Advancing Agricultural Sustainability through Decision Support Systems: A Literature Review

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Abstract: This paper explores the role of Decision Support Systems (DSS) in enhancing agricultural sustainability, focusing on environmental, social, and economic dimensions. Through a non-systematic literature review, we aim to provide a foundation for future research that quantitatively and qualitatively measures the impacts of DSS on agricultural sustainability. Results show that, from an environmental point of view, DSS optimize resource utilization, promote sustainable practices, and enable informed decision-making regarding irrigation, fertilization, and pest management, thereby improving resource efficiency and minimizing environmental impacts. From a social perspective, DSS contribute to food security and rural development by empowering farmers with information and decision-support tools, enhancing their livelihoods and resilience to climate change. Economically, DSS optimize resource allocation, reduce production costs, and increase profitability by improving farm efficiency and revenue generation through informed decision-making. This review introduces a conceptual framework categorizing DSS objectives and application areas, and discusses their direct and indirect impacts on sustainability. Our findings highlight the need for further research to address these challenges and fully realize the potential of DSS in driving sustainable agricultural practices.

Keywords: agriculture, sustainability, agrifood supply chain, agriculture 4.0, decision support system.

1. Introduction

Nowadays the agricultural sector is subjected to diverse sustainability issues. From an environmental point of view, it is extremely sensitive to climate change and one of its main contributors, and scarcity of natural resources and food waste are issues that are strongly impacting this sector (Sott et al., 2020). In the pursuit of global food security and environmental stewardship, agricultural sustainability stands as an imperative (Guo, Wen and Zhu, 2015). Agricultural sustainability encompasses a multifaceted approach to address the challenges of modern agriculture. These challenges include but are not limited to population growth, climate change, soil degradation, water scarcity, biodiversity loss, and the need to enhance resilience against pests and diseases (Tilman et al., 2011).

The emergence of Agriculture 4.0 and smart agricultural technologies marks a transformative shift in the agricultural landscape. Integrating digital innovations with traditional farming practices, Agriculture 4.0 offers promising solutions to tackle the pressing challenges facing global agriculture. Smart technologies such as Internet of Things (IoT) devices, drones, sensors, and automated machinery enable precision agriculture, data-driven decision-making, and resource optimization (Papadopoulos et al., 2024). The use of smart agriculture technologies has the potential to bring many benefits to both farmers and other stakeholders in the agri-food sector, in terms of environmental, social and economic performance agriculture. These benefits range from reducing the use of natural resources and of GHGs emissions to improving farmers' quality of life and enhancing food security while maximizing efficiency of agricultural production (Maffezzoli et al., 2022; Latino et al., 2023).

However, the proliferation of data and information generated by these technologies presents a new set of challenges, particularly in decision-making. The volume, velocity, and variety of data make it increasingly difficult for farmers and agricultural stakeholders to extract actionable insights and make informed decisions in a timely manner (Sofi et al., 2015). The traditional trial-and-error approach to farming is no longer sustainable in the face of rapidly changing environmental conditions and market demands (Pechlivani et al., 2023).

In response to the complexity of modern agricultural systems, Decision Support Systems (DSS) have emerged as essential tools to aid decision-making processes. DSS integrate data analytics, modeling, and visualization techniques to assist farmers, agronomists, researchers, and policymakers in managing the vast amounts of data available to them (Fountas et al., 2015). By providing timely and context-specific recommendations, DSS empower agricultural stakeholders to optimize resource allocation, mitigate risks, and enhance productivity while minimizing environmental impact (Thorburn et al., 2011; Sofi et al., 2015).

Decision support systems (DSS) in agriculture are dynamic software applications designed to assist stakeholders, particularly farmers and their advisers, in making precise, evidence-based decisions. According to (Thorburn et al., 2011), these systems often incorporate models that simulate farming processes and how agricultural outputs respond to varying management practices and climatic conditions. (Pechlivani et al., 2023) highlight the critical role of DSS in processing and analyzing vast amounts of data from precision agriculture technologies, providing actionable insights for improved farm management. Similarly, (Rose et al., 2016) describe decision support tools (DST) as guiding users through decision-making processes by analyzing data and presenting likely outcomes of different management options, thus enabling optimal farm operation strategies. The capabilities of DSS in agriculture include data integration and analysis, predictive modeling, scenario analysis, risk assessment, resource optimization, performance monitoring, and Multi Criteria Analysis.

Within the extensive array of Decision Support Systems (DSS) in agriculture, understanding their precise contributions to sustainability can be challenging. This research aims to address this challenge by proposing a conceptual framework that classifies DSS according to their objectives and application areas. By delineating the roles of DSS in sustainability assessment, resource optimization, and decision support across various agricultural domains, this framework seeks to illuminate the nuanced ways in which DSS influence agricultural sustainability. Through this endeavor, we aim to provide stakeholders with a clearer understanding of how technological innovations in DSS can drive positive change towards a more sustainable agricultural future.

Some contributions in literature review the use of DSS in agriculture. (Zhai *et al.*, 2020) examine the role of DSS in Agriculture 4.0, a concept that emphasizes increased productivity, resource allocation, climate change adaptation, and food waste reduction. Their review identifies and evaluates thirteen DSS, analyzing their interoperability, scalability, and usability, and highlights the challenges and potential improvements for future research in this domain. (Yousaf *et al.*, 2023) conduct a bibliometric analysis of operations research (OR) applications in smart agriculture, highlighting the role of technologies like IoT, AI, and ML. This review identifies research trends and gaps over the past two decades, focusing on how advanced OR theories can optimize agricultural practices and resource allocation, particularly through the use of UAVs and satellite imagery. (Ara *et al.*, 2021) focus on economic DSS for irrigated cropping systems, emphasizing the functional aspects and human factors influencing DSS adoption. The review points out that many DSS are developed through a top-down approach rather than being demand-driven. It also underscores the need for DSS that address both tactical and strategic decisions, account for uncertainty, and align more closely with end-user needs through participatory approaches. (Fountas *et al.*, 2015) review current commercial solutions and examine possible future development opportunities, while (Zhang *et al.*, 2021) investigate challenges and opportunities fodir DSS in precision irrigation. Finally, (Bouma *et al.*, 2003) provides a historical perspective on the use of DSS in Dutch agriculture, particularly for pest control. The review details the evolution of weather-related DSS and their impact on reducing crop damage and the use of active substances in crop protection, thereby contributing to more sustainable agricultural practices.

While these reviews provide comprehensive insights into the technological advancements and applications of DSS in agriculture, they primarily focus on productivity, technological integration, and user adoption. This review addresses the sustainability impacts of DSS in agriculture, assessing how these systems contribute to environmental sustainability, economic viability, and social equity. This approach aims to fill the gap in understanding the broader implications of DSS beyond immediate agricultural productivity.

Moving from here, the research question we aim to address is: "How do Decision Support Systems (DSS) contribute to agricultural sustainability?"

This paper is structured as follows: the methodology section details the literature search and analysis approach; the results section introduces the conceptual framework and presents the objectives, application areas, and sustainability impacts of agricultural DSS; and the paper concludes with the discussion and conclusion section.

2. Methodology

To provide an answer to the research question, we develop a conceptual analysis based on the existing literature. A conceptual analysis builds on carefully selected sources selected with clear criteria (Jaakkola, 2020).

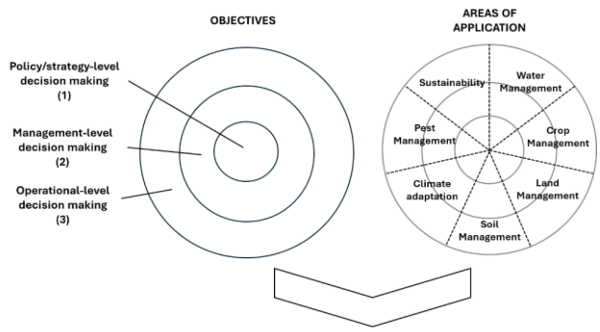
For this non-systematic literature review, Scopus was utilized as the primary database to retrieve relevant scholarly articles. The search query was designed to capture papers discussing the utilization of DSS within the agricultural context, with explicit references to aspects related to sustainability, encompassing environmental, economic, or social dimensions. The query used was: "TITLE-ABS-KEY("decision support system*" AND (agricultur*) AND sustainability AND (impact* OR performance* OR benefit* OR advantage*))". This query was applied to identify articles where discussions around DSS and sustainability intersected. After inserting the query into Scopus, the search results were ordered by relevance to ensure that the most pertinent articles appeared first. Papers were screened based on their titles and abstracts. Articles were selected if they explicitly addressed the integration of DSS in agricultural practices and its implications for sustainability. Specifically, they needed to discuss environmental, economic, or social impacts. The screening continued until a saturation point was reached, meaning no new information regarding the objectives, areas of applications, and sustainability impacts of these DSS was found in additional articles. To further expand the search, snowball sampling was employed. This involved reviewing references and citations from two key literature reviews in the field, which helped identify additional relevant papers. As the papers were analyzed, a framework was created to summarize the findings. This framework, reported in the results section, includes the following elements: objectives, what the DSS aims to achieve in the agricultural context; areas of application, agricultural activities or processes where DSS are applied, sustainability impacts, the environmental, economic, and social benefits or effects of implementing DSS.

The results of the literature review are represented by a conceptual framework developed out of the analysis of the various contributions. The framework in Figure 1 provides a graphical representation of the different typologies of DSS and their contribution to sustainability, favoring a nuanced and organized understanding of a fragmented research domain (Jaakkola, 2020).

3. Results and discussion

First of all, the conceptual framework introduces a twofold classification of agricultural DSS, emphasizing both the objectives guiding their development and implementation, as well as the diverse areas of application where they are utilized. In terms of decision-making, this classification stresses both the objective of the decisions made in the agricultural context and the subject of the decision. Secondly, the impacts in terms of sustainability deriving from their use are classified considering the three dimensions of the triple bottom line. Environmental, economic and social impacts are divided between direct, the immediate, tangible consequences or effects resulting directly from the implementation or use of DSS in agriculture, and indirect, the secondary or consequential effects that occur as a result of the direct impacts of using DSS in agriculture. Direct and indirect impacts derive both from the functions performed by the DSS and by the area where the technology is applied.

In the following paragraphs more details are provided on the different dimensions of the conceptual framework.



	Economic	Environmental	Social
Direct impacts	(a)	(c)	(e)
Indirect impacts	(b)	(d)	(f)

Figure 1: Conceptual framework

3.1 Agricultural DSS: objectives

The objectives of the use of agricultural DSS retrieved in academic literature include: precision agriculture implementation, agricultural planning and management, weather and climate forecasting, risk management, sustainability assessment and policy planning and evaluation.

Precision agriculture: DSS support precision agriculture techniques by integrating data from sensors, satellites, and other sources to create detailed field maps and spatial variability analyses. They help farmers identify optimal planting patterns, variable rate application of inputs (such as fertilizers and pesticides), and irrigation management strategies based on site-specific conditions, maximizing resource efficiency and crop yields while minimizing environmental impact ((Aiello *et al.*, 2018), (Thorburn *et al.*, 2011), (Canaj *et al.*, 2021), Zhang et al., 2021, Nurcahyo et al., 2023).

Agricultural planning and management: DSS can provide information on optimal planting dates, crop selection, and agronomic practices tailored to specific soil and weather conditions. They can help analyzing various scenarios and select the best alternatives in terms of efficiency and sustainability, (Manna *et al.*, 2020), (Martin *et al.*, 2016), (Attia *et al.*, 2021), (Arshad *et al.*, 2022), (Debeljak *et al.*, 2019), (de la Rosa *et al.*, 2009).

Weather and climate forecasting: DSS can be weather and climate forecasting tools that help farmers anticipate and respond to weather-related risks such as droughts, floods, frost, and heat stress. By integrating real-time weather data with historical climate trends and predictive models, DSS enable farmers to make timely decisions about irrigation scheduling, crop protection measures, and harvest planning to mitigate weather-related losses and optimize farm operations (Adekanmbi et al., 2023, Arshad et al., 2022).

Risk management: decision support tools can perform risk assessment, scenario analysis, and can support the development of insurance plans, enabling farmers to identify vulnerabilities, evaluate alternative strategies, and implement risk management measures to protect their crops, livelihoods and investments (Debeljak et al., 2019).

Sustainability assessment: DSS can help farmers and policymakers assess the sustainability performance of different practices, technologies, and policies, often through Multi Criteria methods, in order to identify opportunities for improvement and develop strategies to promote long-term sustainability in agriculture while balancing environmental conservation, economic viability, and social equity (Van Cauwenbergh et al., 2008; Sattler et al., 2010; Jesus et al., 2019).

Policy evaluation: DSS can help in supporting policy making and evaluation by providing valuable insights, data-driven analysis, and simulation capabilities. DSS for policy evaluation can incorporate data from precision agriculture, sustainability assessment and risk management to inform and shape agricultural policies; moreover they can be used to simulate the impacts of potential policy changes (Recio et al., 2005; de la Rosa et al., 2009; Ali, Aziz and Sulong, 2020; Terribile et al., 2024).

As shown in Figure 1, three different levels of analysis can be identified for classifying the objectives of the use of agricultural DSS. Sustainability assessment and policy evaluation are functions at the policy/strategy-level, aiding policymakers, and other stakeholders in evaluating the sustainability performance of agricultural practices and shaping long-term strategic decisions (1). Management-level DSS encompass agricultural planning and management, supporting farm managers in optimizing crop selection and agronomic practices, and risk management strategies (2). Lastly, operational-level DSS include precision agriculture and weather and climate forecasting tools, enhancing efficiency and precision in field-level activities, and enabling farmers to make informed decisions based on real-time weather data (3). In the sample of papers analyzed, strategy and policy level as well as operational level DSS are the most widespread categories, with 10 and 9 occurrences respectively (see Appendix A).

3.2 Agricultural DSS: application areas

Following the classification made by (Sofi et al., 2015), a distinction is made concerning the areas of application of agricultural DSS. The areas addressed by the retrieved studies are water management, pest management, soil management, crop management, land management, climate adaptation and sustainability. Often DSS are designed to operate in more than one area at the same time, but in the sample of paper analyzed there is a clear prevalence of "water management" and "crop management" as areas of application (see Appendix A).

Water management (WM): DSS can support irrigation scheduling and management, water conservation strategies, drainage system management and monitoring of water usage (Recio et al., 2005; Van Cauwenbergh et al., 2008; Debeljak et al., 2019; Attia et al., 2021; Canaj et al., 2021; Zhang et al., 2021).

Pest management (PM): DSS are often used to help with pest detection and identification, pest control strategies and recommendations, Integrated Pest Management (IPM), disease forecasting and mitigation plans (Aiello et al., 2018; Pechlivani et al., 2023).

Soil management (SM): soil fertility assessment and improvement plans, soil type mapping and analysis and nutrient management and optimization are all possible areas where DSS can operate. (de la Rosa et al., 2009; Thorburn et al., 2011; Debeljak et al., 2019; Pechlivani et al., 2023).

Crop management (CM): DSS can be used for selecting appropriate crop varieties, timing planting and harvesting operations, and monitoring crop health (Manna et al., 2020; Arshad et al., 2022).

Land management (LM): DSS can support land management practices such as forest planning, site selection, conservation preserves planning, therefore helping reserving natural habitats and biodiversity (Terribile et al., 2024).

Climate adaptation (CA): DSS can contribute to adapting to changing climate conditions, forecasting impact of climate on crops, long-term climate resilience planning and carbon management (Debeljak et al., 2019; Adekanmbi et al., 2023).

Sustainability (S): monitoring and reducing environmental impacts, biodiversity conservation strategies, sustainable resource use planning (Van Cauwenbergh et al., 2008; Jesus et al., 2019).

3.3 Sustainability impacts deriving from DSS implementation

3.3.1 Economic dimension

In terms of economic sustainability, DSS play a crucial role in improving farm profitability, efficiency, and resilience. All the environmental benefits associated with reduction and optimization of resources can be also seen as economic benefits, as they also lead to cost savings in agricultural activities. By optimizing input use, production processes, and market access, DSS help farmers reduce production costs, increase yields, and enhance competitiveness. Furthermore, DSS support financial planning, risk management, and investment decisions, helping farmers navigate market uncertainties and achieve long-term economic sustainability (Van Cauwenbergh et al., 2008; Sattler et al., 2010; Manna et al., 2020; Canaj et al., 2021; ma, Wibowo and Chong, 2021; Fotia et al., 2021).
Direct economic impacts (a – see Figure 1) include cost savings, deriving from reduced input costs through optimized resource management and reduced waste and decreased reliance on expensive agrochemicals through targeted application and integrated pest management (Sofi et al., 2015; Aiello et al., 2018; Attia et al., 2021; Canaj et al., 2021; Arshad et al., 2022), yield and profitability enhancement, thanks to increased crop yields and profitability through optimized management practices and risk mitigation strategies (Debeljak et al., 2019, 2019; Arshad et al., 2022; Nurcahyo et al., 2023), and reduced financial losses from crop failures and adverse weather events thanks to timely decision-making (Sofi et al., 2015; Aiello et al., 2018; Adekanmbi et al., 2023).

Indirect economic impacts (b) can include improved market access and competitiveness through certification and labeling of sustainably produced agricultural products (Sattler et al., 2010), promotion of innovation and adoption of new technologies through improved access to information (Thorburn et al., 2011; Duan, Wibowo and Chong, 2021), and long-term economic viability thanks to preservation of soil fertility and natural resources through sustainable management practices (Duan, Wibowo and Chong, 2021; Adekanmbi et al., 2023) and maintenance of agricultural productivity and profitability over the long term (Recio et al., 2005; Van Cauwenbergh et al., 2008; Manna et al., 2020; Arshad et al., 2022).

3.3.2 Environmental dimension

One of the primary areas where DSS have a significant impact is environmental sustainability. By providing farmers with precise recommendations for resource management, such as irrigation scheduling, fertilization optimization, and pest management, DSS help minimize resource waste and reduce environmental pollution. For example, precision agriculture techniques enabled by DSS can reduce water consumption, minimize agrochemical use, and preserve soil health, thereby contributing to biodiversity conservation and ecosystem resilience. Additionally, DSS facilitate climate-smart agriculture practices by offering climate suitability models, weather forecasting, and risk assessment tools, empowering farmers to adapt to changing climatic conditions and mitigate the impacts of climate change on agriculture. (de la Rosa et al., 2009; Debeljak et al., 2019; Manna et al., 2020; Canaj et al., 2021; Fotia et al., 2021; Zhang et al., 2021, 2021; Arshad et al., 2022; Pechlivani et al., 2023; Papadopoulos et al., 2024).

Direct environmental impacts (c) include resource efficiency, in terms of water, soil, pesticides and fertilizers (Aiello et al., 2018; Canaj et al., 2021; Terribile et al., 2024), biodiversity conservation, thanks to sustainable land management practices (Van Cauwenbergh et al., 2008; de la Rosa et al., 2009; Sofi et al., 2015) and minimization of habitat destruction through precision agriculture techniques (Debeljak et al., 2019) and climate change mitigation, mainly through reduction in greenhouse gases emissions through optimized inputs (and reduced energy usage) (Aiello et al., 2018; Manna et al., 2020).

Indirect environmental impacts (d) include soil health enhancement (de la Rosa et al., 2009; Nurcahyo et al., 2023), water quality improvement thanks to improved water management practices and optimized fertilizer application (Recio et al., 2005; Van Cauwenbergh et al., 2008; Aiello et al., 2018; Attia et al., 2021) and ecosystem resilience thanks to enhanced resilience to extreme weather events through improved management practices and forecasting capabilities (Debeljak et al., 2019; Adekanmbi et al., 2023).

3.3.3 Social dimension

DSS also contribute to social sustainability improving labor efficiency, farm productivity, and food security. DSS enhance livelihoods, reduce poverty, and foster rural development. By providing smallholder farmers with access to technology, information, and market opportunities, DSS empower them to increase productivity, income, and resilience to socio-economic challenges. This contributes to food security, poverty alleviation, and sustainable rural livelihoods, ultimately promoting social equity and inclusivity in agriculture. Moreover, literature emphasizes the role of DSS in enhancing social learning, as they provide farmers with collaborative platforms to exchange information, shared data and information and visualization tools. (Van Cauwenbergh et al., 2008; Thorburn et al., 2011; Martin et al., 2016; Aiello et al., 2018; Manna et al., 2020, Rader et al. 2009)

Direct social impacts (e) include farmers' empowerment, given by increased autonomy in decision-making (Sofi et al., 2015; Martin et al., 2016; Ali, Aziz and Sulong, 2020), community health and well-being, both through reduced exposure to harmful agrochemicals and pesticides for nearby communities (Debeljak et al., 2019) and improved access to fresh and nutritious food through increased agricultural productivity and diversity (Duan, Wibowo and Chong, 2021) and access to information and education, through increased access to agricultural knowledge and best practices through DSS-enabled extension services (Thorburn et al., 2011; Martin et al., 2016; Debeljak et al., 2019).

Indirect social impacts (f), instead, are associated with rural development, deriving from economic growth and job creation in rural communities through increased agricultural productivity and profitability and enhanced resilience to economic shocks and market fluctuations (Recio et al., 2005; Ali, Aziz and Sulong, 2020) and food security, which is improved by increased crop yields and resilience to climate variability (Sofi et al., 2015; Adekanmbi et al., 2023).

4. Conclusions

Our work contributes to the research on sustainability assessment of smart agricultural technologies by proposing theoretical insights on different levels of analysis to identify "typologies" of agricultural DSS. Identifying the dimensions that distinguish the variants of agricultural DSS appears as a necessary condition to get a more nuanced understanding of the sustainability impacts of DSS. Dimensions (i.e., objectives and areas of applications) act as determinants of the economic, environmental, and social impacts of DSS.

Despite the contribution in categorizing a fragmented body of research, this study presents some limitations connected to its conceptual nature. The conceptual framework proposed, indeed, could benefit from a validation from experts or an integration with primary data to build a more robust conceptual model clarifying the relationships between the various constructs.

We believe that our work can pave the way to different future research directions. First, future works based on empirical evidence could aim at developing patterns based on causal/instrumental relationships between objectives of the application, subject of the decisions (i.e., areas of application) and impacts, which are now reported in our conceptual framework with no connections. Patterns can be tailored on different actors (i.e. policy makers, producers' organizations, or cooperatives and individual farmer) and the focus on direct or indirect impacts depend on who performs the evaluation.

Secondly, by analyzing specific typologies of agricultural DSS, our framework can be enriched with further features of agricultural DSS, for example related to the integration with other technologies or services, thus considering a further set of more technical "attributes" among the determinants of sustainability impact.

Third, future studies can aim at extending the evaluation of sustainability impacts to different supply chain actors, by analyzing the implications of the adoption of DSS at the farm's stage to other agri-food supply chain stage, which could leverage on the data collected and analyzed by a DSS to plan orders, inventories and generate further positive sustainability impacts.

Our findings have significant practical implications, which could be strengthened further by future studies. First of all, there are clear implications for policy makers, farmers and people in a managerial position inside producers' organizations or cooperatives, who, through our study, can have more information on different agricultural DSS typologies and their potential impacts. More specifically, decision makers at different level can gain insights to carefully evaluate whether to adopt DSS. At the same type, also technology providers can gain from our study a better understanding on different dimensions they can lean upon to conceive valuable business models for such technology.

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umAppendix A. FIRST APPENDIX

Table 1: final list of analysed papers

Reference	Objectives	Areas of application	Sustainability impacts
Adekanmbi, T. et al.	3	CA	a, b, d, f
Aiello, G. et al.	3	PM	a, c, d
Ali, M.F. et al., 2020	1, 2	CM, LM, S	e, f
Arshad, J. et al., 2022	3, 2	CM	a, b
Attia, A. et al., 2021	2	WM	a, d
Bonfante, A. et al., 2019	3	WM	a, d
Canaj, K. et al., 2021	3	WM	a, c
Debeljak, M. et al., 2019	2	WM, SM, CA	a, c, d, e
Duan, S.X. et al., 2021	1	S	b, e
Fenu, G. et al., 2020	3	PM, CA	a, c
Fotia, K. et al., 2021	1, 2	WM, S	a, c
Jesus, K.R.E.D. et al., 2019	1	S	a, c, d, e, f
Manna, P. et al., 2020	2, 2	CM	b, c
Martin, G. et al., 2016	1,2	LM, S	e
Nurcahyo, A. et al., 2023	3	WM, CM, SM	a, d
Pechlivani, E.M. et al., 2023	1, 2, 3	PM, SM, S	a, c, d, e, f
Recio, B. et al., 2005	1	WM	b, d
de la Rosa, D. et al., 2009	1,2	SM	c, d
Sattler, C. et al., 2010	1	S	b
Sofi, T. et al., 2015	2	CM, LM, S	a, c, e. f
Terribile, F. et al., 2024	1	LM	c
Thorburn, P.J. et al., 2011	3	SM	b, e,
Van Cauwenbergh, N. et al., 2008	1	VM, S	b, c, d