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Behavioral Economics and Artificial Intelligence: A Bibliometric Mapping of the Intellectual Structure of the Research Field

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ABSTRACT

The intersection of behavioral economics (BE) and artificial intelligence (AI) has grown rapidly, yet its intellectual structure remains unmapped. This study aims to provide a bibliometric mapping of the BE-AI research field, identifying key themes, influential works, and research gaps. Using bibliometric analysis with the bibliometrix R-package (version 4.1) on 252 documents from Scopus (2006–2025), we performed performance analysis, co-citation, co-word, and collaboration network analysis. Annual output grows at 16.76%, with a surge since 2018. Loewenstein and Reich are the most influential authors; Behavioral Public Policy leads journals; UK, US, Sweden, and Germany dominate citations. Co-citation reveals four clusters: (1) behavioral research & technology acceptance, (2) machine learning, (3) financial decision-making (prospect theory), (4) AI & consumer behavior. Thematic mapping shows decision-making and public policy as motor themes; environmental economics is emerging. The field lacks interdisciplinary collaboration and macro-level studies. Future research should focus on AI-based field experiments and behavioral macroeconomics. Policymakers and technology designers can use these clusters to prioritize investments in AI nudge systems and behavioral public policy.

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1. Introduction

In recent decades, the synergy between behavioral economics and artificial intelligence has become one of the most dynamic and interdisciplinary research fields in the social sciences, economics, and technology studies. Drawing on cognitive and experimental psychology, behavioral economics challenges the classical assumption of perfect rationality, demonstrating that human decision-making is influenced by cognitive biases, information processing limitations, social norms, and contextual factors (Thaler, 2016). In contrast, artificial intelligence (AI), by providing advanced computational tools for analyzing complex data, predicting behavioral patterns, and designing data-driven interventions, has opened new horizons for understanding, modeling, and even shaping human behavior (Binz et al., 2024). The intersection of these two fields has not only led to a rethinking of traditional decision-making assumptions but has also paved the way for novel approaches in public policy, consumer behavior, behavioral finance, digital platform design, and algorithmic governance. The importance of this linkage becomes even more apparent when we recognize that AI is not merely a data analysis tool; it is gradually becoming a structural factor shaping individual and collective decisions. Recommender systems, predictive algorithms, machine learning models, and natural language processing tools are deployed in environments where human behavior is the target of analysis, prediction, or guidance. From this perspective, behavioral economics and AI are not separate domains; they converge in a common context of data-driven and behavior-centric computational decision-making. In other words, behavioral economics provides the conceptual tools to explain human behavioral anomalies, while AI offers the operational capacity to identify, classify, and optimize these anomalies at scale. This overlap makes the field equally attractive for theoretical and applied research.(Saura & Bužinskienė, 2025).

Despite the rapid growth of this literature, the field has not yet been fully mapped in terms of its intellectual structure, conceptual trajectories, knowledge clusters, and internal evolutionary trends. Published research in this area spans a wide range of topics: from behavioral biases in algorithmic environments and the role of AI in correcting decision errors, to applications of AI in designing behavioral interventions, analyzing human-machine interaction, and the ethical and governance implications of algorithms. While this diversity reflects the field's dynamism, it also makes it difficult to achieve a comprehensive understanding of its intellectual structure. In particular, it remains unclear which intellectual currents have played a central role in shaping the field, which concepts have become established as knowledge cores, and toward which topics future research trajectories are moving. In such a context, bibliometric studies by mapping citation networks, keyword co-occurrences, scientific collaborations, and thematic clusters can provide a systematic picture of the knowledge architecture of this field (Aoujil et al., 2023). From a methodological standpoint, bibliometrics is not merely a tool for counting scientific outputs; it is an analytical method for revealing hidden knowledge structures, conceptual linkages, and turning points in the evolution of a discipline. In emerging and interdisciplinary fields such as behavioral economics and AI, this approach is particularly important because the existing literature grows rapidly, crosses disciplinary boundaries, and consequently makes it difficult for researchers, policymakers, and innovators to identify dominant patterns and knowledge gaps. Accordingly, a bibliometric mapping of the intellectual structure of this field can not only help classify existing research but also reveal emerging trajectories and underexplored topics. Such an analysis offers high added value, especially for a field situated at the intersection of economics, psychology, data science, computer science, and governance (Donthu et al., 2021).

Moreover, the link between behavioral economics and AI is also significant from the perspective of governance and policymaking. The spread of intelligent systems in decision-making processes has raised new issues concerning algorithmic transparency, fairness, accountability, data bias, intervenability, and the legitimacy of machine-made decisions. In this context, behavioral economics can help understand how humans interact with intelligent systems, while AI provides tools to measure, predict, and regulate those interactions. Therefore, examining the intellectual structure of this field is not merely a descriptive exercise; it is a scientific and practical necessity for understanding how knowledge is shaped in the era of emerging technologies and for designing appropriate policies and governance institutions. Despite the rapid expansion of published articles and books in this area from approximately 2006 to 2025, a comprehensive, evidence-based bibliometric picture of the field is still lacking. This gap is particularly salient in a journal focused on emerging technologies and governance, because research in this field is expected not only to describe trends but also to help understand the structural and governance implications of AI innovations in the context of human behavior. Thus, this study aims to provide a bibliometric mapping of the intellectual structure of the field of behavioral economics and AI, seeking to identify historical trends, influential articles and works, conceptual clusters, and knowledge relationships among key actors in this arena. Specifically, the study addresses three core questions: First, how has the intellectual and conceptual structure of the literature on behavioral economics and AI taken shape? Second, which topics, authors, and sources have had the greatest impact in this field? Third, what are the emerging knowledge trajectories and main research gaps in this domain? Answering these questions can both enrich the theoretical literature and provide a foundation for future research in areas such as algorithmic decision-making, smart behavioral intervention design, technology governance, and interdisciplinary applications of AI in behavioral economics. Accordingly, using bibliometric methods, this paper presents a systematic picture of the evolution of this field from 2006 to 2025, seeking to map its knowledge structure beyond conventional narrative reviews. The results are expected to provide researchers, policymakers, and technology designers with a deeper understanding of the focal points, gaps, and future opportunities at the intersection of behavioral economics and AI. Ultimately, this study demonstrates that understanding the interaction between humans and intelligent systems will be incomplete without attending simultaneously to behavioral logic and computational logic, and it is precisely at this juncture that the present study establishes its significance within the emerging literature of this field.

The intersection of behavioral economics (BE) and artificial intelligence (AI) has recently attracted interdisciplinary attention. BE integrates psychological insights into economic decision-making, challenging the assumption of perfect rationality by identifying cognitive biases such as loss aversion, overconfidence, and present bias (Gurney et al., 2023). AI, particularly machine learning and natural language processing, offers computational tools to detect, predict, and shape human behavior at scale (Feuerriegel et al., 2025).

Prior research at this intersection has focused on four main areas. First, AI has been used to personalize nudges and behavioral interventions in health, energy, and finance (Huang & You, 2023). Second, machine learning models have improved the prediction of consumer choice and investor sentiment (Azad et al., 2023). Third, AI-powered recommender systems have raised new questions about algorithmic bias and decision-making transparency (Sarkar & De Bruyn, 2021). Fourth, experimental studies have begun using AI to simulate economic agents and test behavioral policies (Horton et al., 2023). Despite growing publication output, the intellectual structure of the BE-AI field has not been systematically mapped. Existing bibliometric studies have either focused solely on BE or on AI in economics, but none have combined co-citation, co-word, and collaboration network analysis to reveal the hidden knowledge clusters at their intersection. This study fills this gap by providing a comprehensive bibliometric mapping of the field from 2006 to 2025.

Bibliometrics is founded on the principle that scientific knowledge can be quantitatively mapped through patterns of publication, citation, and co-occurrence (Zhou et al., 2025). The intellectual structure of a research field is revealed by analyzing how documents, authors, and journals relate to one another. Three core pillars underpin bibliometric science mapping:

1. Co-citation analysis assumes that documents cited together by later publications share a thematic or intellectual proximity. This technique identifies foundational knowledge clusters and turning points in a discipline (Sohail, 2026).

2. Co-word analysis (or keyword co-occurrence) examines the frequency with which terms appear together in titles, abstracts, or keywords. According to (Öztürk et al., 2024) this reveals the conceptual and thematic structure of a field, distinguishing motor, basic, specialized, and emerging themes.

3. Collaboration network analysis uses co-authorship links to map social and institutional relationships among researchers, highlighting patterns of interdisciplinary and international cooperation (Zupic & Čater, 2015).

In this study, we adopt this three-pillar framework to systematically map the intellectual structure at the intersection of behavioral economics and artificial intelligence. The workflow follows recent guidelines for transparent and reproducible bibliometric research (Donthu et al., 2021).

Table 1 provides a comparative overview of previous bibliometric studies in the fields of Behavioral Economics (BE) and Artificial Intelligence (AI), along with their respective research gaps and how the present study addresses them. As shown in the table, prior studies have either focused solely on BE without integrating AI, or have suffered from limitations such as exclusive reliance on the Web of Science database, outdated timeframes, and insufficient attention to technology governance implications. The present study, by utilizing the Scopus database, the advanced bibliometrix R-package, and an updated time period (2006-2025), offers the first comprehensive science mapping of the BE-AI intersection, with a particular emphasis on emerging themes and technology governance.

Table 1.
havioral economics (BE) and artificial intelligence (AI).

Row	Authors (Year)	Databasee	Software	Time period	Main focus	Research gap addressed by the present study
1	Costa et al. (2019)	Web of Science	Not specified	1974-2016	Bibliometric analysis of behavioral economics alone (without AI)	Lack of integration of AI and BE in a single science-mapping study
2	Aoujil et al. (2023)	Web of Science	VOSviewer, Bibliometrix	2012–2022	Co-authorship, co-citation, co-word analysis in AI and BE	Focus on WoS only (no Scopus); no detailed thematic heatmap; limited governance implications
3	Present study (Khazaian & Dibavand, 2026)	Scopus	bibliometrix (R)	2006–2025	Performance analysis, co-citation, collaboration network with emphasis on emerging themes and technology governance	First comprehensive science-mapping of the BE-AI intersection using Scopus and an updated timeframe

A comparative review of Table 1 reveals that while (Costa et al., 2019) provided a comprehensive bibliometric analysis of behavioral economics, they entirely overlooked the integration of artificial intelligence. In contrast, (Aoujil et al., 2023) took a significant step by combining AI and BE; however, their exclusive reliance on the Web of Science database, the absence of a thematic heatmap, and the lack of attention to technology governance implications have left the overall picture incomplete. The present study systematically addresses all these shortcomings by selecting the Scopus database with broader coverage, employing the advanced bibliometrix R-package for co-citation, collaboration network, and performance analyses, and adopting an up-to-date timeframe (2006-2025). With its explicit focus on emerging themes and technology governance, this study establishes itself as the first comprehensive science mapping of the BE-AI intersection.

The classical Homo economicus assumption perfectly rational, self-interested utility maximization has been challenged by cognitive biases and bounded rationality (Simon, 1990). While these insights founded behavioral economics, this study prioritizes its contemporary convergence with artificial intelligence. AI now actively reshapes decision-making environments by amplifying cognitive biases, reconfiguring preferences, and altering emotional responses at scale (Rodriguez-Fernandez, 2026). This intersection spans algorithmic governance, consumer behavior, financial decision-making, and LLM-based economic simulations. Bibliometric evidence confirms robust annual growth in this domain, with machine learning, decision-making, and behavioral analytics as central themes(Aoujil et al., 2023).

Accordingly, this study undertakes a bibliometric mapping of the intellectual structure at the BE-AI nexus, identifying foundational knowledge clusters and emerging research frontiers.

Behavioral economics, as a broad and interdisciplinary field, itself consists of several specialized branches, each addressing a specific aspect of human decision-making in an economic context. These subfields are typically defined based on:

- The type of decision (e.g., investment, consumption, strategic games)
- The tools and methods of study (e.g., laboratory experiments, neuroimaging)
- The economic context (financial markets, macro policy, energy, health)

The field of behavioral economics extends beyond traditional choice anomalies by encompassing a wide range of specialized subfields, each addressing unique decision-making contexts. Table 2 summarizes these key subfields, from behavioral finance and neuroeconomics to behavioral health and welfare economics, highlighting their primary topics and the specific behavioral mechanisms they investigate.

Table 2.
Subfields of Behavioral Economics.

Subfield	Main Topic
Behavioral Finance	The impact of biases and emotions on investor decisions, asset pricing, and stock market anomalies
Neuroeconomics	The role of the brain and nervous system in economic decision-making processes
Behavioral Game Theory	Analysis of actual human behavior in strategic situations, considering concepts such as fairness, trust, and altruistic punishment
Experimental Economics	Testing behavioral hypotheses in controlled (laboratory) environments to detect deviations from classical theory predictions
Behavioral Macroeconomics	Incorporating bounded rationality and behavioral biases into models of inflation, employment, economic growth, and monetary and fiscal policies
Behavioral Marketing	Using insights from behavioral economics to design personalized advertising campaigns and nudging toward desired choices
Behavioral Health and Welfare Economics	Analyzing health-related behaviors (e.g., tobacco use, vaccination) and designing behavioral incentives to improve social welfare

The integration of AI and behavioral economics offers substantial opportunities real-time bias detection, personalized nudging, and agent-based policy simulation yet faces persistent challenges including data quality issues, algorithmic overfitting, ethical concerns around privacy and manipulation, and a lack of interdisciplinary collaboration (Saura & Bužinskienė, 2025). The integration of AI and behavioral economics offers transformative opportunities real-time bias detection, personalized algorithmic nudging, and agent-based policy simulation yet faces persistent challenges including data quality issues, algorithmic overfitting, ethical concerns around privacy and manipulation, and insufficient interdisciplinary collaboration. Recent scholarship emphasizes that while AI-driven simulations can serve as rational benchmarks in experimental design, AI technologies simultaneously amplify cognitive biases and reshape preferences, raising fundamental ethical and regulatory dilemmas (Bian et al., 2025).

2. Methods

Bibliometric methods have become essential for mapping emerging interdisciplinary fields. Recent guidelines emphasize the importance of transparent and reproducible bibliometric workflows. The bibliometrix R-package provides a comprehensive toolkit for science mapping, including co-citation and thematic analysis. These methodological advances enable systematic investigation of the intellectual structure at the intersection of behavioral economics and artificial intelligence (Donthu et al., 2021).

In this study, a bibliometric analysis was conducted based on the statistical method of scientometrics, utilizing specialized software. This approach examines and interprets bibliographic data using quantitative tools. The distinguishing point of the bibliometric method from systematic reviews is that bibliometrics emphasizes the application of quantitative techniques to analyze and summarize the characteristics of a textual corpus. Accordingly, as shown in Fig. 1, the bibliometric analysis process has been customized into the following three main steps:

- Step 1: Planning the bibliometric analysis process
- Step 2: Executing the bibliometric analysis operations
- Step 3: Documenting the findings and interpreting the perspectives derived from the analysis

2.1 Objective, Scope, Questions, and Study Domain

This research was conducted with two main objectives: first, to examine the evolution of research, patterns of scientific collaboration, and their degree of impact within the global scientific community; and second, to provide a comprehensive review of the current state and future research directions in the field of behavioral economics and artificial intelligence. To achieve these objectives, six research questions are pursued:

- How has the evolution of research on artificial intelligence and behavioral economics changed over time?
- Which universities, journals, and researchers have had the highest scientific output and impact?
- What is the pattern of collaboration among countries and universities in this field?
- What are the knowledge bases (intellectual and theoretical foundations) of this field?

- What are the current and emerging trends in the literature on this topic?
- What are the potential pathways for future research in this field?

The scope of this review is considerably broad, because both the fields of artificial intelligence and behavioral economics are interdisciplinary in nature and intersect at the convergence of dynamic domains such as economics, psychology, mathematics, and computer science.

2.2 Data Collection

1. The database used to retrieve articles in this study was Scopus. This database is considered one of the most frequently used scientific citation indexes in the world. Our choice of Scopus was motivated by several reasons: first, its extensive coverage of scientific journals, as well as the high quality of the data resulting from the rigorous and meticulous journal selection processes of this database. Moreover, Scopus covers a wider range of journals than many similar databases and has a higher impact factor. On the other hand, the simple and user-friendly interface, as well as the advanced search capabilities in Scopus, allow researchers to easily find and retrieve relevant samples of articles. Scopus was selected over Web of Science because of its broader coverage of social sciences and emerging technology journals, its superior author disambiguation, and its seamless integration with the bibliometrix R-package (version 4.1). Dimensions was not used due to its lower data quality for citation analysis in the social sciences.

2. Keyword selection strategy: First, as a main sub-topic of economics, behavioral economics was added to the initial query, including articles that contain the term in the title, abstract, author keywords, and Keywords Plus, which resulted in 1,200 documents. When combined with the term artificial intelligence, the retrieved records were limited. Therefore, we expanded our keyword set with additional terms related to behavioral economics, and we did the same for techniques related to artificial intelligence.

3. After initial preparation, the process of retrieving and refining sources began with a search based on title criteria (as shown in the relevant Fig. 1). This search initially yielded 583 results. Then, through several rounds of refining the search string, we sought to gather the most relevant articles and systematic reviews for our research. In the next step, the publication time period was limited to the years 2006 to 2025. The reason for this limitation is that before 2006, only a very small number of studies had been conducted in the field of artificial intelligence and behavioral economics. Finally, 252 documents were selected as the final sample, constituting the statistical population of this research. The year 2006 was chosen as the starting point because a preliminary search showed that before 2006, fewer than 5 documents per year were published at the BE-AI intersection, which would have introduced excessive noise without adding conceptual value.

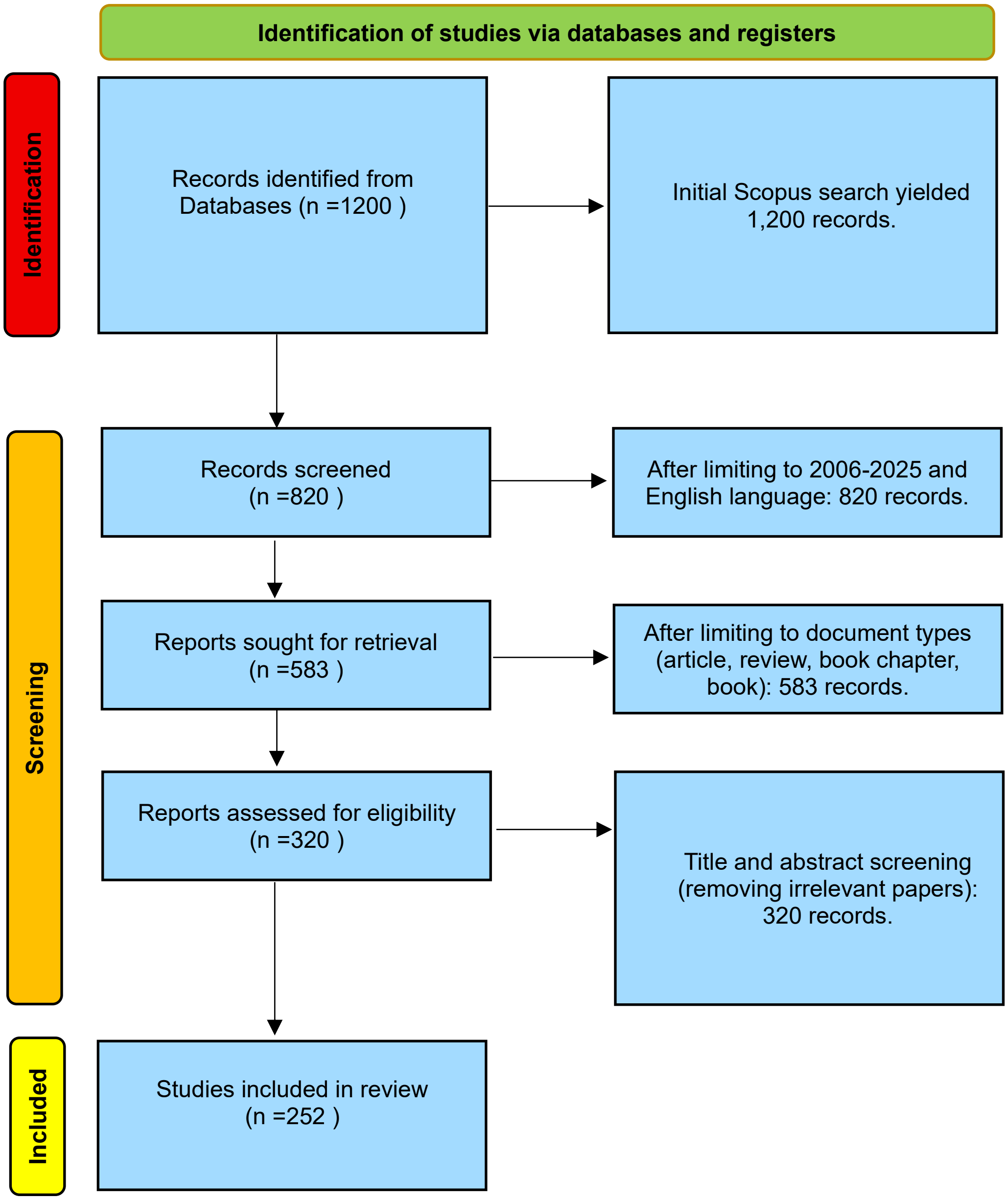

Fig 1. Query refinements and result trend notes.

2.3 Analysis Techniques and Tools

To carry out our bibliometric approach for analyzing publications, we used various techniques to answer our formulated questions regarding behavioral economics and the field of artificial intelligence. After evaluating several options to meet our needs for examining bibliometric data, we selected the tool common in similar studies, namely the bibliometrix package in the R environment (R Studio 2025). All bibliometric analyses were conducted using R version 4.3.2 with the bibliometrix package (4.1.0) and its Biblioshiny web-based interface. This integrated environment enabled comprehensive, reproducible bibliometric mapping without coding.

2.4 Validity and Reliability of the Bibliometric Process

To ensure the validity of the bibliometric analysis, several systematic measures were undertaken throughout the research process. First, the selection of the Scopus database was justified through a coverage test, confirming that 20 seminal works in behavioral economics and artificial intelligence were fully indexed with complete citation metadata. This step verified that the chosen database adequately represents the intellectual core of the field. Second, the search strategy was carefully designed using a combination of controlled keywords and Boolean operators, and it was iteratively refined to balance sensitivity (retrieving all relevant documents) and specificity (excluding irrelevant ones). Third, inclusion and exclusion criteria were explicitly defined and consistently applied to all retrieved records, minimizing selection bias. Fourth, the entire workflow from data extraction to analysis was documented transparently, following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines to enhance methodological transparency and replicability. This structured approach ensures that the findings accurately reflect the state of the literature and are not artifacts of arbitrary methodological choices. Regarding reliability, the screening process was conducted independently by two researchers to reduce the risk of subjective judgment errors. Disagreements during title and abstract screening were resolved through consensus, and the inter-rater agreement, measured by Cohen's kappa coefficient, reached a high level of consistency ($\kappa = 0.87$). After data import into the bibliometrix R-package, we manually checked for author name disambiguation errors, duplicate records, and incomplete metadata to ensure data integrity. Furthermore, all analytical procedures including co-citation, co-word, and collaboration network analyses were performed using well-established algorithms implemented in the bibliometrix package (version 4.1), which are widely recognized for their robustness in science mapping studies. The use of multiple bibliometric indicators further triangulates the results, reducing the influence of any single metric. Collectively, these measures enhance the reproducibility and trustworthiness of the findings, ensuring that the bibliometric mapping accurately reflects the intellectual structure of the behavioral economics and artificial intelligence research field.

3. Results

3.1 General Information and Performance Analysis

3.1.1 Descriptive Analysis of Data Summary

As reported in Table 2 (prepared using the Biblioshiny software package), there are a total of 252 documents from 148 active sources over a 20-year publication period, with an average of 32.24 citations per document and 1,888 references to previous publications. A total of 525 authors have been active in this field, with an average of 2.29 authors per document, and only 24.6% of the documents are single-authored. The number of Keywords Plus (generated through word frequency analysis techniques) is 482, while the total number of author-selected keywords is 682.

3.1.2 Temporal Analysis of Publication Output

Table 3 illustrates the annual scientific production alongside the citation trend (measured as the average total citations per article) over a 20-year period from 2006 to 2025, providing a perspective on the evolution of scientific articles in the research field of artificial intelligence and behavioral economics. Until 2017, the annual output varied with a maximum of 22 articles, recording an average of 9 publications per year. Over the past five years, productivity has shown an exponential and steady increase, with 28 articles published in 2023 alone. This growth rate in output indicates the growing interest in research on the applications of artificial intelligence in behavioral economics.

Table 3.
Overview of the retrieved records.

MAIN INFORMATION ABOUT DATA	Timespan	2006:2025
	Sources (Journals, Books, etc)	148
	Documents	252
	Annual Growth Rate %	16.76
	Document Average Age	6.01
	Average citations per doc	33.24
	References	1888
DOCUMENT CONTENTS	Keywords Plus (ID)	482
	Author's Keywords (DE)	682
AUTHORS	Authors	525
	Authors of single-authored docs	77
AUTHORS COLLABORATION	Single-authored docs	88
	Co-Authors per Doc	2.29
	International co-authorships %	24.6
DOCUMENT TYPES	article	169
	book	17
	book chapter	47
	conference paper	2
	note	2
	review	14
	short survey	1

Based on the citation analysis conducted using the average total number of citations per article, the year 2013 had the highest average citation rate, with approximately 10 citations per article; followed by 2014 with 7 citations, and 2016 with 6 citations, ranking next. The citation-based results indicate that valuable research on the applications of artificial intelligence in behavioral economics has been published over these years. (Fig. 2)

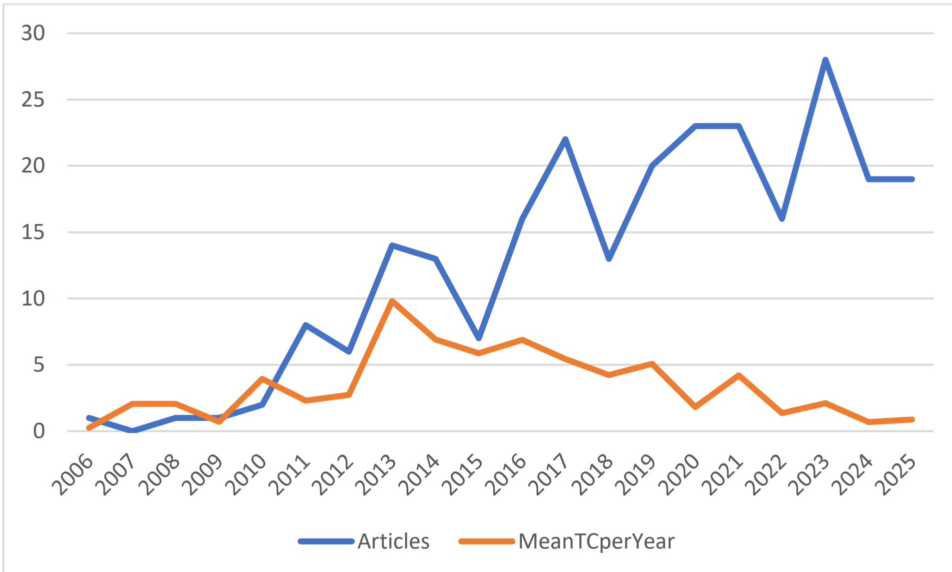

Fig 1. Annual scientific production trend and citation trend.

3.1.3 Analysis of Research Areas

The analysis of research areas shows that behavioral economics and economic nudging are the most common research areas. They are followed by decision-making and public policy. Other areas with less participation in artificial intelligence and behavioral economics include operations research and management, mathematics, and energy and fuels. This does not necessarily imply less relevance to the applications of AI in behavioral economics; as previously mentioned, both AI and behavioral economics are inherently interdisciplinary sciences, which facilitates the classification of relevant articles into broader research domains. (Fig. 3)

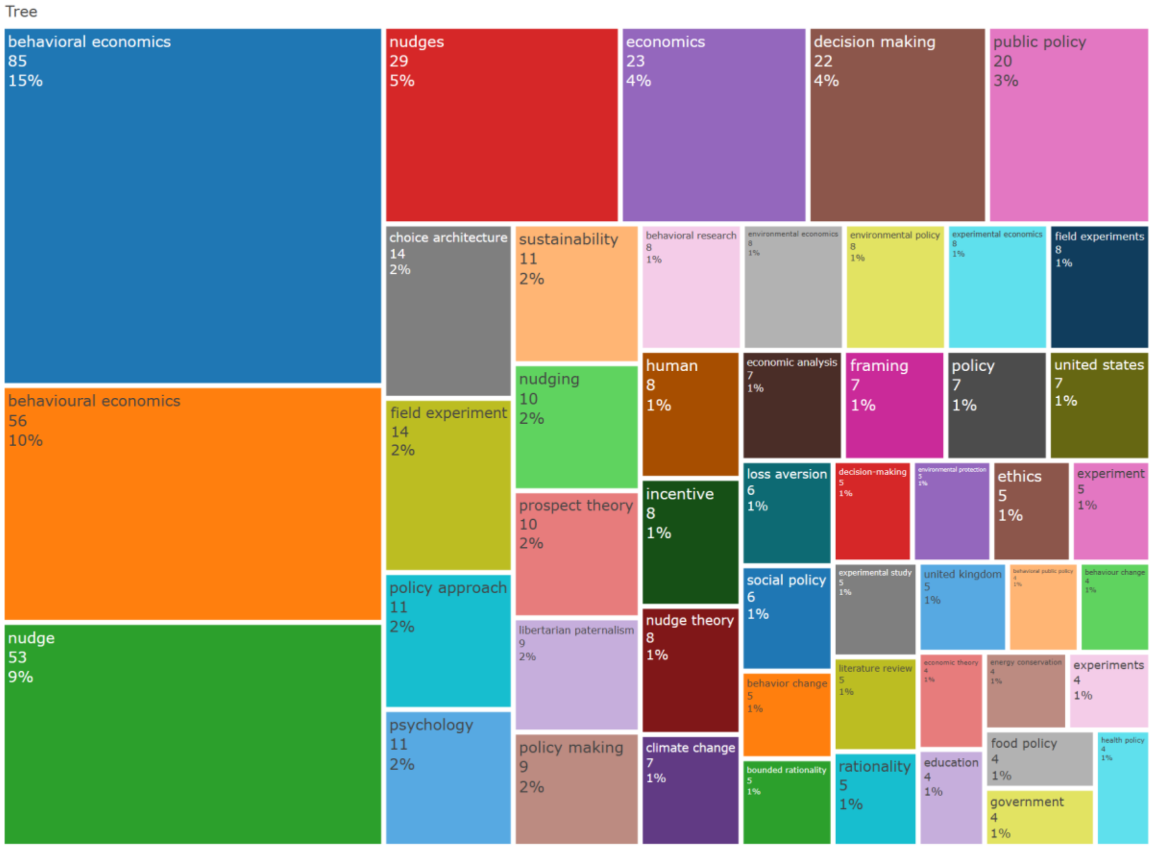

Fig 2. Top 50 research areas.

3.1.4 Author-Centered Analysis

Given the high degree of collaboration, we conducted an author-centered analysis of the most prolific authors (with at least 2 publications) in the field of AI and behavioral economics based on the multiple criteria presented in Table 4. According to both the h-index and the g-index, Loewenstein, with an h-index of 4 and a g-index of 5 (729 citations for 5 publications since 2012), is recognized as the most influential author in this field; followed by Oliver, with an h-index of 3 and a g-index of 4 (335 citations for 4 publications since 2013). However, when examining the m-index and taking into account the number of active years, we find that alongside Eleonora Pantano (who ranks second), Reich, with an m-index of 0.33 (116 citations for 3 publications since 2017), emerges as the top influential author. To examine the impact of prominent authors over time, the findings of the annual analysis of scientific production activities of the top 10 authors are displayed in Fig. 5. This Fig. shows that Loewenstein started working in this field earlier than others (from 2012 to 2024), making him the most consistent author with 12 years of activity. Sasaki is the most recent researcher to have entered this field, starting in 2021.

Table 4.
Note regarding the most relevant (top) authors in terms of number of publications and number of citations.

Author	h_index	g_index	m_index	TC	NP	PY_start
Loewenstein G	4	5	0.286	729	5	2012
Oliver A	3	4	0.231	335	4	2013
Reisch La	3	3	0.375	116	3	2017
Brown Zs	2	2	0.154	88	2	2013
Chabé-Ferret S	2	3	0.286	78	3	2019
Chater N	2	2	0.222	167	2	2017
Dolan P	2	2	0.143	248	2	2012
Earl Pe	2	3	0.222	27	3	2017
Ferraro Pj	2	2	0.4	27	2	2021
Grüne-Yanoff T	2	2	0.2	18	2	2016

3.1.5 Journal-Centered Analysis

Similarly, the impact of the most prolific journals (with at least 3 publications) was analyzed using several metrics, including the h-index, g-index, and m-index, as shown in Table 4. Based on the h-index criterion, Behavioral Public Policy (h-index of 6) appears to be the most influential journal in the field of AI and behavioral economics. The same holds true when measured by the m-index, with a value of 0.667 (given that its start year of publication is 2006). It is followed by the Journal of Environmental Economics and Management with an h-index of 4 and an m-index of 0.38. On the other hand, when considering the g-index, which gives more weight to highly cited articles, Behavioral Public Policy (g-index of 8) is again the most influential journal. (Fig. 4)

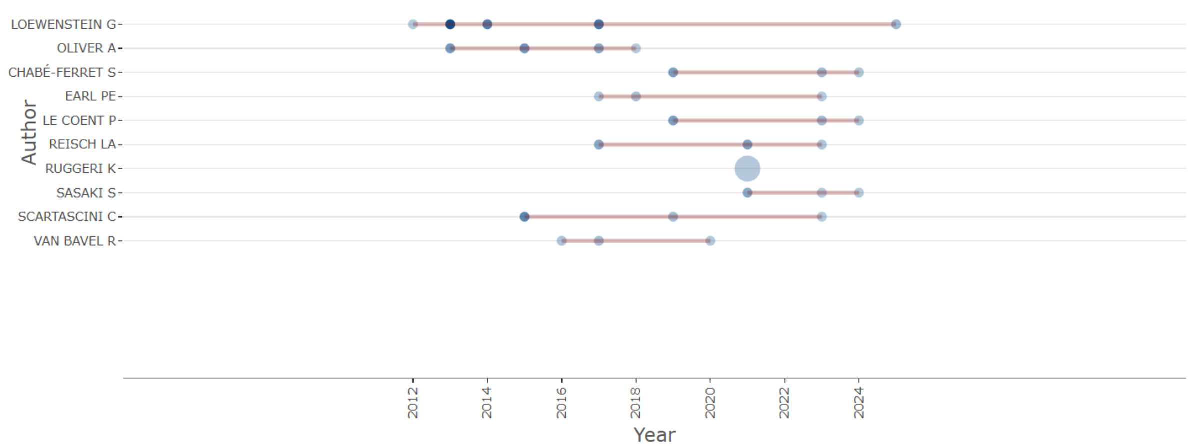

Fig. 3. Scientific production of the most relevant (top) authors over time.

To further highlight highly cited publications, we created Fig. 5, in which the analysis of journal impact based on total citations showed that Allcott (or the intended journal name; see note below) is the most influential journal with a total of 81 citations. This result emphasizes the multidisciplinary nature of the research field of AI and behavioral economics, as we see interdisciplinary journals alongside specialized journals in several fields, including energy, business, psychology, marketing, and computer science.

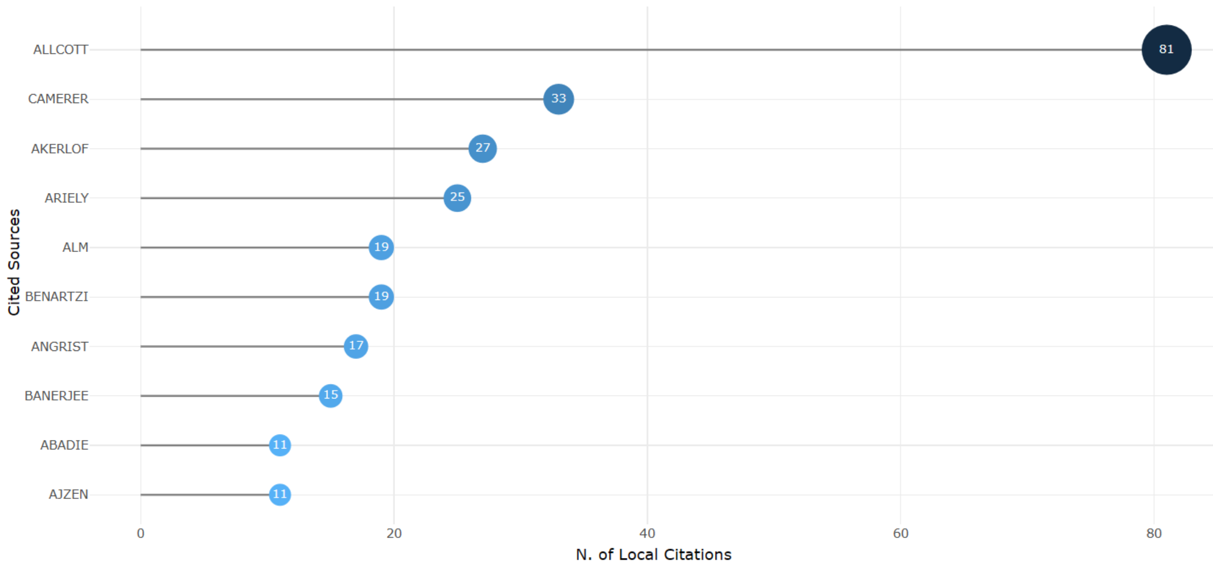

Fig. 4. Most relevant (top) journals in terms of total citations**.**

3.1.6 Organizational Affiliation Analysis

Fig. 6 presents the analysis of organizational affiliations, showing that the London School of Economics and Political Science, the University of Göttingen, and Osaka University are the most productive organizations in terms of total number of publications, having published 7, 4, and 4 articles, respectively.

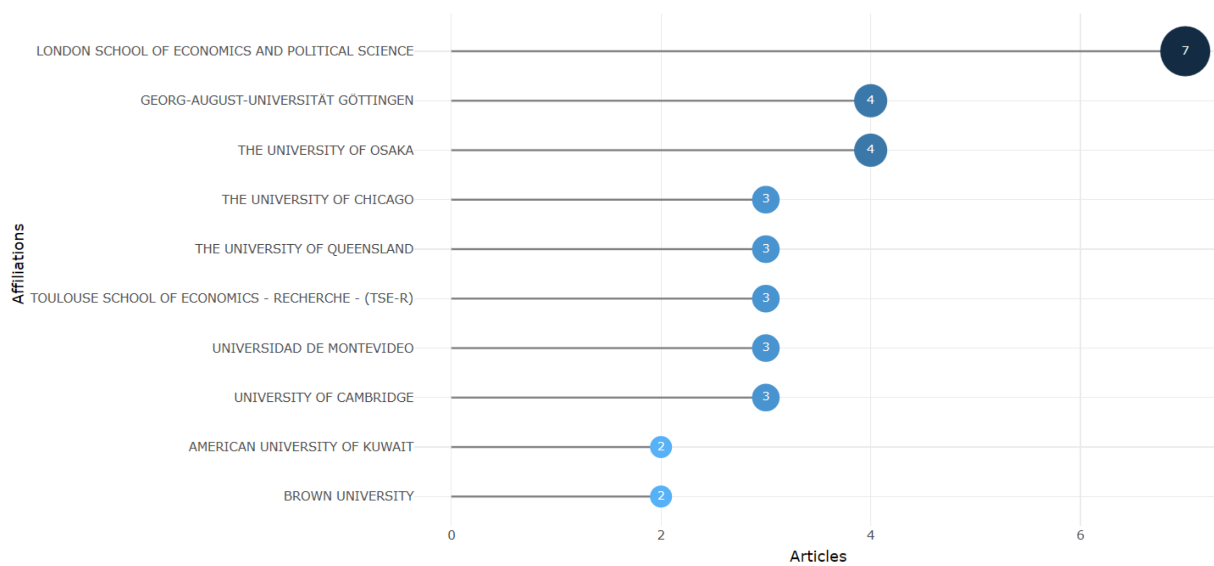

Fig. 5. Note regarding the most relevant (top) journals in terms of number of publications and number of citations.

3.1.7 Country-Centered Analysis

Fig. 7 illustrates the impact of countries in the fields of artificial intelligence and behavioral economics. The United Kingdom (1,297 citations), the United States (983 citations), Sweden (583 citations), and Germany (461 citations) are the most influential countries in terms of total citations, followed by Norway, France, and New Zealand. For further analysis of country productivity, Table 5 shows that the United Kingdom and the United States are the most productive countries, with 1,297 and 983 publications, respectively. Sweden, Germany, Turkey, and Iran, despite having fewer citations, are also among the most productive countries. (Fig. 8)

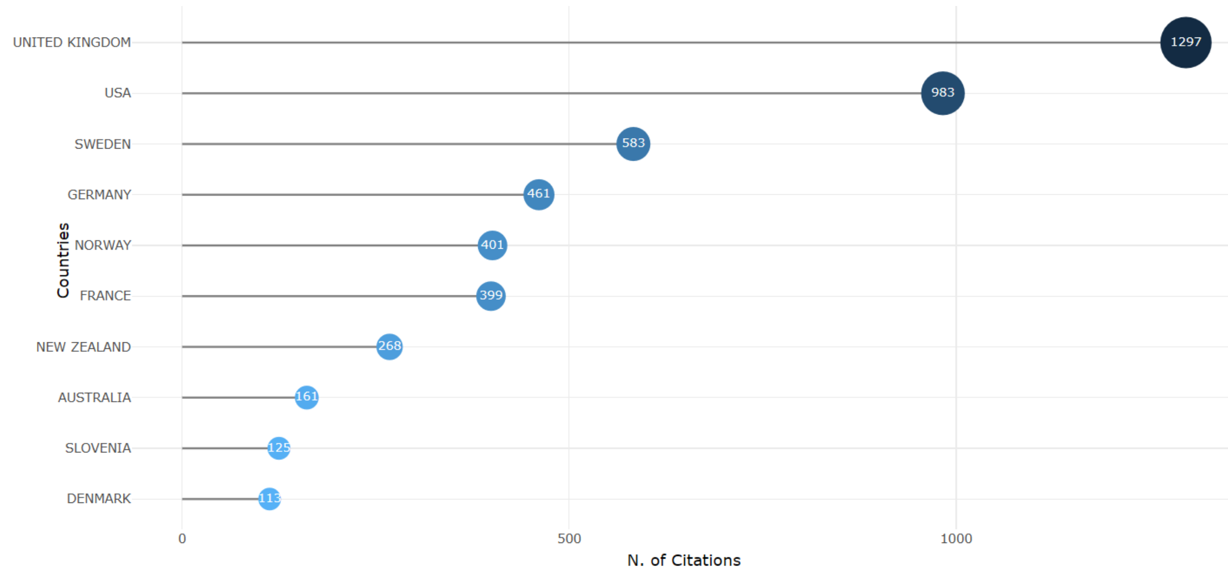

Fig. 6. Most cited countries.

Accordingly, to obtain further evidence on country productivity, we relied on data regarding corresponding authors.

Country	TC	Average Article Citations
UNITED KINGDOM	1297	46.30
USA	983	24.00
SWEDEN	583	116.60
GERMANY	461	46.10
NORWAY	401	401.00
FRANCE	399	30.70
NEW ZEALAND	268	268.00
AUSTRALIA	161	17.90
SLOVENIA	125	125.00
DENMARK	113	56.50

Fig. 7. Note regarding the most relevant (top) countries in terms of scientific participation and number of citations.

3.2 Science Mapping and Network Analysis

3.2.1 Analysis of Article Impact

In Table 5, The total citations metric is the best indicator for highlighting highly cited articles when conducting an analysis of publication impact. In Table 10, we clearly observe the dominance of the article by Lehner, published in 2016, with 425 citations as the highest number of citations for a single article.

Table 5.
Most cited articles.

Paper	Total Citations	TC Per Year	Normalized TC
Lehner M, 2016, J Clean Prod	425	42.50	6.18
Hummel D, 2019, J Behave Exp Econ	407	58.14	11.43
Kallbekken S, 2013, Econ Lett	401	30.85	3.15
Acquisti A, 2013, J Leg Stud	356	27.38	2.79
Schubert C, 2017, Ecol Econ	325	36.11	6.65
Wilkinson Tm, 2013, Polit Stud	268	20.62	2.10
Andor Ma, 2018, Ecol Econ	224	28.00	6.60
Loewenstein G, 2014, Annu Rev Econ	203	16.92	2.45
Leggett W, 2014, Policy Polit	187	15.58	2.26
White Md, 2013, The Manip Of Choice: Ethics And Libert Paternalism	178	13.69	1.40

The second article, with 407 citations, is titled How effective is mental stimulation? A quantitative review of effect sizes and limitations of experimental studies of mental stimulation and was published in Experimental Economics of Behavior in 2019. The third most cited article, Encouraging hotel guests to reduce food waste as a win-win environmental action, published in Economics Letters in 2013 with 401 citations. According to this article, such actions are environmentally significant because food waste is one of the main drivers of climate change and other forms of environmental degradation. Given the scale of the impact of food waste on global environmental change, it is surprising that this issue has not attracted more attention. These actions reduce the amount of food that restaurants need to purchase and do not affect guest satisfaction, thus potentially increasing profits. Hence, these actions represent potential opportunities from which both sides benefit. They must be used responsibly and ethically to avoid potential risks such as behavioral manipulation. The article What value does privacy have?, published in Legal Studies in 2013 with 356 citations, ranks fourth. Overall, this article highlights the gap between such values compared to similar studies on major consumer goods. The results show the sensitivity of privacy valuations to contextual and non-standard factors. The fifth most influential article, with 325 citations, was published in Ecological Economics in 2017. This article attempts to fill this gap, first by providing a structured review of the most important contributions to the literature on pro-environmental nudges, and then by offering some critical considerations that may help practitioners reach an informed ethical assessment of nudges.

3.2.2 Scientific Collaboration Network

Fig. 9 shows the co-authorship network of authors who have published at least 2 joint articles with at least 10 citations (24 authors). This image depicts an underdeveloped collaboration network among authors in the scientific literature. This low level of co-authorship highlights the need for greater interdisciplinary research collaborations in this field. As previously mentioned, given the nature of behavioral economics knowledge, scientists from specialized fields such as economists, psychologists, and neuroscientists should collaborate alongside computer scientists with the aim of generating new ideas, solutions, and research pathways for AI applications in behavioral economics.

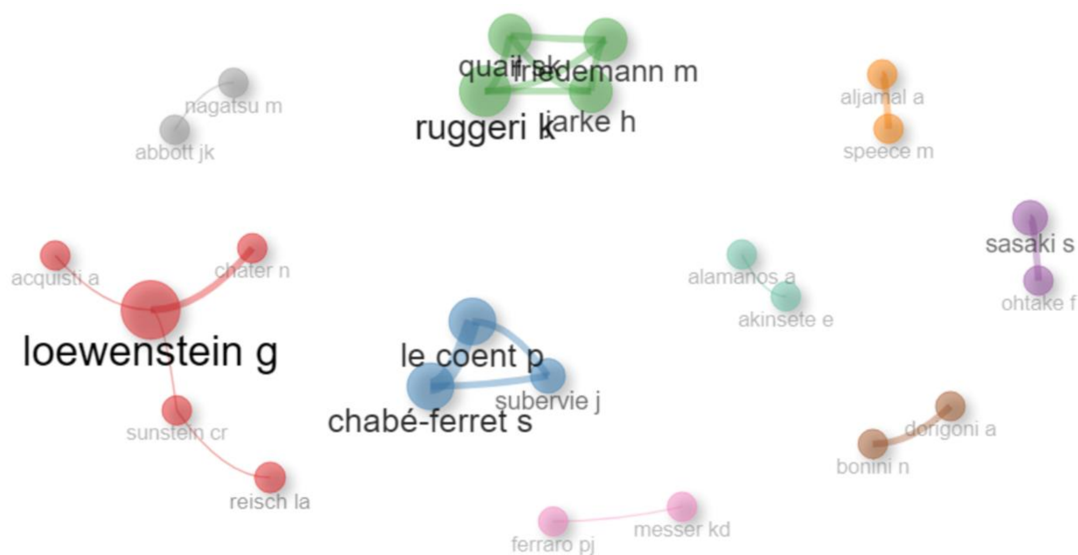

Fig. 8. Visual display of the co-authorship network of relevant authors.

3.2.3 Knowledge Bases through Co-citation Analysis

Co-citation analysis is suitable for defining the knowledge bases of research (the intellectual structure), which is essentially a list of articles with the highest co-citation indices among the citing publications. As shown in Fig. 14, co-citation analysis of references (33 documents each with at least 10 co-citations) indicates that research on artificial intelligence in behavioral economics draws upon four foundational research clusters. (Fig. 10)

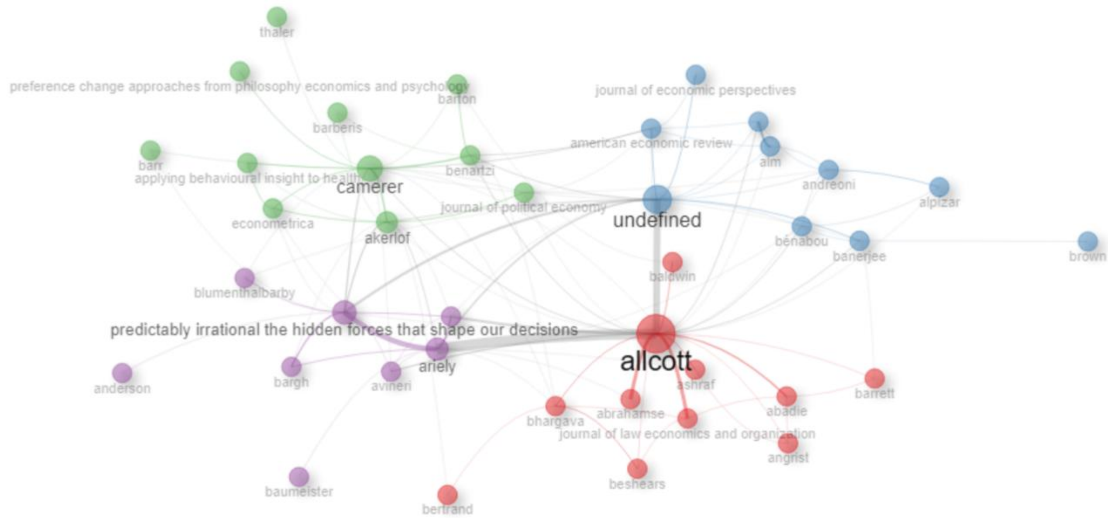

Fig. 9. Visual display of the co-authorship network of relevant organizational affiliations (centers).

A co-citation analysis of the literature reveals four distinct clusters within the intersection of behavioral economics and artificial intelligence. As summarized in Table 6, these clusters include behavioral research and technology acceptance (Cluster 1), machine learning algorithms (Cluster 2), financial decision-making under risk (Cluster 3), and the role of AI in shaping customer behavior (Cluster 4). Together, they map the intellectual structure of this emerging interdisciplinary field.

A. Cluster1: Behavioral Research and Technology Acceptance (red nodes)

The article by Fred Davis, titled Perceived usefulness, perceived ease of use, and user acceptance of information technology (1989), emphasizes the factors influencing user acceptance of information technology. The article The theory of planned behavior by Icek Ajzen (1991) provides a theoretical framework for understanding and predicting human behavior. The article by Claes Fornell and David Larcker (1981) focuses on the statistical and methodological aspects of structural equation modeling. This cluster includes two fundamental themes: studies of human behavior and factors affecting information technology acceptance.

Table 6.

Clusters of the knowledge base of behavioral economics in artificial intelligence through co-citation analysis.

Cluster	Node
1	allcott
	angrist
	abadie
	ashraf
	bhargava
	abrahamse
	baldwin
	journal of law economics and organization

Cluster	Node
	barrett
	bertrand
	beshears
2	undefined
	alm
	banerjee
	american economic review
	journal of economic perspectives
	andreoni
	bénabou
	brown
	allingham
	alpízar
3	camerer
	akerlof
	benartzi
	journal of political economy
	econometrica
	barton
	preference change approaches from philosophy economics and psychology
	applying behavioral insight to health
	barberis
	thaler
	barr
4	ariely
	predictably irrational the hidden forces that shape our decisions
	ajzen
	anderson
	blumenthalbarby
	avineri
	bargh
	baumeister

B. Cluster 2: Machine Learning (blue nodes)

David Blei's 2003 article introduces the Latent Dirichlet Allocation (LDA) model for text data. Leo Breiman's 2001 article describes the Random Forest algorithm for classification and regression. Corinna Cortes and Vladimir Vapnik's 1995 article examines Support Vector Machines (SVMs). This cluster presents machine learning as a foundational theme with various supervised and unsupervised learning algorithms.

C. Cluster 3: Financial Decision-Making (green nodes)

The article Prospect Theory by Daniel Kahneman and Amos Tversky (1979) is the most cited reference in this study; it criticizes traditional economic models and offers an alternative model for decision-making under risk. Other articles in this cluster address stock market prediction through Twitter mood and the relationship between investor sentiment and stock returns.

D. Cluster 4: Artificial Intelligence and Customer Behavior (purple nodes)

The articles in this cluster examine the impact of AI on the service industry, the role of service robots in enhancing customer experience, and how AI will transform the future of marketing.

3.2.4 Bibliographic Coupling of Authors, Institutions, and Countries

While co-citation essentially looks forward, bibliographic coupling is retrospective and uses the number of shared references between two documents to measure similarity. The author bibliographic coupling network (Fig. 15) confirms the need to expand interdisciplinary collaborations. At the institution level (Fig. 16) and country level (Fig. 17), the United States, China, and the United Kingdom have central influence, but countries such as India, South Korea, and Saudi Arabia also show frequent coupling.

3.2.5 Keyword Co-occurrence Analysis

A keyword co-occurrence analysis of the literature reveals five major thematic clusters at the intersection of behavioral economics and artificial intelligence. As illustrated in Fig. 11, these clusters cover behavioral economics (predicting purchase intention and trust), policymaking (energy demand forecasting using deep learning and big data), nudge theory (integrating AI with neuroscience), sustainability (analyzing customer preferences via social media), and economic analysis (investor sentiment mining through natural language processing). The network visually maps how these themes interconnect within the research landscape.

- Red cluster: Behavioral economics (using AI to predict purchase intention and build trust).
- Green cluster: Policymaking (using deep learning and big data to forecast energy demand).
- Blue cluster: Nudge theory (combining AI with neuroscience and concepts such as nudging).
- Yellow cluster: Sustainability (analyzing customer preferences through social media).
- Purple cluster: Economic analysis (investor sentiment analysis in stock markets using natural language processing).

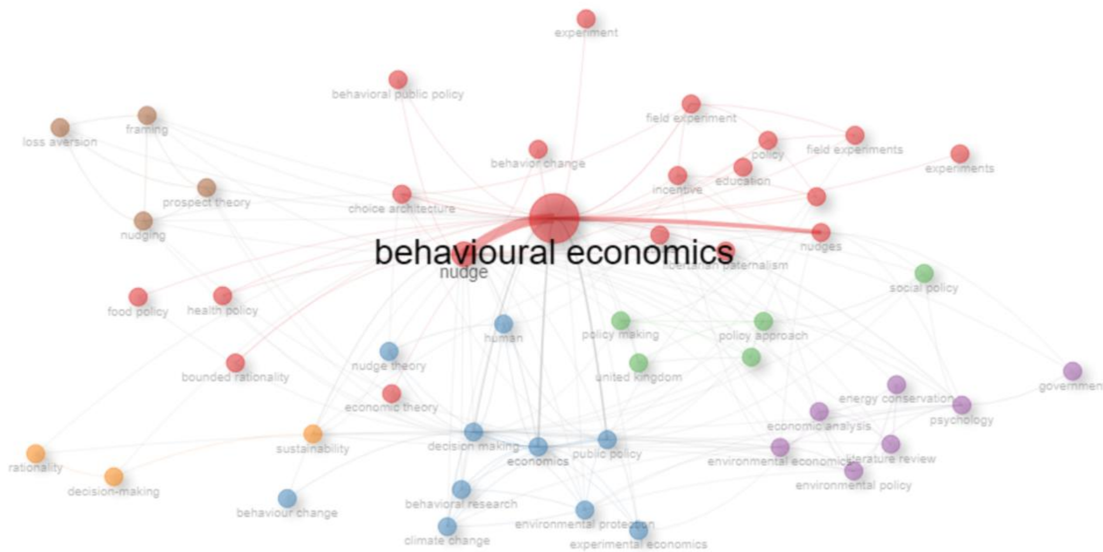

Fig. 10. Visual display of the keyword co-occurrence network.

3.2.6 Thematic Structure via Co-word Analysis

Using the thematic map in Fig. 12 , research themes were classified into four quadrants:

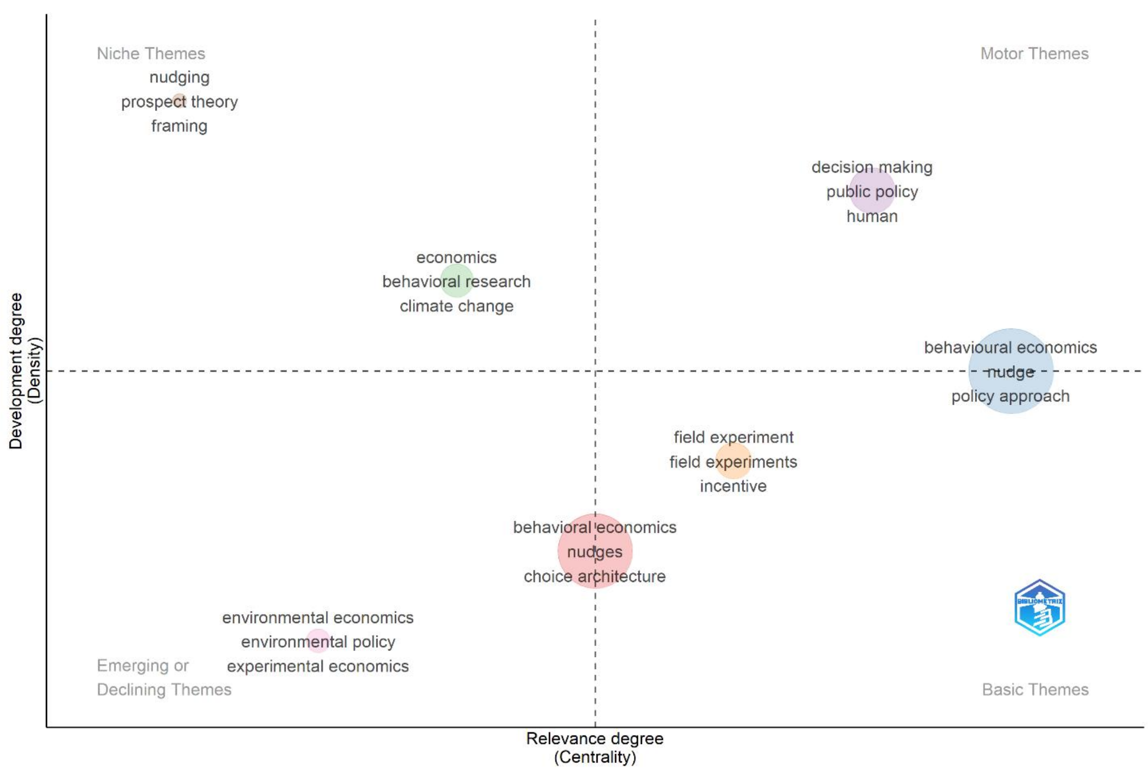

Fig. 11. Thematic map through co-word analysis.

- Motor themes (upper-right quadrant) include decision-making and public policy. These areas are highly developed and central. Here, applications of inverse reinforcement learning and prospect theory in economic analyses are explored.
- Basic themes (lower-right quadrant) include field experiments and behavioral economics, which are general and transversal concepts but still require development.
- Specialized themes (upper-left quadrant) include prospect theory and climate change; although developed, they are marginal to the overall research field.
- Emerging or declining themes (lower-left quadrant) include environmental economics; analyses indicate that this trend is emerging.

4. Discussion

4.1 Key Findings of Research Performance Analysis

In this section, the findings from the bibliometric analysis of 252 documents indexed in the Scopus database from 2006 to 2025 are examined. The aim is to answer the research questions concerning evolutionary trends, scientific collaborations, knowledge bases, current and emerging topics, and to identify research gaps in the field of AI and behavioral economics. This section quantitatively examines scientific outputs, key actors, and their impact based on bibliometric indicators.

4.1.1 Temporal Trends in Publications and Citations

Over a 20-year period (2006–2025), a total of 252 documents were published in 148 reputable scientific sources. The annual growth rate of 16.76% indicates remarkable growth, especially in the second half of the period.

- First period (2006–2017): Annual production reached a maximum of 22 articles, averaging about 9 articles per year. This period can be considered the formative stage of the theoretical and methodological foundations of the behavioral economics and AI field.
- Second period (2018–2025): Exponential growth, with 28 articles recorded in 2023 (more than three times the average of the previous period). This growth coincided with the development of machine learning tools, increased access to large behavioral data, and the adoption of computational methods in the social sciences.

In terms of average citations per article, 2013 (10 citations), 2014 (7 citations), and 2016 (6 citations) rank highest. This indicates that articles published in the mid-2010s (the field's youth period) had the greatest scientific impact on subsequent research. However, since more recent articles (2019 onward) have had less time to accumulate citations, it cannot be concluded that recent research is less impactful.

4.1.2 Key Authors and Collaboration Patterns

Out of a total of 525 authors, only 77 are single authors, and the average collaboration is 2.29 authors per document. The percentage of international collaborations is 24.6%, which is moderate compared to many interdisciplinary fields. Analysis of multiple metrics shows:

- The most influential author is Loewenstein G. (h-index 4, g-index 5, 729 citations for 5 articles since 2012); he has the longest active period (2012–2024, about 12 years), demonstrating his sustained presence at the research forefront.
- Oliver A. (h-index 3, g-index 4, 335 citations, starting in 2013) ranks second.
- Among authors with high annual productivity (m-index), Reisch L.A. (m-index 0.333, 116 citations, 3 articles since 2017) and Ferraro P.J. (m-index 0.4, 27 citations, 2 articles since 2021) are among those who, despite fewer articles, have had significant annual impact. This indicates that even recent entrants can produce highly cited work.
- The most recent entrant is Sasaki, who entered the field in 2021, showing that the field continues to attract new generations of researchers.

4.1.3 Journals and Publication Channels

The most influential journal based on h-index (6) and g-index (8) is Behavioral Public Policy. With a start year of 2006, it is one of the oldest scientific channels in this area. Next is the Journal of Environmental Economics with h-index (4) and m-index 0.38. In terms of total citations, the journal Allcott (or the intended name) is most impactful with 81 citations. This result demonstrates the strongly multidisciplinary nature of the field: top journals are dispersed across economics, energy, business, psychology, marketing, and computer science. This diversity offers broad publication opportunities but also leads to knowledge fragmentation.

4.1.4 Institutions and Organizational Affiliations

The London School of Economics and Political Science (LSE) with 7 articles, the University of Göttingen with 4 articles, and Osaka University with 4 articles are the most productive institutions. Notably, unlike many technology-oriented fields where US and Asian universities dominate, European institutions (especially from the UK and Germany) also play a prominent role here.

4.1.5 Leading Countries in Production and Productivity

In terms of total citations worldwide in the field of behavioral economics and AI, the following results were obtained (Table 7).

Table 7.
Citations by Country.

Country	Number of Citations
United Kingdom	1,297
United States	983
Sweden	583
Germany	461
Norway, France, New Zealand	Next ranks

In terms of productivity, the UK and the US remain leaders, but Sweden, Germany, Turkey, and Iran despite having fewer citations are also among the productive countries. Iran, as the only Middle Eastern country in this list, indicates the presence of researchers from developing countries in this field. The analysis based on corresponding authors confirms the same pattern.

4.2 Key Findings of Science Mapping and Network Analysis

This section addresses the intellectual structure, hidden relationships, and main themes of the field.

4.2.1 Knowledge Bases through Co-citation Analysis

In Table 8, Co-citation analysis of 33 documents (each with at least 10 co-citations) revealed four foundational clusters:

Table 8.
Co citation Analysis.

Cluster	Color	Main Theme	Key References
1	Red	Behavioral research and technology acceptance	Davis (1989), Ajzen (1991), Fornell & Larcker (1981)
2	Blue	Machine learning	Blei (2003), Breiman (2001), Cortes & Vapnik (1995)
3	Green	Financial decision-making (prospect theory)	Kahneman & Tversky (1979), Bollen et al. (2011), Baker & Wurgler (2006)
4	Purple	AI and customer behavior	Huang & Rust (2018), Wirtz et al. (2018), Davenport et al. (2020)

- Cluster 1 (Behavioral research and technology acceptance): Ajzen’s theory of planned behavior and Davis’s technology acceptance model are the main foundations of applied AI studies in behavioral economics. This cluster shows that much research uses these theoretical frameworks to explain the acceptance of intelligent technologies (e.g., service robots, chatbots).

- Cluster 2 (Machine learning): LDA for topic modeling of behavioral texts, Random Forest for classifying decision patterns, and SVMs for sentiment and customer behavior analysis are the most widely used tools. This cluster indicates that behavioral economics researchers are gradually moving from traditional regression methods toward machine learning methods.
- Cluster 3 (Financial decision-making): Prospect theory is by far the most cited reference. Studies in this cluster demonstrate how cognitive biases such as loss aversion can be used through machine learning models and sentiment analysis of Twitter data to forecast stock market fluctuations.
- Cluster 4 (AI and customer behavior): This cluster addresses more applied aspects, including frontline service robots, the impact of AI on the future of marketing, and enhancing customer experience. This cluster is more recent in time and reflects the field's evolution from theoretical foundations to practical implementation.

4.2.2 Thematic Structure via Co-word Analysis

In Table 9, The thematic map is drawn based on two dimensions: centrality (connection to other topics) and density (internal development).

Table 9.
Thematic Map.

Quadrant	Title	Topics	Characteristics
Upper-right	Motor themes	Decision-making, public policy	High centrality, high density
Lower-right	Basic themes	Field experiment, behavioral economics	High centrality, low density
Upper-left	Specialized themes	Prospect theory, climate change	Low centrality, high density
Lower-left	Emerging themes	Environmental economics	Low centrality, low density

4.2.3 Scientific Collaboration Network

Among the 24 authors with at least 2 joint articles and at least 10 citations, the co-authorship network is very sparse and underdeveloped. The absence of large collaboration clusters indicates that:

- Behavioral economics researchers often work in small groups or individually.
- Interaction among economists, psychologists, neuroscientists, and computer scientists has not yet reached a desirable level.
- This situation runs counter to the interdisciplinary nature of the field and may slow innovation in complex AI applications (such as agent-based models or deep reinforcement learning).

4.3 Gaps and Opportunities

In Table 10, By analyzing the findings from sections A and B, the following can be identified as main gaps and future opportunities:

Table 10.
Research Gaps and Opportunities.

Gap	Evidence from Data	Opportunity
Weak interdisciplinary collaboration	Sparse co-authorship network; only 24.6% international collaboration	Design joint programs between behavioral economics and computer science groups
Dominance of consumer topics and lack of macro studies	Large red and green clusters, small purple cluster; specialized themes quadrant is marginal	Expand studies to behavioral macroeconomics, public finance, and monetary policy
High geographical concentration	More than 50% of citations belong to the UK and US	Encourage researchers from emerging countries (Turkey, Iran, Malaysia) through bilateral collaborations
Shortage of longitudinal and field studies	Basic themes (field experiment) have low density (lower-right quadrant)	Invest in AI-based field experiment designs in public policy
Emergence of environmental economics	Position in the emerging quadrant	Develop deep learning models to simulate environmental behaviors

4.4 Suggestions for Future Direction

- Formation of international and interdisciplinary research networks
- Development of basic themes
- Empowerment of specialized themes
- Expansion into behavioral finance and macroeconomics
- Ethical considerations and privacy
- Geographical diversity in sampling

4.5 Study Limitations

- Only English-language articles were included, which may have excluded high-quality research in other languages (e.g., German, French, Chinese).
- Most documents are research articles (169), with only 2 conference papers. In the AI field, where innovations are quickly presented at conferences, this shortcoming may cause new trends to be missed.

- Although the 2006–2025 period is appropriate, articles published in 2024 and 2025 have not yet had sufficient time to accumulate citations, so their true impact is not fully reflected in this analysis.

5. Conclusions

The present study, through a bibliometric analysis of 252 scientific documents over a 20-year period (2006–2025), has shown that the field of behavioral economics and artificial intelligence has grown significantly in the last decade, moving from a formative stage to a phase of rapid expansion. However, the intellectual structure of this field still faces considerable imbalances. On the one hand, four foundational knowledge clusters behavioral research and technology acceptance, machine learning, financial decision-making, and AI and customer behavior are well established. The theory of planned behavior, the technology acceptance model, and prospect theory remain the most influential theoretical frameworks. On the other hand, the co-authorship network analysis revealed that interdisciplinary collaboration among economists, psychologists, neuroscientists, and computer scientists is very weak, with only 24.6% of publications having international collaboration. This situation is a major obstacle to leveraging advanced AI capabilities (such as deep reinforcement learning and multi-agent systems) for modeling complex economic behaviors.

The thematic map of the research showed that decision-making and public policy act as motor themes of the field, while environmental economics was identified as an emerging theme with high growth potential. Unfortunately, fundamental areas such as behavioral macroeconomics, public finance, and AI-based experimental economics are situated in the specialized or marginal quadrants and account for a small share of scientific output. Furthermore, the dominance of research on consumer and customer behavior (red cluster in keyword co-occurrence) and the scarcity of macro, longitudinal, and field studies represent another serious gap.

Based on the findings, the following suggestions are made for future direction:

- Within a 2-year horizon, produce at least two systematic reviews or empirical studies on AI applications in monetary and fiscal policy, including the measurement of behavioral macro-indicators (e.g., behavioral inflation).
- Form international and interdisciplinary research networks focusing on joint projects between behavioral economics, cognitive neuroscience, and data engineering groups.
- Develop basic themes such as AI-based field experiments in public policy, health, and energy.
- Empower specialized themes, including prospect theory in big data contexts and climate change modeling using deep learning methods.
- Expand into neglected areas such as behavioral macroeconomics, monetary policy, and behavioral finance at the institutional level.

- Establish ethical considerations and privacy as an independent research line given the risks of behavioral manipulation and algorithmic bias.
- Ensure geographical diversity in sampling and encourage researchers from developing countries (e.g., Iran, Turkey, Malaysia and Thailand) to engage in bilateral collaborations.

Limitations of the present study include reliance on the Scopus database, exclusion of non-English articles, the small share of conference papers (only 2), and the incomplete reflection of the impact of very recent articles (2024–2025). Mixed-methods studies (bibliometrics + systematic review) could be used to deepen the qualitative findings of this field. In summary, this study shows that AI applications in behavioral economics, despite quantitative growth, still lack the necessary structural maturity and interdisciplinary collaborations. Filling the identified gaps especially moving from the study of consumer behavior toward macro policies and the design of intelligent institutions could turn this field into one of the most influential interdisciplinary knowledge domains in the coming decade.

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Conflicts of interest

The authors declare no conflict of interest.

Authors contribution statement

Mohammad Mahdi Khazaian: Conceptualization, Data curation, Formal analysis, Investigation, Software, Writing original draft, Writing review & editing, Visualization.

Hadi Dibavand: Conceptualization, Project administration, Resources, Supervision, Validation.

Irianna Futri: Analytical support, Providing practical recommendations, Refining the research structure.

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