



Insights from A Bibliometric Review and Integrating Ambidextrous Strategies with Decision Support Systems

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Abstract

Information technology has undergone significant advancements, becoming an integral component of modern business decision-making through decision support systems (DSS). DSS has evolved from simple computer-based tools to human-centered systems capable of dynamic adaptation. This study aims to analyze the trends, citation metrics, publication activities, and collaborative networks among researchers in DSS and strategic decision-making. Additionally, it seeks to identify research challenges and propose a theoretical framework to enhance DSS adoption in strategic decision-making. A bibliometric review methodology was employed to evaluate existing literature on DSS and strategic decision-making, examining publication trends, author contributions, and citation patterns. The analysis highlights leading research areas in DSS, identifies significant challenges in its implementation, and proposes strategies to promote the integration of DSS in strategic decision-making. The findings reveal the critical role of DSS in improving decision quality and fostering organizational resilience through ambidextrous strategies that balance exploitation and exploration. This paper provides valuable insights for academics and practitioners, emphasizing the importance of leveraging DSS tools to enhance strategic decision-making processes. The proposed theoretical framework contributes to advancing DSS applications, offering practical implications for improving organizational decision-making.

Keywords: Bibliometric analysis; decision support systems; strategic decision-making; ambidexterity.

Introduction

Technological advancements have prompted numerous companies to redesign their strategies (Danvila-del Valle, Estévez-Mendoza, & Lara, 2019). Information technology (IT) has progressed from a simple recording medium to an essential component of the decision-making process in modern businesses through decision support systems (DSS). DSS evolved from the management information system (MIS) in the early 1970s owing to the latter's inability to provide data for unstructured decision-making (Hassan, Mathiassen, & Lowry, 2019). DSSs assist managers in various duties, from planning to executing operations, throughout the value chain. Over time, the DSS has evolved from a computer-based decision-making system to a human-centered system capable of gathering information, adapting, and self-organizing in a dynamic environment. Automated systems aiding human decision-making have been utilized since the 1950s, and Bost and Oberman (1996) highlighted the distinct capabilities of humans and computers that may synergize in collaboration. However, advances in artificial intelligence (AI) offer new potential for computers to assist humans as peers in hybrid teams in various challenging problem-solving settings that exceed an individual decision-maker's knowledge and



cognitive capabilities (Bayrak, McComb, Cagan, & Kotovsky, 2021).

The primary purpose of the MIS is to enable quick access to data housed in trans- action processing environments so that managers can make decisions (Arnott & Pervan, 2014). The Fourth Industrial Revolution (Industry 4.0) revolution drives firms to embrace digital technologies (Gupta & Jauhar, 2023). Bayrak et al. (2021) employed computers in collaboration with humans for strategic decision-making (SDM). According to this viewpoint, a computer may gather input from a human partner, actively support human decision-making, and investigate novel solutions to complex real-world problems. Thus, by combining these complementary capabilities, a well-designed hybrid team can make more robust decisions than humans or computers working alone. Likewise, merging human expertise with advanced computational capabilities results in finely tuned decision models (Hodosi, Sule, & Bodis, 2023).

Machine learning (ML) and AI are proficient in repetitive, well-defined tasks that have an immediate impact. These methods are employed across several industries to enhance streamlined operational decision-making (Bertsimas & Kallus, 2020). Although learning-based systems have been successful in operational decision support, they are rarely used in SDM. One probable explanation is that collaboration with supervised algorithmic techniques is much less evident because strategic decision-making frequently entails one-time decisions that are unclear (no labels) and have long-term consequences (Verboven, Berrevoets, Wuytens, Baesens, & Verbeke, 2021). Therefore, SDM has always relied on expert knowledge, even though humans are susceptible to biases (Busenitz & Barney, 1997; Kahneman & Tversky, 1984; Larrick & Feiler, 2015), and managers may have prejudices without an objective basis (J. Doukas & Petmezas, 2007). Nevertheless, data analysis is fundamental to the critical decisions made by business, academic, and political leaders. Modern technologies provide analysts and managers with organized and unorganized data from many sources. Organizations have exceptional probabilities to distinguish themselves through analytics due to the digitalization of international business, the rise of big data, and the advancement of analytical tools (Awan et al., 2021; Grander, Silva, & Santiban~ez Gonzalez, 2021; Jukic, Jukic, Sharma, Nestorov, & Arnold, 2017; Miah, Vu, Gammack, & McGrath, 2017; Sbai & Krichen, 2020; Shamim, Zeng, Khan, & Zia, 2020; Stojanov & Daniel, 2024).

Consequently, DSS research has emerged as a well-established tradition in information systems (IS) research. Their devotion promises to enhance decision-making and practice using relevant technology (Aslam et al., 2017; Miah & McKay, 2016). DSS is a comprehensive instrument in the IS discipline that may help organizations improve their decision-making process (Alyoubi, 2015; Alyoubi, Alyoubi, & Almazmomi, 2019; Kitsios & Kamariotou, 2018), which entails deciding amongst multiple courses of action (alternatives) to achieve an organizational goal (Tariq & Rafi, 2012). Panudju, Rahardja, and Nurilmala (2023) highlighted that DSS is a specialized system designed to aid decision-makers by synthesizing domain-specific and technical knowledge into a user-friendly format accessible to non-experts. SDM provides companies with a competitive edge and prioritizes the essential knowledge and skills required for their future success (Yue & You, 2016).



To understand the synergy between DSS and SDM, this paper undertakes a biblio-metric review of existing literature to analyze the trends and applications of DSS in

the realm of strategic decision-making and proposes a framework based on ambidexterity (Chakma, Paul, & Dhir, 2021; Papachroni, Heracleous, & Paroutis, 2015; Raisch, Birkinshaw, Probst, & Tushman, 2009; N. Turner & Lee-Kelley, 2013) to proliferate the application of data analytics. In particular, the study extends ambidexterity theory to support decision-making and describes how ambidexterity may be adopted to influence choice outcomes in strategic decision management. This model shows that ambidexterity can be encouraged through advanced technological tools. Hence, the objectives of this study are as follows:

- To evaluate citation trends, publication activities, and collaboration status among contributors, we aim to reveal the leading edge of research in DSS tools for strategic decision-making.
- To produce a visualization representation of the key research areas of earlier research related to DSS tools for strategic decision-making.
- To provide insights into significant challenges and propose a theoretical framework to propagate the use of DSS tools for strategic decision-making.

This study employs a bibliometric analysis to systematically examine the literature on DSS for SDM in business organizations. Utilizing the Scopus database, renowned for its extensive and multidisciplinary coverage, ensured a comprehensive dataset for our analysis. In line with existing studies on selecting papers (Bukar et al., 2020; Kitchenham & Charters, 2007; Nidhra, Yanamadala, Afzal, & Torkar, 2013; Sneel, Jusoh, Jabar, & Abdullah, 2022), the search and selection process involved identifying relevant keywords, refining search criteria to include relevant sources, and applying inclusion and exclusion criteria to ensure the relevance and quality of the selected papers. This rigorous approach allows for a thorough understanding of the existing research trends, methodologies, and gaps in the current literature. Accordingly, a breakdown of the techniques and processes is presented in the following sections.

Dataset sources

Several databases, such as Google Scholar, Web of Science (WoS), and Scopus provide citation information. While Google Scholar is more inclusive, WoS and Scopus are more selective in terms of the quality of the journals included. Based on the research techniques and procedures used in other published bibliometric studies (Vaio, Hassan, & Alavoine, 2022; Xu, Ge, Wang, & Skare, 2021; Øyna & Alon, 2018), Scopus was selected to obtain bibliometric content related to DSS and SDM for many reasons. Notably, Scopus sources have credibility, are peer-reviewed, and cover most WoS papers, as well as a wide range of references, abstracts, and summaries in accordance with accepted practices (Fink, 2019). More than 87 million papers and 25,000 active titles are currently available on Scopus. The database has the most comprehensive coverage of any other abstract and citation database spanning multiple disciplines. Accordingly, the database is a trustworthy- thy resource for effectively



and efficiently obtaining global academic knowledge and is regularly updated (Vaio et al., 2022). It is also difficult to disregard the Scopus h-index tool, which determines the caliber of a book, author, or journal (Hirsch, 2010).

Search and selection process

Academic literature publications from the Scopus database were examined to highlight and classify research trends in DSS and SDM. At this point, there were no limitations to the publication period. To find pertinent articles, a search employing combinations of search string categories was carried out, using "Decision Support System" OR "DSS" OR "Decision Support Framework" OR "Decision Support Model" AND "strategic decision-making" OR "strategic decision-making". The articles were considered based on all submissions made on the subject between 1982 and 2024, as revealed by the search results. The search string was designed to identify more relevant and accurate articles on the subject area. This is done to demonstrate the application of DSS in the realm of SDM. The first search string result identified 328 articles. Of the 328 papers, six that were not written in English, which comprised Persian, Russian, Spanish, and Undefined, were excluded. Finally, this study analyzed 322 Scopus articles obtained between 1982 and 2024. Articles were selected exclusively based on the language used. This study downloads and analyses the content related to DSS and SDM. Hence, a breakdown of the search and selection processes is shown in Figure 1.

Accordingly, based on the database obtained, a bibliometric literature analysis was conducted to identify emerging themes in the discipline. An extensive corpus of scientific data was evaluated and investigated. The subject area was limited to computer science, business, management and accounting, decision sciences, social sciences, economics, econometrics, and finance. Document types were extended to articles, conference papers, reviews, book chapters, conference reviews, and short surveys. The source type comprised peer-reviewed journals, conference proceedings, and book series. English publications in the final stage were selected for the examination.

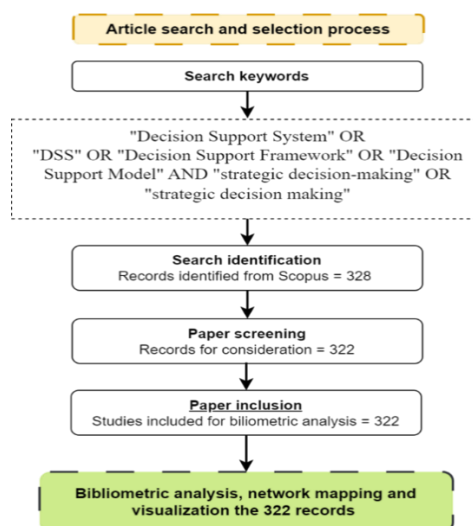


Fig. 1 Research Methodology and Design of Paper Selection



Bibliometric analysis method

The bibliometric approach is a crucial science mapping tool in the field of bibliometrics (Bukar, Sayeed, Razak, Yogarayan, Amodu, & Mahmood, 2023; Eck & Waltman, 2010, 2014). It is often used to quantify the influence and similarity of citation analysis, citation analysis, author analysis, and bibliographical coupling (Zupic & Čater, 2015). A large corpus of scholarly literature has been used to visualize and build co-occurrence networks related to subject areas (Vaio et al., 2022; Xu et al., 2021). This concept is based on the premise that citations can be used as indicators of activity in a scientific field (Garfield, 2004; Garfield & Welljams-Dorof, 1992). This means that a frequently cited article plays a more significant role in the field under study (Nisonger, 1994). Øyna and Alon (2018) added that citation data can be used to identify the most influential papers, both "locally" (within a field) and "globally" (within the entire research community).

Accordingly, citation analysis facilitates the discovery of important research streams, as well as attribution, access, use, management, stewardship, and retrieval of scholarly content (Borgman, 2016). As a result, this methodology aligns with the objectives of this study, and we used the bibliometric program VOSviewer to conduct this analysis (Eck & Waltman, 2014). VOSviewer offers excellent visualization capabilities and can import and export data from various sources (Moral-Mun˜oz, Herrera-Viedma, Santisteban-Espejo, & Cobo, 2020). Specifically, version 1.6.18, which is an open-source program for designing and developing bibliometric networks, was used in this study to analyze bibliometric data (Eck & Waltman, 2014). Bibliometric data were used as inputs to produce a visualization map to gain a better and more insightful understanding of bibliographic information related to DSS and SDM. Text mining is also available in VOSviewer, which was used to analyse the abstracts and titles of the relevant publications.

Analysis and Results

The results obtained in this study cover two distinct aspects: bibliometric analysis of the dataset and text analysis of the titles and abstracts. Specifically, the results addressed various elements including article keywords, sources, and types, as well as the year of publication, country of publication, contributing institutions and authors, and journal titles. This comprehensive analysis provides insights into the trends and patterns within the literature on DSS for strategic decision-making, highlighting key areas of focus and contributions from the academic community. A breakdown of the analysis is shown in Figure 2.

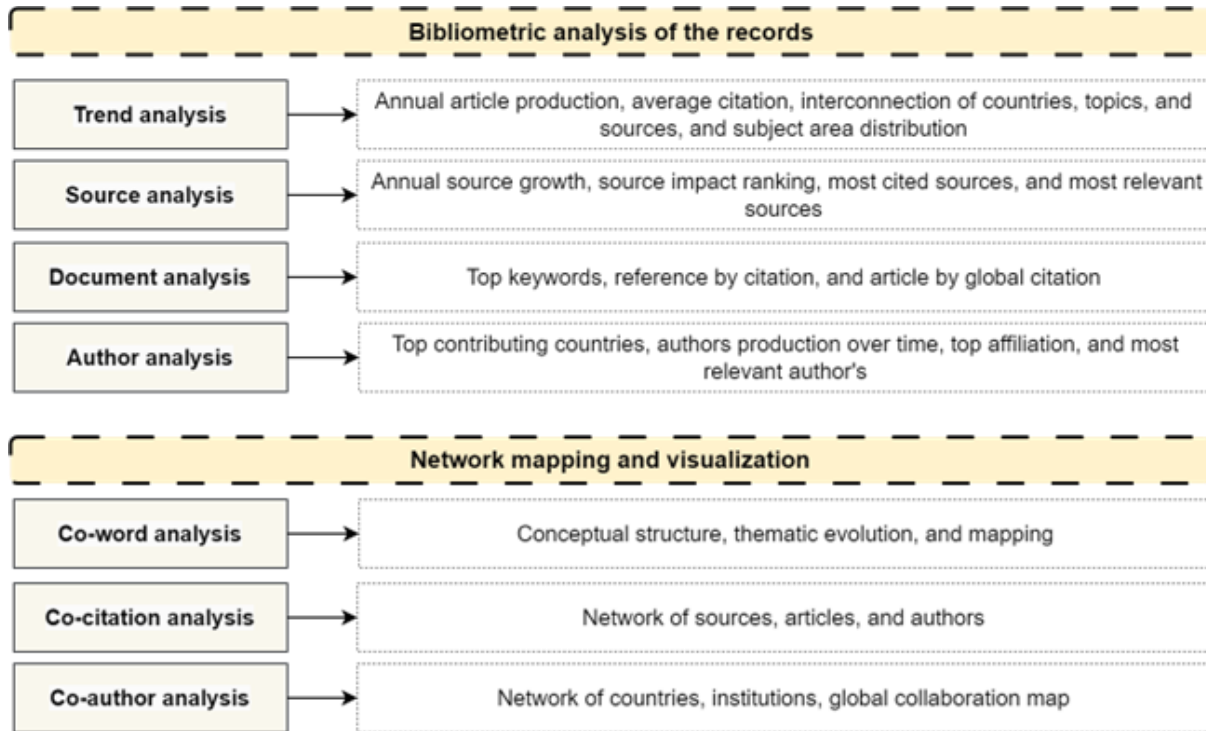


Fig. 2 Bibliometric analysis, network mapping, and visualization process Bibliometric aspect of the articles

The bibliometric aspect of the documents analyzed in this study is discussed based on keyword analysis, document sources, authorship, and citation. The following sections provide a comprehensive discussion of the results obtained.

Keyword analysis

The first analysis conducted in this study was the analysis of author keywords. By using a create map button based on bibliographic data and a unit of analysis based on co-occurrence (Eck & Waltman, 2014), this study visualized the keyword information produced by various publications. Several bibliometric studies have validated this approach (Bukar, Sayeed, Razak, Yogarayan, & Amodu, 2023; Danvila-del Valle et al., 2019; Donthu, Kumar, Mukherjee, Pandey, & Lim, 2021; Donthu, Kumar, Pandey, & Gupta, 2021; Gaviria-Marin, Merigo, & Popa, 2018; Nunen, Li, Reniers, & Ponnet, 2018; Vaio et al., 2022; Xu et al., 2021). The co-occurrence technique for author keywords generates a map that interprets the distance between terms as an indication of the correlation between various keywords. The greater the distance between two or more keywords, the less the significance of the related terms. The co-occurrences of author keywords in publications were analyzed to determine their interconnectedness (Eck & Waltman, 2014). Specifically, the network analysis of the author keywords study included only those terms that appeared in the database at least five (5) times. Similarly, those presented in Table 2 appeared at least five (5) times. This study examined keyword occurrence



carefully to ensure the accuracy of the data, resulting in 47 keywords out of a total of 923 terms, as presented in Figure 3.

Accordingly, duplicates or keywords with synonyms (e.g., ‘decision support systems’ and ‘decision support systems’, ‘strategic decision-making’ and ‘strategic decision making’, ‘decision making’ and decision-making) were merged.

Table 2 Popular Keywords: Minimum Number of Occurrences = 5

Author keywords	Frequency	Percentage
Decision support systems	70	21.8%
Strategic decision-making	40	12.5%
Decision support	30	9.3%
Decision-making	26	8.1%
Simulation	14	4.3%
Artificial intelligence	10	3.1%
Strategic management	9	2.8%
Knowledge management	8	2.5%
Strategic decisions	8	2.5%
Strategic planning	7	2.2%
Data mining	7	2.2%
Business intelligence	6	1.9%
Analytic hierarchy process	5	1.6%
Expert systems	5	1.6%
Clustering	5	1.6%
Optimization	5	1.6%
Big data	5	1.6%

Figure 3 depicts the network visualization map of the authors' keywords, highlighting the terms most used in the existing studies. The size of the words on the map was entirely determined by their presence in the selected articles. According to the results, the major keyword was ‘decision support systems,’ which was used consistently throughout the study period. Similarly, terms such as decision support, strategic decision-making, and decision-making were frequently observed in the literature. Furthermore, a depiction of the keywords and co-occurrence or co-word estimation, as well as the number of well-known issues in the literature, were demonstrated. It is vital to consider color-matching the terms, this co-occurrence measure and quantifies the strength of the interaction between the terms, particularly between DSS and terms such as simulation, artificial intelligence, strategic management, knowledge management, strategic decisions, strategic planning, data mining, business intelligence, analytic hierarchy process, expert systems, clustering, and optimization. Table 2 displays the most prominent terms that have been utilized by numerous researchers in the past.



Short survey	01	0.31%	Undefined	02	0.62%
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Year of publications; evolution of published studies

The progression of publications relating to DSS and SDM can be seen in Figure 4, which covers 1982 through 2024. The study observed a slow but steady increase in the number of publications. Only 12 publications between 1982 to 1989. The publications started to emerge more from 1990 to 1999, which saw growing numbers and subsequently led to a surge in the number of publications between 2000-2009 and 2020-2024. This suggests that scholars are becoming increasingly interested in DSS and SDM. Table 4 presents an overview of the years in which the research studies have been published. The table reveals that 2010-2019 witnessed the highest number of publications (139). As shown in Figure 4, interest in DSS in the realm of strategic decisions is growing. These findings suggest that more publications will be produced in the future, considering the recent steady increase in publications.

Table 4 Year of publications

Year	Frequency	Cumulative percent(N=322)
1982-1989	12	3.73%
1990-1999	51	15.84%
2000-2009	60	18.63%
2010-2019	139	43.17%
2020-2024	60	18.63%
Total	322	100%

Most active source titles

Table 5 provides a summary of the leading and most active journals that have published works related to DSS and SDM, along with their corresponding citation counts. The major source title is “Decision Support Systems,” which leads the list of 18 documents. This journal is a cornerstone in this field, focusing extensively on the development, implementation, and impact of decision-support systems across various industries. The Proceedings of the Annual Hawaii International Conference on System Sciences contributed to ten publications. This conference is well regarded for its broad scope and interdisciplinary approach, making it a significant venue for discussing advancements in DSS and SDM. In addition, Information and Management has five publications, underscoring its role in addressing the interplay between information technology and organizational management. This journal frequently explores how information systems can be leveraged to enhance SDM processes.

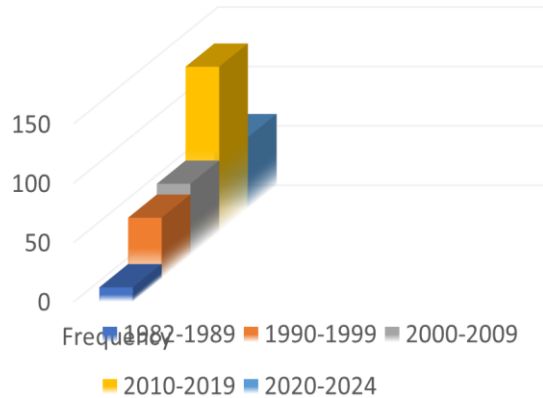


Fig. 4 Document by year

Moreover, the Lecture Notes in Computer Science, including its subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics, and the Journal of Decision Systems each have 4 publications. The Lecture Notes series is notable for its extensive coverage of theoretical and applied computer science, including the integration of artificial intelligence in decision support. The Journal of Decision Systems, on the other hand, provides a dedicated platform for research on decision-making processes and systems. Finally, source titles with three publications each include Studies in Health Technology and Informatics, Proceedings of the Winter Simulation Conference, and Procedia CIRP. Studies in Health Technology and Informatics emphasize the role of DSS in healthcare, exploring how these systems can improve patient outcomes and healthcare management. The Proceeding Winter Simulation Conference focuses on the application of simulation techniques to decision-making, while Procedia CIRP covers advancements in industrial engineering and production management, highlighting the role of DSS in optimizing manufacturing processes. These journals and conferences represent a diverse array of disciplines and methodologies that reflect the interdisciplinary nature of DSS and SDM research. Their contributions are crucial in advancing our understanding of how decision support systems can be effectively designed, implemented, and utilized to improve decision-making across various sectors.

Table 5 Most Active Source Title with At least 3 Publications

Source Title	No of document	%(N=322)	Citations
Decision Support Systems	18	5.59%	174
Proceeding of the Annual Hawii International Conference on System Sciences	10	3.1%	219
Information And Management	5	1.55%	83
Lecture Notes in Computer Science Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics	4	1.24%	5



Journal of Decision Systems	4	1.24%	34
Studies In Health Technology and Informatics	3	0.93%	8
Proceeding Winter Simulation Conference	3	0.93%	0
Procedia CIRP	3	0.93%	55

Distribution of publications geographically

Table 6 outlines the percentage of research contributions made by the top 20 countries in the DSS and SDM fields. This distribution highlights the global landscape of the research activities in this area. Specifically, the United States led 22.4% of all articles. This dominant position underscores the significant investment and focus on DSS research within the country, making it a central hub for advancements and innovations in the field. Australia follows with 8.7% of the contributions, showing a strong presence in the field, reflecting its active research community and the importance placed on DSS for enhancing SDM in various sectors. In addition, the United Kingdom ranks third, contributing 8.4% of the articles, indicating a robust research output and the country's commitment to exploring and developing DSS technologies and methodologies.

Furthermore, Canada and Germany are in fourth place, each contributing 5.9% of the articles. Both countries demonstrated strong engagement in DSS research, with Canada showing a slightly higher impact based on citation counts. India is in fifth place with 5.0% of the contributions, which highlights its growing involvement in the DSS research community and its potential for increased impact in the future. Accordingly, the Netherlands, Finland, and Spain contributed 4.0% of the articles, with 13 publications each. China and Italy contributed 3.4% of the articles, with 11 publications each, reflecting differing degrees of research influence. Greece, Austria, Hong Kong, Sweden, the Russian Federation, and France contributed between 1.9% and 2.5% of the articles each. Hong Kong stands out with a notably high citation count relative to the number of publications, indicating a significant impact.

Finally, Japan, Brazil, and Indonesia are at the bottom of the list, each contributing 1.6% of the articles. These figures suggest that while these countries are engaged in DSS research, their contributions are relatively smaller in volume and impact compared to leading countries. Hence, the United States has emerged as the principal contributor to DSS research, followed by Australia and the United Kingdom as significant contributors. The distribution of research output and citations among the top 20 countries underscores global interest and investment in advancing DSS technologies and their applications in SDM. This analysis highlights the leading roles of specific countries and points to opportunities for increased collaboration and research activity in nations with lower contributions.

Table 6 Top 20 Countries/Regions Contributed to the Publications

Country/region	Frequency	%(N=322)	Citations
United States	72	22.4%	1421



Australia	28	8.7%	633
United Kingdom	27	8.4%	523
Canada	19	5.9%	509
Germany	19	5.9%	298
India	16	5.0%	191
Netherlands	13	4.0%	225
Finland	13	4.0%	58
Spain	13	4.0%	147
China	11	3.4%	79
Italy	11	3.4%	25
Greece	8	2.5%	198
Austria	8	2.5%	47
Hong kong	6	1.9%	766
Sweden	6	1.9%	170
Russian Federation	6	1.9%	6
France	6	1.9%	89
Japan	5	1.6%	59
Brazil	5	1.6%	72
Indonesia	5	1.6%	17
Total	297	92.5%	5311

Authorship

The most productive authors in DSS and SDM fields are listed in Table 7. This highlights the authors who made significant contributions, with a minimum threshold of two documents. Specifically, Khatun M. authored three publications that contributed 0.93% of the total documents. Despite having the highest number of publications, the citation count is relatively low at three, suggesting a low impact of the works in terms of citations that have been revealed. Accordingly, the remaining authors contributed to two documents each, accounting for 0.62% of the total publications. Despite having the same number of publications, their impact varies significantly based on citation counts.

For example, Zobel C. stands out with a remarkably high citation count of 342, despite having the same number of publications as others on the list. This high citation count underscores the significant influence and recognition of Zobel C. work in this field. In addition, Ba Sulin made substantial contributions with two documents that have garnered 60 citations. This indicates the high impact of their work on the DSS and SDM community. Furthermore, Torrecilla-Garcia J.A. has 21 citations for two documents, Shoghli O. has 16 citations, Sasaki H. has received 10 citations, and Jayakrishnan M. and Young W.J. have contributed two documents each, with each author receiving eight citations. Finally, other authors include Brannback M., Al-shawa M., Kivijarvi H., and Yeruwa S. who



contributed two documents with lower citation counts (2, 1, 1, and 2, respectively).

Accordingly, the variation in citation counts among the authors highlights the different levels of impact their work has had within the DSS and SDM research communities. Authors like Zobel C. and Ba Sulin demonstrated that a smaller number of highly cited papers can be more influential than a larger number of less cited publications. This shows that productivity alone cannot determine a high number of citations but the quality and impact of research contributions. In addition, the presence of multiple authors with two publications suggests a competitive research environment.

Table 7 Most Productive Authors (Minimum Document = 2)

Author's name	Documents	%(N=322)	Citations
Khatun M.	3	0.93	3
Ba, Sulin	2	0.62	60
Brannback M.	2	0.62	2
Jayakrishnan M.	2	0.62	8
Al-shawa M.	2	0.62	1
Kivijarvi H.	2	0.62	1
Sasaki H.	2	0.62	10
Shoghli O.	2	0.62	16
Torrecilla-garcia J.A.	2	0.62	21
Yeruwa S.	2	0.62	2
Young W. J	2	0.62	8
Zobel, C.	2	0.62	342

Furthermore, figure 5 illustrates the level of collaboration that exists between academics, using authors and countries as units of study. Specifically, the network obtained for authorship shows no links between the authors. However, in Figure 5, the United States, United Kingdom, and Australia are leading the combined efforts of publications regarding DSS, as identified from the different clusters. The analysis and visualization map demonstrates a comprehensive network of joint efforts spanning across continents.

Schubert and Schubert (2020) stated that co-authorship preferences are determined and shaped by a variety of factors, including cultural relations, geopolitical position, and language. According to the findings of this study, geopolitical proximity and shared language are two of the most important factors for establishing authorship credits across countries. Remarkably, there are a large number of research articles from the United States, United Kingdom, and Australia. This could be as a result of the same language usage. Similar clusters were observed in Germany, the Netherlands, Belgium, and Austria. Nevertheless, according to J. Turner and Baker (2020), collaboration between authors from various disciplines is required to improve any sector. Hence, increased international collaboration is required, especially considering that the network produced in this study shows no relationship between the



authors.

Most influential institutions

The top institutions in DSS and SDM research are listed in Table 8. According to the findings, each of these institutions has contributed at most 2 documents. Remarkably, the Department of Information System at the City University of Hong Kong, located on Kowloon, Tat Chee Avenue, has the highest citation count, with 459 citations. This indicates a significant impact and influence in the field, despite having only 2 publications. This high citation count reflects the quality and relevance of their research output. Other notable institutions include the Westminster Business School at the University of Westminster in London, which has 2 publications with 124 citations, and the Department of Applied Informatics at the University of Macedonia in Thessaloniki, Greece, which has contributed 2 publications with 24 citations. Hence, refer to Table 8 for more details of the top institutions. These findings highlight the substantial contributions and varying levels of impact from different institutions in SDM research. The differences in citation counts underscore the diversity in the influence and reach of the research conducted at these institutions.

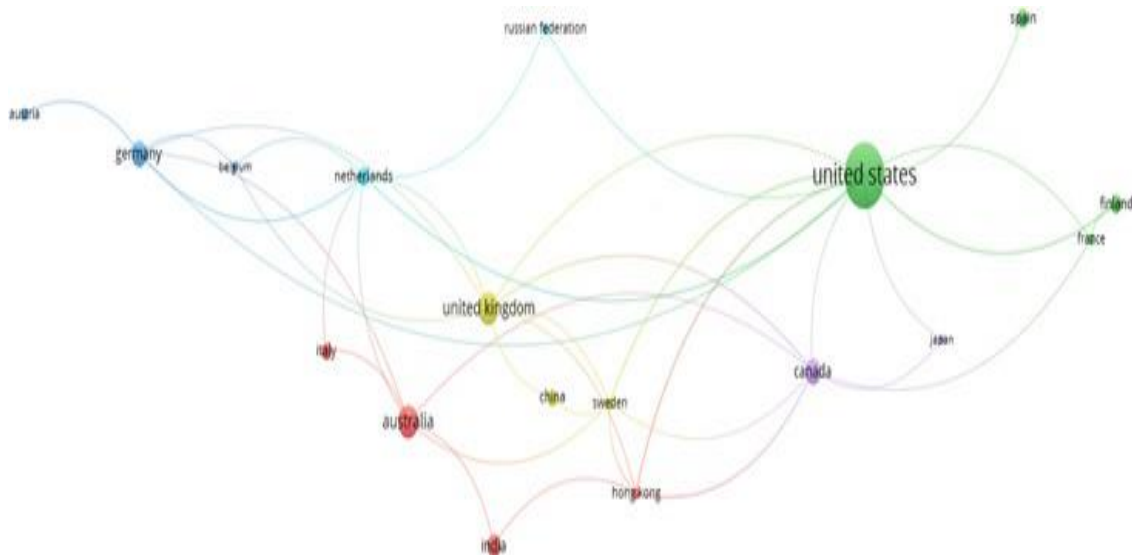


Fig. 5 Network visualization map of the co-authorship. Unit of analysis = Countries, Counting method: Full counting,

Minimum number of documents of a country = 5, Minimum number of citations of a country = 0

Table 8 Most Influential Institutions with Maximum of 2 Publications

Institution	Frequency	% (N=322)	Citations
Department of information system, city university of hong kong, Kowloon, tat chee avenue, hong kong	2	68.8%	459
Wesminster business school, university west-erminster, London, nw1 5ls, 35marylebone road, united	2	18.6%	124



state			
department of applied informatics, university of Macedonia, Thessaloniki, Greece	2	3.6%	24
Dept. of civil and environmental engineering, virginia tech, 117-a patton hall, Blacksburg	2	2.4%	16
North-west university, potcheftroom, south Africa	2	2.2%	15
College of business, victory university, footscray park compus, melbourne, Australia	2	2.2%	15
Univ of Delaware, Newark, united state	2	1.2%	8
Electrical and computer engineering, university of waterloo, waterloo, Canada	2	0.9%	6

Citation analysis

The influence of a piece of research can be measured by the extent to which other researchers have found it beneficial (Ajiferuke & Wolfram, 2010; Bornmann & Daniel, 2008; Moed, 2010). The citation metrics of the 322 records, from 1982 to 2024, are presented in Table IX. The total number of citations over these years is 5258, which breaks down to an average of 122.28 citations per year, 16.33 citations per paper, and 17.13 citations per author. Citations indicate that the quality of several other publications has been improved by a particular publication; whether through its ideas, research findings, or other contributions. Therefore, the number of citations a paper receives serves as a key indicator of its impact on the research community. This means that a highly cited the publication is recognized as a criterion for enhancing the quality of numerous subsequent publications (Bornmann & Daniel, 2008; Tahamtan & Bornmann, 2019). Hence, the citation analysis is presented in Table 9, which highlights the substantial influence and relevance of research outputs in the field of SDM, underscoring the critical role of citations in evaluating the impact and contribution of scholarly work.

Table 9 Citation Analysis and Metrics

Metrics	Data
Publication years	1982—2024
Citation years	1982—2024 (43)
Papers	322
Citations	5258
Citation/year	122.28
Citation/paper	16.33
Citations/author	17.13
Papers/author	1.05
Authors/paper	0.95



Furthermore, the most influential papers in the field, identified by their high citation counts, with a minimum of 105 citations, were analyzed in this study. This provides a succinct overview of key research contributions, showcasing the impactful work that has shaped SDM and related areas. Accordingly, the most influential paper is the work of Martinsons, Davison, and Tse (1999) on the balanced scorecard as the foundation for the strategic management of information systems, with 354 citations and 14.75 citations per year from the year it was published. Second, Zobel (2011) represents perceived tradeoffs in defining disaster resilience, with 280 citations and 20 citations per year. This was followed by Miah et al. (2017) on big data analytics for tourists, with 271 citations and 33.88 citations per year. Hence, refer to Table 10 for more information on the remaining studies. These highly cited papers highlight the significant contributions of these authors to the advancement of knowledge in SDM and related areas.

Textual analysis

VOSviewer can analyze text and present the output in a network structural format. A representation of the co-word network in the form of a map was developed using bibliographic information. It is possible to standardize the principles of involvement in relation to keywords based on the strength of the connection between them (Eck & Waltman, 2007). The approach known as "visualization of similarities" was utilized (Eck & Waltman, 2014) to graphically locate and place each word on a map. This method provides a variety of resolution parameters that enable the detection of a wide variety of clusters. In this study, the keywords that measure the full-strength relative connections and co-occurrence networks were identified. The colors in the visualization differentiate between the unique groups. The graphical depiction of co-words or the co-occurrence of text is shown in Figures 7 and 8.

In particular, the network is produced with respect to the ideas or information contained in earlier literature on DSS in the realm of SDM. These terms are represented by a cluster of varying colors and sizes. The size of the cluster represented by some terms shows more frequent occurrences of the term in abstracts and publication titles (Eck & Waltman, 2014). Moreover, the distance between clusters indicates the strength of the relationship between them. The number of times that both words appeared together in the titles and abstracts of various papers provided evidence for this connection. The inclusion criteria for a term to be selected is at least ten for binary and full counting. The analysis identified four distinct clusters and assigned each of those clusters one of four colors, based on the thematic community they were most closely associated with. Specifically, four clusters (green, yellow, blue, and red) were produced by binary counting (Figure 6), and five clusters (green, yellow, blue, purple, and red) by full counting (Figure 7).

Figure 6 and 7 illustrate the co-occurrence network based on the title and abstract. These data reveal the role and potential of DSS in the realm of SDM to improve overall resource allocation, risk identification, adoption of DSS, strategic planning, insight, assessment, challenges, selection, knowledge management, abilities, and characteristics. Improving this aspect will help the management and decision-making processes in any DSS applications scenario more effectively. As a result, both



the public sector and the well-structured private sector should concentrate their efforts on developing DSS capabilities to improve their data management and decision-making procedures. Consequently, the classification of the articles that were carried out through the schematization of the subtitles and a brief explanation of the intent of those studies reveals that most prior studies have generally analysed the consequences of the relation between DSS and SDM.

Table 10 Most Influential Papers (Highly cited; Minimum Citation: 105)

S/N	Authors	Title	Year	Citation	Citation per year
1	<u>Martinsons et al. (1999)</u>	The balanced scorecard: A foundation for the strategic management of information systems	1999	354	14.75
2	<u>Zobel (2011)</u>	Representing perceived tradeoffs in defining disaster Resilience	2011	280	20
3	<u>Miah et al. (2017)</u>	A Big Data Analytics Method for Tourist Behavior Analysis	2017	271	33.88
4	<u>Tseng and Hung (2014)</u>	A strategic decision-making model considering the social costs of carbon dioxide emissions for sustainable supply chain management	2014	155	14.09
5	<u>Martinsons and Davison (2007)</u>	Strategic decision-making and support systems: Comparing American, Japanese, and Chinese management	2007	131	7.28
6	<u>Abidi (2001)</u>	Knowledge management in healthcare: Towards 'Knowledge-driven' decision-support services	2001	123	5.13
7	<u>Phan, Smart, Capon, Hadwen, and Sahin (2016)</u>	Applications of Bayesian belief networks in water resource management: A systematic review	2016	115	12.78
8	<u>Chen and Lee (2003)</u>	An exploratory cognitive DSS for strategic decision Making	2003	115	5.23
9	<u>Wadhwa, Madaan, and Chan (2009)</u>	Flexible decision modeling of reverse logistics system-tem: A value-adding MCDM approach for alternative selection	2009	107	6.69
10	<u>H Doukas, Nychtis,</u>	Assessing energy-saving measures in buildings through an intelligent decision support model	2009	107	6.69



	and Psarras (2009)				
11	Lau, Liao, Wong, and Chiu (2012)	Web 2.0 Environmental scanning and adaptive decision support for business mergers and acquisitions	2012	105	8.08

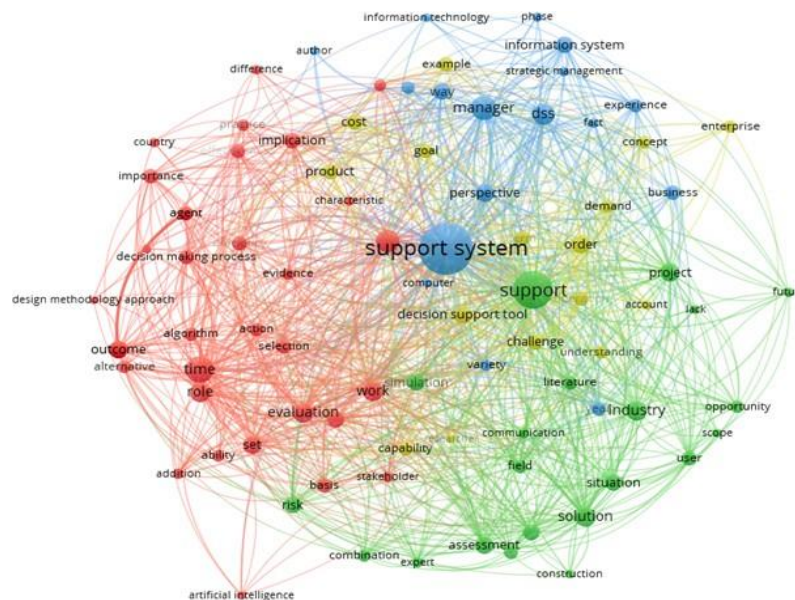


Fig. 6 Network visualization map of term co-occurrence network based on title and abstract. Counting method: Binary counting, Minimum number of term occurrences = 10, Most relevant keywords = 60%.

Discussion

The potential of DSS to revolutionize every aspect of SDM makes it one of the most transformative technologies of the twenty-first century. Applying innovative technologies in SDM has become a critical topic, with increasing public and scientific interest in the concepts, legislation, incentives, and ethical frameworks necessary for businesses to reap the benefits of DSS while minimizing associated risks. Although advanced data analysis is a relatively young field in business studies and there is a lack of discourse on its role and possibilities, it is crucial to view DSS through the lens of providing effective insight to improve overall SDM processes. In recent years, substantial research has been conducted on how advanced data analytics and data quality can assist in strategic decision-making and communication within organizations (Awan et al., 2021; Bammidi, Gutta, Kotagiri, Samayamantri, & Vaddy, 2024; Khong, Yusuf, Nuriman, & Yadila, 2023; Miah et al., 2017; Rana, Chatterjee, Dwivedi, & Akter, 2022; Shamim et al., 2020; Shepherd, Mooi, Elbanna, & Rudd, 2021). However, many organizations are yet to fully implement advanced data analytics to enhance the effectiveness and efficiency of their strategic decisions. Furthermore, the promise of advanced data analytics such as



artificial intelligence and machine learning through the applications of DSS is to improve overall decision-making processes in business contexts, which remains an underexplored field in the academic literature.

Consequently, a review of the literature enabled this study to recognize the significance of DSS and its related advanced analytics tools in relation to SDM processes. As the number of research publications increases annually, academics and practitioners can anticipate convergence across advanced decision-making tools. The diffusion and efficacy of DSS domains in SDM have been identified, clarifying the function of these tools in effective strategic decision-making processes. Hence, by focusing on the capabilities of advanced data analytics tools to provide accurate insights, this study highlights the transformative potential of these systems in improving business performance. The integration of DSS into strategic decision-making frameworks can lead to more informed, agile, and proactive decisions, ultimately driving business success. Considering this aspect, this study conceptualized and presented the concept of ambidexterity to illustrate and enable business organizations to understand the values of advanced analytics tools for strategic decisions.

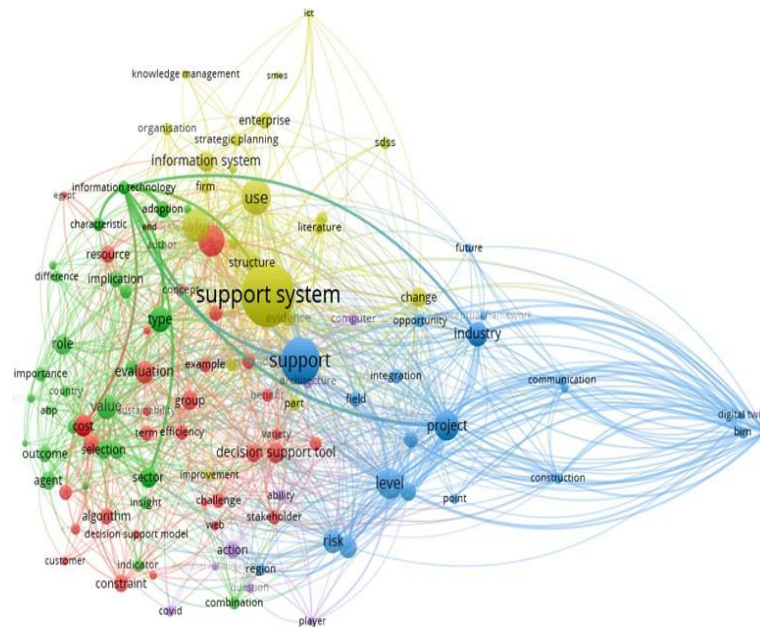


Fig. 7 Network visualization map of term co-occurrence network based on title and abstract. Counting method: Full counting, Minimum number of term occurrences = 10, Most relevant keywords = 60%.

Theoretical framework for DSS to enhance SDM

The “effectiveness of strategic decisions in business organizations is restricted by challenges and abilities as depicted in the network map. In recent years, the proliferation of digital technologies has enabled novel approaches for data collection and analysis. The implementation of decision support systems has garnered significant interest from researchers (Farshidi, Jansen, Espan˜a, & Verkleij,



2020; Liu, Duffy, Whitfield, & Boyle, 2010; Zhai, Mart'inez, Beltran, & Mart'inez, 2020). In the business context, ineffective decision tools can lead to unreliable and suboptimal strategic decisions, potentially causing substantial negative impacts (Bammidi et al., 2024; Claeys & Coombs, 2020; Khong et al., 2023; Rana et al., 2022; Shepherd et al., 2021).

Digital tools and technologies have been widely adopted in various applications such as customer relationship management, supply chain management, and strategic decision-making (Chatterjee, Chaudhuri, & Vrontis, 2022; Nu'nez-Merino, Maqueira- Mar'in, Moyano-Fuentes, & Mart'inez-Jurado, 2020; Soni et al., 2022; Yang, Fu, & Zhang, 2021). Several researchers have highlighted that advanced data analytics significantly improves decision-making efficiency (Awan et al., 2021; Miah et al., 2017; Shamim et al., 2020). Additionally, the use of a sophisticated DSS has been considered a viable option for providing real-time data analysis in scenarios where traditional methods are insufficient or outdated (Kocsi, Matonya, Pusztai, & Budai, 2020; Sbai & Krichen, 2020). Consequently, DSS can enhance decision-making processes by providing actionable data and insights. Business managers can improve their decision-making processes by utilizing a design strategy that leverages the DSS, leading to more intelligent and productive decisions. The primary goal of emerging business technologies is to enhance decision-making and management processes, thereby reducing the time spent on making strategic decisions (Vaio et al., 2022).

Technological advancements and uncertainties in business environments underscore the importance of adaptability and resilience, which is defined as the capacity to react to market changes quickly and effectively. However, strategic decision-making without the use of effective tools is insufficient (Souza, Costa, Oliveira Ramos, & Rosa Righi, 2020). Similarly, effective and efficient business strategies cannot be agile, innovative, and proactive without maximizing the value of technological assets, rapidly deploying existing resources, or minimizing the costs of outdated information. Business managers must understand how effective strategies are developed in the short term and how operations should be coordinated and optimized to deliver value, a capability referred to as alignment (Birkinshaw & Gibson, 2004; Gibson & Birkinshaw, 2004; Gu'nsel, Altındağ, Kılıç Keçeli, Kitapçı, & Hızıroğlu, 2018; Kafetzopoulos, 2021). For a business organization to achieve success in SDM, it must master both adaptability and alignment, commonly referred to as ambidexterity (Birkinshaw & Gibson, 2004; Gibson & Birkinshaw, 2004; Raisch et al., 2009). Hence, organizational ambidexterity refers to the ability to simultaneously achieve the necessary alignment (exploitation; excellence in daily operations) and adaptability (exploration; referring to the organization's capability to innovate and change in response to the environment's evolving needs) as the ability to balance exploitation and exploration in organizational strategies (Birkinshaw & Gibson, 2004; Gibson & Birkinshaw, 2004; Raisch et al., 2009).

Within the scope of this study, data-driven decision support tools were proposed as the primary driver of the organizational ambidexterity framework because of its newer research paradigm in strategic management (Tar'ody, 2016). This is because the theories underpinning SDM



are eclectic, require a multidisciplinary approach, and often appear indistinguishable from general decision-making theories (Ahmed, Bwisa, Otieno, & Karanja, 2014). The theoretical model proposed in this study is driven by data analytics, defined as a set of rapidly collected and analyzed data for accelerated strategic decision-making. Any business organization that successfully utilizes data analytics approaches harnesses a new era of digital maturity, which can be considered a paradigm shift. The purpose of the model, driven by the capability to offer data analytical tools, is to aggregate SDM processes, allowing decision-makers to better understand the significance of readily available data and insights. In other words, the goal of the model is to demonstrate the capability of data analytics as the central focus for strategic decisions in business contexts, enabling managers to assess market conditions and internal performance effectively. Employing this model will enable business organizations to measure and analyze key business metrics, identify opportunities and threats, and disseminate data for quick and informed decision-making. This conceptualization suggests that the application of advanced DSS in SDM significantly affects the decision-making mechanism. This study demonstrates that data analytics tools are crucial for making quick and effective strategic decisions. This is indicated through the visualization map, which illustrates that decision support tools are closely linked to strategic decision-making scenarios that enhance overall business performance. Hence, this study posits that increasing data availability is the first step toward developing predictive analytics capabilities for strategic planning and operational efficiency. This concept, based on the input-process-output, is illustrated in Figure 8.

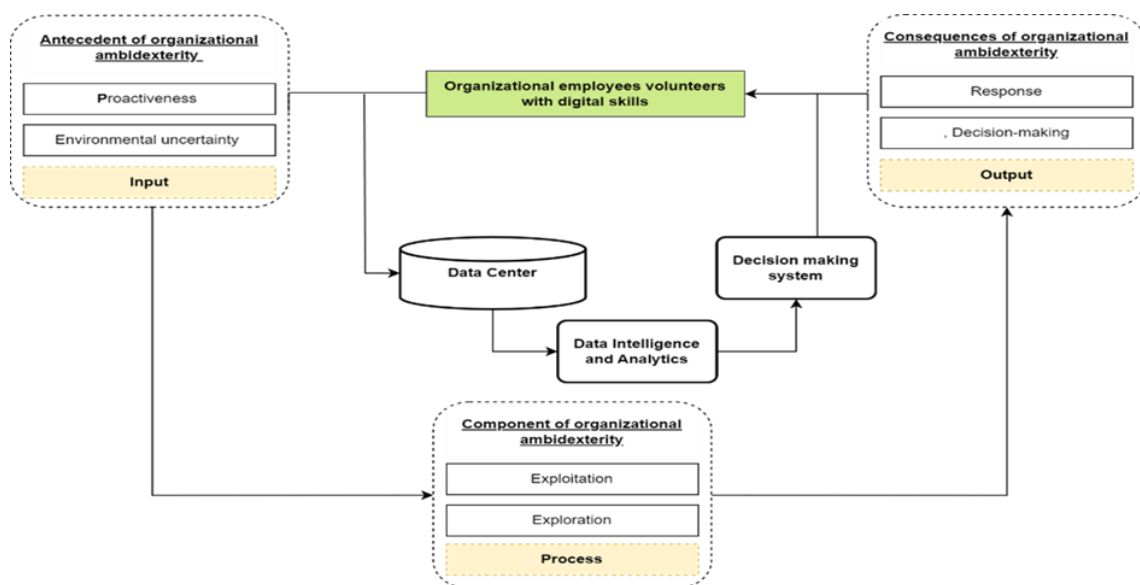


Fig. 8 Organizational Ambidexterity

Implications of the study

This study has theoretical and practical implications. It unifies the existing literature by highlighting the relatively unexplored benefits of utilizing advanced decision-support tools for strategic decision-making. This area warrants further investigation, especially in developing economies where businesses



may benefit significantly from enhanced decision-making capabilities. Hence, this study contributes in several ways. First, it presents a bibliometric analysis of DSS with respect to strategic decision-making processes that challenge business managers' ability to provide efficient technological support through the application of DSS-enabled SDM. Second, this study conceptualizes and proposes a theoretical framework based on ambidexterity to inform business managers to handle strategic decisions, fostering a framework that supports organizational ambidexterity. Third, this study offers early evidence on the effects of ambidexterity by analyzing its influence on the quality of decisions and its impact on decision-makers. These contributions are crucial from a functional standpoint, as business managers must be informed of the procedures to ensure the effective application of advanced decision-support tools.

The significance of ambidexterity theory in proposing technological innovations has been examined and conceptualized (Vaio et al., 2022). The ways in which ambidexterity factors can influence the choices of decision support tools, as well as how ambidexterity can be encouraged and its effects on the outcomes of strategic decision-making. Hence, the key contribution of this paper to the business management literature is demonstrated by two primary attributes. This research is one of the few to incorporate ambidexterity theory to demonstrate the impact of advanced decision-making tools in SDM. Therefore, the findings provide a starting point for academics to investigate how business management can further elucidate decision-support tools adoption in a dynamic organizational environment.

Policy recommendation

The findings of this study can provide advice to business managers. Specifically, the bibliometric analysis of decision support tools in strategic decisions offers insight into the relationship between DSS and SDM. This study investigates how scholars and practitioners perceive and understand DSS to improve strategic decision-making, providing a fresh understanding of the evolution of DSS. Consequently, business managers may allocate resources and strategies within their organizations to investigate this aspect. Moreover, this study's insight has the potential to help business managers understand that leveraging DSS can save time and optimize human resources to meet the dynamic needs of strategic decision-making. Accordingly, considering the fact that DSS play a crucial role in effective and efficient decision-making. Hence, by integrating advanced data analytics with ambidexterity theory, this paper underscores the transformative potential of DSS data analytics capabilities in enhancing strategic decision-making processes. This serves as a foundational piece for future research and practice, encouraging the adoption and optimization of DSS data analytics to drive business success in a rapidly evolving digital landscape.

Limitations of the study and future works

This paper has several limitations that should be acknowledged. First, the information in Scopus is frequently updated, leading to fluctuations in the number of citations and publications (Valenzuela-Fernandez et al., 2019). The data size on a specific day may be questionable because of the continuous



updates of Scopus. Second, scientific mapping and profiling are quantitative methods that provide a comprehensive overview of the study field. However, these methods may not capture all nuances, and co-word analysis (such as keyword co-occurrence) has limitations. The quality of co-word analysis depends on the indexing methods used, over which researchers have limited control (Zupic & Čater, 2015). Third, the current study relied on quantitative methods, which may not fully capture the depth of the research field. In light of these limitations, future research should employ a mixed-methods approach, blending qualitative and quantitative analyses, to gain a more nuanced understanding of DSS applications and their impact on strategic decision-making.

Additionally, this study did not consider business intelligence as a keyword when searching for articles related to DSS and SDM. As a result, additional research should be conducted using BI as a keyword since BI is often used as an umbrella term for large-scale DSS (Arnott, Lizama, & Song, 2017). Moreover, this analysis did not recognize game theory as one of the keywords from both keywords and title and abstract analysis. This suggests that there are limited studies on the application of game theory in DSS and SDM. Considering that game theory is the analysis of strategic decision-making, or as Myerson (Myerson, 1991) puts it, "the study of mathematical models of conflict and cooperation between intelligent rational decision-makers," future studies should investigate the application of game theory in DSS and SDM.

Conclusion

This study was motivated by the rapid growth of DSS and its potential to advance strategic decision-making within organizations. Despite active engagement from both practitioners and academics, there remains a notable absence of framework-based research on ambidexterity, particularly in integrating advanced data analytics technologies and enhancing insight for strategic decision-making. First, the study provides a thorough bibliometric overview and text analysis, making a significant contribution toward consolidating knowledge on DSS applications in strategic decision-making. As advanced data analytics DSS technologies continue to evolve, there is a need for further exploration and understanding. This study advocates the integration of advanced decision support into SDM processes, emphasizing the importance of ambidexterity, the ability to balance exploitation and exploration in organizational strategies. The study offers early insights into the potential impact of DSS on decision-making quality, organizational resilience, and strategic outcomes. This study contributes to the theory of ambidexterity in decision support, offering guidance on fostering ambidextrous capabilities within business contexts to enhance decision-making performance.

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