Academia of Information Computing Research
Vol. 4, 2023, pp. 1-10
ISSN: 2716-6465

Time Allocation Optimization And Priority Determination For Stopping At A Sate Vendor Using The Q-Learning Algorithm

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Abstract— **Mobile satay vendors, as part of Micro, Small, and Medium Enterprises (MSMEs), conduct their sales activities by moving between locations within limited operational hours and under dynamic environmental conditions. However, the determination of stopping locations and duration is still largely based on intuition, which may lead to inefficient time allocation and missed revenue opportunities. This study aims to optimize time allocation and determine stopping priorities for mobile satay vendors using the Q-Learning algorithm, a model-free reinforcement learning method capable of learning directly from interactions with the environment. The environmental conditions (state) are represented by variables such as location, operational time, weather conditions, and student activity, while the actions correspond to decisions to either continue selling at the current location or move to another location. Rewards are assigned based on the effectiveness of stopping time and potential sales. The learning process is conducted through multiple episodes representing daily operational activities, where Q-values are iteratively updated using the Bellman equation to produce an optimal policy that adapts to changing real-world conditions. The result of this study is a decision support system that provides dynamic recommendations for stopping priorities and time allocation. This system is expected to improve the efficiency of operational time utilization and maximize the daily revenue potential of mobile satay vendors, while also serving as a reference for the application of reinforcement learning in the informal MSME sector.**

Keywords— ***Decision Support Systems, Q-Learning, Reinforcement Learning, Time Allocation Optimization, Satay Vendors, MSMEs.***

I. INTRODUCTION

The fashion industry in Indonesia is largely supported by Micro, Small, and Medium Enterprises (MSMEs), particularly in small-scale manufacturing such as tailoring and garment production. The increasing trend of fashion consumption indicates a growing domestic market potential for the industry [1], [2]. Despite this opportunity, many fashion MSMEs still struggle to maintain competitiveness due to limited managerial capabilities, constrained resources, and operational inefficiencies [3]-[5]. Digitalization has been identified as a key driver for improving MSME performance, yet the adoption level remains uneven, leading to disparities in operational efficiency and competitiveness [6]-[8]. Digital maturity further emphasizes not only the use of digital tools but also the integration of data-driven decision-making into business operations [9].

Street food vendors, particularly mobile satay (sate) sellers, represent a significant segment of the Micro, Small, and Medium Enterprise (MSME) sector in Indonesia. These vendors conduct their business by moving between multiple locations within a single operational day, seeking customers in residential areas, school vicinities, and public spaces [1], [2]. Unlike fixed-location food stalls, mobile vendors face a unique operational challenge: the need to dynamically determine where to stop, how long to stay, and when to move to the next location in order to maximize daily revenue [3].

In practice, the decision-making process of mobile satay vendors regarding stopping locations and duration is largely based on personal intuition and habitual routes rather than data-driven analysis [4]. This approach often results in suboptimal time allocation, where vendors may spend excessive time at low-demand locations while missing peak-hour opportunities at more profitable spots. Environmental factors such as weather conditions, time of day, local events, and the activity patterns of potential customers such as school students further complicate this decision-making process [5], [6].

Reinforcement learning (RL) has emerged as a powerful paradigm for solving sequential decision-making problems in dynamic environments [7]. Unlike supervised learning, which requires labeled datasets, RL enables an agent to learn optimal behavior through direct interaction with its environment by receiving reward signals for actions taken. This characteristic makes RL particularly suitable for problems where the optimal strategy must be discovered through trial and error, and where environmental conditions continuously change [8], [9].

Q-Learning, a model-free reinforcement learning algorithm, is one of the most widely applied methods for discrete state-action optimization problems [10]. Through iterative updates of a Q-value table based on the Bellman equation, Q-Learning enables an agent to learn an optimal policy that maximizes cumulative reward over

time without requiring a prior model of the environment [11]. Its simplicity, convergence guarantees under appropriate conditions, and applicability to real-world scenarios make it a strong candidate for solving the location-selection and time-allocation problems faced by mobile vendors [12], [13].

Several prior studies have applied reinforcement learning in the context of route optimization, time management, and resource scheduling. Applications range from autonomous vehicle routing [14] and logistics fleet management [15] to scheduling problems in manufacturing environments [16]. However, the application of Q-Learning specifically to optimize the operational behavior of informal mobile food vendors in developing economies remains largely unexplored, representing a significant gap in the literature [17], [18].

The decision environment for a mobile satay vendor can be modeled as a Markov Decision Process (MDP), where each state encapsulates the current location, time of day, weather condition, and nearby customer activity level. The action space consists of the decision to remain at the current location or relocate to one of several candidate spots. Rewards are defined based on the estimated sales effectiveness at each stopping point, guiding the agent toward higher-yield locations and time windows [19].

Despite the growing body of work on reinforcement learning for operational optimization, most research targets large-scale or technologically advanced systems. The MSME sector, particularly informal street vendors, receives limited attention from the academic community in terms of intelligent decision support systems [20]. This is a critical gap, given that the informal economy constitutes a substantial portion of employment and economic activity in Indonesia and other developing nations [21], [22].

Therefore, this study proposes a Q-Learning-based framework to optimize time allocation and determine stopping priorities for mobile satay vendors. The system models the vendor's daily route as a reinforcement learning environment, where the agent learns through simulated episodes representing typical daily operations. The objective is to derive an optimal policy that dynamically adapts stopping decisions based on contextual state variables, ultimately maximizing revenue and operational efficiency [23].

The remainder of this paper is organized as follows. Section II presents a literature review covering reinforcement learning, Q-Learning, and related work on operational optimization for MSMEs. Section III describes the proposed methodology, including the MDP formulation, state and action definitions, and the Q-Learning training process. Section IV presents the experimental results and discussion. Finally, Section V concludes the paper with key findings and directions for future research.

II. LITERATURE REVIEW

The importance of the manufacturing sector as the foundation of the real economy necessitates the acceleration of technological innovation to maintain national competitiveness. In this case, support from the financial ecosystem, such as Financial Technology (Fintech), has proven to be a key driver in stimulating innovation capacity among manufacturing MSMEs, as demonstrated by Wang [26] through panel data analysis showing that ease of financial access directly contributes to enhancing a company's technological capabilities. However, financial support alone is insufficient without corresponding internal readiness.

Other research conducted by Gao [27] identified a digitalization paradox in which many manufacturing MSMEs are caught in a cycle of reluctance and concern due to a lack of digital literacy. Although the Industrial Internet model offers new opportunities for digital transformation, many business owners still struggle to determine the right pathway for migrating from conventional systems to data-driven systems. This indicates that the challenges of transformation are not merely about the availability of technology, but also about mapping out strategies that align with the characteristics of MSME organizations.

As MSMEs begin to adopt digital technology, the next challenge arises in selecting the right analytical method. There is a tendency to assume that production optimization requires highly sophisticated and complex algorithms. However, Kaiser et al. [28] offer a critical perspective that manufacturing SMEs often face significant limitations in terms of data resources and technical skills. The study confirms that low-cost, simple Machine Learning (ML) solutions are often far more effective and sufficient to meet operational needs compared to high-level models that require tedious parameter tuning.

These requirements for simplicity are reinforced by the research of Ravarini et al. [29], which highlights the barriers to AI implementation from a human resources perspective. AI innovations often fail at the SME level if they create new complexities that cannot be managed by existing operational staff. Therefore, the development of Decision Support Systems must be directed toward models capable of balancing predictive sophistication with ease of use. In the context of order processing optimization, efficient yet accurate approaches such as the use of Learning to Rank models that can automatically prioritize tasks without overburdening computational resources are highly relevant for further exploration.

Although some studies have begun to explore supply chain optimization using cutting-edge technologies such as dynamic hypergraph theory and quantum reinforcement learning [30], these approaches often involve technical barriers and infrastructure requirements that are too demanding for the scale of MSMEs. There is an urgent need to bridge this gap by developing more accessible and efficient decision support systems [31]-[34].

III. METHODS

This study employs a bibliometric approach to systematically map and analyze the research landscape of order processing optimization, with a specific focus on the potential application of machine learning and learning-to-rank algorithms in manufacturing MSMEs. Bibliometric analysis enables researchers to explore publication trends, conceptual structures, and emerging themes through quantitative analysis of scientific literature [35].

A. Data Collection

As shown in Figure 1, the research begins with topic identification, focusing on the domain of order processing optimization. This is followed by defining the research query, which is constructed using the Dimensions.ai to ensure comprehensive coverage of high-quality academic publications. The data were collected using dimensions on April 3, 2026, using keyword "Order Optimization" AND "Learning to Rank".

The data collection process in this study was conducted by retrieving bibliographic data using dimensions (https://app.dimensions.ai/). The collected data include essential metadata such as titles, abstracts, authors, keywords, publication year, and citation information from the selected publications. This study adopts a bibliometric research design, which aims to systematically map research trends, analyze keyword distributions, and identify the conceptual structures within the domain of order processing optimization, particularly seeking intersections with machine learning and prioritization techniques.

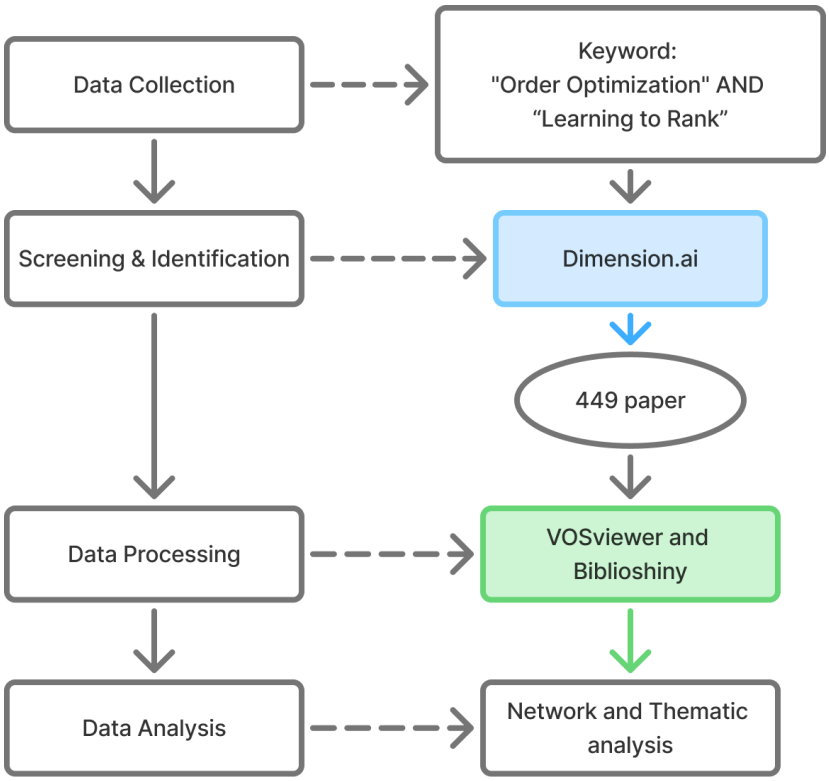

Figure 1: Research framework for bibliometric analysis of order processing optimization

Figure 1 illustrates the research framework employed in this bibliometric study, which consists of four primary phases: 1) Data Collection: The research began by defining a specific search query encompassing order processing optimization and machine learning approaches. The literature search was conducted through the Dimensions.ai academic database to ensure a comprehensive and highly relevant collection of publications. 2) Screening and Identification: Inclusion criteria were applied to limit the search results to publications from the last ten years, specifically the period from 2017 to 2026. From this database extraction and refinement process, a focused dataset of 449 document records was collected to serve as the foundation of the study. 3) Data Processing: The complete metadata from the 449 articles was subsequently exported and further processed using two primary bibliometric analysis tools: VOSviewer and Biblioshiny. 4) Data Analysis: The final phase focused on executing network and thematic analyses. This process aimed to visualize research trends, map the precise relationships among topics, and identify both dominant themes and research gaps within the literature on order processing optimization.

B. Data Analysis

To examine the evolution of research trends, raw data was collected using Dimension.ai and Biblioshiny was utilized to perform a temporal analysis of the refined dataset. This includes evaluating annual scientific production and analyzing thematic evolution over the 2017-2026 period. Through this approach, it is possible to detect shifts in research focus, such as the transition from conventional production scheduling to more advanced machine learning-driven optimization approaches.Furthermore, to explore the conceptual structure of the domain, a co-occurrence network analysis was conducted using VOSviewer. This analysis focuses on identifying key research themes, mapping the precise relationships among keywords, and detecting clusters that represent major research areas within the field of order processing optimization. By utilizing a focused dataset, the visualization is expected to provide more granular insights into the intersection of ranking algorithms and operational efficiency.

Metadata	Description	Missing Counts	Missing %	Status
AB	Abstract	0	0.00	Excellent
DT	Document Type	0	0.00	Excellent
SO	Journal	0	0.00	Excellent
PY	Publication Year	0	0.00	Excellent
TI	Title	0	0.00	Excellent
TC	Total Citation	0	0.00	Excellent
C1	Affiliation	2	0.45	Good
AU	Author	2	0.45	Good
DI	DOI	3	0.67	Good
RP	Corresponding Author	177	39.42	Poor
DE	Keywords	414	92.20	Critical
ID	Keywords Plus	414	92.20	Critical
CR	Cited References	449	100.00	Completely missing
LA	Language	449	100.00	Completely missing
WC	Science Categories	449	100.00	Completely missing

Figure 2: Metadata extracted using Biblioshiny

Based on Figure 2, during the data preprocessing phase, an evaluation of the dataset's metadata revealed that core bibliographic elements including Abstract, Author, Document Type, Publication Year, and Title were perfectly complete (0% missing). However, metadata for Author Keywords and Cited References were largely unavailable from the database export. Consequently, to ensure the reliability of the bibliometric analysis, the thematic mapping and network visualizations in this study were strictly derived through text mining techniques applied directly to the extracted Titles and Abstracts, rather than relying on explicit keyword metadata.

IV. RESULTS AND DISCUSSION

A. Data Overview

This section provides an overview of the characteristics of the datasets successfully imported into Bibluoshiny to offer a broad perspective on the research landscape related to order processing optimization. A summary of key bibliometric indicators including publication timeframes, source diversity, and collaboration patterns is presented in Figure 3 below.

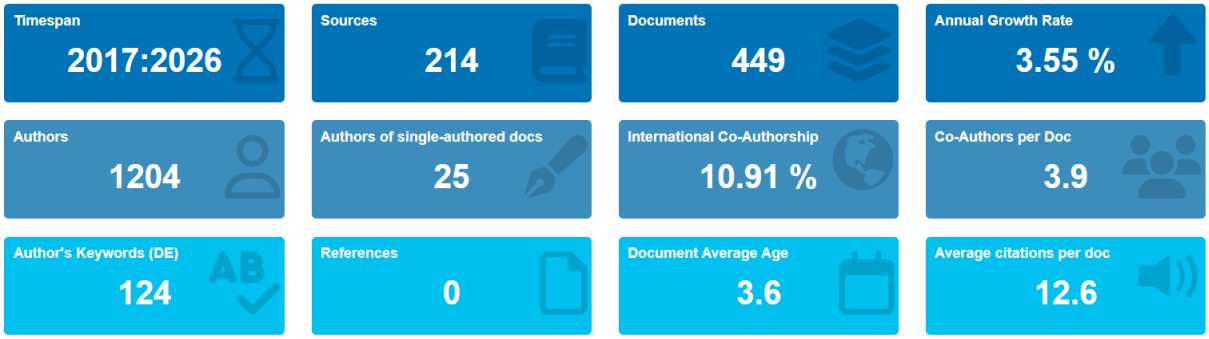

Figure 3: Data overview

Based on Figure 3, an overview of the refined bibliographic dataset reveals a total of 449 documents published across 214 sources between 2017 and 2026. The research domain shows a steady annual growth rate of 3.55%, with an average document age of 3.6 years, indicating a recent and continuously developing academic interest. The scholarly impact of these publications is notable, with an average of 12.6 citations per document. Furthermore, the field is characterized by a high degree of collaboration. The dataset involves 1,204 distinct authors, averaging 3.9 co-authors per document, and features an international co-authorship rate of 10.91%. In contrast, only 25 authors produced single-authored documents, highlighting that research in order processing optimization is predominantly a collaborative effort.

B. Research Category Distribution

To further understand the academic landscape of order processing optimization, the retrieved data was categorized based on the Fields of Research (ANZSRC 2020) classification provided by Dimensions.ai. As illustrated in Table 1, the majority of the research activity is concentrated within the Information and Computing Sciences category, accounting for 401 records.

Table 1 Research Categories

Categories	Research
Information and Computing Sciences	401
Engineering	229
Mathematical Sciences	104
Other Categories	110

This dominance confirms that the optimization of order processing is primarily treated as Information and Computing Sciences. It justifies the use of machine learning and Learning to Rank (LTR) approaches in this study, as these methods are core components of the computing sciences. The second dominance category is Engineering, and Mathematical in the third. Other categories are consist of Biomedical and Clinical Sciences (28 records), Physical Sciences (14 records), Commerce Management Tourism and Services (13 records), Biological Sciences (12 records), Earth Sciences (9 records), Chemical Sciences (8 records), Education (7 records), Built Environment and Design (6 records), Agricultural (4 records), Environmental Sciences (3 records), Economics, Health Sciences, Physiology (2 record each), Human Society, and Language Communication and Culture (1 record each). The total number of records exceeds the number of publications because a single document may be assigned to multiple research categories. The presence of these categories suggests that order optimization and scheduling algorithms are multidisciplinary tools often applied to manage complex workflows in laboratory settings or pharmaceutical production. However, for the purpose of this research, the focus remains on the technological and computational framework required to enhance operational efficiency in manufacturing MSMEs

C. Geographical Distribution

To identify the most influential regions in the global discourse on order processing optimization, a spatial analysis of country-based research production was conducted. This analysis maps the concentration of research expertise and the pace of technology adoption across various global academic hubs. The visualization of this scientific distribution is presented as a heatmap in Figure 4 below. This image is acquired using Biblioshiny, authors, Countries' Scientific Production.

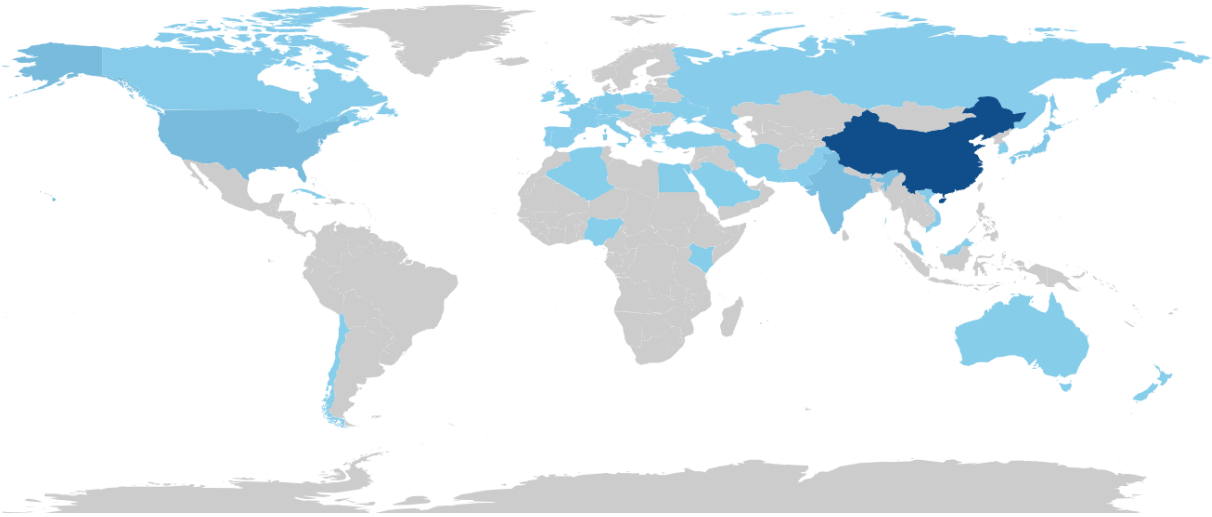

Figure 4: Country's scientific production

As demonstrated in Figure 4, research distribution shows a clear geographical dominance in the East Asian region. China emerges as the most significant single contributor, represented by the darkest blue shade on the map. This indicates a massive strategic investment in the development of optimization computing and machine learning algorithms within the country.

.In addition to China, stable contributions with moderate intensity are observed in other major industrialized nations, such as USA, India, Germany, and Japan. In the Southeast Asian region, Indonesia is recorded on the publication map, albeit with a lighter blue intensity compared to the leading producer nations. This suggests a significant opportunity for local researchers to deepen studies on Learning to Rank (LTR) within the domestic manufacturing sector to bridge the global literature gap, which is currently dominated by major economies.

D. Annual research

The literature was collected from the Dimensions.ai academic database using specific keywords such as "Order Processing Optimization" and "Machine Learning". Inclusion criteria were limited to journal articles and conference proceedings published within the last ten years, specifically from 2017 to 2026. The selection process involved filtering for relevance to ensure the dataset directly addressed the research domain. This research employs a bibliometric analysis using Biblioshiny and VOSviewer. Bibliometric analysis provides a systematic approach to mapping scientific knowledge by quantitatively examining publication data, citation structures, and research trends, enabling researchers to understand the evolution and impact of a particular research domain [35]-[37].

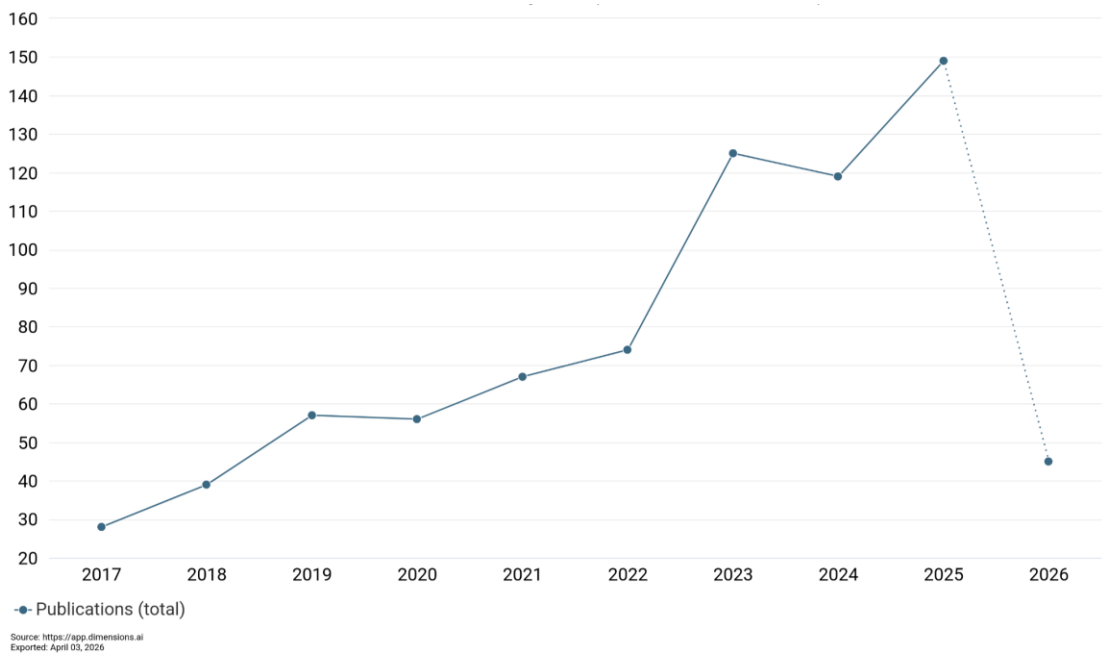

Figure 5: Publication trend per year

Figure 5 shows the number of papers published annually on the topic of “order optimization” and “learning to rank”. Based on the graph in Figure 5, we can divide the time period into three phases. The first phase, from 2017 to 2019, was the initial phase, during which the number of publications rose from 28 in 2017 to 39 in 2018 and 57 in 2019. In the second phase, the increase was more modest, with only 56 publications in 2020, 67 in 2021, and 74 in 2022. In the third phase, there was a sharp rise to 125 publications in 2023. Although there was a decline in 2024, the number of publications remained at 119, which is still far higher than in the previous phase. The following year also saw a rapid increase to 149 publications in 2025. Although the graph shows a decline in 2026, this does not reflect a decline in research interest. The decline was caused by data collection conducted in April 2026, so the recorded figures only represent scientific output from the first quarter of that year.

E. Network Visualization Analysis

Keyword co-occurrence mapping was conducted using VOSviewer to identify thematic relationships among the selected studies. This technique enables the visualization of bibliometric networks by grouping frequently co-occurring terms into clusters that represent shared research topics. VOSviewer applies a clustering algorithm based on association strength, where keywords with stronger co-occurrence links are positioned closer to each other and assigned to the same color-coded group. Consequently, each cluster reflects a coherent thematic domain emerging from the literature. The network visualization further categorizes the literature into several distinct thematic clusters, each distinguished by a specific color to represent a cohesive research area. These clusters provide an overview of dominant research themes and help reveal how different topics are conceptually interconnected within the study domain [38]-[42].

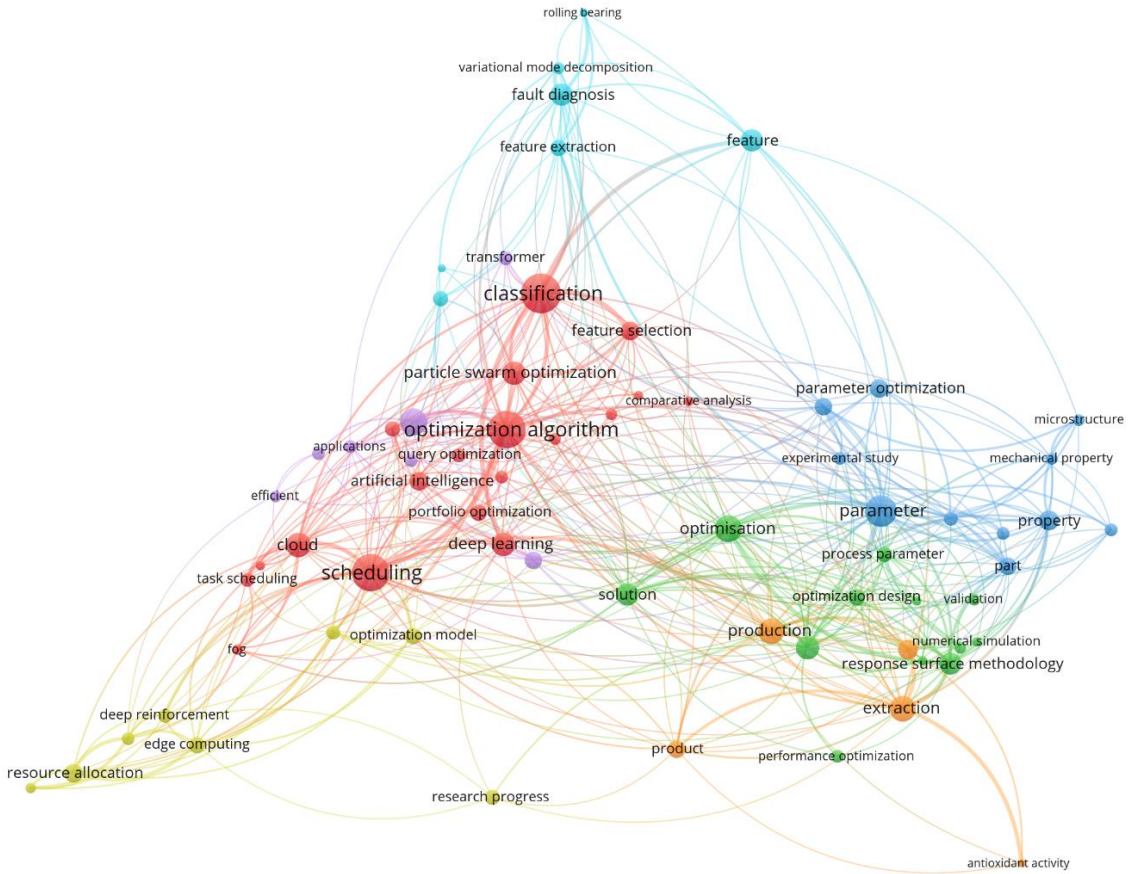

Figure 6: Network Visualization of Research Trends in Order Optimization

Figure 6 presents the network visualization of keyword co-occurrences, providing a comprehensive map of the keywords within the research domain. This visualization is acquired by VOSViewer. In this visualization, the diameter of the nodes (circles) is proportional to the frequency of keyword occurrence, while the thickness of the connecting lines signifies the strength of the link or the frequency of co-occurrence between specific topics. Keywords located in closer proximity to one another indicate a stronger thematic relationship. Systematically, it can be observed that 'classification', 'scheduling', and 'optimization algorithm' emerge as the most dominant nodes.

The Red Cluster represents the most significant foundational element of the field, primarily focusing on the development and implementation of machine learning algorithms. It is highly noteworthy that the three most dominant nodes in the entire map are ‘classification’, ‘scheduling’, and ‘optimization algorithm’. All reside within

this cluster. This indicates that machine learning is the core engine driving contemporary research in order processing. The convergence of these nodes suggests that modern optimization is no longer treated as a series of static rules but has evolved into a dynamic algorithmic challenge, where classification and scheduling are solved through intelligent, data-driven frameworks [43]-[46].

The Green Cluster focuses on the broader scope of optimization methodologies. This cluster indicates a strong methodological alignment toward maximizing operational efficiency and reflects the overarching goal of the literature: to refine industrial processes through systematic, iterative improvements. Complementing this, the Blue Cluster explores the technical parameters and properties of these systems. This highlights the focus on the granular variables and structural attributes that researchers must calibrate to ensure the reliability and precision of optimization models.

Furthermore, the Yellow Cluster identifies advanced and emerging technological frontiers, such as deep reinforcement learning, resource management, and edge computing. The presence of these keywords suggests a shift toward decentralized and highly autonomous systems capable of real-time processing at the network's edge. The Orange Cluster, while consisting of only four nodes, contains significantly large nodes such as ‘extraction’, ‘production’, and ‘product’. The substantial size of these nodes indicates that although the thematic focus is concentrated, these operational aspects are pivotal to the practical application of theoretical models in manufacturing environments. Finally, the Light Blue Cluster represents a more specialized or niche research area, including topics like fault diagnosis and feature extraction. This cluster provides the necessary diagnostic tools and data preprocessing techniques that support robust system maintenance and the initial stages of data analysis.

V. CONCLUSION

This study has provided a comprehensive bibliometric mapping of the research landscape concerning order processing optimization, with a particular focus on machine learning and learning-to-rank (LTR) applications. By analyzing a refined dataset of 449 publications retrieved from Dimensions.ai, several key conclusions can be drawn.

First, scholarly interest in this domain has experienced a significant surge, particularly between 2023 and 2025, indicating that the integration of advanced computational methods into production optimization has become a highly active research area. Second, the distribution of research categories shows a clear dominance of Information and Computing Sciences, justifying the shift from traditional heuristic methods to data-driven algorithmic frameworks. Third, thematic network analysis reveals that machine learning, classification, and scheduling form the core "engine" of contemporary research, acting as the foundation for modern optimization systems.

The geographic mapping reveals that China leads the global scientific production in this field, followed by the United States and India. While Indonesia has begun to appear in the global research landscape, its contribution remains limited. This disparity emphasizes the need for more localized studies, particularly in applying Learning to Rank (LTR) algorithms to optimize order processing within the specific constraints of manufacturing MSMEs in developing economies.

Despite these developments, this study identifies a significant research gap: while general optimization is well-explored, the specific implementation of Learning to Rank algorithms such as the XGBoost Ranker for order prioritization in the context of manufacturing MSMEs remains scarce. Most existing studies focus on large-scale industrial systems, leaving a void in practical, low-resource solutions for small-scale fashion industries. Therefore, future research should prioritize the development of tailored LTR models that can accommodate the unique constraints and manual workflows characteristic of tailoring MSMEs. This study serves as a foundational roadmap for researchers and practitioners aiming to enhance the operational efficiency and digital maturity of the MSME sector through intelligent prioritization.

ACKNOWLEDGEMENT

The author would like to express sincere gratitude and appreciation to Mr. Ir. Rahmat Hidayat, S.T., M.Sc.TI., Ph.D., as the lecturer for the Scientific Writing course, for his invaluable guidance, insights, and support throughout the preparation of this manuscript. Special thanks are also extended to the Department of Information Technology, Politeknik Negeri Padang, for providing the academic environment and resources necessary to complete this study.

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