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Review

How Automated Machine Learning Can Boost Business

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Abstract: Automated Machine Learning (AutoML) is revolutionizing how businesses utilize data, making advanced analytics accessible to a broader range of organizations. By automating complex tasks like data preprocessing, model selection, and hyperparameter tuning, AutoML reduces the time and resources needed to develop and deploy machine learning models. This accelerates decision-making and enables quicker responses to market changes. AutoML empowers businesses to build accurate predictive models using sophisticated algorithms, optimizing model performance for reliable insights and better outcomes. A key advantage of AutoML is its accessibility; even organizations without a dedicated data science team can leverage machine learning, reducing technical barriers and democratizing innovation. As businesses grow, AutoML scales to handle larger datasets and more complex problems without extensive manual intervention. AutoML enhances efficiency, accuracy, and scalability, becoming a crucial driver of business innovation and success. The systematic review will examine the bibliometric literature on how AutoML can boost business, analyzing 74 academic and scientific documents from the Scopus database.

Keywords: automated machine learning; business

1. Introduction

Businesses increasingly depend on data to drive decision-making, optimize processes, and maintain a competitive edge. The surge in data availability, coupled with technological advancements, has led to the rise of machine learning (ML) as a powerful tool for extracting insights from vast datasets [1]. However, traditional machine learning methods, which require specialized knowledge and considerable time investment, have often been a barrier for many organizations, particularly those without dedicated data science teams. This has led to the adopting of Automated Machine Learning (AutoML), which offers a streamlined approach to deploying machine learning models. Chauhan et al. [2] (p.205) define AutoML as the "process of studying a traditional machine learning model development pipeline to segment it into modules and automate each of those to accelerate workflow." It is an innovative approach that automates developing machine learning models' complex and technical steps. According to Ebadi et al. [3], AutoML reduces the time and specialized skills needed to create, use, and maintain predictive models by automating repetitive tasks throughout the data science cycles. The automation accelerates the model-building pace and allows data scientists to focus on other important responsibilities, enhancing performance and workflow.

As businesses continue to generate and accumulate vast amounts of data, the need for efficient and scalable solutions to analyze this data becomes more pressing. AutoML addresses this need by providing a framework that can quickly adapt to the unique challenges of different business environments [2]. AutoML enables businesses to integrate machine learning into their operations with greater ease and speed, from predicting customer behavior to optimizing supply chains or enhancing product recommendations [4]. In addition, AutoML automates tasks such as data

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preprocessing, model selection, and hyperparameter tuning [3]. As a result, this innovation significantly lowers the barriers to entry for businesses looking to leverage the power of machine learning. This democratization of machine learning means that organizations of various sizes and industries can now access advanced predictive analytics without needing deep expertise in the field [5]. Furthermore, the evolution of AutoML reflects a broader trend in technology: the movement toward greater automation and accessibility. Just as other automated tools have transformed industries by making complex processes more manageable, AutoML has the potential to revolutionize how businesses approach data analysis and decision-making. The technology simplifies building and deploying machine learning models, thus allowing companies to focus on using insights to drive innovation and growth.

2. Materials and Methods

This study employed a systematic bibliometric literature review (LRSB) to explore the role and impact of AutoML on business. The systematic review adhered to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 guidelines, ensuring a transparent, comprehensive, and reproducible approach [6]. The Scopus database was selected as the primary source of literature due to its extensive coverage of peer-reviewed journals, conference papers, and other scholarly publications across various disciplines. The search strategy was carefully designed to capture all relevant documents related to AutoML within a business context [7,8].

LRSB utilizes a systematic, scientific, and transparent methodology aimed at minimizing bias by comprehensively examining both published and unpublished literature relevant to the study topic [7–9]. The researcher also includes an audit trail, enabling readers to evaluate the quality of the studies incorporated into the research, as well as their methodologies and findings. LRSB involves a rigorous screening and selection process for information sources to ensure the credibility and accuracy of the data presented. This process is structured into three phases and six steps [7–9] (Table 1).

Table 1. Process of systematic LRSB.

Fase	Step	Description
	Step 2	searching for appropriate literature
	Step 3	critical appraisal of the selected studies
	Step 4	data synthesis from individual sources
Interpretation	Step 5	reporting findings and recommendations
Communication	Step 6	Presentation of the LRSB report

Source: Adapted from Rosário and Dias [8,9].

The researchers used the Scopus database to identify and select reputable sources recognized by the scientific and academic communities. However, it is important to note a limitation of this study: its exclusive reliance on the Scopus database, which may omit other valuable scientific and academic resources. To ensure comprehensive coverage, the literature search should include peer-reviewed scientific and academic publications up to August 2024.

The search process began with the selection of Scopus as the database. The initial search (Table 2) was conducted using Scopus, chosen for its extensive coverage of peer-reviewed literature. The screening and selection process involved multiple stages.

Table 2. Screening methodology.

Scopus Database	Screening	Publications
Initial Query	Keywords: Automated Machine Learning	2,089
First Screening	Keywords: Automated Machine Learning Limited: Business	74
Eligibility criteria	Keywords: Automated Machine Learning	

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Limited: Business
Published until August 2024

Source: Adapted from Rosário and Dias [8,9].

The initial search was conducted using the Scopus database, focusing on documents with the phrase "Automated Machine Learning" in their title, abstract, or keywords. This broad search approach yielded a total of 2,089 papers. To narrow down the results to studies specifically relevant to the business domain, an additional filter was applied to limit the subject area to " Business." In addition, inclusion and exclusion criteria were used to ensure the relevance and quality of the selected literature. Only peer-reviewed journal articles, conference proceedings, and review papers were considered in this case. This selection and screening process resulted in 74 sources synthesized in the final report.

Thematic analysis was employed to analyze and organize the study findings. Rosário and Dias [8] describe thematic analysis as a research method that extracts meaning and concepts from data by identifying, analyzing, and recording common patterns or themes across identified studies. Similarly, Rosário et al. [9] define a theme-centric review as an approach that elucidates how previous publications contribute to a study topic by identifying key themes, concepts, and phenomena of interest. This method enabled the researcher to categorize the results based on recurring patterns or themes, demonstrating how businesses use predictive analytics to anticipate customer behaviors and plan accordingly. We applied both content and thematic analysis methods to identify, examine, and present diverse documents, following the recommendations of Rosário and Dias [7,8]. The 74 scientific and academic documents indexed in Scopus were then analyzed both narratively and bibliometrically to delve deeper into the content and extract common themes that directly address the research question (Figure 1).

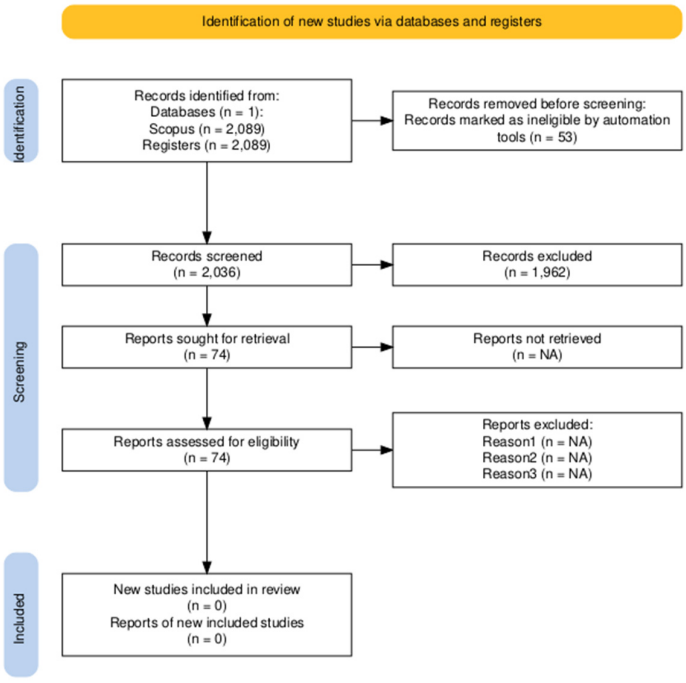

Figure 1. PRISMA 2020 flow diagram of the literature search and screening process [6–8].

The PRISMA 2020 guidelines provide a set of standards designed to enhance the transparency and quality of systematic reviews. These guidelines include a comprehensive checklist and flow diagram to help researchers clearly and thoroughly report their systematic reviews. Adhering to these standards is crucial for ensuring that scientific evidence is robust and reliable, thereby supporting informed decision-making in clinical practice and scientific research [7,8].

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For data analysis, we applied content and thematic analysis methods to categorize and discuss the diverse documents, following the recommendations of Rosário and Dias [8,9]. The 74 documents indexed in Scopus were analyzed both narratively and bibliometrically to deepen our understanding of the content and to identify common themes that directly address the research question [7–9].

Among the selected documents, 36 are articles; 31 are Conference papers; 6 are book chapters; and 1 are book.

3. Publication Distribution

Analyze how automated machine learning can boost business through August 2024. The year 2022 had the highest number of peer-reviewed publications, reaching 17. Figure 2 summarizes the peer-reviewed literature published through August 2024.

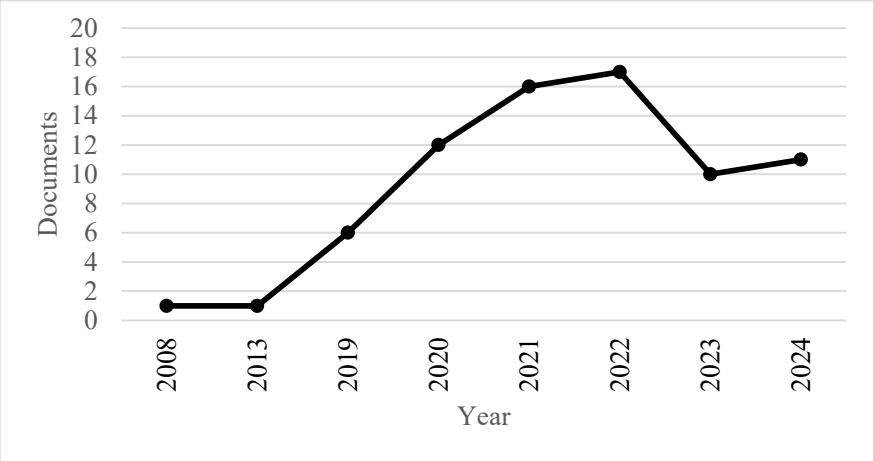

Figure 2. Documents by year.

The publications were organized as follows: International Conference On Information And Knowledge Management Proceedings (11); Knowledge Based Systems (5); Journal Of Cleaner Production (4); Proceedings 18th IEEE International Conference On Machine Learning And Applications Icmla 2019 2); and the remaining publications with 1 document.

Likewise, Figure 3 highlights the regions contributing most significantly to the literature on this topic. China, the USA, India, and Germany emerge as the leading countries with the highest levels of scientific output in related fields, alongside other nations publishing on the subject.

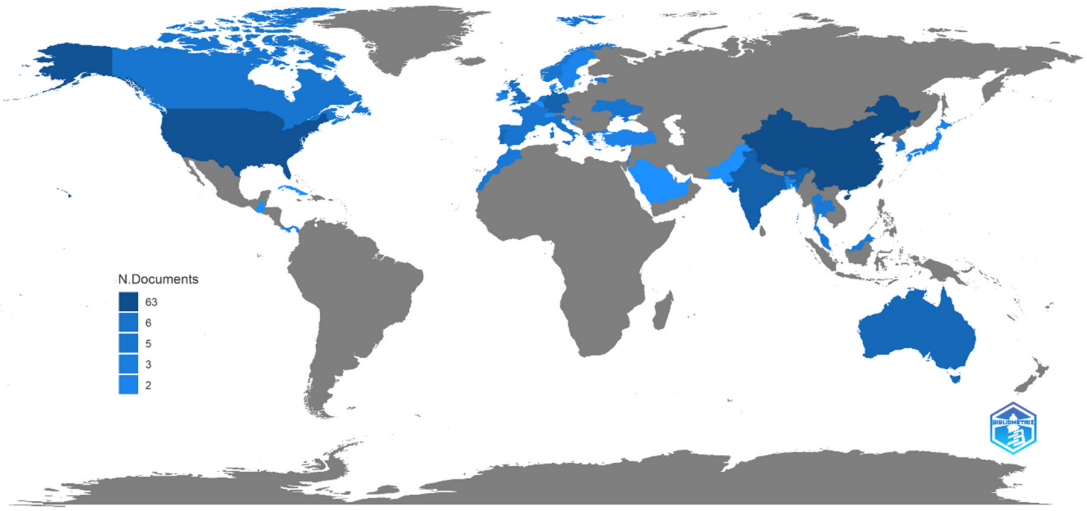

Figure 3. Documents by Geographical Area.

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Table 3, along with Figure 3, visually presents the top 10 countries making significant scientific contributions in the studied domains. This investigation aims to identify nations that are at the forefront of how automated machine learning can boost businesses.

Table 3. Top 10 countries by number of publications.

Country	Number of Publications
CHINA	63
USA	45
INDIA	19
GERMANY	17
AUSTRALIA	12
PORTUGAL	11
UK	7
ITALY	6
CANADA	5
FRANCE	5

Source: own elaboration.

In Table 4 we analyze the Scimago Journal & Country Rank (SJR), the best quartile, and the H index by Business Strategy And The Environment with 3,670 (SJR), Q1, and H index 147. There is a total of 14 publications in Q1, 6 publications in Q2, 5 publications Q3, and 2 publications in Q4. Publications from best quartile Q1 represent 25% of the 55 publications titles; best quartile Q2 represents 11%, best Q3 represents 9% and best Q4 represents 4% of each of the titles of 68 publications.

Table 4. Process of systematic LRSB.

Title	SJR	Best Quartile	H Index
Business Strategy And The Environment	3,670	Q1	147
Journal Of Business Research	3,130	Q1	265
Technological Forecasting And Social Change	3,120	Q1	179
Journal Of Management Information Systems	3,070	Q1	170
ACM Transactions On Information Systems	2,260	Q1	95
Knowledge Based Systems	2,220	Q1	169
Journal Of Cleaner Production	2,060	Q1	309
Journal Of Management Analytics	1,260	Q1	32
Industrial Management And Data Systems	1,210	Q1	125
Benchmarking	1,090	Q1	81
Journal Of Theoretical And Applied Electronic Commerce Research	0,890	Q1	47
Journal Of Financial Data Science	0,850	Q1	13
Journal Of Global Information Management	0,840	Q1	46
Operations Research Perspectives	0,810	Q1	31
International Journal Of Finance And Economics	0,730	Q2	52
Competitiveness Review	0,730	Q2	39
IEEE Engineering Management Review	0,700	Q2	38
Asian Journal Of Technology Innovation	0,680	Q2	24
International Journal Of Sports Marketing And Sponsorship	0,600	Q2	33
Service Oriented Computing And Applications	0,560	Q2	31
Lecture Notes In Business Information Processing	0,340	Q3	63
International Journal Of Clothing Science And Technology	0,320	Q3	42
Eastern European Journal Of Enterprise Technologies	0,290	Q3	36

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TEM Journal	0,240	Q3	22
Lecture Notes On Multidisciplinary Industrial Engineering	0,220	Q3	14
Foundations And Trends In Information Systems	0,190	Q4	3
IEEE Potentials	0,170	Q4	39
International Conference On Information And Knowledge Management Proceedings	0	-*	144
Proceedings 10th IEEE Joint Conference On E Commerce Technology And The 5th Enterprise Computing E Commerce And E Services CEC 2008 And Eee 2008	0	-*	13
Management For Professionals	0	-*	18
International Journal Of Scientific And Technology Research	0	-*	30
International Journal Of Recent Technology And Engineering	0	-*	31
Proceedings 18th IEEE International Conference On Machine Learning And Applications Icmla 2019	-*	-*	-*
Risks Proceedings Of The Conference On Production Systems And Logistics	-*	-*	-*
Proceedings Of The 15th International Conference On Business Information Systems 2020 Developments Opportunities And Challenges Of Digitization Wirtschaftsinformatik 2020	-*	-*	-*
Proceedings 2022 IEEE International Conference On E Business Engineering Icebe 2022	-*	-*	-*
Proceedings 2022 8th International Engineering Sciences And Technology Conference Iestec 2022	-*	-*	-*
Proceedings 2021 IEEE 23rd Conference On Business Informatics CBI 2021 Main Papers	-*	-*	-*
Proceedings 2020 International Conference On Communications Information System And Computer Engineering Cisce 2020	-*	-*	-*
Proceedings 2019 8th IEEE International Conference On Cloud Computing In Emerging Markets Ccem 2019	-*	-*	-*
Handbook Of Research On Applied Data Science And Artificial Intelligence In Business And Industry	-*	-*	-*
Embedded Artificial Intelligence Devices Embedded Systems And Industrial Applications	-*	-*	-*
Eai Endorsed Transactions On Internet Of Things	-*	-*	-*
Automated Machine Learning For Business	-*	-*	-*
Artificial Intelligence For Business Innovation Tools And Practices	-*	-*	-*
AI Book The Artificial Intelligence Handbook For Investors Entrepreneurs And Fintech Visionaries	-*	-*	-*
2023 8th International Conference On Business And Industrial Research Icbir 2023 Proceedings	-*	-*	-*
2022 IEEE Conference On Interdisciplinary Approaches In Technology And Management For Social Innovation Iatmsi 2022	-*	-*	-*
2022 2nd International Conference On Intelligent Technologies Conit 2022	-*	-*	-*
2021 International Conference On Data Analytics For Business And Industry Icdabi 2021	-*	-*	-*
2021 IEEE International Conference On Prognostics And Health Management Icphm 2021	-*	-*	-*
2021 6th International Conference For Convergence In Technology I2ct 2021	-*	-*	-*
17th International Conference On Wirtschaftsinformatik Wi 2022	-*	-*	-*
12th International Conference On Mobile Business Icmb 2013	-*	-*	-*
11th International Symposium On Project Management Ispm 2023	-*	-*	-*

*data not available. Source: own elaboration.

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Finally, 28 publications without indexing data represent 51% of publications. As shown in Table 4, the significant majority of publications do have quartile Q1.

The subject areas covered by the 74 scientific and/or academic documents were: Limited to Business, Management and Accounting (74); Decision Sciences (34); Computer Science (33); Engineering (25); Economics, Econometrics and Finance (11); Mathematics (6); Environmental Science (6); Energy (5); Social Sciences (4); Medicine (2); Psychology (1); Physics and Astronomy (1); and Materials Science (1).

The most cited article was "AutoML: A survey of the state-of-the-art", with 842 published Smart manufacturing 2,220 (SJR), the best quartile (Q1) and with H index (169), in this paper following the DL pipeline, introduces AutoML methods including data preparation, feature engineering, hyperparameter optimization, and neural architecture search (NAS), with special emphasis on NAS as it is a crucial subtopic of AutoML. It summarizes the performance of key NAS algorithms on the CIFAR-10 and ImageNet datasets, and we delve into various aspects of NAS methods, including single- and dual-stage NAS, one-shot NAS, joint hyperparameter and architecture optimization, and Aware NAS. image. In Figure 4 we can analyze citation changes for documents published until August 2024.

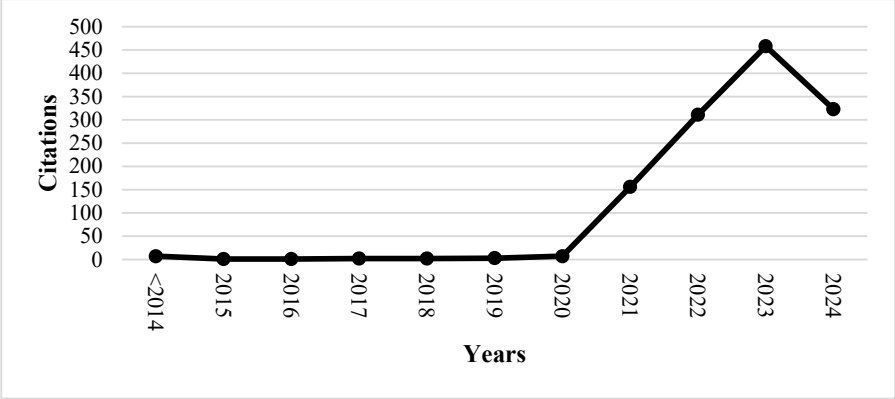

Figure 4. Evolution of citations between 2014 and 2024.

The period 2014-2024 shows a positive net growth in citations with an R2 of 68%, reaching 1,274 citations in August 2024.

The h-index is used to determine the productivity and impact of a published work based on the maximum number of included articles with at least the same number of citations. Of the documents considered for h-index, 12 were cited at least 12 times.

Citations of all scientific and/or academic documents from the period ≤2014 to until August 2024, with a total of 1,274 citations, of the 74 documents 25 were not cited. The self-citation of documents in the period ≤2014 to August 2024 was self-cited 1,194 times.

The bibliometric analysis sought to identify metrics that uncover patterns and trends in the scientific or academic content of documents, with a focus on the main keywords (Figure 5).

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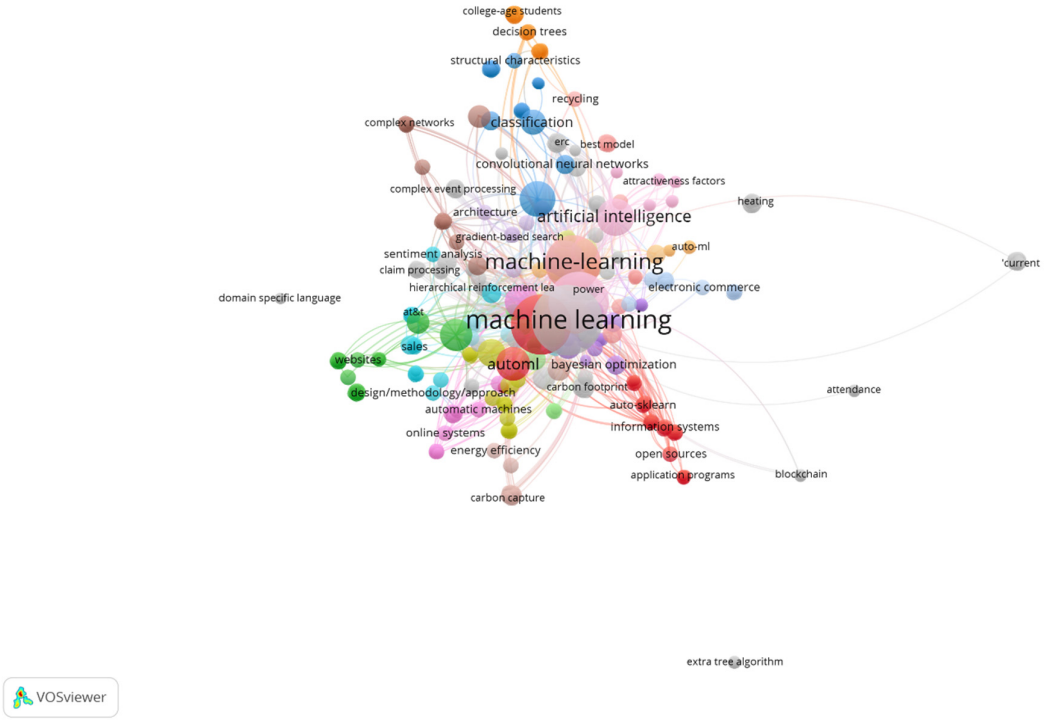

Figure 5. A network of all keywords.

This visualization highlights the predominant nodes within the network, with the size of each node reflecting the frequency of its associated keyword, thus indicating its rate of occurrence. The connections between nodes represent keyword co-occurrences, illustrating which keywords frequently appear together. The thickness of these connections signifies the frequency of these co-occurrences, effectively showcasing how often keywords are linked.

In these diagrams, the size of each node corresponds to the frequency of its associated keyword, while the thickness of the links between nodes indicates the frequency of keyword co-occurrences. Different colors represent various thematic clusters, with each cluster encapsulating a group of related topics. The nodes depict the range of topics within a theme, and the links illustrate the relationships among these topics within the same thematic group.

The results were generated using VOSviewer, a scientific software tool designed to analyze key search terms such as “How automated machine learning can boost business.” The study focused on scientific and academic documents related to these topics. Figure 6 highlights the interconnected keywords, showcasing the network of co-occurring terms within each scientific article. This analysis provides insight into the subjects researchers have explored and identifies emerging trends for future research efforts.

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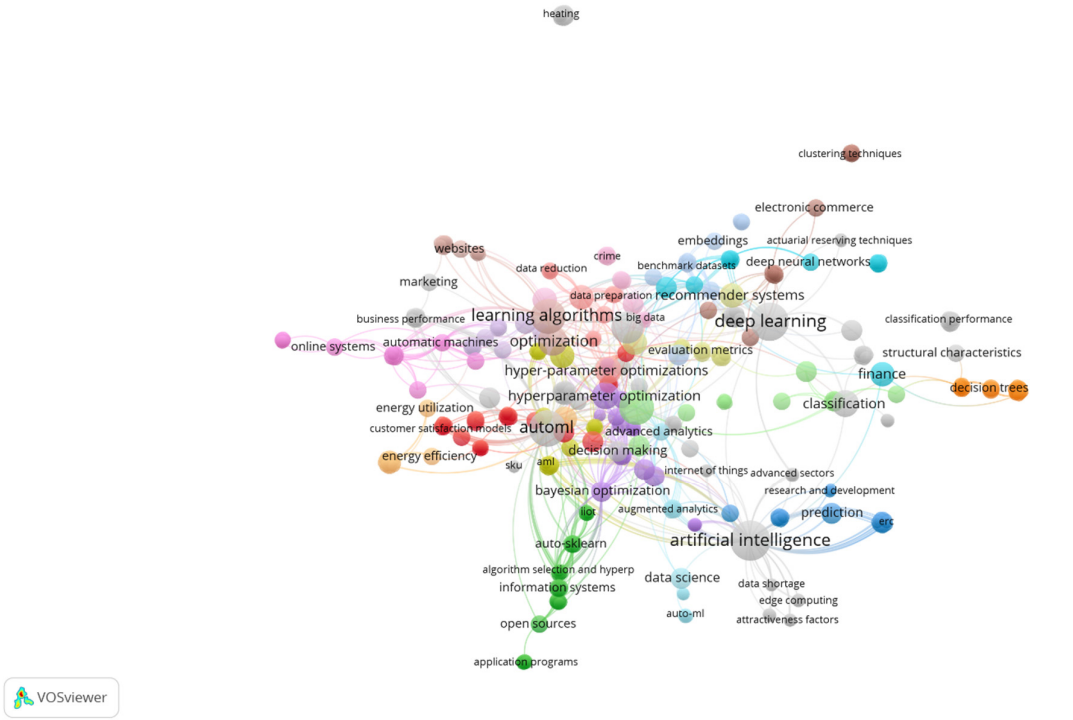

Figure 6. A network of Linked Keywords.

Finally, Figure 7 presents a comprehensive bibliographic coupling based on document analysis, offering an interactive exploration of the co-citation network. This feature allows users to navigate through the network and discover patterns related to "How automated machine learning can boost business" across different studies.

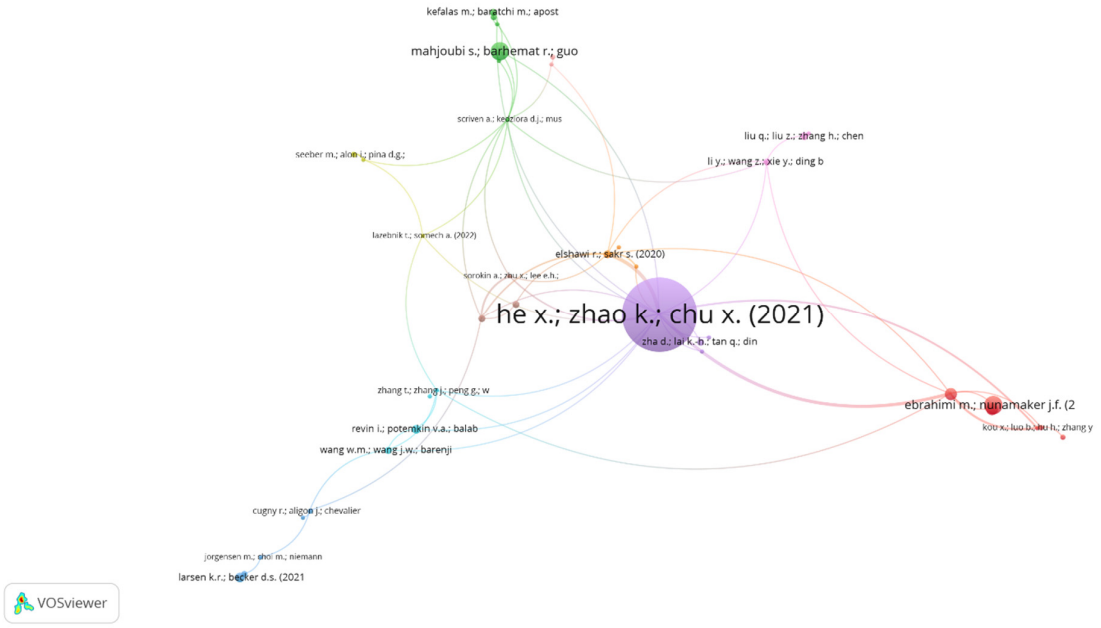

Figure 7. A network of co-citation.

In summary, the chosen methodology ensured precision and yielded comprehensive data, providing a robust foundation for future researchers to expand upon this review. By addressing critical issues, it enhanced the coherence, validity, and reliability of the findings. Adhering to

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established guidelines for systematic reviews and meta-analyses, we upheld a high methodological standard. These aspects will be further elaborated upon in the following sections.

4. Theoretical Perspectives

AutoML has rapidly emerged as a transformative force in the business sector. It offers companies a streamlined approach to harnessing the power of machine learning without the need for extensive expertise [10]. As a result, AutoML's impact has spread across various industries, driving innovation and providing a competitive edge in a rapidly evolving marketplace. This section will explore the key aspects of AutoML in the business context, examining its role and the opportunities it presents for organizations.

4.1. Introduction to Automated Machine Learning (AutoML)

4.1.1. Definition and Scope

AutoML represents a significant advancement in artificial intelligence, aiming to simplify and democratize the machine learning process. Traditionally, developing machine learning models has required a high level of expertise in data science, including deep knowledge of algorithms, data preprocessing techniques, model selection, and hyperparameter tuning [11,12]. AutoML addresses these challenges by automating the entire workflow, enabling non-experts to create and deploy high-quality machine-learning models with minimal manual intervention. Rivas et al. [13] describe AutoML as an emerging sub-area of machine learning where machine learning models are automatically selected, composed, and parametrized to ensure optimal performance. Schuh et al. [14] explain that this is achieved by introducing functions such as no-code or low-code features requiring minimal machine learning and statistics knowledge. The rise of AutoML can be associated with the increased number of software companies that provide customizable software solutions, allowing businesses to tailor their models for specific workloads.

The scope of AutoML extends across various industries and applications, from optimizing marketing strategies to improving supply chain operations and enhancing customer experience. Lazebnik and Somech [15] explain that AutoML automates complex and time-consuming tasks involved in machine learning, allowing businesses to focus on leveraging the insights gained from their data rather than getting bogged down in the technical details of model development. This is evidenced in Schuh et al. [14] research, which found that companies without tech expertise often purchase user-friendly software solutions to create custom machine learning models used in logistics, production, and supporting procedures, such as natural language processing (NLP). This broad applicability makes AutoML a versatile tool for organizations looking to utilize the power of data-driven decision-making.

4.2. Overview of AutoML and its Core Stages

The AutoML process can be divided into several critical stages: auto pre-processing, auto feature engineering, model selection, auto hyperparameter tuning, and model training, as shown in Figure 8. Each stage is vital in building robust and accurate machine-learning models.

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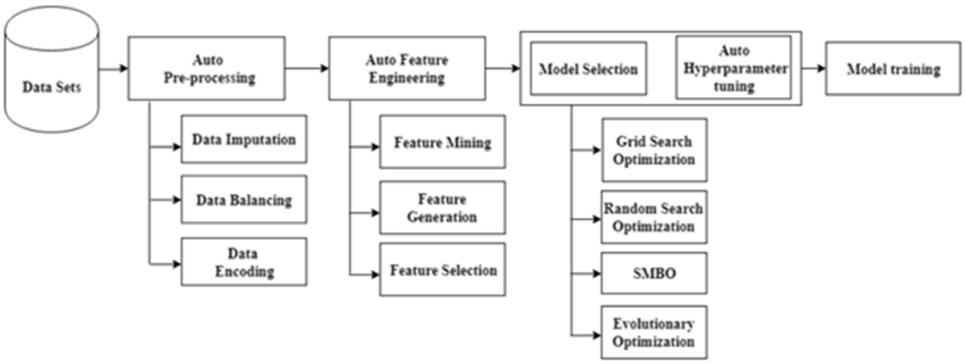

Figure 8. Stages in AutoML [2] (Chauhan et al., 2020).

4.2.1. Auto Pre-Processing

Auto-processing is the first step in the AutoML pipeline, where raw data is transformed into a clean, usable format. According to Chauhan et al. [2], this stage is essential because the quality of the input data directly impacts the performance of the machine learning model. Several key processes are automated during this stage, including data imputation, balancing, and encoding [16]. Data imputation entails automatically identifying and filling missing data using methods like mean substitution or k-nearest neighbors (KNN) to ensure the dataset is complete and gaps-free.

AutoML systems address class imbalances for data balancing, which can lead to biased model predictions [17]. Techniques such as oversampling, undersampling, or synthetic data generation like SMOTE are used to balance the class distribution. Finally, data encoding involves converting categorical variables into a numerical format that machine learning models can process [18].

AutoML automates this task using techniques such as one-hot or label encoding, depending on the nature of the data.

4.2.2. Auto Feature Engineering

Auto feature engineering involves creating and selecting the most relevant features from the data. Features are critical variables that the model uses for making predictions. The processes automated within this stage are feature mining, generation, and selection [2]. AutoML tools automatically extract useful features from raw data, identifying patterns and relationships that may enhance model performance. The generation task involves creating new features from existing data to provide additional insights [19]. For instance, Alon et al. [20] found that interaction terms between variables might be generated, or certain features could be transformed for better model accuracy. The AutoML system then automatically selects the most important features while discarding irrelevant or redundant ones. Data scientists often use techniques like recursive feature elimination (RFE) or regularization methods such as Lasso.

4.2.3. Model Selection

The AutoML system evaluates multiple machine learning algorithms in the model selection stage to determine the best suited to the specific dataset and problem. This stage is critical because different algorithms can produce different results depending on the data [2]. The AutoML system compares models, from simple linear regressions to complex ensemble methods like random forests or gradient-boosting machines. It then selects the model with the highest predictive accuracy or meets other criteria.

4.2.4. Auto Hyperparameter Tuning

After selecting the optimal model, AutoML focuses on auto hyperparameter tuning. This process involves fine-tuning the model's parameters to maximize its performance. Several optimization techniques are used, including grid search optimization, random search optimization, sequential

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model-based optimization (SMBO), and evolutionary optimization [2]. Grid search optimization systematically tests a range of hyperparameter values to find the best combination. Instead of testing all possible combinations, the random search optimization method evaluates a random subset of hyperparameters, which can be more efficient [21]. SMBO builds a model of the performance landscape of the hyperparameters and uses it to focus on the most promising areas [22]. Evolutionary optimization iteratively evolves a population of models, selecting the best-performing ones for further refinement.

4.2.5. Model Training

The final stage in the AutoML process is Model Training. The selected and optimized model is trained on the full dataset at this stage. The AutoML system applies best practices to ensure the model generalizes well to new, unseen data. Once trained, the model is ready for deployment, where it can be used to make predictions or provide insights that inform business decisions and strategies.

4.3. Background and Evolution of AutoML over the Years

AutoML has evolved over the years since the introduction of ML models. According to Baratchi et al. [23], John Rice laid the foundations of modern AutoML when he introduced the algorithm selection problem in 1976. Rice's work focused on the challenge of selecting the most appropriate algorithm for a given task based on the characteristics of the problem to be solved. This concept of algorithm selection is pivotal to AutoML, as it underpins the idea of automating the process of choosing the best model for a specific dataset [24,25]. In the decades following Rice's work, machine learning witnessed substantial advancements, particularly in developing algorithms and computational techniques [26]. However, the evolution of AutoML gained momentum in the early 2000s with the growing recognition of the need for automation in machine learning. This era saw the introduction of more sophisticated techniques to reduce the manual effort required in model development [27,28]. Early AutoML frameworks emerged, offering partial automation for tasks like model selection and hyperparameter optimization. These systems relied on heuristic methods and basic search algorithms to explore the space of possible models and configurations, laying the groundwork for more advanced AutoML solutions.

The 2010s marked a significant turning point in the evolution of AutoML due to advances in computational power and the increasing availability of large datasets. Although the term "AutoML" cannot be attributed to a single author or reference, Barbudo et al. [29] (2023) found that it first emerged in 2014 through the AutoML workshop co-hosted with the International Conference on Machine Learning (ICML) from 2014 to 2021. The introduction of automated machine learning platforms, such as Google's AutoML and Microsoft's Azure Machine Learning, revolutionized the field by providing end-to-end solutions that could handle the entire machine learning pipeline [30,31]. These platforms leveraged cloud computing resources to perform complex tasks such as neural architecture search (NAS), which automates the design of neural network architectures [32]. NAS techniques represented a breakthrough in AutoML, enabling the automatic generation of highly optimized deep-learning models.

As AutoML continued to evolve, the focus shifted toward enhancing usability and accessibility. The late 2010s and early 2020s saw the proliferation of open-source AutoML frameworks, such as TPOT and H2O.ai's Driverless AI, which democratized access to advanced machine learning techniques [33]. These frameworks provided users with powerful tools to automate the entire model development process, from data preprocessing to model deployment. In addition, integrating AutoML with business intelligence platforms and data science workflows made it easier for organizations to adopt machine learning technologies, even without specialized expertise [34,35]. Today, AutoML represents a mature and rapidly growing field that continues to evolve in response to the needs of both academia and industry. Modern AutoML platforms are characterized by their ability to handle increasingly complex data and model types and their focus on interpretability and transparency [36]. Researchers are actively exploring new methods to improve the efficiency and effectiveness of AutoML systems, including the use of meta-learning, transfer learning, and

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explainable AI techniques [37,38] These advancements are driving the adoption of AutoML across a wide range of applications, from healthcare and finance to marketing and manufacturing, where the ability to quickly and accurately build machine learning models is becoming a critical competitive advantage.

4.4. Impact of AutoML on Business Operations

AutoML is driving significant changes in how companies operate and make decisions. Automating the complex and often time-consuming process of developing and deploying machine learning models allows businesses to utilize the power of advanced analytics without requiring extensive technical expertise [39]. Boto Ferreira et al. [40] found that this democratization of machine learning capabilities has profound implications across various aspects of business operations, from efficiency and decision-making to cost management and sustainability. The following sections explore the specific impacts of AutoML on different areas of business, highlighting how it is reshaping traditional processes and enabling organizations to thrive in a data-driven economy.

4.4.1. Efficiency and Productivity

AutoML significantly enhances efficiency and productivity within organizations by automating many of the labor-intensive tasks involved in machine learning model development. Traditional machine learning workflows require extensive manual effort, from data preprocessing and feature engineering to model selection and hyperparameter tuning [41]. These tasks can be time-consuming and require specialized knowledge, often leading to bottlenecks in the development process. AutoML addresses these challenges by automating these stages, enabling businesses to build and deploy models faster and with less human intervention [42,43]. This automation speeds up the time-to-market for new products and services and frees up valuable resources, allowing data scientists and engineers to focus on more strategic tasks.

The ability to quickly iterate and refine models through AutoML also leads to more accurate and reliable outcomes, further boosting productivity [44]. In addition, AutoML's capacity to handle large volumes of data and explore a wide range of models in parallel means that businesses can scale their operations more effectively, tackling more projects in less time and with greater consistency [3].

This efficiency translates into competitive advantages, as companies can respond more rapidly to market changes and customer needs, ultimately driving growth and innovation.

4.4.2. Decision-Making and Strategic Planning

Integrating AutoML into business operations enables organizations to make data-driven decisions more confidently and precisely. Traditional decision-making processes often rely on historical data and manual analysis, which can be time-consuming and prone to human error [45]. AutoML, on the other hand, automates the generation of predictive models that can analyze vast amounts of data in real time, providing businesses with actionable insights that are both timely and accurate [46]. These models can identify patterns, trends, and correlations that might be overlooked by human analysts, leading to more informed decisions.

In strategic planning, AutoML can simulate various scenarios and forecast potential outcomes, allowing businesses to evaluate different strategies and choose the most effective path forward. This capability is particularly valuable in uncertain or rapidly changing environments, where quick and accurate decision-making is crucial for maintaining a competitive edge [47,48].

Furthermore, AutoML enhances the ability to personalize decisions based on specific customer segments or market conditions. This allows businesses to tailor their strategies to better meet the needs of their target audiences [49]. AutoML empowers organizations to align their strategic goals with real-world data by providing a deeper understanding of the factors driving business performance. This practice leads to more effective and sustainable business practices.

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4.4.3. Cost-Effectiveness and ROI

AutoML offers significant cost-effectiveness and improved return on investment (ROI) by reducing the expenses associated with traditional machine learning processes and delivering faster, more accurate results. Developing machine learning models manually often requires substantial investment in specialized talent, computational resources, and time [50]. The iterative nature of model development, which involves experimenting with different algorithms, tuning hyperparameters, and validating results, can be costly and resource-intensive. AutoML mitigates these costs by automating much of the process, reducing the need for highly specialized personnel and extensive computational resources [51]. This automation enables businesses to deploy models more quickly, shortening the time-to-value and allowing for more rapid iteration and improvement.

As a result, companies can achieve better outcomes with less financial investment, directly contributing to higher ROI [52]. In addition, AutoML's ability to optimize models for specific business objectives ensures that the models are accurate and aligned with the organization's goals, further enhancing their value. Streamlining the machine learning process and reducing the associated costs makes advanced analytics accessible to a broader range of businesses, including small and medium-sized enterprises that may not have the resources to invest in traditional data science teams [51,53]. This democratization of machine learning contributes to a more level playing field, where businesses of all sizes can leverage data-driven insights to improve their operations and drive growth.

4.4.4. Accessibility to Non-Experts

One of the most transformative impacts of AutoML is its ability to make advanced machine learning accessible to non-experts, enabling a wider range of professionals to leverage data-driven insights in their work. Traditionally, machine learning has been the domain of data scientists and engineers with specialized knowledge in algorithms, programming, and statistical analysis [54]. This has created barriers for many businesses, particularly smaller organizations or those in industries without a strong technical focus. AutoML removes these barriers by providing user-friendly interfaces and automated workflows that simplify the process of building and deploying machine learning models [55]. These platforms often include drag-and-drop features, pre-built templates, and guided workflows that allow users with little to no machine-learning experience to create sophisticated models.

Consequently, AutoML abstracts away the complexities of model development, empowering business analysts, marketers, and other professionals to use the power of machine learning without needing to understand the underlying algorithms or programming languages [56]. This increased accessibility fosters innovation and experimentation within organizations, as more employees can contribute to data-driven projects and initiatives. Moreover, involving a broader range of stakeholders in the machine learning process leads to more diverse perspectives and solutions, enhancing the overall quality of decision-making and strategy development [57,58]. As AutoML continues to evolve, it is likely to expand its accessibility further, enabling even more individuals and organizations to benefit from the power of machine learning.

4.4.5. Access to Real Time Insights

AutoML's capability to deliver real-time insights is a game-changer for businesses looking to stay competitive in fast-paced markets. Traditional machine learning models often require significant time to develop, train, and deploy, which can delay the availability of actionable insights [59]. In contrast, AutoML platforms are designed to process and analyze data quickly, enabling businesses to generate insights in real time. This immediacy is particularly valuable in industries where conditions can change rapidly, such as finance, retail, and logistics [60]. For example, in the financial sector, real-time insights can inform trading decisions, risk management, and fraud detection, helping companies respond to market fluctuations as they happen [61]. Real-time analysis of customer behavior and sales data in retail can enable businesses to adjust pricing, inventory, and marketing strategies quickly, maximizing revenue and customer satisfaction.

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AutoML's ability to continuously update models with new data ensures that the insights remain relevant and accurate. This allows businesses to maintain a dynamic and responsive approach to decision-making [62]. In addition, real-time insights from AutoML can support predictive maintenance in manufacturing, where early detection of potential equipment failures can prevent costly downtime and extend the life of machinery [63,64]. By providing businesses with the tools to act quickly on the most current data, AutoML enhances their ability to navigate uncertainty and capitalize on emerging opportunities.

4.4.6. Supports Sustainability Initiatives

AutoML optimizes processes and resource usage, reducing the environmental impact of business operations. As organizations increasingly prioritize sustainability, there is a growing need for tools that can help balance economic growth with environmental responsibility. AutoML can contribute to these efforts by enabling businesses to analyze and optimize their energy consumption, supply chain logistics, and waste management practices [65,66]. For instance, AutoML can be used in the energy sector to develop models that predict energy demand and optimize energy distribution, reducing waste and ensuring that resources are used more efficiently. AutoML can optimize production processes in manufacturing to minimize resource usage and reduce emissions, supporting the industry's shift towards more sustainable practices [67]. In addition, AutoML can help companies monitor and report on their sustainability metrics, providing real-time insights into their environmental performance and helping them meet regulatory requirements. By automating the analysis of complex datasets, AutoML enables businesses to identify opportunities for reducing their carbon footprint and improving their overall sustainability.

AutoML's ability to process large volumes of data quickly and accurately makes it valuable for tracking progress toward sustainability goals. This helps ensure that initiatives are effective and scalable [68]. As sustainability becomes an increasingly important aspect of corporate strategy, AutoML will continue to play a key role in helping organizations achieve their environmental objectives.

4.4.7. Fraud Detection in Digital Payment Systems

The rise of digital payment systems has brought about new challenges in fraud detection. AutoML has emerged as a powerful tool in combating fraudulent activities. Traditional fraud detection methods often rely on predefined rules and manual reviews, which can be prone to errors [69]. As fraudsters become more sophisticated, there is a growing need for more advanced and dynamic detection techniques. AutoML addresses this need by automating the creation of machine-learning models that can detect fraudulent patterns in real time, even as they evolve [70]. These models can analyze vast amounts of transaction data, identify anomalies, and flag potentially fraudulent activities with high accuracy. AutoML models can adapt to emerging fraud tactics by continuously learning from new data, ensuring that detection systems remain effective over time [71]. This adaptability is crucial in digital payments, where fraudsters constantly develop new methods to bypass security measures. Moreover, AutoML can enhance the efficiency of fraud detection processes by reducing the number of false positives [72]. This would allow businesses to focus their resources on genuine threats. Ultimately, AutoML helps protect businesses and consumers from financial losses and strengthens the overall security of digital payment systems by providing a more accurate and automated approach to fraud detection.

4.4.8. Measuring Marketing and Business Performance

Traditionally, evaluating the success of marketing campaigns and business initiatives has involved collecting vast amounts of data from various sources, analyzing it, and deriving insights that inform future decisions [73]. However, Kongar and Adebayo [74] indicate that AutoML transforms this process by automating the entire workflow, from data collection to analysis and reporting, providing businesses with rapid and accurate assessments of their marketing and business

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performance. One of the key benefits of AutoML in this context is its ability to process large datasets from multiple channels, including digital marketing platforms, sales records, customer feedback, and social media interactions [75]. By integrating and analyzing this data, AutoML models can identify patterns and trends that would be difficult for human analysts to detect. This enables businesses to understand how different marketing strategies are performing in real time, allowing for quick adjustments to optimize outcomes [76]. For instance, AutoML can help identify customer segments that are most responsive to specific campaigns. Such insights enable businesses to tailor their marketing efforts for maximum impact.

Moreover, AutoML facilitates the continuous monitoring of key performance indicators (KPIs), providing businesses with ongoing insights into their operations. This real-time analysis allows companies to measure the effectiveness of their strategies more accurately and make data-driven decisions that enhance overall performance [77]. According to Cruz et al. [78], AutoML also reduces the reliance on manual reporting and the potential for human error by automating the process of measuring marketing and business outcomes, ensuring that decisions are based on accurate, up-to-date information. Moreover, AutoML's predictive capabilities enable businesses to forecast future performance based on historical data to anticipate market trends and adjust their strategies proactively [79].

This forward-looking approach improves the efficiency of marketing and business operations and supports long-term strategic planning. As a result, companies can better align their marketing initiatives and business objectives, leading to improved ROI and sustained competitive advantage [80].

4.4.9. Equipment Maintenance

AutoML profoundly impacts equipment maintenance by revolutionizing how businesses approach predictive maintenance and asset management. In industries where machinery and equipment play a critical role, such as manufacturing, energy, and transportation, unplanned downtime due to equipment failure can result in significant financial losses and operational disruptions [81]. Traditional maintenance approaches, such as scheduled or reactive maintenance, are often inefficient and costly, as they either involve unnecessary maintenance activities or address issues only after a failure has occurred. AutoML addresses these challenges by enabling predictive maintenance, which leverages machine learning models to predict equipment failures before they happen [82]. With AutoML, businesses can build models that analyze vast amounts of sensor data, historical maintenance records, and environmental factors to identify patterns and anomalies indicative of potential equipment failures [83]. These models can detect early warning signs that might be missed by human operators, such as subtle changes in vibration, temperature, or pressure, allowing for timely interventions that prevent breakdowns. Automating the process of monitoring and analyzing equipment performance reduces the reliance on manual inspections and routine maintenance schedules, leading to more efficient use of resources.

Furthermore, AutoML models continuously learn and improve as they are exposed to new data, making them increasingly accurate over time. This adaptability ensures that maintenance strategies remain effective even as equipment ages or operating conditions change [84,85]. The ability to predict and prevent equipment failures minimizes downtime and maintenance costs and extends the lifespan of assets, providing long-term financial benefits. Additionally, AutoML can help businesses optimize their spare parts inventory and maintenance staffing levels, further reducing costs and improving operational efficiency [86]. Therefore, AutoML transforms equipment maintenance from reactive to proactive, enabling businesses to maintain high levels of productivity, reduce costs, and ensure the reliability of their critical assets.

4.5. Ethical and Societal Implications

The use of AutoML in businesses is associated with multiple ethical and social considerations. This section synthesizes data on the most common.

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4.5.1. Ethical Considerations in the Use of AutoML

The use of AutoML raises several ethical considerations that are critical for businesses and developers to address as they integrate these technologies into their operations. One of the primary ethical concerns is the potential for bias in the models generated by AutoML [87]. Machine learning models, including those produced by AutoML, are only as good as the data on which they are trained. If the training data contains biases, whether related to race, gender, socioeconomic status, or other factors, those biases can be perpetuated or even amplified in the model's predictions [88]. This can lead to unfair or discriminatory outcomes, particularly in sensitive applications such as hiring, lending, or healthcare. The automated nature of AutoML means that these biases can be introduced without the user's awareness, making it crucial for businesses to implement rigorous testing and validation procedures to ensure fairness and equity in the models they deploy.

Another ethical issue is the transparency and interpretability of AutoML models. Unlike traditional machine learning, where data scientists have direct control over model development and can often explain how a model arrives at its predictions, AutoML automates much of this process, creating "black box" models [89]. These models may be highly accurate, but their decision-making processes are opaque, making it difficult for users to understand how specific predictions are made. This lack of transparency can be problematic, particularly in industries like finance or healthcare, where stakeholders need to trust and understand the rationale behind automated decisions [90]. Therefore, ensuring that AutoML platforms include tools for model interpretability and explainability is essential to maintaining ethical standards.

The rise of AutoML has led to increased privacy concerns, especially when handling sensitive or personal data. As AutoML systems often require large datasets to function effectively, there is a risk of violating individuals' privacy rights if data is not handled properly [91]. Businesses must comply with data protection regulations and implement robust data anonymization and security measures. In addition, the automated nature of AutoML could lead to the unintended use of data in ways not originally intended or consented to by data subjects, raising further ethical questions about informed consent and data usage.

Finally, the deployment of AutoML can lead to ethical dilemmas related to accountability. When automated systems make decisions, it can be challenging to determine who is responsible when something goes wrong, whether it's the developers who created the AutoML platform, the businesses that deployed it, or the algorithms themselves. This ambiguity in accountability can complicate efforts to address issues like discrimination or errors in automated decision-making. Therefore, it is crucial for businesses and regulators to establish clear guidelines on accountability and ensure human oversight in deploying AutoML technologies.

4.5.2. The Broader Societal Impact of AutoML on Business and Employment

The broader societal impact of AutoML extends beyond the ethical considerations of its use, influencing the business industry and employment in significant ways. One major impact is the democratization of machine learning [92]. Small and medium-sized enterprises (SMEs), which may lack the resources to hire specialized data scientists, can now use AutoML to gain insights from their data and compete more effectively with larger corporations [85]. This democratization fosters innovation and competition since a wider range of businesses can access the tools needed to optimize operations, improve customer experiences, and develop new products.

However, the widespread adoption of AutoML also raises concerns about the future of employment, particularly for professionals in data science and related fields. As AutoML platforms become more sophisticated, they can automate many tasks traditionally performed by data scientists, such as model selection, feature engineering, and hyperparameter tuning [93,94]. While this automation can increase efficiency and cost savings for businesses, it also risks reducing the demand for data science professionals. In the long term, this could lead to job displacement and require a shift in the skillsets needed in the workforce [95]. This impact of AutoML on employment extends to other industries where machine learning is used to automate tasks that humans previously performed. For example, in manufacturing, AutoML can optimize production processes and predictive maintenance,

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potentially reducing the need for manual labor. As a result, there has been increased fear related to increased unemployment levels and related negative implications.

5. Conclusions

Integrating AutoML into business operations has transformed how organizations leverage data to drive innovation and boost efficiency. AutoML has simplified what was once a complex and resource-intensive machine learning process, making it accessible to a broader range of businesses, regardless of their technical expertise. By automating key tasks such as data preprocessing, feature engineering, model selection, and hyperparameter tuning, AutoML empowers companies to quickly develop and deploy powerful models tailored to their unique needs. This automation not only accelerates the time-to-production for models but also enables organizations to continuously iterate and refine their strategies based on real-time data and shifting market conditions. Consequently, businesses can make faster, more informed decisions, using data to stay competitive and responsive in a rapidly evolving landscape.

The widespread applicability of AutoML across various industries underscores its importance as a powerful tool for driving operational efficiency and strategic innovation. AutoML's ability to streamline complex processes allows businesses of all sizes to harness machine learning, leading to more efficient cost management and a stronger return on investment. Its role in enabling scalability is particularly crucial as companies grow and their data volumes increase, ensuring that their machine learning efforts can evolve in step with their development. However, its adoption's ethical and societal implications are crucial considerations that must be addressed to ensure responsible use. As AutoML automates tasks traditionally performed by data scientists, there is a potential risk of job displacement in roles focused on manual data analysis. This shift necessitates a reimagining of workforce skillsets, with an emphasis on strategic, creative, and ethical oversight within data science. To fully realize the benefits of AutoML, companies must invest in retraining and upskilling initiatives to prepare their employees for this evolving landscape. Ensuring that the adoption of AutoML contributes not only to business success but also to broader societal well-being requires a focus on workforce readiness. Striking a balance between technological advancements and responsible deployment will be essential to maximizing AutoML's positive impact on both industry and society. Automated Machine Learning (AutoML) has the potential to significantly enhance both theoretical frameworks and practical applications in the business world. Contributions AutoML can make to both theory and practice:

(i) Theoretical Contributions: (a) Advancement of Predictive Models: AutoML democratizes access to sophisticated predictive models, allowing for the exploration of more complex theories that were previously constrained by the need for extensive manual data processing and model selection; (b) By automating the model selection and optimization process, AutoML enables the development of more accurate and reliable decision-making models, contributing to the theoretical understanding of decision science in business contexts; (c) AutoML facilitates the scaling of research experiments, allowing for the testing and validation of theoretical models across larger datasets and more diverse business scenarios, which contributes to more robust and generalizable theories; and (d) AutoML supports the integration of techniques from various disciplines such as statistics, computer science, and economics, leading to the development of more comprehensive theories that incorporate insights from multiple fields.

(ii) Practical Contributions: (a) AutoML can streamline and accelerate the model development process, reducing the time and cost associated with manual model building and allowing businesses to deploy data-driven strategies more rapidly; (b) By providing businesses with advanced machine learning capabilities without the need for specialized expertise, AutoML enables companies to leverage data science more effectively, thereby boosting their competitiveness in the market; (c) AutoML optimizes the use of data and computational resources, allowing businesses to achieve more with less. This efficiency can lead to cost savings and better allocation of resources toward other critical business functions; (d) AutoML tools lower the barrier to entry for businesses that may not have access to expert data scientists, empowering a broader range of companies to utilize machine

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learning for decision-making and operational improvement; and (e) By automating routine tasks, AutoML frees up data scientists and analysts to focus on more innovative aspects of business strategy, leading to the development of new products, services, and processes.

AutoML has the potential to make significant contributions to both the theoretical understanding and practical application of machine learning in business, driving innovation, efficiency, and competitiveness across industries.

Exploring future lines of investigation into how Automated Machine Learning (AutoML) can boost business involves identifying emerging trends, challenges, and opportunities that could shape the next phase of research and application. Here are some potential areas of focus: (i) Personalization and Customer Experience: (a) Investigating how AutoML can be used to create highly personalized customer experiences by dynamically adjusting marketing strategies, product recommendations, and customer service responses based on real-time data; (b) Researching how AutoML can enhance understanding and prediction of customer behavior across different touchpoints, leading to more efficient and effective customer journey mapping; (ii) Ethical AI and Transparency: (a) Exploring methods for using AutoML to identify and reduce bias in machine learning models, ensuring fairer outcomes in business decisions, such as hiring, lending, or customer segmentation; (iii) Integration with Business Processes: (a) Researching best practices for integrating AutoML into existing business workflows, ensuring that automated models can be smoothly implemented and maintained within diverse operational contexts; (b) Exploring frameworks where AutoML augments human decision-making rather than replacing it, focusing on the optimal balance between automation and human oversight; (iv) Scalability and Customization: (a) Investigating ways to make AutoML more scalable for large enterprises, addressing challenges related to processing vast amounts of data and deploying models across multiple business units; and (v) Cost-Benefit Analysis and ROI: (a) Conducting studies that measure the return on investment (ROI) from implementing AutoML in various business contexts, helping organizations understand the financial benefits and justify the adoption of AutoML solutions; (b) Researching strategies for reducing the costs associated with deploying AutoML, such as optimizing cloud resource usage or developing more efficient algorithms.

The future of research into how AutoML can boost business is rich with possibilities, spanning from technical advancements to ethical considerations and industry-specific applications. As AutoML continues to evolve, its integration into business strategies will likely become more sophisticated, leading to new opportunities for innovation and growth.

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Appendix A

Table A1. Overview of document citations period ≤2014 to 2024.

Documents		≤2014	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024	Total
Identifying leather type and authenticity by optical coherence tomography	2024	0	0	0	0	0	0	0	0	0	0	1	1
Machine Learning Models in the large-scale prediction of parking space availability for sustainable cities	2024	0	0	0	0	0	0	0	0	0	0	1	1
Prediction of rural domestic water and sewage production based on automated machine learning in northern China	2024	0	0	0	0	0	0	0	0	0	0	3	3
Dynamic Embedding Size Search with Minimum Regret for Streaming Recommender System	2023	0	0	0	0	0	0	0	0	0	0	3	3
SigOpt Mulch: An intelligent system for AutoML of gradient boosted trees	2023	0	0	0	0	0	0	0	0	0	0	1	1
A CEP-driven framework for real-time news impact prediction on financial markets	2023	0	0	0	0	0	0	0	0	0	4	2	6
Automated machine learning approach for time series classification pipelines using evolutionary optimization	2023	0	0	0	0	0	0	0	0	0	2	10	12
AutoML for Deep Recommender Systems: A Survey	2023	0	0	0	0	0	0	0	0	0	11	13	24
Multi-surface Permanent Magnet Synchronous Motor Temperature Estimation based on Automate Machine Learning Approach	2023	0	0	0	0	0	0	0	0	0	1	0	1
Predictors of NFT Prices: An Automated Machine Learning Approach	2023	0	0	0	0	0	0	0	0	0	3	1	4
Greenfield FDI attractiveness index: a machine learning approach	2022	0	0	0	0	0	0	0	0	0	2	2	4
AutoML Approach to Stock Keeping Units Segmentation	2022	0	0	0	0	0	0	0	0	0	1	0	1
Predictors of applying for and winning an ERC Proof-of-Concept grant: An automated machine learning model	2022	0	0	0	0	0	0	0	0	0	1	4	5
AutoXAI: A Framework to Automatically Select the Most Adapted XAI Solution	2022	0	0	0	0	0	0	0	0	0	0	5	5

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Towards Automated Imbalanced Learning with Deep Hierarchical Reinforcement Learning	2022	0	0	0	0	0	0	0	0	1	4	3	8
Chemical signatures to identify the origin of solid ashes for efficient recycling using machine learning	2022	0	0	0	0	0	0	0	0	3	4	2	9
Evaluating and optimizing the cold energy efficiency of power generation and wastewater treatment in LNG-fired power plant based on data-driven approach	2022	0	0	0	0	0	0	0	0	2	9	3	14
Case Studies of Real AI Applications	2022	0	0	0	0	0	0	0	0	0	0	1	1
Partial Discharge Detection in Power Lines Using Automated Machine Learning	2022	0	0	0	0	0	0	0	0	0	0	2	2
Automated Machine Learning for Steel Production: A Case Study of TPOT for Material Mechanical Property Prediction	2022	0	0	0	0	0	0	0	0	0	1	1	2
Boston House Price Prediction Using Regression Models	2022	0	0	0	0	0	0	0	0	0	8	3	11
Prediction and multi-objective optimization of mechanical, economical, and environmental properties for strain-hardening cementitious composites (SHCC) based on automated machine learning and metaheuristic algorithms	2021	0	0	0	0	0	0	0	0	12	22	17	51
AutoML: From Methodology to Application	2021	0	0	0	0	0	0	0	1	3	1	3	8
Efficient Hyperparameter Optimization under Multi-Source Covariate Shift	2021	0	0	0	0	0	0	0	0	0	2	0	2
Mining Cross Features for Financial Credit Risk Assessment	2021	0	0	0	0	0	0	0	0	2	4	5	11
ExperienceThinking: Constrained hyperparameter optimization based on knowledge and pruning	2021	0	0	0	0	0	0	0	0	5	2	2	9
Using artificial intelligence to overcome over-indebtedness and fight poverty	2021	0	0	0	0	0	0	0	2	3	2	7	14
General model for metrics calculation and behavior prediction in the manufacturing	2021	0	0	0	0	0	0	0	0	1	0	0	1

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industry: An automated machine learning approach													
Automated Machine Learning for Remaining Useful Life Estimation of Aircraft Engines	2021	0	0	0	0	0	0	0	1	3	2	3	9
AutoML: A survey of the state-of-the-art	2021	0	0	0	0	0	0	0	121	231	299	190	842
Automated Machine Learning for Business	2021	0	0	0	0	0	0	0	1	5	7	1	14
Waste Classifications Using Convolutional Neural Network	2021	0	0	0	0	0	0	0	0	0	1	1	2
Impact of Social Media Marketing on Business Performance: A Hybrid Performance Measurement Approach Using Data Analytics and Machine Learning	2021	0	0	0	0	0	0	0	0	3	6	5	15
Genetic Meta-Structure Search for Recommendation on Heterogeneous Information Network	2020	0	0	0	0	0	0	0	4	2	11	6	23
NASE:: Learning Knowledge Graph Embedding for Link Prediction via Neural Architecture Search	2020	0	0	0	0	0	0	0	1	0	2	2	5
A rule-based automated machine learning approach in the evaluation of recommender engine	2020	0	0	0	0	0	0	0	1	1	1	2	5
Semi-Supervised Cyber Threat Identification in Dark Net Markets: A Transductive and Deep Learning Approach	2020	0	0	0	0	0	0	2	7	12	17	12	50
Analysis on Approaches and Structures of Automated Machine Learning Frameworks	2020	0	0	0	0	0	0	0	3	2	10	1	16
Hyperparameter Optimization for Portfolio Selection	2020	0	0	0	0	0	0	1	2	1	1	0	5
Multi-class detection of abusive language using automated machine learning	2020	0	0	0	0	0	0	0	0	1	0	0	1
AUTOMATIC MACHINE LEARNING ALGORITHMS FOR FRAUD DETECTION IN DIGITAL PAYMENT SYSTEMS	2020	0	0	0	0	0	0	0	2	2	4	0	8
Automated Machine Learning: Techniques and Frameworks	2020	0	0	0	0	0	0	0	0	5	1	4	10
Fusing visual and textual information to determine content safety	2019	0	0	0	0	0	0	0	0	0	1	0	1

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How can automated machine learning help business data science teams?	2019	0	0	0	0	0	0	1	3	2	0	0	6
Outcome Classification in Cricket Using Deep Learning	2019	0	0	0	0	0	0	1	3	5	6	0	15
Modeling of individual customer delivery satisfaction: an AutoML and multi-agent system approach	2019	0	0	0	0	0	0	1	2	3	1	1	8
Developing an Automated Machine Learning Approach to Test Discontinuity in DNA for Detecting Tuberculosis	2019	0	0	0	0	0	2	1	1	0	4	0	8
AT&T VS VERIZON: MINING TWITTER FOR CUSTOMER SATISFACTION TOWARDS NORTH AMERICAN MOBILE OPERATORS.	2013	0	0	0	1	1	0	0	0	0	0	0	2
Tracking topic evolution in news environments	2008	8	1	1	1	1	1	0	1	1	0	0	15
	Total	8	1	1	2	2	3	7	156	311	458	323	1,274

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