered valuable insights into the quantitative aspects of research trends, employing a systematic review approach in future research and narrowing the scope of the study can provide a more in-depth and contextual understanding of the qualitative aspects of the literature, providing a more robust understanding of the research field where AI and behavioral economics overlap.

VI. CONCLUSION

In conclusion, this bibliographic analysis stands as a foundational exploration into the intersection of AI and behavioral economics, encapsulating a decade of academic activity. The analysis highlights the increasing interest in this field, with a growing number of studies examining the use of AI techniques to understand and predict human behavior. Still, further research is needed to fully realize the potential of AI in behavioral economics, especially concerning areas such as macroeconomics and healthcare, where the full scope of AI's impact is yet to be comprehensively explored. Moreover, this analysis emphasizes the need for sustained interdisciplinary collaboration between AI and behavioral economics scholars. The synergy between these fields is fundamental for uncovering profound insights into human decision-making processes. This collaboration can pave the way for substantial advancements not only in theoretical understanding but also in practical applications. From shaping energy policies to providing innovative solutions to complex societal challenges and enhancing service industries like hospitality.

While the collaborative efforts of AI and behavioral economics researchers can initiate positive transformations across diverse domains, they also raise challenges and constraints that cannot be overlooked. Ethical concerns surrounding privacy, algorithmic biases, and the risk of job displacement demand significant attention. Additionally, the potential dehumanization of decision-making processes requires a subtle and refined approach. Experts' active involvement in integrating ethics and policy-making is crucial. By addressing these challenges transparently and responsibly, positive, equitable, and socially responsible outcomes can surely be achieved.

Overall, this study is not just a culmination of past research; it is a stepping stone toward a future where the overlap of AI and behavioral economics reshape paradigms, enrich our understanding of human decision-making, and ultimately contribute to a more insightful and compassionate world.

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REFERENCES

[1] R. H. Thaler, "Behavioral economics: Past, present, and future," *Amer. Econ. Rev.*, vol. 106, no. 7, pp. 1577–1600, Jul. 2016.

[2] N. Ashraf, C. F. Camerer, and G. Loewenstein, "Adam smith, behavioral economist," *J. Econ. Perspect.*, vol. 19, no. 3, pp. 131–145, Aug. 2005.

[3] G. A. Akerlof and R. J. Shiller, *Animal Spirits: How Human Psychology Drives the Economy, and Why it Matters for Global Capitalism*. Princeton, NJ, USA: Princeton Univ. Press, 2010.

[4] D. Kahneman and A. Tversky, "Prospect theory: An analysis of decision under risk," *Econometrica*, vol. 47, no. 2, p. 263, Mar. 1979.

[5] S. J. Russell, *Artificial Intelligence a Modern Approach*. London, U.K.: Pearson, 2010.

[6] T. Hastie, R. Tibshirani, J. H. Friedman, and J. H. Friedman, *The Elements of Statistical Learning: Data Mining, Inference, and Prediction*, vol. 2. Cham, Switzerland: Springer, 2009.

[7] H. R. Varian, "Big data: New tricks for econometrics," *J. Econ. Perspect.*, vol. 28, no. 2, pp. 3–28, May 2014.

[8] H. Chen, R. H. L. Chiang, and V. C. Storey, "Business intelligence and analytics: From big data to big impact," *MIS Quart.*, vol. 36, no. 4, p. 1165, 2012.

[9] F. Königstorfer and S. Thalmann, "Applications of artificial intelligence in commercial banks—A research agenda for behavioral finance," *J. Behav. Experim. Finance*, vol. 27, Sep. 2020, Art. no. 100352.

[10] Z. Wei, C. Wu, X. Wang, A. Supratak, P. Wang, and Y. Guo, "Using support vector machine on EEG for advertisement impact assessment," *Frontiers Neurosci.*, vol. 12, p. 76, Mar. 2018.

[11] L. Abrardi, C. Cambini, and L. Rondi, "Artificial intelligence, firms and consumer behavior: A survey," *J. Econ. Surveys*, vol. 36, no. 4, pp. 969–991, Sep. 2022.

[12] J. Bollen, H. Mao, and X. Zeng, "Twitter mood predicts the stock market," *J. Comput. Sci.*, vol. 2, no. 1, pp. 1–8, Mar. 2011.

[13] A. Huang and H. You, "Artificial intelligence in financial decision making," in *Handbook of Financial Decision Making, Forthcoming*. Cheltenham, U.K.: Edward Elgar Publishing, 2022.

[14] A. Banal-Estañol and A. R. Micola, "Behavioural simulations in spot electricity markets," *Eur. J. Oper. Res.*, vol. 214, no. 1, pp. 147–159, Oct. 2011.

[15] R. H. Thaler, "From homo economicus to homo sapiens," *J. Econ. Perspect.*, vol. 14, no. 1, pp. 133–141, Feb. 2000.

[16] J. P. Henderson, "The theory of marginal cost pricing," *Sci. Soc.*, vol. 10, pp. 135–141, Mar. 1956.

[17] S.-Y.-T. Lee, "Bundling strategy in base-supplemental goods markets: The case of Microsoft," *Eur. J. Inf. Syst.*, vol. 9, no. 4, pp. 217–225, Dec. 2000.

[18] H. A. Simon, *Bounded Rationality*. London, U.K.: Palgrave Macmillan, 1990, pp. 15–18.

[19] D. F. Costa, F. D. M. Carvalho, and B. C. D. M. Moreira, "Behavioral economics and behavioral finance: A bibliometric analysis of the scientific fields," *J. Econ. Surv.*, vol. 33, no. 1, pp. 3–24, Feb. 2019.

[20] A. E. A. Journal of Economic Literature. (2019). *Jel Classification System*. [Online]. Available: https://www.aeaweb.org/econlit/jelCodes.php

[21] D. A. Ferrucci, "Introduction to 'this is Watson,"' *IBM J. Res. Develop.*, vol. 56, no. 3, pp. 1:1–1:15, May 2012.

[22] T. B. Brown et al., "Language models are few-shot learners," in *Proc. Adv. Neural Inf. Process. Sys.*, vol. 33, pp. 1877–1901, 2020.

[23] D. Hassabis, D. Kumaran, C. Summerfield, and M. Botvinick, "Neuroscience-inspired artificial intelligence," *Neuron*, vol. 95, no. 2, pp. 245–258, Jul. 2017.

[24] C. F. Camerer, "Artificial intelligence and behavioral economics," in *The Economics of Artificial Intelligence: An Agenda*. Chicago, IL, USA: Univ. Chicago Press, 2018, pp. 587–608.

[25] T. S. Smith and G. T. Stevens, "Emergence, self-organization, and social interaction: Arousal-dependent structure in social systems," *Sociol. Theory*, vol. 14, no. 2, p. 131, Jul. 1996.

[26] S. V. Patil, P. E. Tetlock, and B. A. Mellers, "Accountability systems and group norms: Balancing the risks of mindless conformity and reckless deviation," *J. Behav. Decis. Making*, vol. 30, no. 2, pp. 282–303, Apr. 2017.

[27] M. Sarkar and A. De Bruyn, "LSTM response models for direct marketing analytics: Replacing feature engineering with deep learning," *J. Interact. Marketing*, vol. 53, pp. 80–95, Feb. 2021.

[28] Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," *Nature*, vol. 521, no. 7553, pp. 436–444, 2015.

[29] Y. Huang, X. Liu, R. Li, and L. Zhang, "The science of team science (SciTS): An emerging and evolving field of interdisciplinary collaboration," *Profesional Información*, vol. 32, no. 2, pp. 1–12, Mar. 2023.

[30] R. Chatila and J. C. Havens, *The IEEE Global Initiative on Ethics of Autonomous and Intelligent Systems*. Cham, Switzerland: Springer, 2019, pp. 11–16.

[31] M. Boukhlif, M. Hanine, and N. Kharmoum, "A decade of intelligent software testing research: A bibliometric analysis," *Electronics*, vol. 12, no. 9, p. 2109, May 2023.

[32] N. E. Akrami, M. Hanine, E. S. Flores, D. G. Aray, and I. Ashraf, "Unleashing the potential of blockchain and machine learning: Insights and emerging trends from bibliometric analysis," *IEEE Access*, vol. 11, pp. 78879–78903, 2023.

[33] N. Donthu, S. Kumar, D. Mukherjee, N. Pandey, and W. M. Lim, "How to conduct a bibliometric analysis: An overview and guidelines," *J. Bus. Res.*, vol. 133, pp. 285–296, Sep. 2021.

[34] X. Wang, Z. Fang, and X. Sun, "Usage patterns of scholarly articles on web of science: A study on web of science usage count," *Scientometrics*, vol. 109, no. 2, pp. 917–926, Nov. 2016.

[35] A. A. Chadegani, H. Salehi, M. M. Yunus, H. Farhadi, M. Fooladi, M. Farhadi, and N. A. Ebrahim, "A comparison between two main academic literature collections: Web of science and scopus databases," 2013, *arXiv:1305.0377*.

[36] M. Aria and C. Cuccurullo, "*bibliometrix*: An R-tool for comprehensive science mapping analysis," *J. Informetrics*, vol. 11, no. 4, pp. 959–975, 2017, doi: 10.1016/j.joi.2017.08.007.

[37] N. J. van Eck and L. Waltman, "Software survey: VOSviewer, a computer program for bibliometric mapping," *Scientometrics*, vol. 84, no. 2, pp. 523–538, Aug. 2010.

[38] Y. Wang, Q. Chen, T. Hong, and C. Kang, "Review of smart meter data analytics: Applications, methodologies, and challenges," *IEEE Trans. Smart Grid*, vol. 10, no. 3, pp. 3125–3148, May 2019.

[39] T. Davenport, A. Guha, D. Grewal, and T. Bressgott, "How artificial intelligence will change the future of marketing," *J. Acad. Marketing Sci.*, vol. 48, no. 1, pp. 24–42, Jan. 2020.

[40] Y. K. Dwivedi, E. Ismagilova, D. L. Hughes, J. Carlson, R. Filieri, J. Jacobson, V. Jain, H. Karjaluoto, H. Kefi, A. S. Krishen, V. Kumar, M. M. Rahman, R. Raman, P. A. Rauschnabel, J. Rowley, J. Salo, G. A. Tran, and Y. Wang, "Setting the future of digital and social media marketing research: Perspectives and research propositions," *Int. J. Inf. Manage.*, vol. 59, Aug. 2021, Art. no. 102168. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0268401220308082

[41] F. L. Quilumba, W.-J. Lee, H. Huang, D. Y. Wang, and R. L. Szabados, "Using smart meter data to improve the accuracy of intraday load forecasting considering customer behavior similarities," *IEEE Trans. Smart Grid*, vol. 6, no. 2, pp. 911–918, Mar. 2015.

[42] A. Y.-L. Chong, "Predicting m-commerce adoption determinants: A neural network approach," *Expert Syst. Appl.*, vol. 40, no. 2, pp. 523–530, Feb. 2013.

[43] W. Wei, J. Li, L. Cao, Y. Ou, and J. Chen, "Effective detection of sophisticated online banking fraud on extremely imbalanced data," *World Wide Web*, vol. 16, no. 4, pp. 449–475, Jul. 2013.

[44] J.-J. Hew, L.-Y. Leong, G. W.-H. Tan, V.-H. Lee, and K.-B. Ooi, "Mobile social tourism shopping: A dual-stage analysis of a multi-mediation model," *Tourism Manage.*, vol. 66, pp. 121–139, Jun. 2018. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0261517717302248

[45] A. Lak, W. R. Stauffer, and W. Schultz, "Dopamine prediction error responses integrate subjective value from different reward dimensions," *Proc. Nat. Acad. Sci. USA*, vol. 111, no. 6, pp. 2343–2348, Feb. 2014.

[46] O. Claveria and S. Torra, "Forecasting tourism demand to catalonia: Neural networks vs. Time series models," *Econ. Model.*, vol. 36, pp. 220–228, Jan. 2014. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0264999313003842

[47] C. Fornell and D. F. Larcker, "Evaluating structural equation models with unobservable variables and measurement error," *J. Marketing Res.*, vol. 18, no. 1, p. 39, Feb. 1981.

[48] F. D. Davis, "Perceived usefulness, perceived ease of use, and user acceptance of information technology," *MIS Quart.*, vol. 13, no. 3, p. 319, Sep. 1989.

[49] I. Ajzen, "The theory of planned behavior," *Org. Behav. Hum. Decision Process.*, vol. 50, no. 2, pp. 179–211, 1991.

[50] L. Breiman, "Random forests," *Mach. Learn.*, vol. 45, no. 1, pp. 5–32, 2001.

[51] C. Cortes and V. Vapnik, "Support-vector networks," *Mach. Learn.*, vol. 20, no. 3, pp. 273–297, Jan. 1995.

[52] D. M. Blei, A. Y. Ng, and M. I. Jordan, "Latent Dirichlet allocation," *J. Mach. Learn. Res.*, vol. 3, pp. 993–1022, Mar. 2003.

[53] M. Baker and J. Wurgler, "Investor sentiment and the cross-section of stock returns," *The J. Finance*, vol. 61, no. 4, pp. 1645–1680, 2006.

[54] M.-H. Huang and R. T. Rust, "Artificial intelligence in service," *J. Service Res.*, vol. 21, no. 2, pp. 155–172, 2018.

[55] J. Wirtz, P. G. Patterson, W. H. Kunz, T. Gruber, V. N. Lu, S. Paluch, and A. Martins, "Brave new world: Service robots in the frontline," *J. Service Manage.*, vol. 29, no. 5, pp. 907–931, Nov. 2018.

[56] H. Small, "Co-citation in the scientific literature: A new measure of the relationship between documents," *J. Amer. Soc. Inf. Sci.*, vol. 42, pp. 676–684, Jan. 1973.

[57] I. Zupic and T. Čater, "Bibliometric methods in management and organization," *Organizational Res. Methods*, vol. 18, no. 3, pp. 429–472, Jul. 2015.

[58] N. J. Van Eck and L. Waltman, "Vosviewer manual," *Manual VOSviewer Version*, vol. 1, p. 10, Sep. 2011.

[59] M. J. Cobo, A. G. López-Herrera, E. Herrera-Viedma, and F. Herrera, "An approach for detecting, quantifying, and visualizing the evolution of a research field: A practical application to the fuzzy sets theory field," *J. Informetrics*, vol. 5, no. 1, pp. 146–166, Jan. 2011.

[60] M. N. Burton-Chellew and S. A. West, "The black box as a control for payoff-based learning in economic games," *Games*, vol. 13, no. 6, p. 76, Nov. 2022.

[61] I. Vlaev and P. Dolan, "Action change theory: A reinforcement learning perspective on behavior change," *Rev. Gen. Psychol.*, vol. 19, no. 1, pp. 69–95, Mar. 2015.

[62] F. D'Orlando, "Social interaction, envy, and the basic income: Do remedies to technological unemployment reduce well-being?" *Basic Income Stud.*, vol. 17, no. 1, pp. 53–93, Jun. 2022.

[63] M. Petticrew, N. Maani, L. Pettigrew, H. Rutter, and M. C. Van Schalkwyk, "Dark nudges and sludge in big alcohol: Behavioral economics, cognitive biases, and alcohol industry corporate social responsibility," *Milbank Quart.*, vol. 98, no. 4, pp. 1290–1328, Dec. 2020.

[64] D. Juárez-Varón, V. Tur-Viñes, A. Rabasa-Dolado, and K. Polotskaya, "An adaptive machine learning methodology applied to neuromarketing analysis: Prediction of consumer behaviour regarding the key elements of the packaging design of an educational toy," *Social Sci.*, vol. 9, no. 9, p. 162, Sep. 2020.

[65] J. E. Burgos and Ó. García-Leal, "Autoshaped choice in artificial neural networks: Implications for behavioral economics and neuroeconomics," *Behavioural Processes*, vol. 114, pp. 63–71, Jan. 2015.

[66] W. Hoiles, V. Krishnamurthy, and K. Pattanayak, "Rationally inattentive inverse reinforcement learning explains YouTube commenting behavior," *J. Mach. Learn. Res.*, vol. 21, no. 1, pp. 6879–6917, 2020.

[67] H. İ. Erçen, H. Özdeşer, and T. Türsoy, "The impact of macroeconomic sustainability on exchange rate: Hybrid machine-learning approach," *Sustainability*, vol. 14, no. 9, p. 5357, Apr. 2022.

[68] H. Taherian, M. R. Aghaebrahimi, L. Baringo, and S. R. Goldani, "Optimal dynamic pricing for an electricity retailer in the price-responsive environment of smart grid," *Int. J. Electr. Power Energy Syst.*, vol. 130, Sep. 2021, Art. no. 107004.

[69] H. Taherian, M. R. Aghaebrahimi, and L. Baringo, "Profit maximization for an electricity retailer using a novel customers' behavior leaning in a smart grid environment," *Energy Rep.*, vol. 8, pp. 908–915, Nov. 2022.

[70] M. Panda, "Intelligent data analysis for sustainable smart grids using hybrid classification by genetic algorithm based discretization," *Intell. Decis. Technol.*, vol. 11, no. 2, pp. 137–151, Jun. 2017.

[71] I. Toumia and A. B. Hassine, "Impact of input data structure on convolutional neural network energy prediction model," *Int. J. Adv. Comput. Sci. Appl.*, vol. 13, no. 10, pp. 1–12, 2022.

[72] J. Kim, H. Ji, S. Oh, S. Hwang, E. Park, and A. P. del Pobil, "A deep hybrid learning model for customer repurchase behavior," *J. Retailing Consum. Services*, vol. 59, Mar. 2021, Art. no. 102381.

[73] D. Ayvaz, R. Aydoğan, M. T. Akçura, and M. Şensoy, "Campaign participation prediction with deep learning," *Electron. Commerce Res. Appl.*, vol. 48, Jan. 2021, Art. no. 101058.

[74] L. Saha, H. K. Tripathy, F. Masmoudi, and T. Gaber, "A machine learning model for personalized tariff plan based on customer's behavior in the telecom industry," *Int. J. Adv. Comput. Sci. Appl.*, vol. 13, no. 10, 2022.

[75] Y. Dai and T. Wang, "Prediction of customer engagement behaviour response to marketing posts based on machine learning," *Connection Sci.*, vol. 33, no. 4, pp. 891–910, Oct. 2021.

[76] P. Sánchez-Núñez, M. J. Cobo, C. D. L. Heras-Pedrosa, J. I. Peláez, and E. Herrera-Viedma, "Opinion mining, sentiment analysis and emotion understanding in advertising: A bibliometric analysis," *IEEE Access*, vol. 8, pp. 134563–134576, 2020.

[77] S.-V. Oprea, A. Bâra, B. G. Tudorică, M. I. Călinoiu, and M. A. Botezatu, "Insights into demand-side management with big data analytics in electricity consumers' behaviour," *Comput. Electr. Eng.*, vol. 89, Jan. 2021, Art. no. 106902.

[78] M. S. Rahim, K. A. Nguyen, R. A. Stewart, T. Ahmed, D. Giurco, and M. Blumenstein, "A clustering solution for analyzing residential water consumption patterns," *Knowl.-Based Syst.*, vol. 233, Dec. 2021, Art. no. 107522.

[79] W. N. Wassouf, R. Alkhatib, K. Salloum, and S. Balloul, "Predictive analytics using big data for increased customer loyalty: Syriatel telecom company case study," *J. Big Data*, vol. 7, no. 1, pp. 1–24, 2020.

[80] T. Xu, Y. Ma, and K. Kim, "Telecom churn prediction system based on ensemble learning using feature grouping," *Appl. Sci.*, vol. 11, no. 11, p. 4742, May 2021.

[81] S.-V. Oprea and A. Bâra, "Setting the time-of-use tariff rates with NoSQL and machine learning to a sustainable environment," *IEEE Access*, vol. 8, pp. 25521–25530, 2020.

[82] D. C. Gkikas, P. K. Theodoridis, and G. N. Beligiannis, "Enhanced marketing decision making for consumer behaviour classification using binary decision trees and a genetic algorithm wrapper," *Informatics*, vol. 9, no. 2, p. 45, May 2022.

[83] P. Brzustewicz and A. Singh, "Sustainable consumption in consumer behavior in the time of COVID-19: Topic modeling on Twitter data using LDA," *Energies*, vol. 14, no. 18, p. 5787, Sep. 2021.

[84] F. Safara, "A computational model to predict consumer behaviour during COVID-19 pandemic," *Comput. Econ.*, vol. 59, no. 4, pp. 1525–1538, Apr. 2022.

[85] I. Popchev, R. Ketipov, and V. Angelova, "Risk averseness and emotional stability in e-commerce," *Cybern. Inf. Technol.*, vol. 21, no. 3, pp. 73–84, Sep. 2021.

[86] J. Yadav, M. Misra, N. P. Rana, K. Singh, and S. Goundar, "Netizens' behavior towards a blockchain-based esports framework: A TPB and machine learning integrated approach," *Int. J. Sports Marketing Sponsorship*, vol. 23, no. 4, pp. 665–683, Aug. 2022.

[87] F. R. Mashrur, K. M. Rahman, M. T. I. Miya, R. Vaidyanathan, S. F. Anwar, F. Sarker, and K. A. Mamun, "BCI-based consumers' choice prediction from EEG signals: An intelligent neuromarketing framework," *Frontiers Hum. Neurosci.*, vol. 16, p. 311, May 2022.

[88] R. Pillai and B. Sivathanu, "Adoption of AI-based chatbots for hospitality and tourism," *Int. J. Contemp. Hospitality Manage.*, vol. 32, no. 10, pp. 3199–3226, Sep. 2020.

[89] D. Belanche, L. V. Casaló, and C. Flavián, "Frontline robots in tourism and hospitality: Service enhancement or cost reduction?" *Electron. Markets*, vol. 31, no. 3, pp. 477–492, Sep. 2021.

[90] K. H. Seo and J. H. Lee, "The emergence of service robots at restaurants: Integrating trust, perceived risk, and satisfaction," *Sustainability*, vol. 13, no. 8, p. 4431, Apr. 2021.

[91] A. Alabed, A. Javornik, and D. Gregory-Smith, "AI anthropomorphism and its effect on users' self-congruence and self–AI integration: A theoretical framework and research agenda," *Technol. Forecasting Social Change*, vol. 182, Sep. 2022, Art. no. 121786.

[92] R. Hasan, R. Shams, and M. Rahman, "Consumer trust and perceived risk for voice-controlled artificial intelligence: The case of Siri," *J. Bus. Res.*, vol. 131, pp. 591–597, Jul. 2021.

[93] S. H. Hsieh and C. T. Lee, "Hey Alexa: Examining the effect of perceived socialness in usage intentions of AI assistant-enabled smart speaker," *J. Res. Interact. Marketing*, vol. 15, no. 2, pp. 267–294, Jun. 2021.

[94] A. Giovanis, I. Rizomyliotis, K. Konstantoulaki, and S. Magrizos, "Mining the hidden seam of proximity m-payment adoption: A hybrid PLS-artificial neural network analytical approach," *Eur. Manage. J.*, vol. 40, no. 4, pp. 618–631, Aug. 2022.

[95] S. C. Paul, N. Bartmann, and J. L. Clark, "Customizability in conversational agents and their impact on health engagement," *Hum. Behav. Emerg. Technol.*, vol. 3, no. 5, pp. 1141–1152, Dec. 2021.

[96] P. Ebrahimi, M. Basirat, A. Yousefi, M. Nekmahmud, A. Gholampour, and M. Fekete-Farkas, "Social networks marketing and consumer purchase behavior: The combination of SEM and unsupervised machine learning approaches," *Big Data Cognit. Comput.*, vol. 6, no. 2, p. 35, Mar. 2022.

[97] K. Obaid and K. Pukthuanthong, "A picture is worth a thousand words: Measuring investor sentiment by combining machine learning and photos from news," *J. Financial Econ.*, vol. 144, no. 1, pp. 273–297, Apr. 2022.

[98] P. Houlihan and G. G. Creamer, "Can sentiment analysis and options volume anticipate future returns?" *Comput. Econ.*, vol. 50, no. 4, pp. 669–685, Dec. 2017.

[99] Y. Apartsin, Y. Maymon, Y. Cohen, and G. Singer, "Nationality and risk attitude: Testing differences and similarities of investors' behavior in selected financial markets," *Global Finance J.*, vol. 24, no. 2, pp. 114–118, 2013.

[100] S. Saurabh and K. Dey, "Unraveling the relationship between social moods and the stock market: Evidence from the united kingdom," *J. Behav. Experim. Finance*, vol. 26, Jun. 2020, Art. no. 100300.

[101] S. Talwar, M. Talwar, V. Tarjanne, and A. Dhir, "Why retail investors traded equity during the pandemic? An application of artificial neural networks to examine behavioral biases," *Psychol. Marketing*, vol. 38, no. 11, pp. 2142–2163, Nov. 2021.

[102] B. Ghosh, "Bankruptcy modelling of Indian public sector banks: Evidence from neural trace," *Int. J. Appl. Behav. Econ.*, vol. 6, no. 2, pp. 52–65, Apr. 2017.

[103] P. Eachempati and P. R. Srivastava, "Accounting for unadjusted news sentiment for asset pricing," *Qualitative Res. Financial Markets*, vol. 13, no. 3, pp. 383–422, Jun. 2021.

[104] S. Fraiberger, D. Lee, D. Puy, and R. Ranciere, "Media sentiment and international asset prices," *IMF Work. Papers*, vol. 18, no. 274, p. 1, 2018.

[105] M. Zielińska-Sitkiewicz, M. Chrzanowska, K. Furmańczyk, and K. Paczutkowski, "Analysis of electricity consumption in Poland using prediction models and neural networks," *Energies*, vol. 14, no. 20, p. 6619, Oct. 2021.

[106] C. Burr, N. Cristianini, and J. Ladyman, "An analysis of the interaction between intelligent software agents and human users," *Minds Mach.*, vol. 28, no. 4, pp. 735–774, Dec. 2018.

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