Recommendation Systems in Nutrition Field: A Scoping Review

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Abstract

Background: Recommendation systems (RS) have been widely used in the field of nutrition to promote the nutritional self-management, but few NRSs have been widely adopted due to various reasons. Limited studies have reviewed the RSs in food, with some methodological flaws including limited databases searches, high heterogeneity among included studies and rapidly evolving nature of evidence.

Objective: We conducted a scoping review to summarize currently available recommendation systems applied in nutrition (NRS) including published articles, patents and application software and explore the potential gaps between development and implementation.

Methods: We conducted a comprehensive search of seven bibliographic databases, two patent databases, four mobile apps store and three websites engines for this scoping reviews. Data extraction was conducted by four reviewers, a pilot study was performed before formal extraction, and the interrater agreement percentage needed to be >75%. Discrepancies were resolved by consensus or the involvement of a third reviewer. Frequency count and narrative summaries were performed for each study.

Results: A total of 877 NRSs were included and half of them were released after 2022 (n=423, 48.2%) and 155 (17.7%) were from China. The most users were overweight or obese population (n=152, 17.3%), the primary inputs being self-reported data on nutritional status, diet, and exercise (the same n=157, 17.9% for every one), the primary output being nutrition plans (n=254, 29.0%), and the main audience being general population (n=244, 27.8%). Of 49 studies published in journals or essays, a few researchers from the nutrition filed were reported (n=4, 3.6%), the primary data were from public survey (n=22, 46.8%). Forty studies reported the evaluation stage, with incomplete processes and the lack of nutritional outcome. Of the 18 artificial intelligence technologies used in the studies, four could automatically update systems by themselves, and two were technologies proposed in the last decade. In addition, three recommendation algorithms were identified, only one was the latest knowledge-based algorithm that can improve precise matching.

Conclusions: While NRSs has primarily focused on the general population, there is a growing demand for professional NRSs tailored to special populations that incorporate dynamic updates and enhanced individual identification. Standardized evaluation of NRSs based on their technical performance and clinical impact can effectively support their public application in future. Clinical Trial: The protocol was registered on the Open Science Framework (https://doi.org/10.17605/OSF.IO/VF7NB)

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ABSTRACT

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Conclusion

While NRSs has primarily focused on the general population, there is a growing demand for professional NRSs tailored to special populations that incorporate dynamic updates and enhanced individual identification. Standardized evaluation of NRSs based on their technical performance and clinical impact can effectively support their public application in future.

KEYWORDS Nutrition, Recommendation Systems, Scoping Review

INTRODUCTION

Good nutrition is essential for healthy development and basic survival, as well as for well-being and disease prevention [1]. Unhealthy diet and lack of physical activity are the leading global risk factors for death and contribute to the development of many noncommunicable diseases such as cardiovascular disease, hypertension, and diabetes [1-3]. The double burden of malnutrition, which includes both undernutrition and overnutrition, has become even more pronounced as the number of people over the age of 65 continues to rise around the world [4-5]. Current estimates indicate that about a quarter of adults aged 65 and older are malnourished or at risk of malnutrition [6]. Several organizations, including the Rockefeller Foundation and the American Heart Association, have announced initiatives to promote better integration of nutrition and health by 2022 [7]. While many people, especially those who are obese, have chronic diseases, or are over the age of 65, are aware of the importance of diet for health, the vast amount of nutrition information, a shortage of nutritionists and other health professionals, a lack of basic health and nutrition knowledge and misleading advertising and marketing prevent them from making healthy food choices or receiving individualized nutrition interventions [8-12].

With the advancement and widespread use of internet and mobile technologies, computer-based health intervention has received increasing attention, and recommendation system is one of the advanced approaches that increase user engagement in health management [13-14]. Recommendation systems (RSs), which leverage artificial intelligence, are designed to help users find the information that matches their preferences and needs in an overloaded search space [15-16]. RSs have been widely applied in the e-commerce and leisure domains and their use in the nutrition has also increased recently. Nutrition recommendation systems (NRSs) not only suggest healthy dietary choices based on users' preferences but also provide recommendations for nutrition support interventions, including individualised nutritional advice, counselling, and suggestions for oral nutritional supplements and fortified food that are beneficial for health self-management [17].

Unfortunately, few NRSs have been widely adopted due to reasons such as limited ability to provide personalized recommendations, inadequate suitability of existing algorithms for evolving nutritional needs, low quality and reliability of the data, low involvement of nutrition experts and so on [18-24]. A few studies have reviewed RSs in the food domain, addressing the technical aspects and research challenges of RSs [25-27]. However, these findings were limited by focusing on specific aspects or types of RS, and by some methodological flaws such as the focus on technical domains, limited databases searching, high heterogeneity among included studies, and rapidly evolving nature of the evidence.

Given the immense potential of the application of RSs in nutrition and the potential gaps between development and implementation, it is necessary to provide a multidisciplinary overview of

NRSs. Therefore, we conducted a scoping review to (1) examine the volume, distribution and application forms of NRSs; (2) summarize the topics, purposes, human-NRS interactions, technological issues, development stages, evaluation methods, metrics and outcomes of the NRSs; (3) identify gaps in the design, development and implementation of NRSs.

METHODS

We followed Arksey and O'Malley's framework on scoping review to guide our study and reported in terms of PRISMA ScR reporting guideline [28-29]. The protocol was registered on the Open Science Framework (https://doi.org/10.17605/OSF.IO/VF7NB)

Eligibility criteria

We defined a recommendation system as a software or algorithm that analyze user data and preferences to provide personalized suggestions or recommendations for items or content that the user may find relevant or interesting [30-32]. We included all NRSs that met the following criteria: (1) were designed for humans; (2) used to provide recommendations for healthy dietary choices and nutrition support interventions. We excluded NRSs that (1) were used for laboratory nutrition testing; (2) were related to industrial food processing; (3) were associated with online logistics sales; and (4) were published in any language other than English and Chinese.

Identify relevant studies

Considering that some NRSs may not be published or disseminated in bibliographic databases, we conducted a comprehensive search that included patent databases, mobile apps and websites. For bibliographic databases, we searched from PubMed, Embase, CINAHL, WOS, IEEE Xplore, Wanfang Data Knowledge Service and China National Knowledge Infrastructure (CNKI) from the inception to February 2024, with an update to June 2024.

We also searched patent databases (e.g. WOS and CNIPA), mobile apps (e.g. App Store, Microsoft Store, Google Play Store and Yingyongbao) and some web search engines (e.g. Google Chrome, Iresearch and DataAI). The search strategy was not restricted by study design, and an expert information specialist collaborated with the research team. The search strategies are listed in **Appendix 1**.

Study selection

We calculated Inter-rater agreement for study inclusion using percent agreement. If the agreement exceeds 75% among the team members, we proceeded to the next stage. All title and abstract screening and full-text screening were performed independently by at least two review authors using a pre-defined form. Any discrepancies were resolved through consensus or involving a third reviewer when necessary.

Charting the data

The following general information was collected from all included NRSs: published or developed year, countries, topic (words from titles, patent names and product names), users (those who directly interacted with the NRS) [33-35], audiences (the targeted beneficiaries of the NRS) [36-38], input variables (e.g. user login, dietary pattern, or medical history), output variables (e.g. nutrition knowledge or plan), and application forms of systems (e.g. application software or online tool on web page) [39-41]. We extracted data on application software usage from Iresearch (https://www.iresearch.com/) and DataAI (https://www.data.ai/). The data included the number of accounts utilizing the application software, measured by monitoring online data traffic.

For studies retrieved from bibliographic databases with more detailed information, we extracted additional general information about authors' expertise, funding sources, purposes of NRS (e.g. records of weight reduction and energy intake belonged to nutrition monitoring; providing healthy diets belonged to nutrition recommendation), development stages (e.g. system design, internal test or external verification), evaluation methods (e.g. running previous data, acquiring feedback from users or running real world data), evaluation metrics (e.g. accuracy, error rate or F1 index), and measured outcomes of NRS.

We also collected information on technological aspects, including the recommendation algorithm (e.g. collaborative filtering, content-based, knowledge-based and hybrid) and artificial intelligence (AI) techniques employed (e.g. neural network, long-short term memory, decision tree or attention mechanism) [42-45].

Data extraction from each NRS was conducted by four reviewers, a pilot study was performed before formal extraction, and the interrater agreement percentage needed to be >75%. Discrepancies were resolved by consensus or the involvement of a third reviewer.

Summarizing the data

Frequency count and narrative summaries were performed for each study. For narrative summaries, two reviewers independently categorized the key components, and the results were subsequently discussed by the research team. Graphics (e.g. word cloud, Sankey diagram, histogram or fishbone diagram) were generated using Word Processing System Office Software and the online tools ProcessOn on web page (https://www.processon.com/).

RESULTS

Search and selection of NRS

A total of 15718 NRSs were identified from 15 data sources, and 5609 NRSs were included for screening after duplication. After reading relevant full-text paper or introductions of 1830 NRS, 49 studies with details were identified from journals or essays (**Figure 1, Appendix 2**) and 828 patents and software with limited information were sourced from WOS, CNIPA and mobile apps were finally included (**Figure 1, Appendix 3**).

General information of all included NRSs

All NRSs included in our scoping review were released from 2007 to 2023, with approximately half released after 2022 (n=423, 48.2%) (**Figure 2**). Among the included NRSs, 155 (17.7%) were released in China, followed by the United States (n=80, 9.1%) and the United Kingdom (n=43, 4.9%). The topics covered in the reviews were diverse, with "health" being the most common topic based on its highest frequency of occurrences (n=53, 6.0%) (**Appendix 4**).

The Sankey diagram illustrated the service chain facilitated by NRSs, representing the flow from user input to output and audience engagement, with user usage reflecting direct feedback. Among users, the largest proportion were from the overweight or obese population (n=152, 17.3%), while the smallest proportion were from the medical care population (n=43, 4.9%). Primary inputs included information on food and beverage types and intake (n=157, 17.9%), methods and duration of physical activity (n=157, 17.9%) and anthropometric measurements (n=157, 17.9%), such as height, weight, body circumference (**Figure 3**). The most common audience for NRS was the general population (n=244, 27.8%), followed by patients (n=174, 19.8%) and overweight or obese population (n=152, 17.3%). The primary output was nutritional recommendations (n=254, 29.0%), which provide comprehensive advice on energy or nutrient intake, diet and exercise. This was followed by a monitoring record (n=217, 24.7%) containing input details about daily life and nutritional status assessment.

The majority of NRSs were accessed through application software installed on mobile phones, computers, tablet PCs and other smart devices (n=766, 87.3%). Additionally, some NRSs were available as web-based online tools (n=103, 11.7%) without the need for account registration (**Figure 4**).

Additional information of NRS published in journals or essay

Of 49 studies published in journals or essays, the majority of researchers involved in the development of NRSs were from computer science (n=28, 25.2%), followed by public health (n=14, 12.6%) and management (n=13, 11.7%). A smaller proportion involved researchers from the nutrition filed (n=4, 3.6%) (**Appendix 5**). Thirty-eight (77.6%) received industry funding, while five

(10.2%) received non-industry funding. The design stages were primarily at the internal test stage (n=21, 42.9%), followed by external verification (n=14, 28.6%) and public usage (n=7, 14.3%).

The primary data source for most NRSs was public survey (n=22, 46.8%), followed by public database (n=10, 21.3%) and literature (n=8, 17.0%). The main evaluation methods included running internal tests using data randomly isolated from the original dataset before system design (n=10, 21.7%) and collecting user feedback (n=10, 21.7%) (**Appendix 6**). The majority of designers used data to build prediction models (n=27, 57.4%) or construct semantic analysis (n=12, 25.5%). The main purposes of NRSs were recommending nutrition plan (n=25, 53.1%) and predicting nutrition status (n=12, 26.5%) (**Figure 5**).

Forty studies reported evaluation metrics, with the most commonly indicators being accuracy (n=17, 21.8%), success rate of system execution (n=13, 16.7%) and area under the receiver operating characteristic curve (AUC) (n=7, 9.0%). However, technological indicators such as CPU usage were less used (n=1, 1.3%) (**Figure 6**). Among the studies (n=46) that reported evaluation outcomes, the operability of NRS was 100.0%. The lowest satisfaction rate among users was 93.0%, while the lowest recommendation accuracy was 81.0%. The lowest authenticity of output contents was 74.0%, and user compliance was at its lowest at 53.0% (**Appendix 7**).

Technological information of NRS published in journals or essays

Eighteen AI technologies were used in those NRSs, with the convolutional neural network (n=7, 12.7%) and random decision forests algorithm (n=7, 12.7%) being the most commonly used model. The conditional random field was the only unsupervised model (n=2, 3.6%). Among the supervised technologies, four (20.0%) could automatically update systems by themselves, with the artificial neural network being the most frequently used (n=4, 7.3%). Only two technologies proposed in the last decade were employed (n=4, 7.3%), with the hyperband algorithm being the latest in 2016 (n=2, 3.6%) (**Figure 7**).

Three recommendation algorithms were identified, with the content-based algorithm being the most commonly used (n=15, 51.7%), followed by the collaborative filtering (n=9, 31.0%). One content-based algorithm (n=2, 6.9%) proposed in 2014 and one knowledge-based algorithm (n=5, 17.2%) were the latest recommendation algorithms (**Figure 7**).

DISCUSSION

We conducted a comprehensive scoping review including 877 nutrition recommendation systems (NRSs) over the past decade. RS directly interacts with users through input and output, with particular emphasis on the output recommendation content, which should meet users' expectations. Our review found a significant increase in the number of NRSs worldwide, however, not all of these

NRSs provide recommendation content to directly guide users in improving their nutrition behaviors. Therefore, when defining the purpose, NRSs should at least include the fundamental characteristics found in RS outputs.

The development of NRSs benefits from multidisciplinary collaboration, where researchers in nutrition, computer science, and other fields leverage their respective strengths. However, our findings highlight a significant oversight in the integration of nutrition professionals in NRS development. Consequently, nutrition recommendations are often perceived primarily as technical research outcomes. Meanwhile, many NRSs prioritize public health nutrition for general population and overlook its potential role in treatment or health daily management and specialized NRSs designed for specific user groups underutilized. NRSs focused on general nutrition self-management benefit from broad user application, accessing data and samples to enhance development. However, the shift towards personalized smart management services suggests that generic nutrition recommendations based on population data may not meet individual needs, particularly those with specific requirements [46]. Therefore, the future direction of professional NRSs remains crucial, emphasizing the need for further development and adaptation to meet diverse individual needs.

The quality of NRs, including preliminary data, used techniques and evaluation methods, directly affect their application and effectiveness for users [47]. The preliminary data for the design of NRSs, especially AI-driven NRSs, should be as objective as possible [48]. The data used for machine learning must accurately reflect the recommendation items and corresponding nutritional requirements [49]. However, our review identified shortcomings in preliminary data quality control and reporting. For instance, the majority of data sources were direct collections from public surveys, often lacking detailed descriptions of data preparation processes. Additionally, inconsistencies between user groups and audience groups in some NRSs suggest that preliminary data collection may have been limited to a single human group, potentially reducing representativeness. The data at the recommendation core should contain more detailed information, leading to more accurate output recommendations [50]. However, few NRSs prioritize collecting detailed individual information such as daily activities, user location, or medical history. This is despite the availability of various interaction methods with NRSs, including photo submission via smartphones, data recording via smartwatch sensors, and accessing outputs through online tools on web pages. Furthermore, ensuring good representation of samples can incorporate individual variations, thereby diversifying output contents. Leveraging comprehensive user data from various sources can improve recommendation accuracy and effectiveness. When users and audiences represent different populations, data collection should not be limited to the user population alone.

In terms of techniques used, the combination of AI models and content-based recommendation algorithms has outperformed the classic single collaborative filtering algorithm. While most of the AI models used have been well-developed and enhance the interpretability of NRS [51], they may not adequately accommodate the dynamic changes in individual nutritional requirements. Hence, there is significant potential for the integration and application of self-renewing or more recent models in NRSs [52]. Furthermore, considering the differences between essential functions and roles played by recommendation algorithms and AI models, it is important to note that the latter are primarily used for data analysis through machine learning before being applied in the former. However, many studies report these processes confusedly or incompletely.

Our review also revealed that the evaluation stage of NRSs is incomplete, with methods of internal testing, external verification, and application assessment being applied inconsistently and often confusedly. Some methods, such as using simulation data, may overlap and serve as both internal testing and external verification data [53]. Additionally, the evaluation metrics in the included NRSs focused primarily on accuracy, operability, feasibility, and authenticity. While measuring pure technological performance is crucial to achieve nutrition management with high efficiency, clinical outcomes and changes in healthy behavior should be also assessed. We also found Many NRSs have not been widely applied or had low usage volume, and the development processes of NRSs are often reported without sufficient detail and transparent. To overcome the research gap and facilitate the application of NRS, we summarized the problems and possible solutions in **Table 1.**

Compared to previous review studies of RSs used in general health or food management [54-56], we conducted a scoping review specifically focused on NRSs due to the unique role of nutrition in improving health. Two previous systematic reviews of NRSs summarized the design purposes, technical characteristics, main modules and applied platforms of NRSs, primarily focusing on computational methods, AI models and recommendation algorithms [26, 57]. Additionally, a systematic review of the NRSs for polycystic ovary syndrome explored the challenges and limitations of using and designing these systems and algorithms, particularly the NRSs providing food recommendations [58]. In comparison, we included NRSs for all the medical or healthy conditions from studies, patents and apps to summarize the complete development process in detail and identify potential solutions to improve quality and promote application. Besides updating the technique summary, our study considered about other factors such as the structure of development team, the quality control of preliminary data and the need for standardized evaluation. Similarly, a systematic review of diabetic food RSs reported that their evaluation frameworks were very limited and insufficient [25]. It is worth noting that the integration of RSs into medical interventions is becoming an overwhelming trend, with the relevant randomized controlled trial already being conducted [59]. More high quality clinical studies should be designed to evaluation the effect of NRSs.

We conducted a scoping review of studies, patents and software products to provide a comprehensive view of current state of NRS and potential solution to facilitate the development of

NRS. However, our study has several limitations. First, we included all published NRSs including from patent databases and app stores, relying on publicly available information, which may introduce bias due to missing details. Secondly, most NRSs were released through patents or directly put into operation, with limited documentation in scientific research or clinical studies. Finally, we planned to identify the gaps in the design, development and application of NRSs to optimize the design of RS, however, limited information about effectiveness of NRSs were found. Specifically, the lack of acquired evaluations or feedback for NRS apps necessitated indirect methods, such as usage volume analysis.

CONCLUSION

The rise of big data and data analytics technologies has elevated the importance of recommendation systems in personalized nutrition management. While the development of NRSs has primarily focused on the general population, there is an increasing demand for systems tailored to unique populations that incorporate dynamic updates and enhanced individual identification. Nutrition recommendation is a comprehensive field of research, not just a technological endeavor. The success of these intelligent systems should be evaluated based on their technical performance and clinical impact. To support the plan, design, and evaluation of these systems, guides such as consensus documents, standards and guidelines are essential.

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USED ARTIFICIAL INTELLIGENCE IN WRITING

The authors did not use any artificial intelligence technologies in this study.

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AUTHOR DISCLOSURES

The authors report no conflicts of interest.

SUPPLEMENTS

“**Appendix 1-6**” are available from the “Supplementary data” link in the online posting of the article.

ABBREVIATIONS

AI: artificial intelligence;

AUC: area under the receiver operating characteristic curve;

CINAHL: Cumulative Index to Nursing and Allied Health Literature;

CNIPA: China National Intellectual Property Administration;

CNKI: China National Knowledge Infrastructure;

CPU: central processing unit;

IEEE Xplore: Institute of Electrical and Electronics Engineers;

NRS: nutrition recommendation system;

PRISMA-ScR: Preferred Reporting Items for Systematic reviews and Meta-Analyses extension for Scoping Reviews;

RS: recommendation system;

WOS: Web of Science.

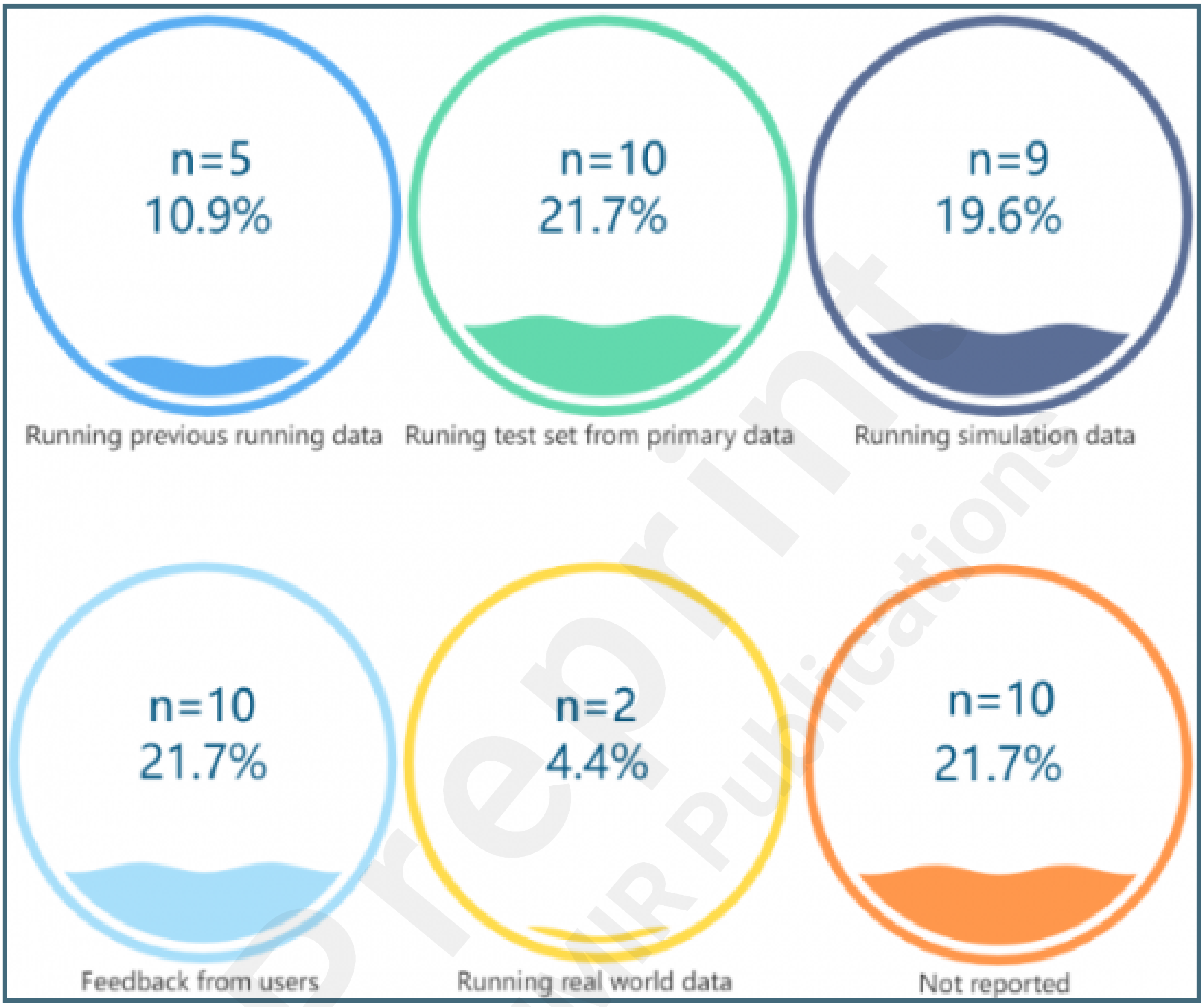
Table 1 Problems and possible solutions of NRSs.

PROBLES	POSSIBLE SOLUTIONS
NRSs did not include the fundamental characteristics found in RS outputs.	• NRSs should provide recommendations in their output that directly help or guide users to optimize and improve their lifestyles and behaviors.
Lack of NRSs that provide professional nutrition suggestions and recommendations	• Nutrition professionals are encouraged to participate in the development of NRS, such as by providing professional nutrition interventions or prevention strategies. • Additional NRSs should be developed to focus on specific patients (e.g., patients with multiple chronic diseases simultaneously) or the populations with special nutritional needs.
The quality of preliminary data for NRSs is uncertain.	• The sample used as a data source should be representative enough to capture individual variations as much as possible. • Preliminary data should incorporate additional contextual information from the perspective of the individual's real-life circumstances. • It is recommended to implement systematic assessment, registry-based collection and other quality control for preliminary data, at least for the training data set.
Current NRS techniques do not adequately accommodate the dynamic changes in individual nutritional requirements	• It is recommended to adopt novel AI technologies, such as graph convolutional neural networks, which feature auto-update functions and enhanced interpretability. • It is recommended to use novel knowledge-based recommendation algorithms, such as semantic networks, which excel at processing complex information efficiently and offering a more humanized interaction with users
Lack of scientific and transparent evaluation of NRSs.	• The evaluation process should be standardized, including methods, metrics, outcomes and reporting form. • Clinical outcomes or changes in nutritional behaviors can be observed as early as possible. • Technological evaluation should combine to medical evaluation.
Many NRSs have not been widely applied or had low usage volume, and research on NRSs seemed disconnected from their application.	• Both audiences and users identified from the design purpose should be considered for profile or persona analysis. • Increased number of multi-model techniques, such as short video, graph, text and others, can be used in input and output. • Interfaces can be designed in various patterns to accommodate different user roles or the same user in different

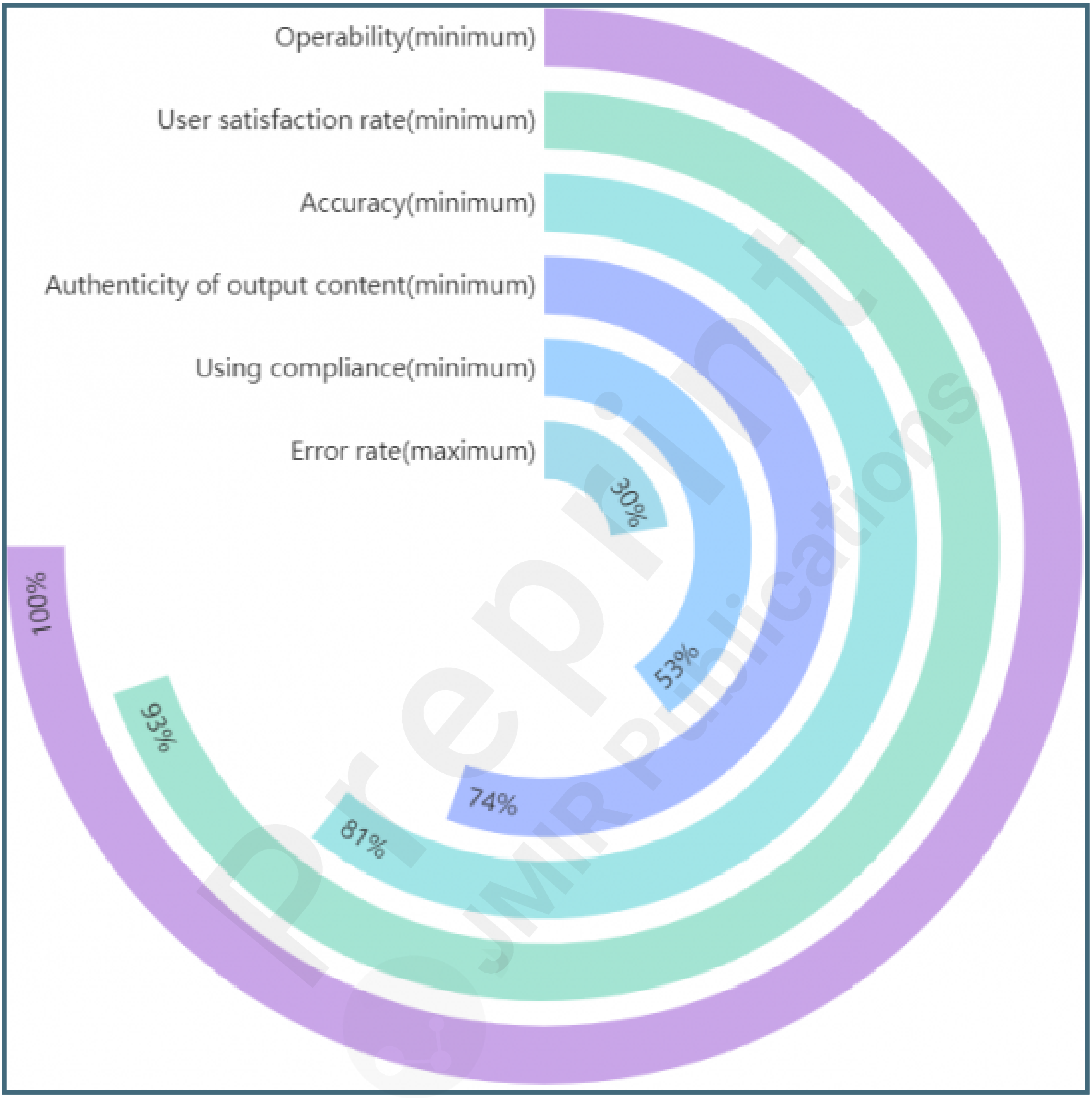
	situations. • When optimizing NRSs, acquiring individual, professional, feasible and lucid recommendations should be the first premise.
Lack of guides for developing the NRS	• All the processes should be reported in detail and transparently, if allowed by intellectual property rights. • Guides, including consensus documents, standards and guidelines, are necessary to support scientific development of NRSs.

Supplementary Files

Appendix 5 Evaluation methods.



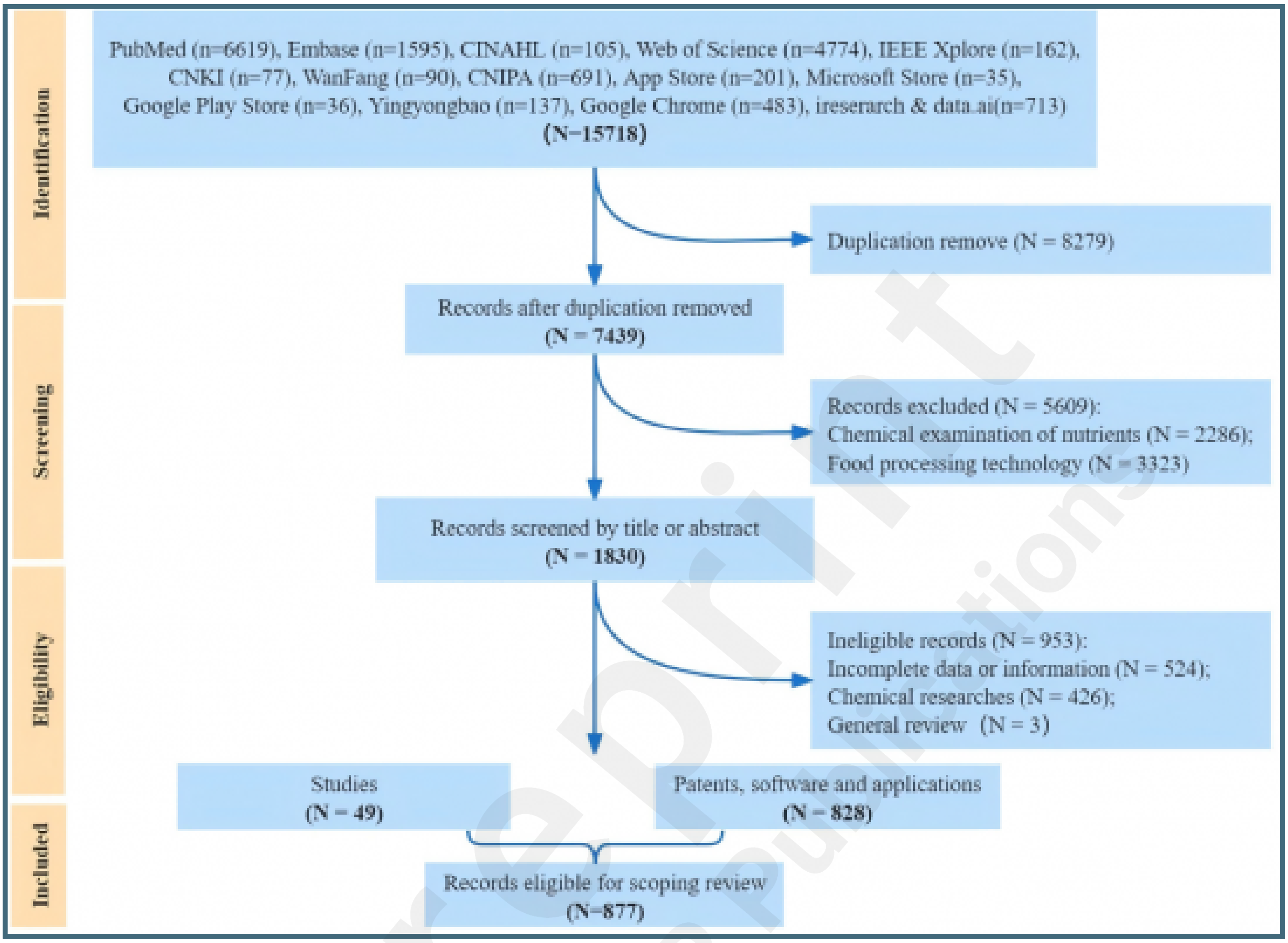
Appendix 6 Evaluation outcomes.



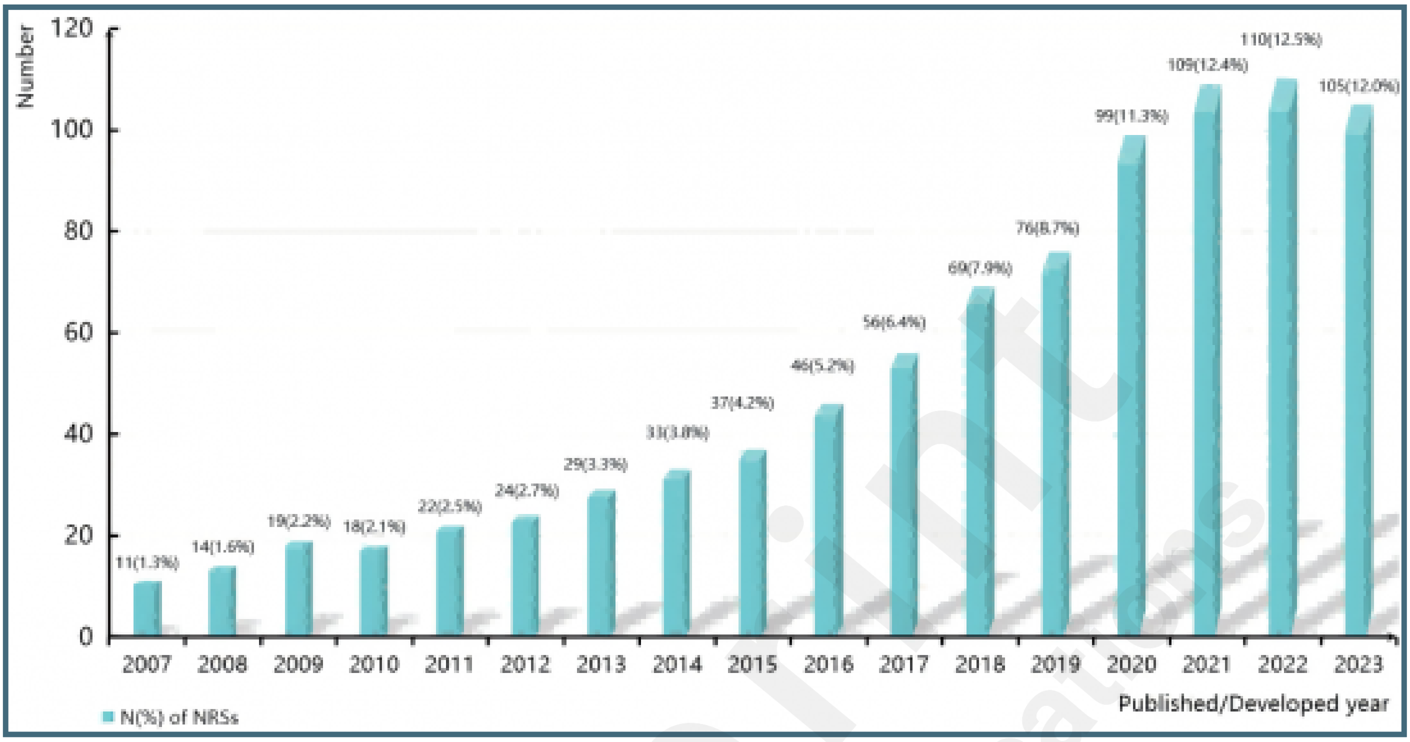
Appendix 7 Words cloud of topic words.

Figures

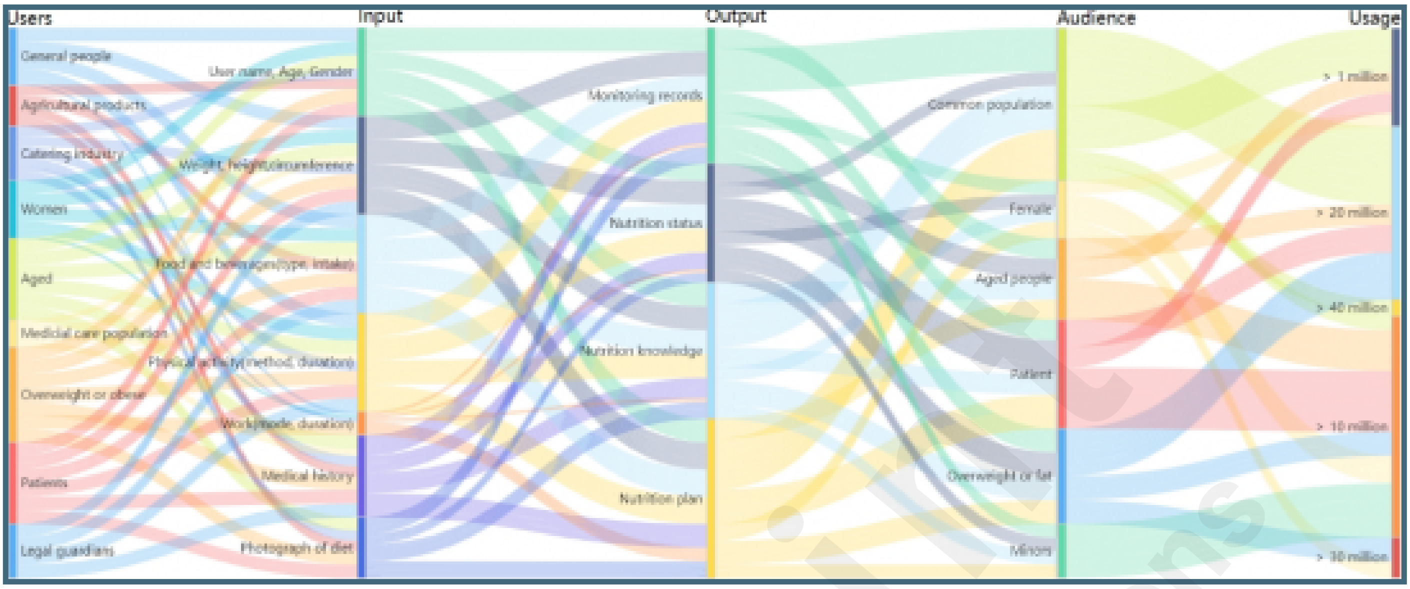
Screening process.



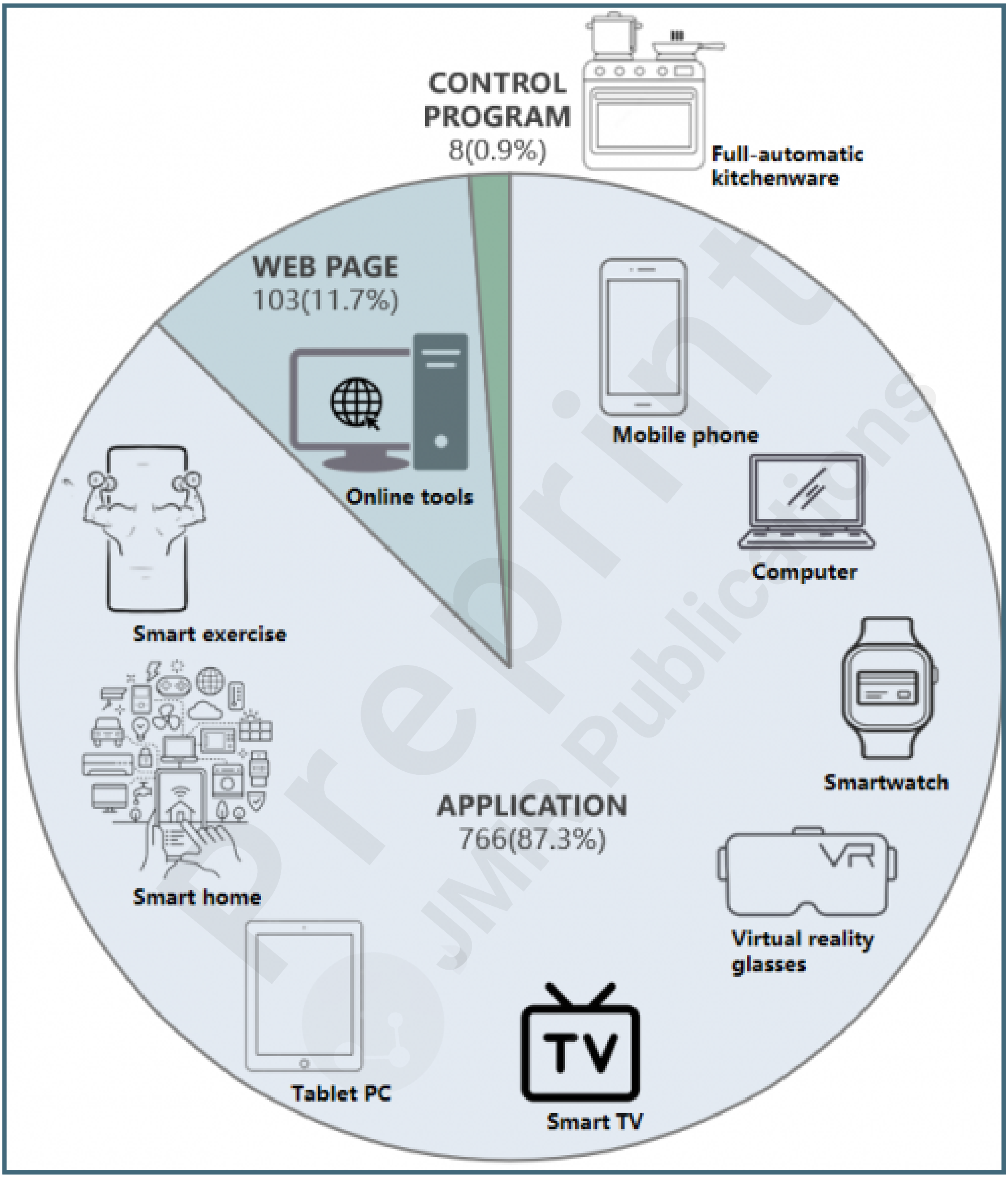
Publications Trend by years.



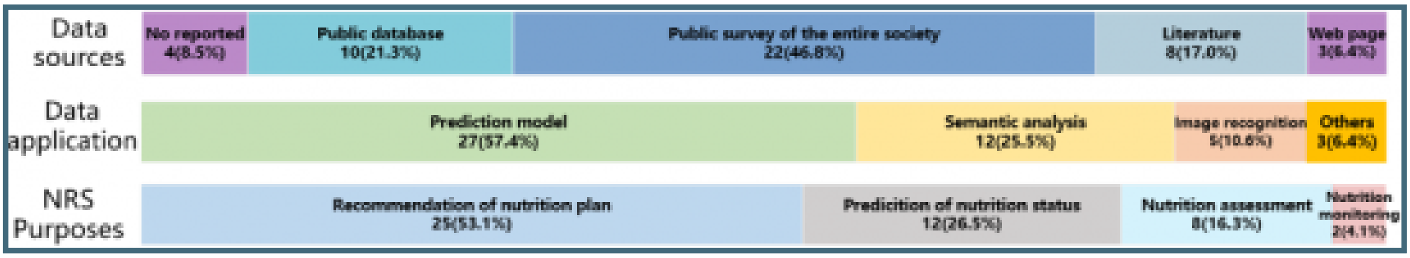
Human-NRS interaction and usage.



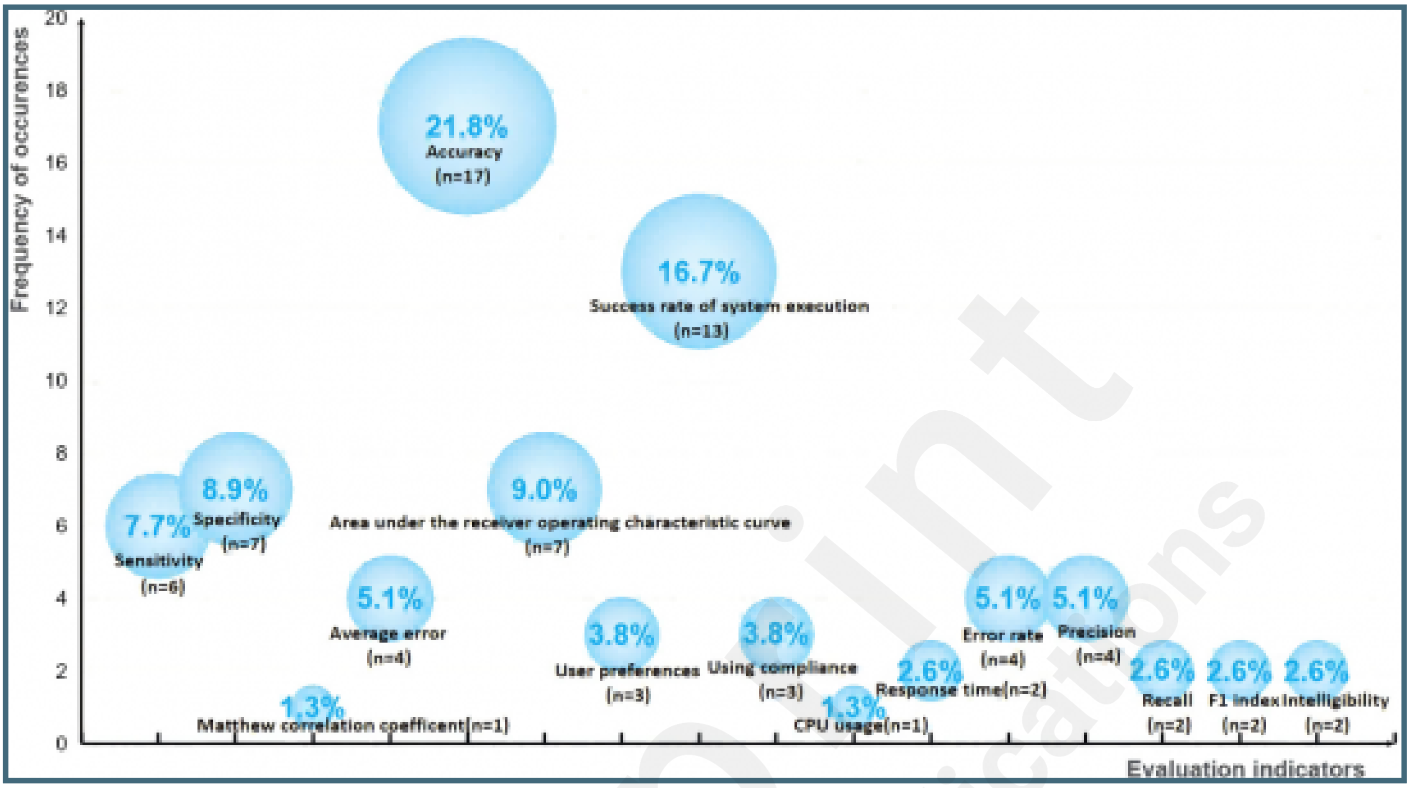
Appliation forms of NRSs.



Data sources-data application-NRS purposes.



Evaluation metrics.



Used technologies by advent years.