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Recommender systems and sustainability: a dual perspective

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HIGHLIGHTS

- This survey distinguishes two key dimensions: Recommender Systems (RS) for Sustainability and Sustainability of RS.
- The work reviews existing studies that promote sustainable behaviors or embed sustainability principles in their design.
- The work identifies critical gaps in current research and outlines a roadmap for developing sustainable recommender systems.

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ABSTRACT

The concept of sustainability, as outlined by the United Nations' Sustainable Development Goals (SDGs), refers to the ability to meet the needs of the present without compromising the ability of future generations to meet their own needs. This vision is addressed by combining goals concerning the *environmental*, *social*, and *economic* spheres. In this context, Recommender Systems (RS) have emerged as tools that can foster these principles by nudging responsible user behavior and promoting sustainable decision-making. However, the interplay between RS and sustainability is inherently complex since it can be analyzed from two different perspectives: *(i) RS for Sustainability*, which focuses on how recommendation algorithms can support the achievement of SDGs, and *(ii) Sustainability of RS*, which focuses on developing recommendation models that inherently adhere to sustainability principles. While the integration of both these perspectives is beneficial and crucial, unfortunately, the current literature has addressed these aspects independently. Accordingly, in this survey, we first provide a comprehensive review of the existing literature on RS that either promotes sustainable behaviors aligned with the SDGs or embeds sustainability principles into their algorithmic design. Next, we identify current gaps and propose key research directions toward an integrated, holistic approach that concurrently addresses both aspects to advance the development of sustainable RS.

1. Introduction

Sustainability is a multidimensional concept that aims to meet present needs without harming future generations. First defined in the Brundtland Report of 1987,[1] this principle has evolved into a global framework for action, exemplified by the United Nations' SDGs and Agenda 2030 [23]. Adopted in 2015, the SDGs represent a universal call to action: 17 interconnected goals defined to address critical challenges through collaborative efforts involving governments, businesses, and civil society.

A popular taxonomy to classify and describe the different SDGs relies on the three pillars of sustainability: *society, economy, and environment* [71]. As supported by growing evidence, the *social* pillar emphasizes equity, inclusivity, and well-being, ensuring all individuals and communities benefit from progress while addressing systemic inequalities.

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[1] https://digitallibrary.un.org/record/139811?v=pdf.

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It also prioritizes human rights, access to education, and the empowerment of marginalized groups. The *economic* pillar fosters growth and innovation while ensuring resource efficiency and long-term viability. This requires aligning financial practices with sustainable production and consumption to avoid compromising future resources. The *environmental* pillar is centered on preserving natural resources, reducing ecological footprints, and mitigating climate change to maintain the planet's health for future generations. These pillars are deeply interdependent; economic growth is unsustainable without environmental preservation, and social equity cannot be achieved without addressing economic and environmental factors.

As confirmed by several pieces of evidence [74,101], Artificial Intelligence (AI) and related technologies have emerged as transformative tools in advancing these objectives and meeting sustainability goals. In particular, Recommender Systems (RS) hold significant potential to drive sustainability [36] by influencing user behavior. For example, in e-commerce, RS can prioritize eco-friendly products by guiding consumers toward sustainable choices [32]. Moreover, RS can improve awareness about sustainability issues, fostering informed and responsible decisions. In energy management, for instance, RS can support users with recommendations to optimize energy usage patterns [75]. Finally, RS can promote well-being by recommending healthier dietary choices that balance nutritional value with user preferences [96]. This multidimensional vision allows us to examine the interplay between RS and sustainability through two complementary lenses

All the above-mentioned works show that much effort is being put into developing recommendation strategies that address SDGs. However, regardless of the specific domain of application and the decision-making task an RS aims to support, it is equally important that the design and the development of recommendation algorithms follow the principles indicated by SDGs. This includes designing algorithms that consider socio-economic aspects, such as *fairness* and *transparency*, and ensure a *low environmental impact*.

Based on this multidimensional vision, the interplay between sustainability and RS can be analyzed from two perspectives (see Fig. 1), inspired by the well-known definition of *AI and Sustainability* [101]:

- **RS for Sustainability:** this perspective focuses on designing RS that promote sustainable practices and contribute to achieving SDGs and sustainability pillars.
- **Sustainability of RS:** this perspective emphasizes the development of recommendation algorithms that align with SDG principles by minimizing environmental impact, ensuring ethical practices, and optimizing resource consumption.

While these perspectives are strongly interconnected, most of the literature has addressed these aspects in isolation, *i.e.,* RS supporting SDGs through their recommendations rarely follows sustainability principles. Conversely, to fully implement the vision behind SDGs, it is necessary

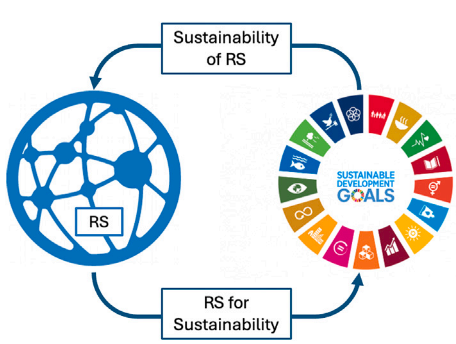

Fig. 1. The dual perspective of Sustainability in RS: driving SDGs while being designed and implemented sustainably following the SDGs.

to introduce a novel and *holistic* vision of the research in the area of sustainable RS, where both perspectives are addressed simultaneously. Accordingly, the aim of this survey is to provide an overview of the state of the art, emphasize current gaps, and draw attention to the urgent need for a comprehensive approach to sustainability in RS.

To address this gap, our work offers the following contributions: (1) a new taxonomy for classifying existing literature on RS and sustainability based on our *dual* perspective; (2) an analysis of the limitations and existing gaps of the current methods; (3) a definition in a research path to address both the perspectives of sustainability and to develop a novel generation of sustainable RS.

In summary, this work aims to provide an answer to the following questions:

1. **RQ1:** How can recommender systems be designed to not just reflect user preferences, but to actively promote sustainable behaviors and societal good?
2. **RQ2:** What are the hidden environmental and ethical costs of deploying large-scale recommender systems, and how can we redesign them to align with sustainability principles?
3. **RQ3:** Can we envision a future where recommender systems both enable sustainable choices and are themselves sustainable, without compromising performance or user experience?

To the best of our knowledge, this is the first work that provides a contribution in this direction: in fact, the existing surveys are not focused on how to address both the proposed perspectives between RS and sustainability. The reporting of this review is guided by the standards of the Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) Statement.

The survey is organized as follows: in Section 2 we present our methodology for data collection and we discuss related papers. In Section 3 and Section 4, we present and analyze representative approaches addressing the different SDGs and exploiting the principles of a sustainability pillar in their implementation, respectively. Next, in Section 5, we review solution methods that achieve a tighter degree of integration of both the pillars and the dual sustainable perspective, with identification and discussion of both of them. In Section 6, we provide concluding remarks and highlight promising research directions.

2. Methodology

In this section, we describe the methodology adopted to collect and analyze relevant literature related to the intersection of recommender systems and sustainability. First, we explain the strategy used to gather works under both perspectives outlined in this survey: RS for Sustainability and the Sustainability of RS. Then, we outline how our work positions itself with respect to existing reviews.

2.1. Literature search strategy

To ensure a comprehensive and systematic selection of relevant studies, we followed a PRISMA-inspired protocol.[2] Given the dual perspective of this survey, we conducted two separate but complementary searches:

- RS for Sustainability: research efforts where RS have been applied to promote sustainable development goals (SDGs) across the environmental, social, and economic pillars.
- Sustainability of RS: research aimed at designing recommendation algorithms that are themselves sustainable in terms of fairness, transparency, energy consumption, and economic efficiency.

[2] Sohrabi et al. PRISMA 2020 statement: What's new and the importance of reporting guidelines, 2021.

The search was conducted in April 2025 using leading digital libraries, including Google Scholar, Scopus, DBLP, and ACM Digital Library. We crafted keyword-based queries aligned with our dual objectives. Examples of representative queries include:

- "recommender systems" AND ("sustainability" OR "green AI")
- "sustainable development goals" AND "recommender systems"
- "fairness" AND "recommender systems"
- ("eco-aware" OR "carbon footprint") AND "recommender systems"
- ("value-aware" OR "profit-aware") AND "recommender systems"

Date restriction was applied to include contributions defined after the establishment of the Sustainable Development Agenda (2015). The top 50 results, ranked by relevance, were collected from each query and screened. Duplicates were removed, and the remaining records were screened according to the following inclusion criteria:

- The work proposes or evaluates a recommender system that aims to support one or more SDGs.
- The work addresses principles of sustainability (e.g., fairness, environmental impact, affordability) in the design or evaluation of RS.
- The work provides methodological or conceptual insights into sustainability in RS design or applications.

Studies were excluded if they: (1) do not focus on RS or sustainability; (2) are not peer-reviewed (e.g., editorials, non-reviewed workshop papers); (3) were duplicate records or inaccessible. Fig. 2 shows a report of the outcomes of the literature search for each phase.

A total of 250 records were retrieved initially. After duplicate removal and screening, 109 papers were included in the final analysis: 45 focusing more on Recommender Systems for Sustainability, e.g., systems designed to promote sustainable behaviors and support one or more Sustainable Development Goals as well as some technical aspects of RS; 33 addressing the Sustainability of Recommender Systems, through the integration of principles such as fairness, transparency, and energy efficiency in RS design; 17 exploring integrated or dual-perspective approaches, including multi-objective optimization, multi-pillar applications, and cross-disciplinary collaboration; the remaining papers consist of contextual/background references on sustainability and technical details related to recommender systems. These were further categorized by pillar (social, environmental, economic) and by topic (e.g., fairness, carbon footprint, multi-objective optimization).

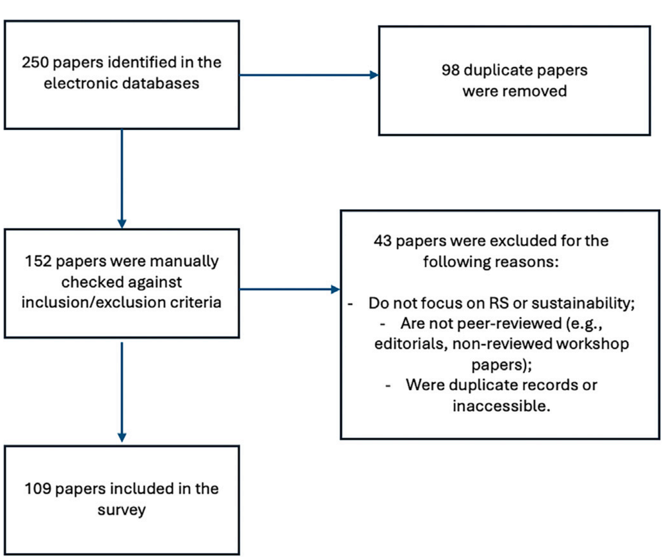

Fig. 2. Flow diagram of the literature search.

For the sake of transparency and reproducibility, the complete list of the 109 analyzed papers, together with their classification according to the sustainability perspective, pillar(s), SDG(s), application domain, and sustainability focus, is reported in Appendix A (Table A.4).

2.2. Related surveys and positioning

The intersection of RS and sustainability is gaining increasing attention, yet existing surveys often address only one side of this interplay. For example, Felfernig et al. [36] and Regona et al. [74] provide broad overviews of AI applications for SDGs but treat RS as a sub-topic. De Biasio et al. [28] focus on economically-aware recommendations, while Van Wynsberghe [101] emphasizes the ethical challenges of sustainable AI. However, no prior work offers a structured, dual-perspective analysis of how RS can both promote sustainability and embody sustainability principles.

Accordingly, this survey fills a clear gap by integrating both angles into a unified framework. In doing so, it aims to guide both researchers and practitioners toward developing RS that not only deliver value but also contribute meaningfully to global sustainability goals.

3. Perspective 1: RS for sustainability

To address RQ1 - *How can recommender systems be designed to not just reflect user preferences, but to actively promote sustainable behaviors and societal good?* - this section explores how RS have been applied across the social, environmental, and economic pillars of sustainability to support the achievement of various Sustainable Development Goals.

As pointed out in [36], RS can be important in supporting the achievement of the United Nations' SDGs. As shown in Table 1, the application of RS to promote sustainable behaviors spans diverse areas, with the ability to address both *macro-level* (organizations, countries) and *micro-level* (individuals, companies) needs.

In the following, we provide an extensive analysis of existing approaches. For the sake of readability, we split the discussion by pillar, and for each pillar, we discuss the applications addressing the goals of a specific SDG. Our choice follows the well-known state-of-the-art classification of SDGs presented in [74], which is sketched in Fig. 3. To further emphasize the connection between SDGs and the pillars of sustainability, we present this literature analysis by categorizing existing methodologies.

It is important to highlight that SDG 17, which focuses on partnerships for the goals, serves as a unifying objective for all the SDGs. It is considered at the top of the classification since its primary aim is to strengthen global collaborations by connecting stakeholders and fostering cooperative efforts to accelerate progress toward achieving sustainability objectives [74].

While this section discusses representative approaches grouped by sustainability pillar and SDG, a detailed paper-by-paper classification of all reviewed works falling under the *RS for Sustainability* perspective is provided in Appendix A (Table A.4).

3.1. Social pillar

First, we analyze recent RS addressing the SDGs classified in the *social pillar*. This pillar focuses on sustainable development with regard to equality, welfare, and prosperity at individual and community levels. These goals can be addressed by a broad range of RS applications, which will be discussed next.

In this pillar, **SDG1** focuses on eradicating poverty globally. Poverty is often described in monetary terms, such as the inability to meet basic living needs. At an individual level, poverty can result from poor financial decisions, and RS can support better decision-making, such as portfolio management, by providing users with consistently appropriate solutions or additional selling opportunities [32,41,43]. At a macro-level, [20,52] demonstrates how RS can help identify export

Table 1
Categorization of Recommender Systems Applications for Sustainability by Pillar and related SDGs.

Pillars	SDGs	Application Areas	References
Social	**SDG 1:** No Poverty	Export diversification strategies, portfolio management	[20,32,41,43,52]
	SDG 2: Zero Hunger	Food security through crop disease detection, logistical support for food rescue organizations	[2,16,63,84,85]
	SDG 3: Good Health and Well-being	Tailored health messages for public campaigns, healthy food, personal well-being	[4,17,50,55,61,65,68,78,91,96]
	SDG 4: Quality Education	Personalized learning experiences, educational resource recommendations	[26,40,45,48,53,57,77]
	SDG 5, 10: Gender Equality, Reduced Inequalities	Recommendations for job recruitment, suggest user eligibility for loan options	[1,14,56,70,86,88,90]
	SDG 11: Sustainable Cities	Sustainable urban planning, tourist guidance toward sustainable destinations	[6,10–12,59,72,95]
	SDG 16: Peace, Justice, and Strong Institutions	Crime analysis and legal assistance, combating misinformation on social platforms	[3,31,39,80,106]
Environmental	**SDG 6:** Clean Water and Sanitation	Sanitation management infrastructure, and water-saving suggestions	[8,19,54,73]
	SDG 7: Affordable and Clean Energy	Energy infrastructure planning, and energy-saving behavior recommendations	[64,66,75,98,104]
	SDG 12: Responsible Consumption and Production	Waste reuse, circular and economy practices, sustainable fashion recommendation	[24,37,58,100]
	SDG 13: Climate Action	Adoption of renewable energy, optimization of local energy consumption	[22,62,81,83,107]
	SDG 14, 15: Life Below Water, Life on Land	Aquaculture support, crop recommendations, wildlife protection	[60,69,87,89,99]
Economic	**SDG 8:** Decent Work and Economic Growth	Open innovation, participatory design, job and partnership recommendations	[35,42,47,51,79]
	SDG 9: Industry, Innovation, and Infrastructure	Sustainable industrial processes and conscious consumer guidance	[29,35,44,109]

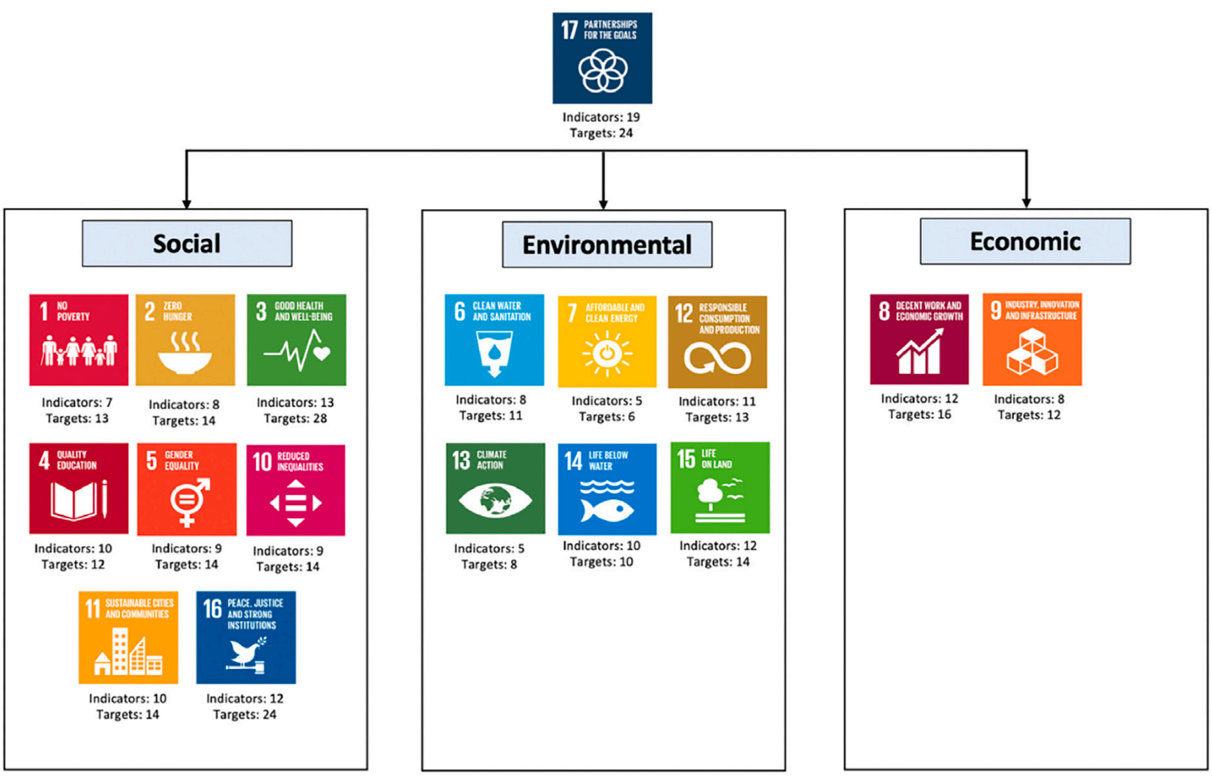

Fig. 3. Classification of SDGs in the three pillars of sustainability [74].

diversification strategies that leverage a country's latent competitive advantages. Limited financial resources often result in malnutrition and food insecurity, making it essential to leverage RS technologies in strategies to eliminate hunger.

Next, **SDG2** focuses on eliminating hunger, enhancing nutrition, and achieving food security while promoting sustainable agricultural practices. Unlike RS designed for healthy living, achieving zero hunger emphasizes mindful food consumption and sustainable food production by *(e.g.,)* assisting in crop disease detection [2,16,63]. Additionally, RS can help food rescue organizations, which collect and distribute food donations to those in need, in facing logistical challenges, such as finding volunteers for specific tasks [84,85]. Addressing food security is closely tied to promoting good health. In this context, recommender systems technologies can support public health initiatives, contributing to the next described goal in the social pillar.

SDG3 is based on ensuring healthy lives and promoting overall well-being. As highlighted by [17,50], public health campaigns greatly benefit from delivering tailored health messages, and RS can easily support this task. Moreover, by focusing on an individual perspective, RS can be exploited for healthy food [61,68,78,96] and personal well-being recommendations [4,91]. In this context, physical activity recommendations can provide tailored suggestions to patients, e.g., to perform their activities to improve sleep [65]. Also drug recommendation systems can be designed to help patients and health-care professionals to identify medications for certain patient conditions or to predict drug side-effects [55]. Ensuring physical and mental well-being is closely linked to the possibility of access to education, which is the main focus of the next goal.

SDG4 focused on providing quality education, along with lifelong learning opportunities, requires integrating communication technologies and personalization strategies to deliver tailored learning experiences [40,45,48]. Several recommendation methods can support learners by suggesting educational resources or helping students assess their knowledge [53,57,77]. Some open challenges are discussed in [26], about how RS should be able to understand the learning goals and the prior knowledge of the student, while also taking into account personal characteristics, such as the student's learning strategy. Education is also a powerful tool for promoting gender equality and reducing social disparities, a central aspect of the next goals.

SDG5 and SDG10 are based on promoting gender equality and reducing inequalities in different application domains. For instance, recommender systems can assist in job recruitment recommendations to avoid inequalities and discrimination [14,56]. Recommender systems can also be effective in decreasing historical inequalities that often limit matching performance in matching organ donors and patients, or in blood bank systems for hospitals to save the patient life in case of emergencies [86,90]. Recommendation technologies can also help in mortgage approval by analyzing factors to assess a borrower's eligibility and suggest suitable loan options for different users [1,70,88].

SDG11 focuses on making cities inclusive, safe, resilient, and sustainable. In this case, RS can assist city planners, policymakers, and citizens by supporting strategic decision-making tailored to a city's specific context and providing explanations that enhance user understanding and sustainability awareness [6,10,12]. Similarly, RS can guide tourists toward environmentally friendly points of interest while minimizing negative impacts on local communities, cultural heritage, and natural resources [11,59,72,95].

Finally, **SDG16** aims to achieve peaceful societies and justice for all. This requires effective, inclusive institutions, and RS can support law enforcement by analyzing co-offender networks, helping identify connections for investigations by comparing current cases with past ones, and using text-based similarity metrics to uncover strong arguments or precedents [3,31,106]. Additionally, RS can address ethical concerns on social media platforms by preventing the risk of creating echo chambers of misinformation [39,80].

3.2. Environmental pillar

While the social pillar focuses on human well-being and equity, the environmental pillar concerns safeguarding and preserving the environment and sustainable resource management. The RS community's attention to addressing these SDGs, which relate to ensuring clean water, sanitation, and clean energy, shares a common focus on leveraging systems to promote resource efficiency and environmentally conscious behavior. Again, in the following, we provide an overview of recent RS applications addressing the SDGs in the environmental pillar.

First, **SDG6** is based on the water management domain, where RS can support the planning and operation of sanitation infrastructure [19,54]. By analyzing consumption data, these systems can also provide personalized suggestions, such as using low-flow fixtures, accompanied by explanations [8], and be used for personalized recommendations to encourage water-conscious behavior [73].

SDG7 is focused on achieving affordable, reliable, and sustainable energy. In this context, RS can optimize infrastructure planning and efficiency [66,104]. These systems can also support public campaigns by delivering personalized recommendations on energy-saving behaviors, tailored to individual household characteristics and consumption patterns [64,75,98], to foster sustainable habits in both water and energy domains.

Next, sustainable consumption and production is the focus of **SDG12**. In this case, RS can help optimize resource use and foster sustainable practices across industries and households. Such systems can recommend opportunities for waste reuse and collaboration between companies, minimizing industrial waste and promoting circular economy practices [37,100]. In the fashion industry, RS can encourage sustainable consumption by reducing product returns, enabling customers to choose higher-quality items, and creating product bundles that alleviate decision-making while promoting sustainability [24,58].

SDG13 focuses on the fight against climate change. RS can help empower the adoption of renewable energy by identifying optimal clusters of prosumers to maximize local energy consumption and reduce reliance on external energy sources [62,83,107]. RS can also help improve individual awareness regarding the impact of daily routines' on the environment [22,81].

Finally, **SDG14** and **SDG15** focus on the sustainable management of marine and terrestrial ecosystems. For oceans and marine ecosystems, RS can recommend suitable species for specific conditions, assist in disease prevention and infrastructure maintenance [89,99], and aid in combating illegal fishing by proposing strategic actions [69]. Sustainable management of terrestrial ecosystems can benefit from similar technologies. In the fight against biodiversity loss, RS can support efforts to prevent wildlife poaching by analyzing behavioral data to predict and suggest counteractions for illegal activities [60,87].

3.3. Economic pillar

The economic pillar focuses on individual and global welfare, emphasizing economic prosperity, sustainable industrialization, and innovation. The analysis of recent RS applications classified under this pillar primarily relates to SDGs 8 and 9.

SDG8 is focused on fostering economic growth and quality employment. In this context, RS can be crucial in facilitating open innovation and participatory design. By recommending relevant ideas to community members or collaborators, RS support idea generation and help identify acceptable solutions for sustainability [35,47]. They also enhance people-to-people connections by recommending partnerships, jobs, or collaborators, which contribute to enterprise stability and economic growth [42,51,79].

To conclude, **SDG9** is based on industrialization, and RS serves as a knowledge transfer tool, helping industries identify opportunities for process optimization and sustainable materials [44]. They can also guide customers in making environmentally conscious choices by offering insights into the properties of the products, such as environmental impact or animal welfare. This addresses the gap in accessing information regarding sustainability and supports industries in achieving sustainability goals [29,35,109].

3.4. Discussion and limitations

The application of RS to promote sustainability and achieve SDGs demonstrates significant promise. As discussed throughout this section, RS has the potential to address a wide spectrum of sustainability challenges. However, despite its potential, certain limitations and challenges must be addressed to enhance its impact and efficacy.

Bridging theory and real-world implementation. A significant limitation is the gap between theoretical approaches and real-world implementations. While numerous methodologies have been proposed, their deployment often faces practical constraints, such as scalability, infrastructure requirements, and cultural or behavioral barriers among end-users. Furthermore, integrating RS into existing systems and workflows, especially in domains like agriculture or energy, can be complex and resource-intensive. To speed up this process, it is also necessary to introduce novel ad-hoc metrics to quantitatively assess how much an RS contributes to achieving a particular SDG. This can be particularly useful in critical domains, *i.e.,* health, where the effectiveness of nudging and behavior change strategies is hard to assess [46].

Unexplored potential of multi-pillar applications. So far, most attempts to address SDGs through RS have been designed and evaluated by focusing on a single goal. Unfortunately, this choice has not fully unveiled the potential of this technology since RS could be designed to impact multiple SDGs simultaneously. For instance, applications that aim at sustainable consumption and production (SDG 12), can also intersect the environmental and economic pillars. This can be achieved by optimizing resource use while supporting cost-efficient industrial practices and consumer decision-making. Similarly, applications addressing urban sustainability and tourism (SDG 11) generally focus on social goals like inclusivity and livability. These can be extended to simultaneously consider environmental objectives, such as minimizing ecological impact. In healthcare (SDG 3), personalized recommendations improve individual well-being while boosting workforce productivity and reducing economic healthcare burdens. Additionally, clean energy and climate action initiatives (SDGs 7 and 13) bridge environmental sustainability with economic stability by reducing emissions and lowering energy costs. While some preliminary studies have already addressed multiple SDGs, they have primarily focused on accuracy-based metrics rather than explicitly evaluating the extent to which multiple SDGs are met. A more comprehensive evaluation is necessary to measure the broader effects of RS on multiple SDGs beyond standard performance metrics.

To answer RQ1, our overview showed that RS can significantly advance SDGs. However, to fully realize this potential, it is crucial to address their limitations by pushing inter-pillar applications. This can be achieved through interdisciplinary collaboration and a more robust evaluation of the frameworks, especially in real-world settings. These limitations also highlight the need for appropriate multi-objective evaluation metrics to support RS that can simultaneously optimize for multiple sustainability objectives (see Section 5).

4. Perspective 2: Sustainability of RS

To explore RQ2 - *What are the hidden environmental and ethical costs of deploying large-scale recommender systems, and how can we redesign them to align with sustainability principles?* - this section investigates how current RS models incorporate social, environmental, and economic sustainability into their design, training, and evaluation.

While the use of RS to achieve sustainability goals shows great potential and many relevant applications, it is equally important to emphasize that the design and development of the recommendation algorithms should follow sustainability principles as well, regardless of the specific SDG they aim to address [101].

This intuition fits into the research regarding *beyond-accuracy* objectives of RS [49], *i.e.*, research proposing methods and metrics to evaluate aspects different from the accuracy of the recommendations. This includes addressing principles aligned with sustainability, such as *diversity, fairness, transparency, affordability*, and the *environmental impact*. Before analyzing the current state of the field, it is useful to first introduce a general pipeline sketching the stages that characterize the life cycle of a RS. Fig. 4 illustrates the essential steps to deliver personalized recommendations.

First, the process begins with choosing a recommendation model, which represents the algorithm that underpins the RS. This stage involves selecting the recommendation paradigm, such as collaborative filtering, content-based filtering, or hybrid approaches [76], tuning the hyperparameters, and training the model. Of course, a dataset is needed to carry out the training. Data exploited in this phase include users' characteristics and past interactions, sometimes together with some information that describes the items. Some paradigms also explicitly encode knowledge that can be used to drive the algorithm's behavior. After the training, the model can finally deliver recommendations to end-users that are evaluated based on several metrics.

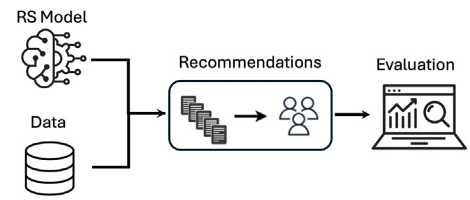

Fig. 4. Lifecycle of a RS.

Based on this lifecycle, it becomes evident that sustainability principles must be addressed at every stage. Regarding the choice of the model, the algorithm should be fair, transparent, and have a low environmental impact. Similarly, the data should avoid the presence of *biases* and should be kept to a minimum to reduce the energy consumption of the training. Of course, ad-hoc evaluation metrics can be exploited to assess the extent to which a certain principle is addressed.

In the following, we discuss how sustainability principles have influenced the design and development of current RS. An overview of the attempts discussed in this section is presented in Table 2. Similar to the previous section, for the sake of readability, we split the discussion pillar by pillar. Moreover, all contributions addressing the *Sustainability of RS* perspective are systematically listed and categorized in Appendix A (Table A.4), enabling readers to trace each discussed principle back to the corresponding primary sources.

4.1. Social pillar

Social and ethical considerations are central to the design of sustainable RS, as they directly influence how fairly and responsibly these systems operate. In particular, the social pillar can be addressed by implementing *fair* recommendation algorithms. This ensures that RS mitigate or eliminate biases in the input data as well as in their output, thereby reducing disparities in treating different user demographics or items with varying popularity levels [30]. As pointed out in [15], an RS shall expose fair behavior also from the provider's perspective. For example, in e-commerce platforms, suggesting products from a limited range of brands or price points may inadvertently exclude smaller or less popular sellers. Conversely, by addressing fairness, RS can ensure that all sellers, regardless of size, are represented fairly to users.

In RS, fairness can be addressed either by design [92], *i.e.,* implementing models that provide recommendations that are already fair, or by exploiting post-hoc strategies, *i.e.*, strategies that re-rank an unfair recommendation list [25]. Regarding fairness, it is worth emphasizing that this principle can also be addressed at a dataset level. This includes implementing debiasing strategies [21] to increase fairness in the training data, *(e.g.,)*, through data augmentation techniques.

Moreover, RS can be designed to address other principles emphasized in the social pillar, such as *explainability, diversity*, and *transparency* [33]. Again, RS can prioritize these principles by design [9] or can implement strategies to re-rank a recommendation list and promote options that are more explainable or diverse [18]. Generally speaking, all these strategies enable stakeholders to oversee and evaluate these systems, ensuring they function fairly and transparently. Indeed, when users can understand the decision-making processes behind recommendations, they are more likely to trust and engage with these systems, resulting in a more positive user experience [103].

Table 2
How sustainability principles are addressed in the different stages of a recommendation pipeline.

Pillars	Model Selection and Training	Dataset Building and Selection	Evaluation Metrics	SoTA Ref.
Social	- Fairness and explainability by design - Post-hoc re-ranking to enhance fairness or explainability	- Debiasing Strategies (*i.e.,* through Data Augmentation)	- Fairness across users - Fairness across items - Diversity & Coverage - Serendipity & Novelty - Explainability - Transparency	[9,15,18,21,25,30,33,92,103]
Environmental	- Benchmarking energy consumption in RS - Finding ideal trade-off between carbon emissions and performance - Automatic hyperparameter optimization	- Data reduction techniques	- Carbon footprint - Energy consumption	[5,7,13,82,93,94,102]
Economic	- Customer-oriented: price sensitivity, economic utility model - Organization oriented: profit awareness, long-term value	- User segmentation and encoding of economic-aware features	-Business-Oriented Metrics (*e.g.*, Click-through rate) - User adoption - User engagement	[27,28,38,67,108]

4.2. Environmental pillar

The increasing complexity of RS has raised pressing concerns about its energy consumption and environmental impact. Addressing these challenges requires detailed analysis to balance efficiency with the carbon emissions of the algorithms [5].

Accordingly, the interest in RS that minimize their environmental impact while guaranteeing good predictive accuracy is relatively recent [82]. In particular, the first works in the area started benchmarking the carbon emissions of RS [102] and assessing the trade-off between overall performance and their environmental impact. For example, a recent analysis by [93] showed that less complex recommendation algorithms generally offer the best compromise between accuracy and the amount of CO_2 emissions of the models.

To mitigate the environmental impact of RS, recent research has explored data reduction techniques: down-sampling large datasets is an environmentally conscious strategy, as extensive data volumes are not always necessary for training or evaluating recommender algorithms effectively [7,94]. Similarly, hyperparameter optimization techniques have emerged as an environmentally sustainable alternative to reduce computational requirements while preserving accuracy [13].

4.3. Economic pillar

Regarding the aspects related to the economic dimension, in [28], the authors provide a systematic review highlighting how recommendation models can directly target organizational economic goals by integrating considerations such as price awareness and profitability. For example, in [67], a value-aware strategy to maximize the profit in an e-commerce platform is presented. Of course, to address the economic dimension of sustainability, it is necessary to include customer-oriented approaches. In this research line, [108] introduces the concept of *affordability* and price-aware recommendation. The dichotomy between customer-oriented and organization-oriented approaches is finally investigated in [38], which explores the tension between consumer trust and provider profit in recommendation strategies by demonstrating that strategies balancing consumer utility and profitability yield the highest long-term benefits.

All these works highlight the importance of designing *value-aware RS* [27] that optimize the economic value for multiple stakeholders simultaneously.

4.4. Discussion and limitations

As shown in Table 2, the principles spread by the environmental, social, and economic pillars of sustainability have already influenced design and the development of RS at different levels. However, while significant progress has been made, several limitations still persist.

Lack of standards for impact assessment. As regards the *environmental* perspective, the majority of research focuses on measuring energy consumption and $CO2$ emissions of RS models. However, there is a lack of standardized tools and protocols to evaluate them in a fair and reproducible manner. Moreover, methods to automatically find the trade-off between accuracy and emissions or strategies to automatically adapt training data to minimize the environmental impact of the algorithm while keeping a good accuracy are still at an early stage. Next, regarding the *social* dimension, many mechanisms to mitigate biases and improve explainability have been proposed. However, the literature shows a lack of real-world implementation of these algorithms and limited studies to assess the impact of these strategies on real users. Finally, in the *economic* dimension, research has demonstrated that profitability and consumer satisfaction can coexist, but operationalizing this balance in real-world systems remains challenging. Furthermore, the economic evaluation of RS is context-dependent, and generalizable methods for assessing profitability and cost-efficiency are still unexplored.

Need for multi-objective RS. Regarding the evaluation metrics, it is worth emphasizing that most of them were defined and proposed before the advent of SDGs. This particularly holds for metrics that fall into the social dimension, such as *fairness* and *explainability*. Accordingly, it is unsurprising that most current literature addresses and analyzes these metrics in isolation,*i.e.,* without considering other pillars and other goals. In this case, it is necessary to push the research toward *multi-objective RS*, where multiple evaluation metrics and potentially multiple stakeholders are considered simultaneously. Our vision regarding multi-pillar and multi-objective RS will be better discussed in the next section.

In conclusion and to answer RQ2, we can confirm that promising strategies have emerged to reduce the ethical and environmental costs of recommender systems. However, addressing these challenges at scale demands standardized impact assessments, multi-objective optimization, and a stronger commitment to embedding sustainability principles throughout the entire RS lifecycle.

5. The dual perspective of sustainability and RS: Towards a research path

The overview of the research presented in the previous sections has confirmed the strong interplay between two perspectives: *(i)* the application of RS to achieve SDGs; *(ii)* the adoption of sustainability principles to design and develop the recommendation algorithm itself. However, as we depicted in Fig. 1, a comprehensive integration of both perspectives, *i.e., RS for Sustainability* and *Sustainability of RS*, is necessary to fully exploit the potential of this research direction.

Moreover, as the analysis of the current literature shows, existing approaches rarely address more than one pillar, and there is a scarcity of work proposing multi-objective approaches combining multiple pillars simultaneously. Accordingly, this section outlines our vision to further advance research in RS and sustainability and sketches a research path for a more holistic exploitation of these perspectives.

To address RQ3 - *Can we envision a future where recommender systems both enable sustainable choices and are themselves sustainable, without compromising performance or user experience?* - this section outlines a research roadmap toward integrating both perspectives of sustainability in RS: their application for societal good and their responsible, low-impact design.

5.1. Fostering multi-pillar applications

As shown in Table 1, most applications exploiting RS to address SDGs focus on a single pillar of sustainability without fully leveraging their interconnected nature. To further advance research in the area, it is necessary to design more comprehensive approaches impacting multiple pillars. While this can be seamlessly achieved, *i.e.*, the output of a specific application impacts different SDGs without any specific design decision, further emphasis and design innovation are needed to meet this requirement.

In this sense, increasing researchers' and practitioners' knowledge and awareness of SDG-related goals and further emphasizing the importance of interdisciplinary approaches can be helpful. This will allow for the design of more sophisticated applications that may impact all the pillars simultaneously. For example, recommending products and services that minimize environmental impacts [24] can also influence the economic pillar. Similarly, promoting sustainable behaviors, such as encouraging energy-saving actions [104], also impacts goals in the social pillar. In this direction, some attempts have recently begun developing multi-pillar applications, such as recommending food options that are healthy and sustainable at the same time [68]. However, to fully exploit the potential of RS to achieve SDGs, more effort is needed.

5.2. Multi-objective RS and multi-pillar evaluation

The effectiveness of RS in addressing SDGs is generally evaluated using accuracy-based evaluation metrics, which are insufficient to assess whether and how a particular RS achieves sustainability goals. Conversely, metrics that assess carbon footprint, energy efficiency, and resource utilization are essential for evaluating *environmental* sustainability. Similarly, fairness, diversity, and inclusivity metrics are crucial for assessing *social* sustainability, while *economic* sustainability requires metrics that measure profitability, cost-effectiveness, and long-term user retention.

While there is a growing need for evaluation frameworks that capture the broader impacts of RS [34], most of these metrics are generally overlooked in RS literature. Moreover, even when considered, they are evaluated in isolation, *i.e.*, by ignoring evaluation metrics concerning other pillars. On the contrary, a tighter integration of sustainability metrics across pillars is essential, and more effort is needed to combine them into more comprehensive evaluation protocols.

Beyond the evaluation phase, the investigation of *multi-objective optimization* techniques [105] represents another fundamental cornerstone, which is necessary to fully implement the vision behind SDGs. These methods can balance competing goals such as accuracy, fairness, and economic impact within a single framework. In this way, they can lead to applications that tackle multiple sustainability pillars simultaneously, *i.e.,* providing fair recommendations while minimizing the environmental impact of the algorithm. While some attempts in this direction have already been proposed, there is room for improvement since current strategies do not simultaneously embrace *all* sustainability pillars.

5.3. Towards holistic and sustainable recommender systems

In our vision, a research path that fully implements the dual perspective of sustainability and RS should embrace a broader and more *holistic* approach. First, algorithms must be designed and implemented to address all the pillars simultaneously. As previously stated, this can be achieved through multi-objective optimization techniques. To sum up, holistic and sustainable RS shall support a wide array of human values [97]: they should be *fair*, avoid *biases*, be *environmental-friendly*, and also be *transparent*, empowering users to understand the rationale behind recommendations and their alignment with sustainability goals. Moreover, they shall have the ability to operate in a *multi-stakeholder* setting, optimizing multiple goals at the same time.

Next, a recommendation model designed according to all these principles, can be applied to a specific use case and shall impact more than one pillar simultaneously. In other terms, it is necessary to go in the direction of *multi-pillar applications that follow a multi-objective design*. Of course, to assess the effectiveness of such a new vision, it is also necessary to introduce more comprehensive evaluation frameworks that successfully combine metrics from multiple pillars. Moreover, large-scale human evaluations will be fundamental to definitively assess the effectiveness of these models.

5.4. Current gaps in the state of the art

To further support the research gaps outlined in Table 3, we provide concrete examples from the literature that address each of the four highlighted research directions: multi-pillar applications, multi-objective recommender systems, evaluation frameworks beyond accuracy, and cross-disciplinary collaborations. While some promising studies have emerged, our review confirms that such efforts are still relatively rare and often fragmented.

Multi-pillar RS applications. Although most studies focus on a single sustainability pillar, a few works explicitly target multiple pillars simultaneously. For example, Petruzzelli et al. [68] proposed a recommender system for healthy and sustainable meals, which integrates both social (health) and environmental sustainability objectives. Similarly, Cossatin et al. [24] developed a fashion RS that reduces returns and waste (environmental) while promoting higher-value purchasing decisions (economic). Banerjee et al. [11] presented a tourism RS that guides users toward environmentally friendly travel choices while also considering social and cultural impacts on local communities. These cases demonstrate the feasibility of designing RS that span across pillars, though such multi-pillar applications remain underexplored and rarely evaluated holistically.

Multi-objective recommender systems. Several studies embrace a multi-objective paradigm by optimizing two or more conflicting goals. For instance, Pei et al. [67] and Ghanem et al. [38] introduce RS that jointly optimize accuracy and profit, reflecting both user satisfaction and economic viability. Spillo et al. [93] and Vente et al. [102] explore trade-offs between recommendation performance and carbon footprint, introducing environmental constraints into the RS design. Cui et al. [25] propose post-hoc strategies to re-balance recommendation fairness while preserving utility. These studies show the growing relevance of multi-objective optimization in RS, but they typically consider only two objectives and rarely incorporate all three sustainability pillars together.

Evaluation frameworks beyond accuracy. Traditional evaluation approaches remain dominant, but several efforts aim to broaden this scope. Spillo et al. [93] evaluate RS using environmental impact metrics such as energy consumption and $CO2$ emissions. Deldjoo et al. [30] and Ekstrand et al. [34] advocate for fairness-aware and distributionally-informed evaluation methods, expanding metrics to include equity and user diversity. Kaminskas and Bridge [49] offer a framework for measuring diversity, novelty, and serendipity in RS, while Beel et al. [13] call for the integration of green metrics into RS evaluation pipelines. Despite this progress, standardized and unified frameworks for beyond-accuracy evaluation remain lacking, particularly those that capture sustainability across multiple dimensions.

Table 3
State of the Art (SoTA) and gaps in sustainable recommender systems research.

Research direction	SoTA maturity	SoTA Ref.	Current practices	Main gaps
Developing Multi-Pillar RS Applications	Low	[11,24,68]	Some systems address 2 pillars (e.g., health + environment)	Rarely address all three pillars (environmental, social, economic) simultaneously
Creating Multi-Objective RS	Medium	[25,38,67,93,102]	Recognized interest in balancing fairness and accuracy, emerging interest in balancing environmental aspects and accuracy	Lack of frameworks that balance environmental, social and economic objectives concurrently
Designing Evaluation Frameworks Beyond Accuracy	Medium	[13,30,34,49,93]	Some works use either fairness metrics or carbon footprint separately	Evaluations are mostly isolated; no integrated multi-pillar evaluation protocols
Establishing Cross Disciplinary Collaborations	Low	[35,68,97]	Few cases involve stakeholders beyond computer science	Missing practical, interdisciplinary teams including economists, environmentalists, policymakers

Cross-disciplinary collaborations. Addressing sustainability in RS inherently requires input from diverse fields. While cross-disciplinary collaborations are still uncommon, several studies exemplify this approach. For instance, Petruzzelli et al. [68] and Fayed & Wohlgemuth [35] integrate health, environmental science, and AI to design multi-purpose RS. Stray et al. [97] explicitly propose an interdisciplinary synthesis combining ethics, sociology, and AI for human-centric RS design. These examples illustrate the value of cross-sectoral collaboration, though current practices are limited and often lack institutionalized frameworks for interdisciplinary research.

In summary, while Table 3 highlights significant research gaps, emerging studies demonstrate that addressing these four dimensions is both feasible and impactful. Appendix A (Table A.4) also highlights a subset of works explicitly addressing integrated perspectives, namely multi-pillar, multi-objective, cross-disciplinary, and beyond accuracy evaluation approaches as discussed in this section.

To answer RQ3, accelerating progress in these areas requires deeper integration of sustainability objectives into RS design, broader evaluation frameworks, and stronger partnerships across domains.

6. Conclusions and open challenges

This survey has emphasized the dual role of RS in advancing sustainability: as tools to promote sustainable behaviors and as technologies that must be designed sustainably. While significant progress has been made, several key challenges remain unresolved, and future research must address these gaps to fully realize the potential of sustainable RS. Integrating sustainability into RS requires a holistic approach considering the interconnected social, economic, and environmental pillars. Current evaluation practices are insufficient, and they must evolve to include sustainability-specific metrics that capture broader impacts. Additionally, future systems should employ multi-objective optimization techniques capable of balancing competing sustainability goals.

One critical area for future work is the need for standardized metrics and evaluation frameworks that comprehensively assess the sustainability impacts of RS. These frameworks should include direct measures, such as carbon emissions, and indirect outcomes, such as user inclusivity. Cross-disciplinary collaboration will also be crucial, as sustainability challenges span technical, social, and economic domains. Partnerships between computer scientists, environmentalists, economists, and policymakers can help create effective and practical. solutions. Additionally, real-world deployments and pilot studies are necessary to bridge the gap between theoretical advancements and practical implementations, providing valuable insights into the scalability and effectiveness of sustainable RS. In conclusion, RS hold immense potential to drive sustainability across various domains. By adopting a twofold perspective that integrates sustainability into both their application and design, researchers and practitioners can create systems that not only meet user needs but also contribute to a more sustainable future.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A

The following table provides a comprehensive overview of all the 109 papers included in this survey. Each work is explicitly classified according to: (i) the sustainability perspective adopted (RS for Sustainability, Sustainability of RS); (ii) the sustainability pillar(s) addressed (social, environmental, economic); (iii) the main Sustainable Development Goal(s) targeted; (iv) the application domain; and (v) the specific sustainability focus. We also highlight a subset of works explicitly addressing multi-pillar, multi-objective, cross-disciplinary, or beyond accuracy evaluation approaches as discussed in Section 5. This structured representation complements the analysis presented in the main body of the paper, and it allows for easily identifying research trend areas across the state of the art.

Out of the 109 analyzed papers, 76 focus primarily on the *RS for Sustainability* perspective, 23 address the *Sustainability of RS*, and (among them) 10 explicitly adopt an integrated approach in the direction of a dual perspective. The remaining contributions provide background or contextual foundations on sustainability and recommender systems.

This extended table confirms the analysis presented in Section 5. Only a limited fraction of the reviewed literature explicitly addresses multiple sustainability pillars simultaneously. Multi-pillar approaches are still relatively rare and are mostly confined to specific domains such as food, tourism, and fashion, highlighting a significant gap in the current state of the art.

This clearly indicates that, while the literature on RS and sustainability is rapidly growing, most existing approaches remain siloed, either focusing on a single sustainability pillar or addressing only one of the two perspectives. This fragmentation motivates the need for holistic, multi-objective, and multi-pillar recommender systems.

Data availability

No data was used for the research described in the article.

Table A.4
Complete list of papers classified based on the proposed dual perspective.

Ref.	Sustainability Perspective	Pillar(s)	Main SDG(s)	Application Domain	Sustainability Focus
[1]	RS for Sustainability	Social	SDG 10	Finance	Loan approval for social inclusion
[2]	RS for Sustainability	Social	SDG 2	Agriculture	Crop disease detection
[3]	RS for Sustainability	Social	SDG 16	Public safety	Crime analysis
[4]	RS for Sustainability	Social	SDG 3	Health	Personal Well-being
[5]	Sustainability of RS	Environmental	SDG 13	ML systems	CO_2 analysis
[6]	RS for Sustainability	Social	SDG 11	Smart cities	Urban sustainability
[7]	Sustainability of RS	Environmental	SDG 13	RS methodology	Data reduction techniques
[8]	RS for Sustainability	Environmental	SDG 6	Water management	Water-saving behavior
[9]	Sustainability of RS	Social	SDG 16	RS methodology	Explainability of RS
[10]	RS for Sustainability	Social	SDG 11	Tourism	Sustainable tourism
[11]	RS for Sustainability (Multi-Pillar RS)	Social, Environmental	SDG 11, SDG 13	Tourism	CO_2-aware trip planning
[12]	RS for Sustainability	Social	SDG 11	Tourism	Responsible travel
[13]	Sustainability of RS (Beyond Accuracy)	Environmental	SDG 13	RS evaluation	Green metrics
[14]	RS for Sustainability	Social	SDG 10	Human resources	Fair recruitment
[15]	Sustainability of RS	Social	SDG 10	E-commerce	Bias mitigation
[16]	RS for Sustainability	Social	SDG 2	Agriculture	Sustainable farming
[17]	RS for Sustainability	Social	SDG 3	Health	Tailored campaigns
[18]	Sustainability of RS	Social	SDG 16	RS methodology	Diversity promotion in RS
[19]	RS for Sustainability	Environmental	SDG 6	Water management	Source water protection
[20]	RS for Sustainability	Social	SDG 1	Export policy	Export diversification
[21]	Sustainability of RS	Social	SDG 10	RS methodology	Debiasing strategies
[22]	RS for Sustainability	Environmental	SDG 13	Environmental education	Climate awareness
[23]	Background	–	–	Policy	SDGs framework
[24]	RS for Sustainability (Multi-Pillar RS)	Environmental, Economic	SDG 12, SDG 9	Fashion	Waste reduction
[25]	Sustainability of RS (Multi-Objective RS)	Social	SDG 10, SDG 16	RS methodology	Fair ranking
[26]	RS for Sustainability	Social	SDG 4	Education	Educational RS survey
[27]	Sustainability of RS	Economic	SDG 8	RS methodology	Value-aware RS
[28]	Sustainability of RS	Economic	SDG 9	RS methodology	Business value analysis of RS
[29]	RS for Sustainability	Economic	SDG 9	Sustainable Communities	Personal values in RS
[30]	Sustainability of RS (Beyond Accuracy)	Social	SDG 10	RS methodology	Fairness in RS
[31]	RS for Sustainability	Social	SDG 16	Legal	Legal assistance
[32]	RS for Sustainability	Social	SDG 1	E-commerce	Eco-conscious consumers
[33]	Sustainability of RS	Social	SDG 10	Musical industry	Bias mitigation
[34]	Background	–	–	RS evaluation	Evaluation frameworks
[35]	RS for Sustainability (Cross Disciplinary)	Economic, Environmental	SDG 8, SDG 9, SDG 7	Industry	Resource efficiency
[36]	Background	–	–	Survey	RS and sustainability
[37]	RS for Sustainability	Environmental	SDG 12	Waste management	Smart waste systems
[38]	Sustainability of RS (Multi-Objective RS)	Economic	SDG 8, SDG 9	E-commerce	Profit-trust trade-off
[39]	RS for Sustainability	Social	SDG 16	Media	Fake news detection
[40]	RS for Sustainability	Social	SDG 4	Digital education	Personalized learning
[41]	RS for Sustainability	Social	SDG 1	Online platforms	Exposure of consumers
[42]	RS for Sustainability	Economic	SDG 8	Job recommendations	User-driven interaction for RS
[43]	RS for Sustainability	Social	SDG 1	Finance	Decision support for social inclusion
[44]	RS for Sustainability	Economic	SDG 9	Sustainable innovation	Sustainable report analysis
[45]	RS for Sustainability	Social	SDG 4	Education	Learning engagement
[46]	Background	–	–	Survey	Nudging effect of RS
[47]	RS for Sustainability	Economic	SDG 8	Design	Human-AI collaboration
[48]	RS for Sustainability	Social	SDG 4	Education	Academic recommendation
[49]	Background	–	–	RS evaluation	Evaluation frameworks
[50]	RS for Sustainability	Social	SDG 3	Health	Tailored messages
[51]	RS for Sustainability	Economic	SDG 8	Economic growth	Partnership and job recommendations
[52]	RS for Sustainability	Social	SDG 1	International trade	Country fitness modeling
[53]	RS for Sustainability	Social	SDG 4	Education	Adaptive learning
[54]	RS for Sustainability	Environmental	SDG 6	Water sanitation	Infrastructure planning
[55]	RS for Sustainability	Social	SDG 3	Health	Drug recommendation
[56]	RS for Sustainability	Social	SDG 10	Human resources	Fair Recruitment
[57]	RS for Sustainability	Social	SDG 4	Education	Learning resources
[58]	RS for Sustainability	Environmental	SDG 12	Tourism	Congestion reduction
[59]	RS for Sustainability	Social	SDG 11	Tourism	Urban sustainability
[60]	RS for Sustainability	Environmental	SDG 15	Wildlife	Conservation support
[61]	RS for Sustainability	Social	SDG 3	Food	Explainable food RS

(*continued on next page*)

Table A.4
(*continued*)

Ref.	Sustainability Perspective	Pillar(s)	Main SDG(s)	Application Domain	Sustainability Focus
[62]	RS for Sustainability	Environmental	SDG 13	Urban planning	Climate impact reduction
[63]	RS for Sustainability	Social	SDG 2	Agriculture	Crop disease detection
[64]	RS for Sustainability	Environmental	SDG 7	Energy	Prosumer support
[65]	RS for Sustainability	Social	SDG 3	Health	Lifestyle improvement
[66]	RS for Sustainability	Environmental	SDG 7	Energy	Renewable energy planning
[67]	Sustainability of RS (Multi-Objective RS)	Economic	SDG 8, SDG 9	E-commerce	Profit-aware systems
[68]	RS for Sustainability (Multi-Pillar, Cross Disciplinary)	Social, Environmental	SDG 3, SDG 12	Food	Healthy and sustainable meals
[69]	RS for Sustainability	Environmental	SDG 14	Aquaculture	Fish farming optimization
[70]	RS for Sustainability	Social	SDG 10	Banking	Fair customer experience
[71]	Background	–	–	Theory	Sustainability pillars
[72]	RS for Sustainability	Social	SDG 11	Smart cities	Intent-aware systems
[73]	RS for Sustainability	Environmental	SDG 6	Water	Consumption awareness
[74]	Background	–	–	Survey	AI and SDGs
[75]	RS for Sustainability	Environmental	SDG 7	Energy	Energy efficiency
[76]	Background	–	–	RS	RS foundations
[77]	RS for Sustainability	Social	SDG 4	Education	Educational Resource recommendations
[78]	RS for Sustainability	Social	SDG 3	Food	Healthy diets
[79]	RS for Sustainability	Economic	SDG 8	Employment	Job matching
[80]	RS for Sustainability	Social	SDG 16	Media	Trust and misinformation
[81]	RS for Sustainability	Environmental	SDG 13	Energy	Energy efficiency
[82]	Sustainability of RS	Environmental	SDG 13	Information Retrieval	Green Search
[83]	RS for Sustainability	Environmental	SDG 13	Energy	Renewable energy recommendations
[84]	RS for Sustainability	Social	SDG 2	Food	Crowdsourcing food rescue platforms
[85]	RS for Sustainability	Social	SDG 2	Food	Food rescue platforms
[86]	RS for Sustainability	Social	SDG 10	Health	Organ matching
[87]	RS for Sustainability	Environmental	SDG 15	Wildlife	Geo-based recommendation
[88]	RS for Sustainability	Social	SDG 10	Finance	Fair debt collection process
[89]	RS for Sustainability	Environmental	SDG 14	Products	Ecosystem protection
[90]	RS for Sustainability	Social	SDG 10	Health	Fair donation systems
[91]	RS for Sustainability	Social	SDG 3	Health	Well-being management
[92]	Sustainability of RS	Social	SDG 10	RS modeling	Multi-sided fairness
[93]	Sustainability of RS (Multi-Objective + Beyond Accuracy)	Environmental	SDG 7, SDG 13	RS evaluation	Carbon/Accuracy trade-offs
[94]	Sustainability of RS	Environmental	SDG 13	RS evaluation	Energy-aware evaluation
[95]	RS for Sustainability	Social	SDG 11	Smart Cities	Sustainable recommendations
[96]	RS for Sustainability	Social	SDG 3	Health	Explainable recipe recommendations
[97]	Sustainability of RS (Cross Disciplinary)	Social, Environmental	SDG 1, SDG 10, SDG 13	Ethics	Human-centric AI
[98]	Sustainability of RS	Environmental	SDG 7	Energy management	Energy efficiency
[99]	RS for Sustainability	Environmental	SDG 14	Life under water	Marine ecosystems preservation
[100]	RS for Sustainability	Environmental	SDG 12	Consumption	Sustainable choice support
[101]	Background	–	–	Theory	AI and Sustainability
[102]	Sustainability of RS (Multi-Objective RS)	Environmental	SDG 7, SDG 13	RS evaluation	Carbon benchmarking
[103]	Sustainability of RS	Social	SDG 16	RS governance	Trustworthy recommendation
[104]	RS for Sustainability	Environmental	SDG 7	Energy	Renewable energy recommendations
[105]	Background	–	–	RS methodology	Multi-objective optimization
[106]	RS for Sustainability	Social	SDG 16	Legal	Legal case recommendations
[107]	RS for Sustainability	Environmental	SDG 13	Energy	Personalized recommendations
[108]	Sustainability of RS	Economic	SDG 9	E-commerce	Affordability of RS
[109]	RS for Sustainability	Economic	SDG 9	Finance	RS for driving organizations

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