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Ontology-based decision support systems for diabetes nutrition therapy: A systematic literature review

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ABSTRACT

Diabetes is a non-communicable disease that has reached epidemic proportions, affecting 537 million people globally. Artificial Intelligence can support patients or clinicians in diabetes nutrition therapy – the first medical therapy in most cases of Type 1 and Type 2 diabetes. In particular, ontology-based recommender and decision support systems can deliver a computable representation of experts' knowledge, thus delivering patient-tailored nutritional recommendations or supporting clinical personnel in identifying the most suitable diet. This work proposes a systematic literature review of the domain ontologies describing diabetes in such systems, identifying their underlying conceptualizations, the users targeted by the systems, the type(s) of diabetes tackled, and the nutritional recommendations provided. This review also delves into the structure of the domain ontologies, highlighting several aspects that may hinder (or foster) their adoption in recommender and decision support systems for diabetes nutrition therapy. The results of this review process allow to underline how recommendations are formulated and the role of clinical experts in developing domain ontologies, outlining the research trends characterizing this research area. The results also allow for identifying research directions that can foster a preeminent role for clinical experts and clinical guidelines in a cooperative effort to make ontologies more interoperable – thus enabling them to play a significant role in the decision-making processes about diabetes nutrition therapy.

1. Introduction

Diabetes is a non-communicable disease affecting patients of all ages in every country of the world. The International Diabetes Federation estimated that in 2021, the total number of individuals affected by this disease (aged between 20 and 79 years old) was 537 million. This figure is expected to increase significantly by 2030 (643 million) and by 2045 (783 million) [1]. Untreated diabetes leads to elevated amounts of blood glucose, which can determine serious health consequences, both acute (e.g., hyperosmolar coma, ketoacidemic, hypoglycaemic, etc.) and chronic complications (e.g., damage to the heart and cardiovascular system, vision impairments, kidney failure, etc.) – which are responsible for 1.5 million deaths every year. For these reasons, it is a major global concern. In December 2022, the World Health Organization (WHO) drafted a research agenda intending to halt the rise in diabetes and obesity by the end of 2025 [2]: among the initiatives traced, the role of medical devices in managing diabetes was stressed. Patients affected by Type 2 Diabetes Mellitus (T2D) can be treated with medical nutrition therapy – i.e., a balanced and clinically developed diet – and physical activity, sometimes even before considering pharmacological and insulin-based therapies [3]. In contrast, patients affected by Type 1 Diabetes Mellitus (T1D) can take advantage of nutrition therapy and pharmacological therapy. Therefore, countries developed different local guidelines to give patients general dietary recommendations to prevent the development of health issues (particularly T2D). Such guidelines are characterized by a high degree of difference among them, as they need to address population- or country-based dietary habits. Nonetheless, they share some commonalities – e.g., the criteria for defining a diabetic patient, some food categories and shares of nutrients to be consumed daily, etc. [4]. Guidelines proved to be an efficient way to manage

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diabetes (in particular T2D). However, they cannot answer to specific individual's needs, as the glycemic responses to diet can significantly vary from person to person [5]. Moreover, guidelines can support family doctors and general physicians in managing diabetic patients, considering that not all clinicians are trained to manage appropriate and personalized nutritional interventions for managing diabetic patients [6].

The availability of general guidelines stimulated researchers to develop recommending systems devoted to supporting diabetic patients or clinical personnel in managing the disease's consequences and comorbidities and its exacerbations [7]. In particular, leveraging expert knowledge, such systems can automate some of the clinicians' work and enable diabetic patients' monitoring. Domain ontologies [8] can efficiently represent in a formal way diabetes, diabetic patients' characteristics, and nutritional facts and evidence while fostering data interoperability. Furthermore, leveraging monotonic reasoning techniques to infer logically entailed information, ontologies can be adopted as part of Artificial Intelligence (AI) systems [9]. These features enabled the adoption of ontologies and, more in general, Semantic Web technologies in recommender and decision support systems aimed at supporting diagnostic processes [10] or identifying possible solutions to health-related issues [11]. Ontologies can also play a pivotal role in explainable AI systems, since the semantic reasoning – which resembles human inference capabilities [12] – can mitigate the risks perceived regarding the adoption of AI systems in healthcare: recent researches have underlined clinicians' reluctancy to adopt such systems in clinical practice ([13–15]). Among the reasons that prevent the wide adoption of AI systems in the healthcare industry, the most cumbersome is the lack of transparency in the decision making process – also referred to as the "black box" model [16]. Therefore, domain ontologies in healthcare (which heavily rely on clinicians' expertise and knowledge to develop a formalization of a domain) are a promising solution for the adoption of AI-based systems in healthcare and in clinical practice.

Considering the roles ontologies cover in recommender and decision support systems for supporting the management of diabetes, this work aims to review existing scientific literature and domain ontologies describing this disease and its patients. In detail, this review is aimed at investigating the following Research Questions (RQs):

- RQ1: Identifying the types of diabetes treated by the systems, what information is required as input for obtaining recommendations (output), as well as the type of the recommendation provided (diet plan, nutrients recommendation, etc.);
- RQ2: Examining the target users (family doctors, dieticians, patients, etc.) for which the systems were developed;
- RQ3: Investigating how ontologies are adopted to represent diabetes, i.e., which entities are fundamental to model this disease and its patients. From an ontology engineering perspective, this question entails:
    - RQ3a – investigating the conceptualization underlying diabetes ontological formalization (whether existing conceptualizations support it or it is developed from scratch);
    - RQ3b – analyzing the languages adopted to formalize the domain ontologies and rules (if used);
    - RQ3c – if domain ontologies reuse existing models – a best practice of ontology engineering;
    - RQ3d – whether ontologies adopt Ontology Design Patterns (ODPs) for modelling recurrent knowledge engineering problems;
    - RQ3e – if ontologists adopted ontology engineering methodologies (OEMs) or techniques to develop ontologies on diabetes, and if the engineering process was conducted in collaboration with domain experts;
    - RQ3f – whether the inferences generated by the ontology (and by the systems) were validated with real case tests, patient data, or with support from clinical personnel.

This review contributes to the research on knowledge engineering of diabetes and its related ontology-based recommender and decision support systems aimed at providing support in nutrition therapy; this work identifies existing ontology-based models and examines the main trends researchers adopt in the ontology engineering processes for diabetes.

This paper is organized as follows: Section 2 presents the review methodology adopted and the databases searched. Section 3 illustrates the quantitative results of the review process, while Section 4 discusses them in light of the RQs described above. Section 5 delves into the implications of the findings – from a nutrition therapy and knowledge engineering perspective – while Section 6 leverages the findings of previous Sections to sketch possible research directions for knowledge-based systems devoted to diabetic patients and clinicians. Finally, the Conclusions summarize the main outcomes of this review.

2. Review methodology

This review adopts the Preferred Reporting Items for Systematic reviews (PRISMA) [17] to conduct a systematic search in scientific literature to investigate the aspects entailed by the three RQs. The PRISMA approach enables identifying and selecting relevant works through a step-by-step and transparent process. This review focuses on conference proceedings, book chapters, and journal articles published between January 2000 and June 2023, selecting solely works published in English.

2.1. Databases and search

To answer the RQs, ISI Web of Science, Scopus, and PubMed databases were searched. All databases are accessible online and enable queries with logical operators; moreover, these databases allow to restric the research to specific types of articles (in the case of this review, journal articles, conference proceedings, and book chapters). Considering the specific RQs and their focus on ontology-based recommender and decision support systems for diabetes, the search was limited to the Computer science, Engineering, and Decision sciences subject areas.

The resulting query searches scientific literature for:

((ontolog* AND diabet*) OR (semantic* AND diabet*)) AND (nutrition* OR diet*)

in the databases, focusing on publication years >1999 and < 2024 (to include among the retrieved results those works accepted for publication within 2023 but expected to be published in 2024 issues) and limiting the search in the "Title", "Abstract" and "Keywords" fields of each record.

Publication years range was selected considering that in the early 2000s, domain ontologies started to be developed and published adopting W3C-endorsed languages (i.e., Ontology Web Language (OWL), dated 2004). The database search was conducted in March 2023 and updated in September 2023.

2.2. Articles selection process and criteria

Following the PRISMA approach, the process of identification for the works able to answer to the RQs is the following:

1. *Retrieval* of relevant articles as a result of databases' search. In this step, 240 articles were retrieved from the three databases (journal articles, book chapters, conference proceedings). Works considered "in press" but already indexed by the databases were included.
2. *Screening* of the retrieved articles. The screening process is divided into two sub-steps. The first consists of the removal of those works that were inaccessible – i.e., they could not be retrieved in their complete form for full-reading – (1) and duplicated works – i.e., works that were retrieved from two or more databases – (30). The second sub-step consists of the analysis of the remaining 209 papers'

abstract and title fields to assess whether the papers addressed the domain of ontology-based recommender or decision support systems for supporting nutrition in diabetic patients. Following this sub-step, a total of 145 articles were removed.

3. *Inclusion* of the remaining articles (64) was based on the papers' full reading. Each author individually read the articles and stated the reasons for their inclusion according to the following two criteria (*a* ˆ *b*):
   a. The article presents a recommender or decision support system focused on diabetes, involving at least one ontological representation of one or more aspects related to this disease (diabetic patient, disease definition, nutritional profiles of diabetic patients, medical nutrition therapy, dietary plan management, etc.).
   b. The article enlists, among its findings, the provision of suggestions or recommendations about nutritional aspects.

At the end of this step, 43 papers were removed. The number of the included works after the process is 21. Fig. 1 details the article selection process as a PRISMA flow diagram.

3. Results

This Section presents the result of the review process. Bibliometric results and Content analysis results are illustrated in the following subsections, while their discussion is addressed in Section 4. The presentation of bibliometric results focuses on the articles' temporal distribution, typology, and geographical distribution; content analysis results are aimed at answering the RQs listed in the Introduction by quantitatively analyzing and clustering the papers included in this review.

3.1. Bibliometric distribution of the articles by year

3.1.1. Temporal distribution of articles by year

The temporal distribution of the works included in this review – depicted in Fig. 2 – indicates that the first contribution addressing the topics pertaining to the RQs is dated 2008, thus later than the lower end of the time frame considered in the search phase. Interestingly, relevant articles are found each year except for years 2009, 2010, and 2016. The temporal distribution highlights 2014, 2018, and 2021 as the years with the highest number of contributions. Starting from 2017, at least one relevant article per year is found.

3.1.2. Typology of the articles by year

The selection process considered three types of works – journal articles, conference proceedings, and book chapters. Fig. 3 illustrates the number of works for each type included in this review, detailing their distribution through the time frame.

The distribution by typology clearly indicates the absence of book chapters from the included works. Also, it illustrates that most of the included works belong to the type Conference proceeding (14), with two peaks in 2018 and 2021. A total of 7 journal articles were distributed between 2013 and 2021, with 2014 reporting 2 journal articles.

3.1.3. Geographical distribution of the authors

To investigate in which countries the topics pertaining ontological modelling of diabetes and its management from a nutritional perspective were addressed, the articles were analyzed according to the authors' geographical distribution. Each of the authors listed in the manuscript was considered. The authors' affiliation(s) declared at the time of paper publication were scrutinized, and each author was considered only once (the same author contributing to two different papers, with two different affiliations pertaining to two different countries, was considered twice). Table 1 summarizes the geographical distribution of the contributors of included works by country, grouped by continent.

Asian countries registered more authors than other continents (45), with countries such as Taiwan (14) and South Korea (11) accounting for >50 % of all authors. Europe registers 21 authors, followed by North America (11) and Africa (2). In detail, Taiwan, South Korea, the USA (10), and Italy (9) are the countries with the highest number of authors.

3.2. Content analysis

The results from the analysis of the content of the 21 works included allow to shed light on the types of diabetes represented in the ontologies and the information required for the ontology to provide its recommendation(s) (RQ1). The users for which the ontology-based systems are developed are also investigated (RQ2), as well as the conceptualizations, techniques, and patterns adopted to model the ontologies (RQ3). This Section presents the quantitative results of the content analysis, which are discussed in Section 4.

3.2.1. Types of diabetes, input, and output

To provide an answer to RQ1, it is necessary to cluster the included papers according to the type(s) of diabetes they address. Considering that different types of recommendations can be provided to diabetic patients, the works are also clustered according to this criterion. Finally,

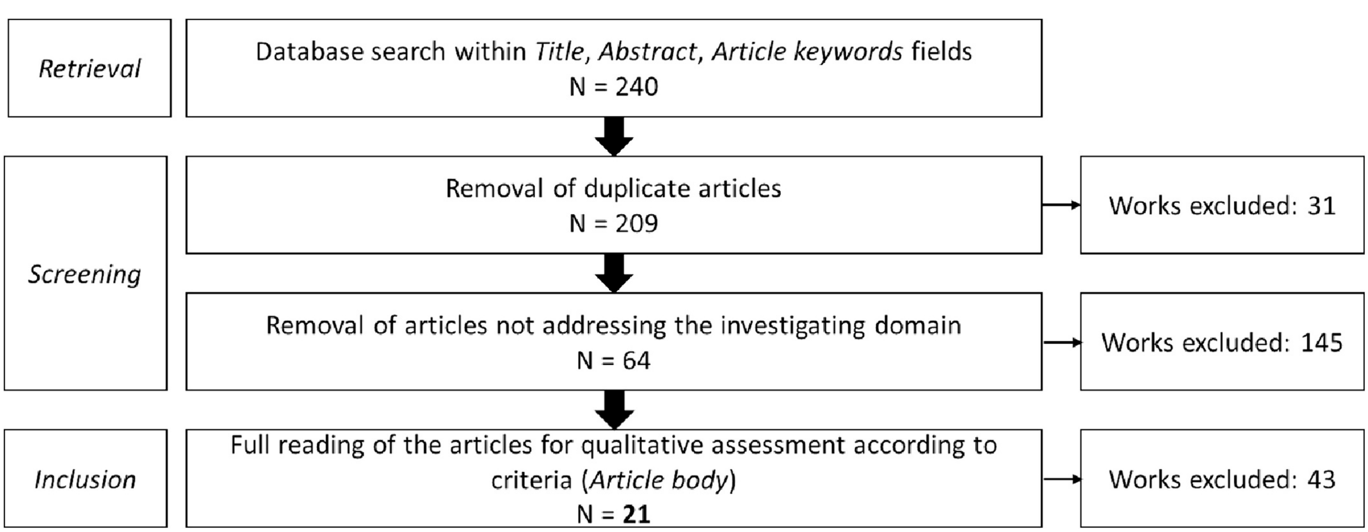

Fig. 1. The PRISMA flow diagram for the articles' retrieval, screening, and inclusion.

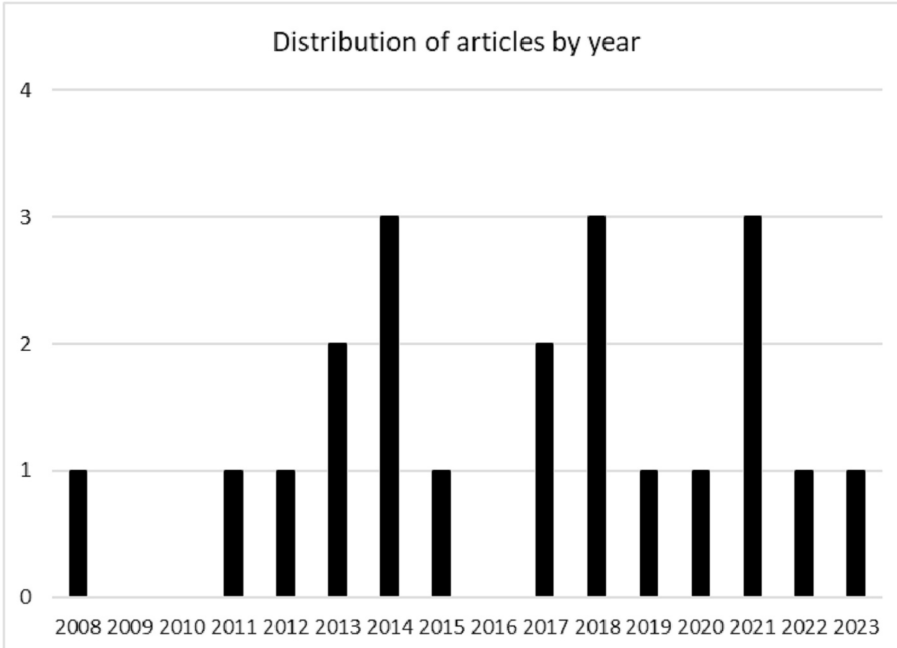

Fig. 2. Distribution of the articles by year.

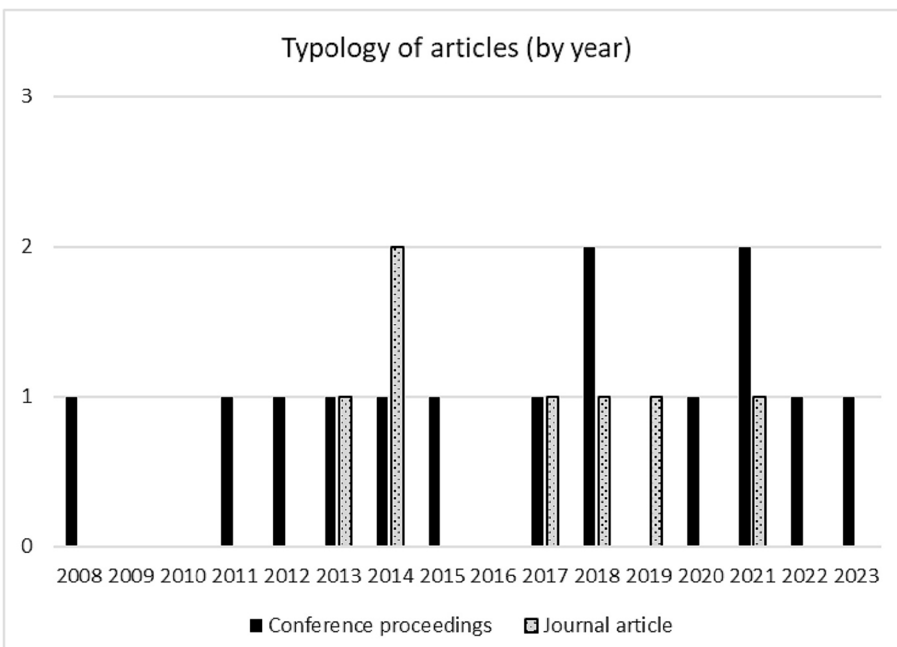

Fig. 3. Distribution of articles by year, grouped by their types.

it is required to identify the information that is necessary for the ontology (input) to provide the recommendation(s) foreseen (output). Diabetes is classified into four types:

- Prediabetes (a condition characterized by a higher level of sugars in blood, but not high enough for a T2D diagnosis);
- Type 1 diabetes (also referred to as "juvenile" or "insulin-dependent" diabetes) (T1D);
- Type 2 diabetes (also indicated as "non-insulin-dependent" diabetes) (T2D);
- Gestational diabetes (characterizing pregnant women).

According to different sources, T2D accounts for the vast majority of diabetic conditions worldwide (90 %) [18,19], while Prediabetes is a condition that is characterized by an impaired glucose tolerance or fasting glucose, leading to a higher risk of developing T2D (and its related complications) [18]. There also exist rarer conditions that are caused by a genetic mutation and result in Neonatal diabetes or Maturity onset diabetes of the young (MODY); also, diabetes can be associated with other conditions (e.g., diseases of the exocrine pancreas such as pancreatitis, pancreatectomy, pancreatic tumors, cystic fibrosis; endocrinopathies such as Cushing's acromegaly, pheochromocytoma, glucagonoma) or genetic syndromes (Down, Klinefelter, Turner, Wolfram, Friedreich). However, these conditions are infrequent and afflict <2 %

Table 1
The geographical distribution of the authors of the included articles.

Continent	Country	Number of unique authors
Africa	Egypt	2
Asia	India	2
	Indonesia	5
	Japan	2
	Malaysia	2
	Pakistan	5
	Qatar	2
	South Korea	11
	Taiwan	14
	Turkey	2
Europe	Bulgaria	4
	Italy	9
	Norway	2
	Spain	3
	United Kingdom	3
North America	Panama	1
	USA	10

of the population [20]. Therefore, the four main types of diabetes are adopted to cluster the analyzed works.

To cluster papers according to the outcome their systems prescribe, the following criteria were adopted:

- Diet: the systems aim to provide a *diet* or a *menu* (i.e., a set of meals organized on a time period, with indications of food quantities or amounts and meal frequencies), whether it is on a daily basis or longer periods;
- Meal composition: the systems aim to propose qualitative sets of *foods* or *recipes* that a patient or his/her clinician (or caregiver) can organize in meals;
- Nutrient(s) amount: the systems are aimed to provide one or more *specific nutrients* or *calories intake* indications;
- Management: the systems' purpose is to support diabetic patients (or clinical personnel) in managing their *insulin intake* or *glucose level*.

These categories are not mutually exclusive since recommender systems can provide both a list of foods (*Meal composition*) and suggest the number of insulin units to be administered (*Management*). It is also interesting to assess whether the investigated recommender systems were developed specifically for diabetes and is consequences, or rather in the framework of other chronic conditions (with diabetes being one of them). Table 2 summarizes the result of the clustering process.

According to the quantitative results, the majority of the papers (17) address the T2D, with only 3 works dedicated to T1D; the system depicted in [21] specifies that the proposed system addresses both T1D and T2D, while the solutions described in [22,23] does not explicitly mention the type of diabetes addressed. The number of papers proposing solutions specifically for diabetes is 10, with the remaining articles (11) addressing diabetes as one of the possible chronic health conditions that can affect a population – and that can be treated by means of nutritional advice or therapy.

With regard to the inputs required by the investigated recommender systems, the majority of recommender systems (67 %) require the *gender* of the diabetic patient to be identified, as well as his/her *age*. The vast majority of the ontologies underlying the systems (71 %) request the patient's current weight, although only 5 works require the *ideal weight* of the patient. Similarly, *height* is adopted as input by 62 % of the analyzed works. Other measurements related to the patient's condition are less adopted: *Body Mass Index (BMI)* is used in 8 articles (38 %), while *Basal metabolic rate (BMR)* is exploited in 7 systems (33 %). One work [24] do not specify any input data to provide recommendations. Two fundamental indicators of diabetic condition – *glycated hemoglobin (Hb)* and *glucose* level – are also represented (respectively, by 38 % and 52 % of the works). Finally, half of the systems (52 %) require diabetic patients to register their *physical activity*, while 38 % ask for *data regarding meals*.

Most works provide recommendations about the *meal composition*, suggesting recipes to patients or caregivers (9). A complete *diet* is the recommendation of 7 articles, while the *management* of particular aspects of diabetes is addressed in 6 papers. The specification of *Nutrients amounts* is addressed in 4 works. Out of the 21 papers investigated, 4 provide mixed types of output. Interestingly, *diet* is the only output category that is never mixed with others.

3.2.2. *Target users*

To provide an answer to RQ2, the articles were carefully scrutinized to search for explicit references to target users. In particular, the recommender or decision support systems described in the works need to explicitly refer to whether the solutions were devoted to supporting *diabetic patients* or to supporting *clinical personnel* in performing some activities related to diabetes management.

All the papers explicitly referenced the target users foreseen by their system. The vast majority of works address patients (17), while a smaller portion (4) of articles described systems thought for clinical personnel. In particular, Wang et al. [25] and El-Sappagh et al. [26] make general reference to *clinicians*, including the team of clinical experts managing the disease; on the contrary, in [27] the addressees of the depicted systems are *nutritionists*, while the system described in [28] is thought for supporting *general practice doctors* and *family clinicians*.

3.2.3. *Domain ontologies analysis*

To answer RQ3, domain ontologies underlying the recommender and decision support systems retrieved were analyzed. In particular, this review focused on investigating whether the domain ontologies rely on an existing conceptualization for diabetes and its features (e.g., international standards, national guidelines, scientific or clinical frameworks, etc.) or if they were developed from scratch (for example, leveraging experts in diabetes' knowledge to develop a peculiar perspective on the disease) (RQ3a); it also investigates the ontological languages adopted to formalize the models and the rules leveraged to generate inferences (RQ3b). Taking into account that ontology reuse is one of the "best practices" in ontology engineering [29], it is also interesting to observe if the domain ontologies reuse any existing ontological model (RQ3c) or if they adopt Ontology Design Patterns (ODPs) [30] to increase domain ontologies' alignment with other models and shareability (RQ3d). Moreover, from an ontology engineering perspective, understanding whether domain ontologies are developed following an ontology engineering methodology (OEM) that fosters cooperation between domain experts and ontologists is essential, especially in the healthcare domain [31] (RQ3e). Finally, the included works are scrutinized to understand whether the domain ontologies (and the systems exploiting them) underwent a validation or test phase, whether with clinical cases (e.g., real-patient data, simulation, etc.) or expert assessment (e.g., with clinical personnel, stakeholders, etc.) (RQ3f).

The quantitative results of this analysis are presented in Table 3 (dedicated to RQa, RQc, RQd, RQe, RQf) and 4 (detailing RQb).

Regarding the conceptualization of diabetes, most of the analyzed papers acknowledge *expert knowledge* (e.g., clinical guidelines and standards, scientific papers, documents, etc.) as a source for conceptualizing the disease. In particular, 4 of these works detailed the documents, clinical standards, and clinical practice guidelines that were adopted: American and Canadian Clinical Practice Guidelines for Diabetes Type 1 management [26], International Classification of Functioning, Disability and Health (ICF) and the International Classification of Diseases (ICD) [27,32], the Italian Standard for Diabetes Care [28]. The ontologies underlying two recommender systems ([28,33]) were engineered leveraging the support of *domain experts* with their knowledge and professional experience (in both cases, clinical personnel treating diabetic patients and clinical nutrition experts). A total of 6 works lack indications about the underlying conceptualization of

Table 2
The type of diabetes, the input data, and the output provided as described in the analyzed papers.

	Diabetes type	Focus on diabetes	Clinical data required (input)											Output
			Gender	*Age*	*Height*	*Weight (current)*	*Weight (ideal)*	*BMI*	*BMR*	*Hb*	*Glucose*	*Physical activity*	*Meal data*	
Lee et al. (2008) [33]	T2	generic	yes	yes	yes	yes	no	no	yes	no	no	no	yes	Meal composition
Akkoç and Cicekli (2011) [24]	T1	specific	*unspecified personal and clinical data*							no	no	no	yes	Meal composition, Management
Alhazbi et al. (2012) [21]	T1, T2	generic	yes	yes	yes	yes	yes	no	yes	no	no	yes	no	Nutrients amount
Arwan et al. (2013) [43]	T2	specific	no	no	yes	yes	yes	yes	no	no	no	yes	no	Diet
Wang et al. (2013) [25]	T2	generic	yes	yes	yes	yes	no	yes	no	no	no	no	yes	Diet
Villarreal et al. (2014) [22]	not specified	generic	yes	yes	no	yes	no	no	no	no	yes	yes	no	Management
Faiz et al. (2014) [44]	T2	specific	yes	yes	yes	yes	yes	yes	yes	no	no	yes	no	Diet
Latha and Kumar (2014) [34]	T2	generic	yes	yes	yes	yes	no	no	yes	no	no	no	no	Diet
Lo et al. (2015) [40]	T2	generic	no	no	no	no	no	no	no	no	no	no	no	Meal composition
Chen et al. (2017) [49]	T2	generic	yes	yes	yes	yes	yes	no	no	no	no	yes	yes	Meal composition
Yusof and Noha (2017) [35]	T2	generic	no	no	no	no	no	yes	no	no	no	no	no	Diet
Ali et al. (2018) [23]	not specified	generic	no	yes	no	yes	no	no	yes	no	yes	yes	no	Meal composition, Management
Tarabi and Juric (2018) [45]	T2	specific	no	no	no	no	no	no	no	no	yes	yes	no	Diet
Li and Alian (2018) [46]	T2	specific	yes	no	yes	yes	no	yes	no	no	no	yes	no	Meal composition
El-Sappagh et al. (2019) [26]	T1	specific	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	Nutrients amount, Management
Spoladore and Sacco (2020) [27]	T2	generic	yes	yes	no	no	no	no	no	no	no	no	yes	Meal composition
Spoladore et al. (2021) [32]	T2	specific	yes	yes	yes	yes	no	yes	no	no	no	yes	no	Meal composition
Rawte et al. (2021) [38]	T2	generic	yes	yes	yes	yes	no	no	no	no	yes	no	yes	Management
Nisheva et al. (2021) [39]	T2	specific	no	no	no	no	no	no	no	yes	yes	no	yes	Diet
Woo et al. (2022) [54]	T2	specific	yes	yes	yes	yes	no	yes	no	no	yes	no	no	Meal composition, Nutrients amount, Management
Spoladore et al. (2023) [28]	T2	specific	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	no	Nutrients amount

diabetes ([21–23,25,34,35]).

The majority of the included works detailed the ontological languages adopted for developing the domain ontologies (19 papers) and provided details about the language adopted for specifying inference rules (15 papers). However, only 11 articles detailed the logic profile adopted (which can be relevant for OWL-developed ontology, considering that different profiles can support different types of reasoning [36]). The same amount of works indicated the language adopted to query the domain ontologies. Almost all systems specifying an ontological language adopted W3C-endorsed OWL (16); the same can be registered for a query language, with W3C-endorsed SPARQL used by 8 systems. Considering there is no W3C recommendation for rule languages, it is interesting to observe that Semantic Web Rule Language (SWRL) [37] is used by 11 systems – out of the 15 specifying a rule language.

The reuse of ontological resources related to diabetes is attested in 6 works – one-third of the investigated papers ([22,26,27,32,33,38,39]). In those articles describing complex systems dedicated to chronic diseases – thus, not specifically dedicated to tackling diabetes – other domain ontologies are reused to cover different domains (for example, Villarreal et al. [22] adopt a domain ontology for context modelling, while the articles [27,32] made use of Friend of A Friend (FOAF) to describe patients' general information). Two papers indicate the adoption of existing databases, although it is not specified whether the databases' schemas are somehow adopted as part of the ontologies' TBox ([35,40]). Reused ontologies can be *imported* into the target model (completely or in some of their parts) to support the description of a portion of a domain, or they can be modelled into the target domain ontology by referencing the reused entities with their URIs (a practice named *soft reuse* [29]). The import of the reused model in the target

Table 3
Analysis of the domain ontologies from selected articles (*Expert knowledge*: e.g., clinical guidelines and standards, scientific papers, documents, etc.; *Developed with experts*: clinicians' knowledge and expertise).

	Diabetes concept.	Reuse		Adoption of ODPs	Maintenance		Engineering			Validation
		Reused ontologies	*Type of reuse*		*Accessibility*	*Alignment*	*OEM adopted*	*Collaborative approach*	*Ontology editor*	
Lee et al. (2008) [33]	Developed with experts	Taiwanese Food Ontology; Personal food ontology	import	no	no		not specified	yes	not specified	real-patient data
Akkoç and Cicekli (2011) [24]	Expert knowledge	no		no	no		not specified	no	Protégé	
Alhazbi et al. (2012) [21]	not specified	no		no	no		not specified	no	not specified	
Arwan et al. (2013) [43]	Expert knowledge	no		no	no		not specified	yes	Protégé	real-patient data
Wang et al. (2013) [25]	not specified	no		no	no		not specified	no	not specified	
Villarreal et al. (2014) [22]	not specified	PIPS project food ontology	not specified	no	no		not specified	no	not specified	real-patient data
Faiz et al. (2014) [44]	Expert knowledge	no		no	no		not specified	no	Protégé	expert assessment
Latha and Kumar (2014) [34]	not specified	no		no	no		not specified	no	not specified	
Lo et al. (2015) [40]	Expert knowledge	non-ontological resource		no	no		not specified	yes	Protégé	
Chen et al. (2017) [49]	Expert knowledge	no		no	no		not specified	no	not specified	real-patient data
Yusof and Noha (2017) [35]	not specified	non-ontological resource		no	no		Ontology 101	no	Protégé	
Ali et al. (2018) [23]	not specified	no		no	no		not specified	no	Protégé	real-patient data; expert assessment
Tarabi and Juric (2018) [45]	Expert knowledge (USA CPGs; Canadian	no		no	no		not specified	no	Protégé	
Li and Alian (2018) [46]	Expert knowledge	no		no	no		custom	yes	Protégé	real-patient data
El-Sappagh et al. (2019) [26]	Expert knowledge	BFO	not specified	no	yes[a]	DOLCE, BFO, DMTO, DDO	custom	yes	Protégé	expert assessment
Spoladore and Sacco (2020) [27]	Expert knowledge (ICF; ICD)	ICD, ICF	soft	Reification	no		NeOn	yes	Protégé	
Spoladore et al. (2021) [32]	Expert knowledge (ICF; ICD)	ICD, ICF	soft	Health condition	no		custom	yes	Protégé	real-patient data
Rawte et al. (2021) [38]	Expert knowledge	FoodOn	import	no	yes[b]		not specified	no	not specified	
Nisheva et al. (2021) [39]	Expert knowledge	DMTO	import	no	no		custom	no	not specified	
Woo et al. (2022) [54]	Expert knowledge	no		no	no		custom	yes	not specified	real-patient data; expert assessment

(*continued on next page*)

Table 3 (*continued*)

	Diabetes concept.	Reuse		Adoption of ODPs	Maintenance		Engineering			Validation
		Reused ontologies	*Type of reuse*		*Accessibility*	*Alignment*	*OEM adopted*	*Collaborative approach*	*Ontology editor*	
Spoladore et al. (2023) [28]	Developed with experts; Expert knowledge (AMD-SID)	no		Health condition	yes[c]		AgiSCOnt	yes	Protégé	real-patient data; expert assessment

[a] https://bioportal.bioontology.org/ontologies/FASTO
[b] https://github.com/ITWSXInformatics/DiabetesNutritionInformationSystem
[c] https://www.stiima.cnr.it/wp-content/uploads/DSS_diabetes_validated.txt

ontology is the most represented way of reuse ([33,38,39]), with soft reuse represented in two cases ([27,32]), while in two other cases, the type of reuse was not detailed ([22,26]). The adoption of ODPs is limited to three works ([27,28,32]), although none of them is specifically dedicated to representing diabetes. The most adopted pattern is a content ODP that enables the representation of a patient's health condition (both represented as OWL individuals) via an object property – so that it is possible to characterize a health condition with different features without impacting the person [41]. The second ODP is a well-known strategy for representing-ary relationships [42].

A total of 18 works adopted a representation of foods in their model. Of these, 8 works developed their own food ontologies leveraging on existing conceptualizations or guidelines ([21,24,25,34,43–46]), while 6 systems leveraged existing domain ontologies ([33] reused the Taiwanese food ontology; [22] adopted a model described in [47]; the systems described in [27,32,38] reused parts of FoodOn [48]). As already mentioned, 2 articles made use of non-ontological resources ([35,40]) that involved the representation of foods and their properties, while one work [49] does not specify the source of information related to foods to be recommended.

Out of the 21 ontologies described in the included articles, only 3 are fully accessible (i.e., there exists a downloadable file containing the full ontology) at the time of this literature review. The models proposed in [26,28,38] are accessible via the web (Table 3). The alignment of the investigated domain ontologies with upper models (or other existing models) is limited to [26], which is the only paper explicitly describing the mapping between the proposed domain ontology with Descriptive Ontology for Linguistic and Cognitive Engineering (DOLCE) [50] and Basic Formal Ontology (BFO) [51], and with the domain ontologies Diabetes Mellitus Treatment Ontology (DMTO) [52] and Diabetes Diagnosis Ontology (DDO) [53].

The majority of the articles investigated do not specify any OEM (13), while 5 domain ontologies were developed following a custom approach ([26,32,39,46,54]). The three works leveraging an OEM selected the waterfall approach Ontology 101 [55], the lifecycle methodology NeOn [56], and the agile AgiSCOnt [57]. In line with poor adhesion to methodologies, less than half of the domain ontologies (9) were developed in collaboration with domain experts ([26–28,32,33,40,43,46,54]). Stanford University open-source ontology editor Protégé [58] is the most appreciated choice, as 12 articles indicated its use – both within the article text or by illustrating excerpts of the ontologies using the editor. The remaining 9 papers did not specify the ontology editor adopted.

Finally, 10 papers described and conducted tests to validate the results produced by (or by means of) the domain ontologies (RQ3f); in particular, 5 works ([22,32,33,43,49]) adopted data from patients (clinical cases), 2 papers ([26,44]) relied on expert assessment, and 3 articles validated with both approaches ([28,46,54]). A detailed report of the information available for the validation phases of the systems is represented in Table 5. The functional validation (i.e., the process of verifying that the output generated by the systems [59]) is conducted in all works – with the exception of [22] – with different means (relying on clinical cases or experts), while the structural validation (i.e., the verification of the system's logical consistency [59]) is conducted in only two works ([26,46]). One work devotes the validation phase to the assessment of the technology acceptance [22].

4. Discussion

In this Section, the quantitative results illustrated in Section 3 are discussed in light of some characteristics and findings of the research on diabetes and ontology engineering.

4.1. Diabetes in domain ontologies

4.1.1. The epidemic characteristics of diabetes

The geographical distribution of authors underlines the global concern for diabetes: in almost all continents, the issue of representing diabetes semantically emerged. In particular, Asian countries accounted for the majority of authors. This phenomenon could be explained in the light of recent data on the age-standardized diabetes prevalence rates [60]: adults aged between 20 and 79 affected by diabetes in this region (including Taiwan and South Korea, 9.7 % and 6.8 % respectively) range from 6 % to 10 %, with peaks of 14 % in China, Kazakhstan, and Pakistan, and the notable prevalence between 14 % and 18 % in Afghanistan. In 2021, central Asia and high-income Asian countries (South Korea, Japan, Singapore, Brunei) registered a significant increase in age-standardized cases, primarily due to obesity and exposure to risk factors [60]. According to IDF, China's healthcare expenditure for diabetic patients touched 165.3 billion USD [18]. No global data are available for Taiwan and South Korea expenditures. Still, a comparison can be drawn if considering the data regarding diabetes-related expenditure per diabetic person: South Korea spends 2554.6 USD, and China reaches 1173.5 USD (no data are available for Taiwan).

The second geographical cluster comprises authors from Europe, which amounts to 21. European countries also saw a notable increase in the estimations of diabetic patients (+13 %) in 2021, bringing the total of diabetic cases up to 61.4 million adults, according to IDF [18]. The total European healthcare expenditure for those patients is estimated at 189.3 billion USD annually. In particular, Germany's expenditure reaches 41.3 billion USD, France's is estimated at 22.7 billion USD, and Spain and Italy are about 15 billion USD.

North America, the third cluster of authors, also registers an increase in the number of cases of diabetes. The IDF estimates that the number of adults suffering from this disease in the USA increased by 8.5 million people in ten years (in 2011 there were 23.7 million diabetic adults), bringing the total amount of diabetic patients to 32.3 million adults. This geographical area is in the lead for diabetes-related healthcare expenditures, with an estimation rising to 415 billion USD – which accounts for 43 % of the global expenditure.

The global increase in cases and expenditure (estimated at 966 billion USD, with an increase of 734 billion USD in 16 years [18]) can be seen as a strong driver for motivating the research in the field of systems for the diagnosis, prevention, and management of this disease. However, the case of African countries (fourth cluster) seems to contradict such a claim: although data from IDF are not complete, Ong et al. (2023)

recently highlighted that North Africa has the highest age-standardized rate (9.3 %). This region also registers the second lowest diabetes-related expenditure (12.6 billion USD) [18]. It is important to observe that the rise in age-standardized rate, together with more complete data, is very recent; therefore, it is plausible to expect an increase in attention toward diabetes in scientific research in the following years.

Considering the temporal distribution of articles, the research on recommender and decision support systems for managing diabetes via nutrition therapy has never stopped since 2008. There is a paucity of works related to this topic before that year: this result is in line with the findings of [61], who investigated the use of AI techniques related to diabetes. They highlighted that 2008 was the first year to mark >2500 articles produced on this topic. Also, IDF's reports on diabetes started in 2000, while WHO started to publish materials dedicated to diabetes (together with IDF) a few years later (in 2004 [62]). The years between 2000 and today have seen a significant rise in the number of diabetic patients; therefore, a lot of attention is now paid to this chronic condition that has reached epidemic proportions. Estimations by IDF suggest that by 2045, 783 million people (12.2 % of the population) will have diabetes [18]. This emergency is also reflected in the number of papers that try to tackle this disease with AI – which, according to [61], overcame 10,000 works in 2017. Finally, another notable factor contributing to the release of domain ontologies in this research field is related to technologies: the W3C released Ontology Web Language 2 (OWL 2) in 2009 [63], thus offering a more complete tool for the semantic representation of information. This – together with the development of rule languages, ontology editors, query languages, and research on authoring [64] – pushed ontology engineering forward, resulting in several attempts to model diabetes in domain ontologies.

Therefore, the epidemic characteristics of diabetes, which led to the generation of validated and revised local guidelines for its management, together with the availability of reliable ontological languages, enabled the engineering of a variety of domain models related to the disease – including the works here included tackling nutritional management of the disease.

4.1.2. Prevalence of type 2 diabetes mellitus and support systems

As highlighted by the answers to RQ1 and RQ2, the majority of papers addressed T2D and are dedicated to patients. These findings can be explained by the fact that T2D accounts for 90 % of cases worldwide – a trend characterizing also new cases [18]. The active role of patients in managing T2D is essential since the first therapeutic response consists of changing the patient's lifestyle, acting on nutrition to keep blood glucose levels under control, and physical activity. This helps shed light on the type of outputs provided by the investigated systems, which mainly falls into the *Meal composition* and *Diet* categories. In fact, while listing ingredients and suggesting recipes (and their combinations into meals or dietary plans) is easy to grasp even for non-nutrition experts, the output composed of *Nutrients amount* may be arduous for patients: only [21] provides users with the caloric intake and their daily distribution, while the other two works falling into this category either provide some easy-to-read output [54] or are devoted to clinical personnel [28]. Not for nothing, local patient-dedicated guidelines for managing this chronic condition do not refer to nutrients, preferring the adoption of "portions" as a unit of measurement of foods or grams [65].

The included articles illustrate different approaches to providing recommendations involving several input types. It is worth observing that the pharmacological management and diagnosis of Diabetes (in particular, T2D) have been represented in several international publications. However, nutrition management of this condition still presents a fragmented framework. This phenomenon could be in part due to the cultural differences characterizing countries – which influence local guidelines to some extent – and to the evolution of evidence-based nutrition guidelines for the management of the disease (underlining some characteristics that are common to all populations): the latter were able to generalize the various evidence- and expert-based guidelines into medical nutrition recommendations, which are later re-elaborated and progressively incorporated by local guidelines [66]. This is evident also from those works that adopted specific *conceptualizations* for the formalization of diabetes management: the majority of such conceptualizations rely on the same input (diabetic patient's gender, height, age, and weight) – which are also adopted in evidence-based studies. However, only a few studies adopted well-known inputs like BMI and ideal weight (i.e., the weight a patient should have according to his/her height). BMI is deemed essential in indicating underweight, overweight, or obesity conditions, which can heavily impact the caloric intake to be suggested [67]. However, BMI is adopted in only 9 systems ([25,26,28,32,35,43,44,46,54]). Similar results are collected regarding the calculation of the diabetic patient's BMR. In this case, the majority of the included works do not specify any equation or method to calculate BMR (14 works). The remaining works all adopt Harris-Benedict equations for estimating patients' BMRs. However, among these articles, only one ([28]) underlines the need to use these equations together with Mifflin-St. Jeor, which is more indicated to estimate obese patients' BMR [68]. The role of BMR in diabetic patients is crucial since this indicator tends to be higher than in non-diabetic populations, meaning that nutritional corrections should be considered when composing a diet. Also, an accurate estimation of BMR can support the early identification of diabetic-related secondary issues in T2D patients (e.g., peripheral neuropathy) [69].

Collected data from the included articles may indicate that the conceptualizations adopted – and the underlying input – may not suffice to identify diabetic patients' BMR accurately. Moreover, the limited adoption of BMI suggests that the systems depicted by the selected works may refer to "ideal" diabetic patients (i.e., patients not characterized by overweight, obesity, or underweight anthropometric phenotypes). However, in such cases, the inferences produced via such systems may be inadequate for real diabetic patients, as many of them (especially T2D diabetic patients) present either overweight or obesity characteristics – a prevalent risk factor for this chronic disease. Therefore, it is unsurprising that 8 out of 9 articles involving BMI as one of the input proposed systems specifically dedicated to diabetic patients (or clinicians). At the same time, the adoption of Harris-Benedict equations is registered in those works ([21,23,33,34]) referring to diabetes as one of the many chronic conditions that could be aided by a recommender or a decision support system: the estimation of BMR can indeed play a significant role in many other conditions [70]. Similarly, the limited representation of the level of physical activity conducted by patients (11 papers) may lead to thinking that an important piece of information is missing. This is particularly relevant for those systems proposing dietary plans – 7 out of 10 articles not adopting the level of physical activity as an input present systems that do not address diabetes *specifically*.

4.1.3. Validation of the included systems

As illustrated in Table 5, half the systems described in the selected works underwent a form of validation (10 papers). This finding is in line with those reported by Contreras and Vehi (2018), who also highlighted that AI-based systems for the prevention and management of diabetes usually undergo a validation phase. For recommender and decision support systems, the functional validation aims at verifying that the output generated by the systems is compliant with the semantic of the domain [59]: results show that in almost all papers this validation is conducted (in 4 cases relying only on clinical cases ([32,33,43,49]), in three cases relying on experts' opinions ([28,46,54]), and in two cases relying on a combination of both ([26,44])).

The structural verification is taken for granted in almost all of the papers investigated – i.e., the system's logical formalism is consistent, which is something that a reasoner can easily verify – with the notable exceptions of [26,46]. While the first relies on a varied set of experts to assess the ontology's quality (leveraging on CQs validated with SPARQL), the second involves experts in a thorough evaluation of the developed ontology: considering the scope of the FASTO ontology (a medical domain ontology heavily connected to biomedical standard ontologies), such a meticulous evaluation is not surprising. However, the lack of details pertaining the structural validation for the remaining works could be explained by the fact the functional validation requires the adoption of a DL reasoner – therefore, at least the ontological consistency of the domain ontologies should be granted.

The functional validation of the systems is mostly devoted to assessing the correctness of the inferences generated by the reasoning process. In three works [32,33,46], clinical cases are used as tests to check whether the inferences produced are sound – if compared to guidelines and knowledge modelled within the ontology. However, those works involving domain experts in the validation process conduct an assessment of the inferences with experts' opinion: clinicians' takes on the recommendations cover a central role in assessing the functionality of SWRL rules [44] and also when it is necessary to provide an evaluation of the whole recommendation outputs ([26,28,54]). In two cases, the functional validation of the systems is conducted differently from the majority of the papers: Arwan et al. [43] matched ontologically modelled patient information with caloric information contained in the food model; combining weighted tree similarity method and SPARQL queries, the food items with the highest degrees of similarities are selected to compose a diet. In Chen et al. [49], accuracy is the metric adopted to evaluate the functionality of the system: recommended food items (combined in a diet) are compared with dieticians-prepared diets; the ratio of between the dieticians-prepared food items and the inferred items constitutes the accuracy metric of the system (which, in the case of this paper, is 100 %).

Interestingly, in the incidence of cooperative approaches in ontology engineering is partially reflected also in aspects, with domain experts providing access to patients' data or formulating real use cases ([28,32,33,43,46,54]). However, this type of validation is combined only in a few cases with expert assessment, which could have further strengthened the results gained by the system – or it could have possibly fostered a maintenance phase aimed at fine-tuning some aspects of the ontologies, relying on both results' data and domain experts' interpretation of such results. With regard to the type of experts involved in the validation, Faiz et al. [44] detailed clinical personnel expertise (endocrinologists, nutritionist, dieticians) without specifying the number of people involved. El-Sappagh et al. [26] also do not provide details regarding the professionals involved in the structural and validation phases (although, it is evident that clinicians must have been involved at some point). Both [28,54] relied on two clinicians (1 nutritionist and 1 dietician) while [46] extended the validation phases also AI professionals. These findings strengthen the role of domain experts – a role not limited to the engineering phases, rather extended to the validation.

It is also worth noticing that 9 papers relied on an existing conceptualization to formalize diabetes ([26,28,32,33,43,44,46,49,54]). The possibility of adopting an existing conceptualization and guidelines about diabetes' nutritional management could be a facilitator for the validation, as experts and clinical cases could be assessed against the (ontologically formalized) rules detailed in the conceptualizations. In such cases, conceptualizations – whether they are obtained by scientific literature, clinical guidelines, or domain experts – do not act only as a "starting point" for domain conceptualization tasks. Still, they also provide a set of constraints against which to assess the system.

A completely different validation of the system is performed in [22]: twenty patients were involved in assessing the acceptability and usability of the proposed system, which included an evaluation of the usefulness of the recommendations provided by the system. It is striking that no clinicians were asked to assess whether the recommendations were safe for patients and their health conditions. While the absence of clinical personnel may raise some doubts, this work underlines a fundamental aspect that is neglected in all other articles: end users assessment of the systems. Tests conducted with end users (patients, but also clinicians when the recommender systems are developed as clinical decision support systems) are an essential step to understand technology acceptance and usability of a digital solution. The lack of investigation in this area may be motivated by the fact that most of the articles describe prototypical digital solutions – while the system presented in [22] seems to be in a more advanced state. Nevertheless, none of the investigated papers foresees a framework for testing the recommender systems with their target users (Section 3.2.2).

Finally, it is worth noting that half of the included systems do not propose any type of validation, whether the described systems recommend food items, diets, or nutrients amount to patients or where devoted to supporting clinical personnel in managing diabetic patients.

4.1.4. The focus on foods

The role of foods (specific food items and nutrients) and diabetic patients' habits are fundamental for nutrition therapy and are underlined in every guideline. Diabetic patients are suggested to consume specific foods – and abstain from other types – to avoid disease exacerbations and better control blood glucose levels throughout the day [71]. Therefore, it is unsurprising that food representation is considered by a relevant amount of the works included (86 %), particularly those tackling T2D. The representation of foods responds to the need to represent specific characteristics, such as the calories, amount of nutrients, and servings and frequencies. This can explain why the reuse of existing domain ontologies for foods is limited. Authors often preferred focusing on foods' specific features rather than reusing large domain ontologies. In those systems reusing an existing domain ontology for food, only three articles allow for a deeper analysis regarding the possible reasons for the adoption of FoodOnt ([27,32,38]) – the other works refer to non-accessible ontologies [22,33]. FoodOn presents a comprehensive and articulated hierarchy of foods, formalizing >9500 food products. This feature is interesting for those systems that indicate replacing a food with another according to some rules. Moreover, FoodOn offers different perspectives for the description and representation of foods, enabling the possibility to represent the transformations ingredients are subjected to and cooking methods.

4.1.5. Strategies for recommendations generation

It is interesting to observe the different strategies underlying the recommender and decision support systems depicted in the included works. In particular, reporting how inferences are generated can foster a deeper comprehension of the role of domain ontologies in such systems. As reported in the previous Section (and in Table 4), most of the systems relied on ontologies developed with OWL – with only the work from Woo et al. (2022) adopting the RL profile, the preferred profile for reasoning with logical implications. It is interesting to observe that 11 articles used SWRL to generate inferences. This finding aligns with research underlining the role of "If-Then" rules in ontology-driven recommendations. In clinical contexts, this type of rule is adopted to safely infer entailed knowledge [72] – sometimes with other reasoning mechanisms, such as in [25], where "If-Then" clauses were combined with fuzzy reasoning. In general, reasoning with rules in knowledge-based systems dedicated to clinical aspects presents similarities with the human cognitive processes of decision-making, making it easier to follow and explain [73]. This could explain the broad adoption of rule-based languages, even to manage knowledge vagueness – exemplified by two works adopting Type-2 fuzzy logic [25,46]. Also, the findings of this review are aligned with those by [74], devoted to recommender systems for nutrition in general: the role of ontology and rule-based systems is pivotal in this field. The transparency rule-based recommendation offers could explain the prevalence of such systems over more advanced AI techniques. Rules are explicit, results produced by these systems are auditable, and human users can potentially trace the inference mechanism to understand the inference produced via rules entirely [12]. This feature is particularly appreciated in clinical domains since data-driven systems may be perceived as unreliable – both by patients [75] and clinicians ([14,15]) thus, the role of rule-based (and, more in general, knowledge-based) systems in explainable AI remains central in the

Table 4
The ontological languages adopted to develop and query the domain ontologies from selected articles.

	Ontological languages	Logic profile	Rule language	Query language
Lee et al. (2008) [33]	not specified	not specified	not specified	not specified
Akkoç and Cicekli (2011) [24]	RDF, OWL	not specified	Jena	SPARQL
Alhazbi et al. (2012) [21]	not specified	not specified	not specified	not specified
Arwan et al. (2013) [43]	OWL	DL	SWRL	SPARQL
Wang et al. (2013) [25]	Fuzzy markup language	Type-2 fuzzy	Fuzzy markup language	not specified
Villarreal et al. (2014) [22]	not specified	not specified	not specified	not specified
Faiz et al. (2014) [44]	OWL	not specified	SWRL	not specified
Latha and Kumar (2014) [34]	not specified	not specified	not specified	not specified
Lo et al. (2015) [40]	OWL	DL	Jena	SPARQL
Chen et al. (2017) [49]	RDF, OWL	Fuzzy	Jena	not specified
Yusof and Noha (2017) [35]	OWL	not specified	not specified	SPARQL
Ali et al. (2018) [23]	RDF, OWL 2	Type-2 fuzzy	SWRL	SPARQL
Tarabi and Juric (2018) [45]	OWL	not specified	SWRL	SQL
Li and Alian (2018) [46]	OWL	DL	SWRL	SPARQL
El-Sappagh et al. (2019) [26]	RDF, OWL 2	DL	SWRL	SPARQL
Spoladore and Sacco (2020) [27]	RDF, OWL 2	DL	SWRL	SPARQL
Spoladore et al. (2021) [32]	RDF, OWL 2	DL	SWRL	SPARQL
Rawte et al. (2021) [38]	OWL	not specified	not specified	not specified
Nisheva et al. (2021) [39]	RDF, OWL 2	not specified	SWRL	not specified
Woo et al. (2022) [54]	RDF, OWL 2	RL	SWRL	not specified
Spoladore et al. (2023) [28]	RDF, OWL 2	DL	SWRL	SPARQL

development of tools for diagnosis, prediction, recommendation [76]. Among the included papers, rules seem to be developed – either with SWRL or Jena – when ontologists rely on expert knowledge (from guidelines or clinical standards) or experts: out of the 13 works out of the 15 adopting rules relied on domain experts or existing conceptualizations, including scientific literature and standards on diabetes detailing how to develop inference rules. This supports the importance of experts' role in ontology-based clinical recommender systems [72], and further underlines the need for expert knowledge-based solutions to improve explainable AI tools in clinical contexts.

Comparing the results of Table 2 regarding the outputs provided by the systems with the considerations expressed in Sections 4.1.2 and 4.1.4 regarding the role of *nutrients amount* recommendation, it is necessary to note that while this recommendation approach might result inefficient for systems addressing diabetic patients, it is interesting for clinical personnel. In fact, the correct identification of nutrients is the basic step for tailored dietary plans development by clinicians. The dietician, in order to develop a customized diet plan, takes into account the disease-specific available guidelines, but then adapts the guidelines to the single patient, considering his or her medical and dietetic history, as well as the short- and medium-term goals to be achieved with that nutritional intervention, and his or her preferences [77]. Starting with

Table 5
A summary of the validation proposed by the surveyed systems.

	Validation type	Clinical cases sample and detail	Number and types of experts	Investigated features and validation characteristics
Lee et al. (2008)	Clinical cases	11 clinical cases; gender, age, height, weight (current), meal record	–	*Functional validation* - checking the correctness of inferences for meal (dinner) composition according to favourite foods and "Six foods groups"
Arwan et al. (2013)	Clinical cases	30 clinical cases; age, height, weight, activity, BMR	–	*Functional validation* - generation of inferences and similarity calculation between patients and food items
Faiz et al. (2014)	Expert validation	–	nutritionists, dieticians (unspecified number)	*Functional validation* - the correctness of inferences for food items recommendation provided via SWRL are evaluated by experts
Villarreal et al. (2014)	Clinical cases	20 clinical cases; glucose level, gender, age, weight (current)	–	*Acceptance* - patients were asked to rate application's response time, usability, and quality of the recommendations generated
Chen et al. (2017)	Clinical cases	10 clinical cases; gender, weight (current), height, activity level, BMI, chronic disease (hypertension or nephritic syndrome or high cholesterol or renal insufficiency), meal record (7 days)	–	*Functional validation* - the recommendations generated by the ontology are evaluated by calculating "recommendation accuracy"
Li and Alian (2018)	Clinical cases + expert validation	unspecified number of clinical cases; gender, BMI, activity level	AI experts, nutritionists, dieticians, diabetes doctors (unspecified number)	*Structural validation* - ontology's evaluation conducted by ontologists with CQs generated by experts and using SPARQL *Functional validation* - inferences on dietary recommendations generated with SWRL

(*continued on next page*)

Table 5 (*continued*)

	Validation type	Clinical cases sample and detail	Number and types of experts	Investigated features and validation characteristics
El-Sappagh et al. (2019)	Expert validation	unspecified number of experts	unspecified type and number of clinicians	*Structural validation* - ontology correctness, completeness, extensibility, organizational fitness assessed by domain experts *Functional validation* - inferences assessed by domain experts + system's full functionality validated with a one patient's complete real-time monitoring and recommendation process (therapy plan including dietary recommendations)
Spoladore et al. (2021)	Clinical cases	2 clinical cases; gender, height, age, weight (current), BMI, activity level, chronic disease	–	*Functional validation* - for each clinical case, the food item suggestions and meal compositions correctness were assessed by ontologists leveraging guidelines
Woo et al. (2022)	Clinical cases + expert validation	1 clinical case; gender, age, height, weight (current), BMI, glucose level	1 nutritionist, 1 dietician	*Functional validation* - results generated by the system were assessed and rated by experts
Spoladore et al. (2023)	Clinical cases + expert validation	2 clinicians 6 clinical cases; gender, age, height, weight (ideal and current), BMI, BMR, glycated hemoglobin, activity level	1 nutritionist, 1 dietician	*Functional validation* - results generated by the system were assessed and rated by experts

the calculation of the patient's energy and macro- and micronutrient requirements, the dietician proceeds with qualitative and quantitative food choices that overcome the amount of macronutrients offered in the nutritional plan. However, clinical outcomes of MNT can vary individually, and considering genetic variations that may affect the specific metabolic response to individual macronutrients opens new perspectives for precision MNT [78].

Therefore, from a clinical perspective, it could be argued that a promising approach in the development of tailored nutritional recommendations for diabetic patients may derive from a two-steps reasoning process aimed at identifying the nutrients and, then, developing a diet. However, such an approach is only partially represented in the works surveyed here: Spoladore et al. (2023) [28] retrieves only the amounts and shares of micro- and macro-nutrients, without extending the reasoning process to the composition of a diet; on the contrary (as illustrated in 4.1.2 and 4.1.3) most of the works adopt a few anthropometrical characteristics (weight, height, gender, age) to infer the caloric amount and, from that, food items – neglecting the role of nutrients.

Table 6
Evaluation of the accessible ontologies.

OEM outcome features		El-Sappagh et al. (2019) [26]	Rawte et al. (2018) [38][a]	Spoladore et al. (2023) [28]
Reused models	*Non-ontological*	American and Canadian Clinical Practice Guidelines for Diabetes Type 1 management; FHIR standard	Expert knowledge from scientific literature	AMD-SID guidelines
	Ontologies	BFO	FoodOn	ICD, ICF
Documentation delivery	*List of Competency Questions*	yes	no	no
	Glossary / Lexicon	yes	no	no
Relevance of the model	*Conceptual map*	yes	yes	yes
	Domain and range defined	yes	partial	yes
	Disjunctions defined	yes	no	yes
	Restrictions defined	yes	no	yes
	Unsatisfiable concepts	no	no	no
Structural measures		9577 classes, 658 object properties, 164 datatype properties, 460 individual, 59,976 axioms, 140 SWRL rules, 127 annotation properties	6 classes 2 object properties 15 datatype properties	19 classes, 4 object properties, 56 datatype properties, 30 individuals, 539 axioms, 95 SWRL rules, 2 annotation properties
Logical consistency		yes	yes	yes

[a] Structural measures for this paper do not include entities from FoodOn since they are not included in the online version of the ontology.

4.2. Domain ontologies for recommender and decision support systems for diabetes nutrition therapy: engineering, reuse, and validation

The results for answering RQ3 provide some insights into the general state of domain ontologies adopted as a backbone of recommender and decision support systems for diabetes.

4.2.1. Domain conceptualization: strategies for representing diabetes

The ontology engineering activities pertaining to the *conceptualization* of the domain at hand are among the first to be conducted. Although there is no standardized method or technique to conduct such activities, several OEMs proposed different approaches [79]. In general, domain ontologies can rely on existing models or insights on the domain to be modelled (e.g., thesauri, dictionaries, technical documentation, etc.) or even adopt domain experts' advice [80]. The included papers present two-thirds of the domain ontologies being developed relying on an existing conceptualization, usually in the form of expert knowledge (provided by clinical standards, reference frameworks, guidelines, domain experts, or a combination of such elements). For the remaining works, the conceptualization of diabetes might appear somehow neglected at first glance; however, this could not be the case. Those articles not specifying any conceptualization for diabetes ([21,22,25,34,35,38,46]) still manage to produce some nutritional recommendations – in two cases even specifying rules [25,46] –, which indicates that some sort of conceptual model for the representation of diabetes and its functioning must be underlying the proposed systems. This may lead to the consideration that, in some works, the specification of the conceptualization is somehow neglected, either because of the epidemic characteristic of the disease (i.e., it is taken for granted how diabetes works) or because the focus of those works is not specifically on diabetes (i.e., the articles are focused on chronic conditions in general).

Nevertheless, it is interesting to note that only a few works ([26,27,32]) leveraged WHO standards or specified clinical guidelines to the point of enabling an evaluation of the type of entities adopted to represent diabetes: in these cases, concepts derived from the adopted knowledge resources were modelled as OWL classes ([26]) or both as classes and datatype properties ([27,32]). For the remaining papers, by analyzing the rules presented, it is possible to safely assume that many of the data required for the recommender or decision support systems to work were represented as datatype properties. This phenomenon strengthens the idea that, in general, conceptualization in diabetes domain ontologies is not scrupulously presented, omitting details that could have enabled an in-depth analysis of the ontologies underlying the systems.

It is worth observing that many articles adopted local guidelines for the development of portions of the conceptualization, including rules ([28,33,35,40,43,44,46,49,54]). This underlines the local (national) level of diabetes management and the role of guidelines in defining thresholds, amounts of nutrients, categories, and types of foods, and – where applicable – drugs' dosage and administration.

Similarly, the conceptualization of another relevant aspect of diabetes – nutrition – does not follow specific rules in the ontologies investigated. While the reuse of existing ontologies in this specific field is limited, part of the varied conceptualizations regarding foods may be due to the necessity of representing local needs (e.g., foods' availability, restrictions on food consumption due to culture, etc.) and to the representation of specific perspectives on foods (e.g., amounts of nutrients, quantity, portions, etc.). In this regard, once again, local guidelines may play a central role in guiding ontologists toward those concepts that should be given more attention.

4.2.2. Reuse of existing ontological and non-ontological resources

The reuse of existing ontologies specifically dedicated to diabetes is attested only in [39], who adopted DMTO [52] as part of their model, while 6 papers reused existing ontologies that provide concepts or relationships reusable for diabetes' representation; therefore, <29 % of the included works reused existing resources. The rate increases to 43 % if we also consider those papers that reuse non-ontological resources [35,40] and those works reusing ontologies not directly related to diabetes and its formalization (but connected with foods or person's representation). The paucity of reuse is in line with the findings by Fernández-López et al. [81], who investigated the reuse of ontologies within the same domains by conducting an empirical evaluation – concluding that the reuse rate attested around 30 %.

Except for very few papers not indicating how reused ontological resources were adopted, the majority of the systems reusing an ontology (or a portion of it) specify the type of reuse, or it was possible to assess the type of reuse conducted ([26,27,32,38,39,54]), with *import* being preferred over *soft reuse*. This partially contrasts with the considerations reported by Tudorache [64], who highlighted how identifying ontologies to be reused is easier than putting reuse into practice. For the case of the papers investigated, it seems that the identification of reusable domain ontologies is pretty limited, while the ways to reuse the few models identified were quite clear.

It is worth noting that the reuse of ontologies started to be more consistent around 2019, with well-known ontologies being considered reusable: El-Sappagh et al. [26] opted for BFO, while the two works ([27,32]) relied on WHO classifications ICF and ICD to describe diabetes and its related conditions, [38] imported FoodOn for the representation of foods, and [39] reusing DMTO. If the reuse of WHO classification might be seen as part of a trend leveraging standards to model health-related conditions [82], the reuse of BFO, FoodOn, and DMTO underlines the pivotal role these models cover in their respective domain as influential sources.

4.2.3. Ontology engineering, ODPs reuse, and maintenance

The majority of systems reusing an ontological resource leveraged on an OEM to move from an informal to a formal representation of the diabetes domain: this agrees with the general purposes of a methodology – effectively support engineering activities, including the identification and reuse of existing resources, insights on how to conceptualize the domain, formalizing the ontology's goals. Nonetheless, only 8 works specified the methodology followed to develop the domain ontologies described in the papers. This phenomenon could be, in part, explained by the fact that expert ontologists may prefer relying on different and personalized approaches rather than existing OEMs [83]; this explanation is also supported by the presence of articles ([26,32,39,46,54]) clearly adopting a custom approach, showing the presence of some features of ontology engineering (e.g., competency questions, collaborative development processes, reuse, etc.) without endorsing any existing OEM. The adoption of (parts of) the activities described in many methodologies and their rearrangement into a custom methodology is widely documented in recent trends in ontology engineering [79], supporting the claim that expert ontologists recognize the role and advantages of following an OEM – still, they can personalize the approach to ontology engineering according to their needs. The OEMs reported in the included work are exemplary of the “types” of methodologies developed over two decades of research on ontology engineering: [35] opted for Ontology 101 [55], which is among the first methodologies to be developed and includes support at authoring level (thus, guiding ontologists in “how to model” the domain by selecting constructs and entities); [27] selected the NeOn methodology [56], which can be used both as a waterfall and a lifecycle OEM, with a focus on supporting the reuse of ontological and non-ontological resources; finally, [28] relied on AgiSCOnt [84], an agile OEM underlining the role of conceptualization leveraging collaborative engineering processes.

The importance of collaborative ontology engineering in health-related domains has been stressed considerably in the past years ([31,64,79]): in such domains, the possibility of relying on clinical experts (e.g., physicians, specialized personnel, etc.) and stakeholders (e.g., patients, rehabilitators, etc.) can result in the development of more effective domain conceptualizations, thus enhancing the ontology's output. The collaborative approach involving ontologists and domain experts is nowadays pervasive in any methodology [79] – including the most recent agile paradigm [85]. However, less than half of the included works leveraged experts to develop their knowledge bases in any ontology engineering phase. Interestingly, in 7 articles ([26,28,32,33,43,46,54]) the collaboration with domain experts led to a validation of the recommender and decision support systems adopting the domain ontologies. Moreover, all articles developing their ontologies collaboratively resorted to an existing conceptual model as a framework for the conceptualization of the diabetes domain. Also, collaboration is attested in 4 of the 7 reuse cases, while 6 works adopted a custom or existing OEM for the ontology engineering process. The general lack of collaboration in the development of domain ontologies may be seen as a consequence of the scarce adoption of existing methodologies – which could have underlined the role of domain experts throughout the ontology engineering process. The cooperation with clinical personnel and their expertise in diabetes could have granted access to real use cases or patients' data for the validation of the systems described.

The lack of cooperation is somewhat surprising, considering that 12 domain ontologies were developed leveraging Protégé, an ontology editor that enables online cooperative engineering of models. Considering that this editor is free of charge, maintained by a community of 360,000 active users [64], and periodically updated with new features, plug-ins, and new versions, scarce cooperation cannot be ascribed to the absence of cooperative tools.

Also limited is the adoption of ODPs: no significant patterns were adopted to describe diabetes' specific characteristics, while only a general content pattern representing patients and health conditions [41] and a pattern for the representation of n-ary relationships were adopted. Moreover, no further patterns emerge by investigating the (few) available ontologies. The limited reuse of ODPs in domain ontologies related to diabetes retraces a result that is common in the healthcare domain (see, for example, the reuse of ODPs in domain ontologies describing disabilities [82]). Among the different research areas and industries investigated by researchers involved in ODPs, the healthcare domain is the least studied, with a notable and well-known resistance to adopting patterns (as attested in [86]).

OEMs can also support ontologists in maintenance actives, although no standardized methodologies or techniques are devoted to support them in this task. Each methodology focuses on one or more particular aspects of the engineering process; therefore, ontology engineers choose the methodology that best suits their needs. In particular, maintenance is aimed at updating domain ontologies and making them available; thus, it takes place after the development (and testing, if foreseen) phase. However, only 3 domain ontologies among the included works are accessible. Thus, the general lack of maintenance may be ascribed to the specific OEMs selected or the set of activities composing custom methodologies – which may not foresee a maintenance phase. Nevertheless, the poor rate of accessible domain ontologies on diabetes indicates that the “lost” ontologies (those not accessible nor retrievable) are destined not to be reused, forcing ontologists to find reusable models elsewhere [64].

4.2.4. *Evaluation of the accessible ontologies and their systems*

As illustrated in the previous Sections, three papers published online the ontologies they present. These three models can be thus investigated to assess their quality in representing diabetes and to understand the role they play in providing recommendations. However, it is important to observe that there is no standard ontology evaluation framework or methodology (ontologies are always content and ontologists' perspective dependent). Nonetheless, it is still possible to observe some of the ontologies' metrics to get an indication of the models overall quality by reusing an evaluation framework proposed in [85]. The framework summarizes some of the main metrics that can provide some hints regarding an ontology's overall quality:

- Reused models: check if the ontology reuses existing models.
- Documentation delivery: check if the documents (CQs, glossaries, conceptual maps), comments and labels (within the ontologies), or any other form of description are present to support users in understanding the conceptualization underlying the ontology
- Relevance of the models: evaluates how the ontology provides the information expected to be modelled using domain and range definitions, class restrictions or disjunctions, unsatisfiable concepts
- Structural measures: surveys the features available in the ontology language and that are used to describe the domain at hand (e.g., SWRL rules, datatype or object properties, individuals, classes, etc.)
- Logical consistency: assess the DL-consistency of the model using a reasoner

The results of the evaluation conducted on the three available ontologies are reported in Table 6.

At first glance, it is obvious that the three ontologies are very different among them. In terms of reused models, [26] is a medical model deeply rooted in biomedical ontologies, reusing BFO and leveraging different standards for diabetes management and healthcare data interoperability, while the other two ontologies are domain ones. The difference can be observed also in terms of *documentation delivery*, where [28,38] do not provide many details – while, on the contrary, [26] presents a complete documentation, with lexicon represented within the ontology by means of annotation properties.

In the *relevance of the model* and *structural measures* the differences between the ontologies are even more marked: [26] presents all the characteristics of a large medical ontology, founded on BFO, while the ontology in [28] is a complete domain ontology limited to its purpose. However, the ontology in [38] is scant: the only features adopted to model the domain are ranges on datatype properties. Taking into account the three ontologies' characteristics, it could be concluded that [26,28] are two domain ontologies (although, the first is a large medical domain ontology and the second is more contained and lightweight), while [38] presents an application ontology – a model developed to answer data representation needs within a specific application.

It is interesting to observe that while ontologists were tackling similar domains and sometimes adopted similar and predictable modelling choices for some domain features (e.g., the use of datatype properties to model nutrients amount and patient's clinical data), the output consists of very different ontologies. The differences can be partially explained by the purposes of the three systems and the ways selected to pursue them.

The remarkable differences among the three ontologies are mirrored in the validation of their systems (Section 4.1.3): [26] proposes a detailed validation conducted with domain experts, encompassing both structural and functional aspects; a simpler functional validation is presented in [28], devoted to assess the quality and correctness of the inferences generated by the ontology; no validation at all is proposed in [38]. There seems to be a correlation between the completeness of the models (observable via the *relevance of the model* and *structural measures* features) and their validation.

5. Implications

5.1. *Implications for ontology-based recommender and decision support systems for diabetes nutrition therapy: Balancing general guidelines and personalization*

Most of the systems depicted in the included works are devoted to proposing a set of food items to patients based on some criteria (*meal composition*). While this approach underlines the pivotal role of clinical nutritionists and dieticians in composing a patient's diet, it proves its limitations as a patient-based recommendation. This type of food item recommendation implies patients can compose a healthy and nutritionally balanced diet independently. On the contrary, the *Diet* type of recommender and decision support systems can provide more specific and strict indications to patients. The *management* type of systems can support both clinicians and patients in handling some day-to-day aspects of the chronic disease, thus supporting patients in preventing the exacerbation of diabetes. Finally, those systems mainly focused on suggesting specific *nutrient* amounts can provide only partial support to patients (i.e., they can help them manage their caloric intake) while greatly aiding clinical personnel (who can discern the appropriate amounts of nutrients according to the patient's needs). The variety of recommender and decision support systems underlines that, from a nutrition therapy perspective, diabetes is a complex chronic condition – perhaps even too complex to be handled by a single knowledge-based system. All the systems described in the included papers can only cover a portion of the guidelines they adopted as a framework, thus providing only support to specific aspects.

An example of the limitations traced in all systems pertains to the age of the end users: all the systems are devoted to adult patients – or do not specify any age range. However, diabetes nutrition therapy is different according to the patient's age, as the pediatric population's outputs must consider the growth process and cannot simply rework the indications given to the adult. Another important point to be highlighted is the weight used by the systems to give quantitative nutritional recommendations: users should be informed about the differences in the consideration of real or ideal weight, together with a clear explanation of how the ideal weight has been calculated.

Considering the rule-based strategies for generating recommendations, more transparency for the guidelines and formulas used for anthropometric and nutritional calculations is required, also from a national and international perspective. Furthermore, considering the accessibility of information directly provided to the patient in terms of meal composition, *meal composition* and *diet* types should relate to social and cultural backgrounds. Indeed, in clinical practice, dietitians/nutritionists try to adapt diets or menus to the eating habits of patients with different cultures and dietary habits while following the guidelines for the specific disease. The cultural, religious, and social background, however, is considered by very few papers ([25,35,46,54]). For some individuals with diabetes, adherence to nutritional recommendations could be challenging in terms of adoption and maintenance of the health behavior [87]: systems dedicated to patients may not yield any health and nutritional improvement due to the lack of a professional intermediary to educate and motivate patients to change their dietary habits. The role of experts and specialized clinical personnel is pivotal for the success of *diet* and *meal composition* activities in clinical practice – thus, it is more central in recommender and decision support systems. In fact, one of the most common mistakes made when planning a nutritional intervention is the absence of personalized diet adjustment. This means that the number and time of meals and the amount of macro and micronutrients per meal and portions, when not adjusted to the patients' metabolic targets or to oral or insulin therapy, may lead to diabetic patients' non-adherence to nutrition therapy [88]. Standardized recommendations are often given in clinical practice without any personalization, and they do not take into account any comorbidity. In addition to being ineffective, this can make such recommendations a cause of failure to meet the individual patient's metabolic, glycemic, weight, and body composition targets. For example, a common goal is to reduce body weight, even in the case of patients who are not obese or clearly overweight. In these cases, caloric restriction is likely to have a negative impact on lean mass (the metabolically active mass) without providing benefits in the course of the diabetic disease.

Considering the perspective of clinical personnel, who daily deal with the treatment and monitoring of patients of all ages with diabetes, several observations can be offered. Given the increasing prevalence of non-communicable diseases requiring long-term management, including diabetes, and the scarcity of human and economic resources within the healthcare sector [89], recommender and decision support systems will increasingly support clinical and nutritional treatment. For this reason, it seems fundamental to define the end-user of these systems, starting from the conceptualization and design phase up to the validation. Whether it be the healthcare staff or the patient/target who uses such systems directly without the support of professionals, systems should always be designed around the patient and his/her needs to tailor the information and make it accessible, understandable, easy-to-use and not harmful. The value generated by these systems should always lie in their use under close monitoring and continuous re-evaluation by healthcare professionals so that systems may be capable of identifying those borderline cases that could not benefit from nutritional recommendations without adjustments – e.g., individuals with comorbidities requiring a careful clinical anamnesis and dedicated nutritional indications.

5.2. Implications for ontology engineering and maintenance in the field of nutrition therapy decision support

The discussion of the results allows us to shed some light regarding the practices of ontology engineering and maintenance in this field. Regarding ontology engineering, the role of OEMs seems to be clearer in the articles starting from 2017: either custom or existing OEMs, the adoption of methodologies is enforced in most of the papers after this year. Also, the adoption of OEMs can be linked to a more consistent presence of systems' validation and cooperative approaches. It is worth noting that ontologists – in particular, experts – often adopt custom approaches to ontology engineering, i.e., they stress some particular aspects of the domain analysis, conceptualization, or development processes in a way that suits their research interests and possibilities (e.g., access to domain experts, validation opportunities, access to patients' data, etc.). This phenomenon continues a trend already registered in 2014 by Vigo et al. [83] which strengthened during the past decade [79]. The road to move ontology engineering from a form of art to a craft [90] marked a few steps more in the direction of the wider adoption of the methodologies – still, despite the recent advancements, many challenges need to be tackled [64]. OEMs can play a central role in key activities such as conceptualization and knowledge acquisition – on which the quality of the recommendations depends – and they can foster the development of technical documentation for maintenance activities. However, the included works underline an effort in the adoption of guidelines or domain experts' knowledge in the conceptualization and knowledge acquisition activities, while the maintenance of the developed model remains significantly neglected; therefore, more efforts need to be enforced to make ontologies accessible (and reusable). The issue of ontologies' maintenance and their accessibility is common among “small” domain ontologies (a feature shared with other healthcare domains [82]). Still, it significantly impacts the diffusion of domain ontologies for their reuse. Similarly, the lack of mapping between domain ontologies and existing upper ontologies hinders the adoption of domain ontologies. The lack of attention to update and maintenance activities hints at a larger issue characterizing ontology engineering: current OEMs seem to be unable to support ontologists in these activities, resulting in a set of consolidated instructions or guidelines for the domain analysis activities (which usually include knowledge identification and acquisition, conceptualization, reuse activities [80]) but lacking guidance in central tasks devoted to development (for example, authoring) and dedicated to keeping the ontologies “alive” (maintenance and alignment).

However, as already highlighted in other works [31], the role of cooperation remains pivotal – especially in healthcare, where the expert knowledge deriving from clinical personnel, standards, clinical guidelines, and patients' data is essential. The results from the included articles underline that the cooperative approach has become more and more present starting in 2018. This could indicate that ontologists “learned the lesson” about cooperation, also thanks to the evolution of methodologies – lifecycle and agile OEMs all stress the fundamental role of domain experts and continuous cooperation throughout all the phases of the ontology engineering process ([64,79,85]). In the majority of the works involved, the availability of “ready-to-use” clinical guidelines may have acted as a partial substitute for domain experts; however, expert knowledge derived from clinical experts remains pivotal for diabetic patients, in particular when a higher degree of personalization is required (both for patients [32,46,54] and clinicians [26–28]). Moreover, the cooperative approach seems to remain the privileged path to validation since it is fundamental to access patients' data to interpret the results generated via the reasoning processes and enable rules' fine-tuning.

From a practical perspective, when developing domain ontologies for the nutrition therapy of diabetic patients, ontologists should leverage clinical personnel's expertise. Expert knowledge and clinical experience in managing such patients can offer precious insights to non-experts in interpreting (and adapting, if necessary) guidelines and standards. Among the included papers, only one [28] adopted two sets of equations (Harris-Benedict and Mifflin-St. Jeor) to estimate patients' BMR – which enables the identification of more precise estimations for obese patients [68]. It is plausible to assume that in most of the included works, ontologists referred to guidelines that did not take into account this finding, while clinical experts did not participate in the knowledge elicitation activities – which could have underlined the possibility of relying on two sets of equations, rather than one. Therefore, it is important to stress that clinicians' role in ontology engineering should not be limited to a "simple check" of acquired knowledge; on the contrary, clinical personnel should actively participate in the identification of relevant pieces of information and their re-elaboration into a coherent model to be conceptualized.

In such a scenario, clinical guidelines, standards, and scientific literature – together with the knowledge modelled in existing and reused ontologies – should act as a general reference framework upon which ontologists and domain experts cooperate to produce a coherent conceptual model. Therefore, considering the role and diffusion of clinical standards and practical guidelines for the management of diabetes, ontologists should be oriented toward their adoption as a general reference framework – but they should actively involve physicians, dieticians, clinical nutritionists, and all clinical professionals involved with diabetes' management in the re-elaboration of such knowledge sources.

In this regard, OEMs can support collaborative tasks ranging from knowledge elicitation and acquisition: methodologies can help identify an ontology's scope, thus enabling all the participants in the engineering process to focus their attention on relevant information. Agile OEMs were also developed to help ontologists in decentralized settings [78]. Most agile methodologies provide ontologists with techniques and tools to support cooperation at different levels and throughout the engineering process, especially in contexts characterized by many stakeholders and domain experts. Ontologists' activities would, thus, include an "active investigation" role, interviewing domain experts and "challenging" their conceptual models to reach a shared and "irrefutable" conceptualization to be later developed into a domain ontology. Moreover, after a collaborative inspection by all participants in the ontology engineering process, these activities would enable the identification of candidate ontologies to be reused (partially or entirely) or ODPs that could be modelled.

Finally, regardless of the type of approach characterizing a methodology (waterfall, lifecycle, agile, or custom), the OEM adopted should foresee suggestions or at least general instructions for update and maintenance activities, including the possibility of aligning the developed domain ontology with existing (upper) ones to increase its interoperability. For these tasks, modular approaches can support ontologists in managing portions of the ontology and mapping them with existing models [91].

5.3. Ontology-based recommender systems for diabetic patients in the framework of AI-based systems and personalized nutrition

The role of knowledge-based technologies in AI-based systems was pointed out in the previous sections – ontologies as components of explainable AI systems. However, it is important to put the findings of this review in the perspective of recent findings and trends in AI for diabetes (and, more in general, nutrition), since the latter can have meaningful implications for the future trends of knowledge-based recommender systems for diabetic patients.

Dietary recommendations and AI: an integrative role? According to the findings of Contreras and Vehi [61], AI techniques are mostly adopted to detect adverse glycemic events, predict and control blood glucose, calculate and manage the insulin intake, and provide accurate patient stratifications. The identification of meals and physical exercise is less represented, and also AI techniques for daily-life support in managing the chronic condition do not take into account nutritional recommendations. In other words, while the authors identify an acceleration in the number of works describing the use of AI techniques for diabetic patients, less papers are focused on nutritional recommendations – thus, preferring to investigate other aspects. This may open a new perspective for knowledge-based systems: their role in supporting nutritional management of diabetes is clear and well-established ([74,92]), therefore ontology-based recommender systems could play a complementary role in providing a more complete coverage of the different aspects characterizing the file of diabetic patients. Systems leveraging AI techniques to predict and control blood glucose could benefit from dynamic and expert-based dietary recommendations, granting an even more tailored adherence to patients' real-time conditions.

Personalized nutrition. Personalized nutrition, or Precision nutrition, is a recent discipline that exploits patients' personal information to provide a more accurate and more tailored nutritional advice. Considering the biological variability of people in response to nutrition, personalized nutrition recognizes that many variables intervene in the process of defining an individual's response to dietary interventions: biochemical parameters, genetic characteristics, metabolic syndromes, anthropometric characteristics, etc. AI techniques, particularly machine learning [93], are a promising way to develop predictive model suitable for precision nutrition. In a recent and comprehensive systematic review of literature, Kirk et al. [93] surveyed scientific papers to investigate applications of machine learning to this discipline. Among their findings, they underlined that most of works relied on supervised approaches, with classification tasks playing a relevant role. In this regard, ontologies (particularly, biomedical ones) can be adopted to harmonize heterogeneous data, supporting the integration of large volumes of data [94] – thus contributing to tackle a challenge for AI techniques [95].

From a technical perspective, the review highlighted that AI techniques for diabetic patients are adopted to classify glucose response, provide dietary guidance, and predict metabolic conditions (including diabetes onsets). Leveraging machine learning, it is possible to overcome the "one-size-fits-all" approach of general guidelines and move toward a more accurate patient stratification.

Prevention. The papers surveyed in this review lack in proposing recommendations to non-diabetic or pre-diabetic individuals, who may benefit from tailored suggestions to avoid diabetes onset. AI-based personalized nutrition systems can support this type of tasks [96], providing tailored and personalized nutrition intakes and interventions. Prevention of diabetes, according to [61], are being revitalized by AI approaches, with a significant acceleration in research in the past 8 years. This phenomenon might indicate that ontology-based solutions alone may not be able to foster the delivery of preventive recommendations, thus it requires them to be combined with data-driven (and, possibly, personalized nutrition) approaches.

Adding data from sensors. Personalized nutrition systems rely on data acquired from patients (via wearable devices, clinical measurements, identification of consumed meals, etc.) [97]. However, the articles surveyed in this review indicate that the recommender systems require patients (or clinicians) to input this type of data. In other words, the ontological models do not seem to be ready to conceptualize sensors and acquired data for real-time and long-term patient monitoring. Nonetheless, the inclusion of such aspects can foster more accurate and tailored recommendations, as well as using ontologies to homogenize data coming from different sources. A notable exception to this trend is [26], whose ontology integrates the Semantic Sensor Network (SSN) ontology [98]. Also, a few works indicating physical activity as a therapeutic indication provide some concepts to capture the semantics of data acquired via wearables [22,32] – but not in a structured and solid way. Considering the role semantic models can cover in harmonizing data deriving from sensors, ontologies can – again – be adopted to label data in machine learning supervised tasks.

5.4. Practical implications for the development of ontology-based systems in the context of nutritional recommendation to diabetic patients

From the analysis of the works surveyed in this review, it is possible to summarize some recommendations for the development of knowledge-based recommender systems for diabetic patients aimed at providing nutrition therapy guidance. Although the following recommendations are based on a limited number of papers, there are a few generalizable observations that are worth mentioning.

Patient-based systems. Any recommender system in this field should be patient-based: a thorough, extensive, and complete formalization of the concepts pertaining the patients and their conditions must be granted a significant effort during the ontology engineering process. This means that the (collaborative) effort devoted to conceptualizing the patients must be focused on providing those details essential to a suitable classification of their conditions. Concepts like phenotypes, BMI, BMR (properly assessed using the necessary equations according to the patient's phenotype [68]), age, and comorbidities are essential, and domain experts can support in unveiling the connections among these concepts. The richer the patient representation is, the more personalized and accurate the recommendations provided can be. Relying on a complete "map" of the relationships holding among concepts can support ontologists in developing rules that take into account exceptions (e.g., some patients characterized by a particular conditions receive different recommendations than others), thus contributing to providing patient-tailored recommendations. Moreover, leveraging semantic reasoning, the "map" can be enriched by making entailed information explicit.

Whenever possible, patients' information should be mapped to existing (and shared) health standards, such as Electronic Health Records frameworks or international health classifications (e.g., ICF, ICD): this would enhance the ontology (and the results of the systems adopting it) interoperability with other systems.

Recommendations. Recommendations should be in line with the aim of the recommender system – i.e., the purpose of the system and the data required for its functioning must be explicit. In the case of ontology-based systems, recommendations must be based on expert knowledge (e.g., guidelines or scientific literature) or clinicians' expertise. Clinical practice should not be neglected, as it may underline some areas in which the recommender system could support its end users (patients or clinicians). It is interesting to highlight that very few works suggest to identifying the amount and types of nutrients, preferring to recommend food items or diets. However, nutrients' quantities and percentages, together with the calculation of a patient-adequate caloric intake, constitute the basis for an accurate definition of a nutrition therapy plan. In fact, dieticians and nutritionists' work in nutrition therapy starts with the identification of the nutrients requirements to develop a patient-tailored diet. Moreover, clinicians and in particular dietitians are able to provide nutrition counseling, creating a specific connection with patients, listening and motivating them and thus facilitating the achievement of goals. Therefore, the identification of patient-tailored needs in terms of micro- and macro-nutrients is a promising way to provide personalized and clinician-driven nutrition recommendations for diabetic patients, adapting the recommendations to patient's needs in terms of food choices and to the priority of clinical objectives to be achieved. The use of AI could be successful in healthcare practice, but it needs to be developed and monitored by healthcare professionals [99].

Ontology. With regard to the ontologies that can underlying the recommendation systems, the review highlighted some practices – mostly ascribable to ontology engineering best practices – that should be followed. The role of domain experts (i.e., clinicians with expertise of diabetic patients) is always essential: clinical personnel should be actively involved in almost all phases of ontology engineering, leveraging a collaborative [31] and agile approach to maximize the effort – even in decentralized settings ([57,85]). Clinicians' role does not end with the conceptualization phase: domain experts can play a central role in the preliminary validation of the developed ontology and in the assessment of the quality of the generated inferences (particularly, if the recommender system relies on rules to generate recommendations): thus, clinical personnel can provide meaningful insights in the functional validation phases and, possibly, help ontologists in rectifying and enhancing the developed ontology [80]. Moreover, domain experts can provide insights on how to further enhance or evolve the developed ontology, supporting the identification of related health domains that could be potentially represented.

Another significant issue retrieved in this review pertaining the ontologies underlying the analyzed systems is the scarcity of mapping. Ontology alignment is essential to increase a domain ontology's shareability, since it contributes to put the developed ontology in the context of existing (and well-established) models. Therefore, ontologists should always refer to guidelines for ontology mapping during the last phases of the ontology engineering process, including using automatic matching systems [100]. This problem is strictly related to another maintenance issue: the majority of the ontologies investigated in this paper are no longer accessible online, and this phenomenon is common for domain ontologies ([64,82]). However, only by divulging and sharing the developed ontology it is possible to get essential feedback to evolve the model. It is worth observing that the problem of ontology availability does not seem to reflect on machine learning datasets, which are made accessible in most of the cases (as surveyed in [93]).

System. A recommender system is likely to be data-driven or hybrid (i.e., combining data-driven AI techniques with knowledge bases). The role of AI techniques should be made explicit and the inferences generated by AI should be explainable. As highlighted in the Introduction and in Section 4.1.5, it is preferable to rely on explainable AI to allow clinicians to have a clear understanding of the rules guiding the recommendation process [13]. In this regard, the role of domain experts in assessing the system as a whole and its outputs is even more relevant. It is important to note that in knowledge-based systems clinicians role is not limited to the functional validation of the system, but it extends also to structural one: they can check the logical formalism of the ontology, identifying missing pieces of knowledge and rectify the incomplete (or wrong) ones, together with ontologists.

As pointed out in the previous Section, ontologies can be a component of more sophisticated AI-based recommender systems. In this case, their role would be "ancillary" – i.e., they can support data labelling to reach personalized nutrition predictions.

Validation. Whether it is the validation of the whole system and its recommendations or the ontology, the functional validation cannot disregard patients – and patient data. In particular, the majority of the works reviewed in this paper relied on patient data to assess different functional aspects of the systems. However, if the validation activity is conducted combining clinical cases and domain experts' opinion, it can support the identification of structural flaws in the knowledge base, as well as identifying possibilities to evolve the ontology or the system ([31,80,85]). The role of experts should not be limited to the engineering phases, rather it should be extended to the (structural and functional) validation phases to maximize their expertise, the shareability of the model, and stakeholders' feedback.

Finally, the validation of prototypical recommenders systems should also encompass – for those systems designed to be used by patients or clinicians – a proper assessment of the interface's usability and overall technology acceptance; to this regard, tests should be conducted on different populations (using, for instance, questionnaires such as the *Simple Usability Scale (SUS)* [101] or the *Technology Acceptance Model (TAM)* [102]). It should be kept in mind that opaque reasoning may result unpopular among some clinicians ([13,14]), therefore both systems and validation should take into account ways to make reasoning processes clear and transparent to human users.

6. Possible research directions

The previous Sections enabled the identification of some challenges characterizing the field of ontology-based recommender and decision support systems for diabetes nutrition therapy.

Adoption of reference frameworks. The results highlighted that the included works adopted local guidelines as frameworks for conceptualizing diabetes. However, diabetes is a disease that can be described using WHO standards such as the ICD and ICF– thus, global classification. While the first enables the identification of the chronic disease unequivocally, the second provides a set of qualities (body functions and structures affected by diabetes, social and cognitive activities impaired by some aspects of the disease, physical and psychosocial environmental limitations or facilitators characterizing the patient's surroundings). These two classifications can act as a common language for clinicians, enabling clinical information interoperability, and can also underline the main aspects on which to focus the action of support systems. For example, the ICF Core set for Diabetes [103,104] can support ontologists and domain experts in the identification of concepts and entities to be tackled by the recommender or decision support systems' aims, facilitating clinical personnel's work and helping ontology engineers in focusing the attention on specific concepts. While the adoption of these two WHO classifications is ascertained in some fields of ontology-based systems [82], diabetes research has not taken ICD and ICF into proper consideration yet.

Patient-tailored recommendations. Having observed that rule-based reasoning is central in the type of recommender and decision support systems analyzed, it is relevant to observe that most of the selected works present some degrees of approximation that do not sit well with accurate and tailored nutritional recommendations for diabetic patients. Therefore, relying on shared standards and experts' knowledge can foster the development of more patient-tailored recommendations. Failing to tailor the diet to an individual's needs is a common mistake in diabetes nutrition therapy. Personalization should consider factors such as the number and timing of meals and the patient's cultural restrictions. To avoid errors in nutritional therapy, the role of domain experts is central: health professionals can individualize and implement recommendations providing nutrition care for patients with diabetes, personalize diet, and provide patient-tailored recommendations, thus enhancing the potential benefits of nutrition therapy.

Healthcare 5.0 and Precision nutrition. These considerations may acquire more importance in a Healthcare 5.0 paradigm, where digital tools and applications are expected to cooperate effectively toward a patient-centered and personalized approach [105]. In such a context, the role of AI-based applications for diagnosis, recommendations, and predictions can leverage domain ontologies' ability to formalize expert clinical knowledge in computable models. Therefore, the challenges related to domain conceptualization need to be tackled to enhance the role of ontology-based applications in Healthcare 5.0. In particular, it is important to underline the role that ontology-based systems cover in health-related explainable AI contexts, in which the possibility to provide human-understandable explanations of inferences is essential for the effective adoption of smart technologies in clinical practice [106]. Moreover, the push toward AI-based systems underline the role of ontologies as tools to support data labelling, while the systems are mostly devoted to prediction and monitoring. In this regard, the nutritional recommendations provided by knowledge-based approaches can integrate and enhance machine learning-based systems, leveraging on more accurate patient stratifications – and, thus, contributing to move toward precision nutrition systems.

Tackling the traditional limitations of ontology engineering. The results of this review also contribute to highlighting some of the traditional limitations characterizing the adoption of ontologies for decision support systems – e.g., the lack of standard OEMs or standardized sets of activities to support ontologists in the domain analysis phase; the scarcity of supporting tools; the absence of reliable methodologies for the evaluation of domain ontologies; the need for support in key activities such as maintenance and collaboration.

An effort toward the standardization of ontology engineering activities, particularly cooperative ones, is necessary to enable ontology-based systems to step up in the healthcare field. While, on the one hand, relying on standard classifications can foster those activities about conceptualization, on the other hand, relying on structured and technical-enabled approaches can result in more interoperable ontologies [90] and foster the reuse of existing ones. As shown by the results of this review, ontology reuse is a subjective practice, often performed manually by expert ontologists. Ontology engineering could dedicate more effort to developing methodologies and techniques to provide (expert or novice) ontologists with operative instructions on which ontologies to reuse – and how to reuse them, including supporting ontologists at an authoring level. This should also take into account the reuse of ODPs. However, the research on patterns also suffers from some limitations (for example, most patterns are implicit and not explicitly documented [107]). Moreover, the adoption of patterns in health-related ontologies is scarcely attested and poorly documented [86], underlining the need for researchers to devote efforts to this area.

Ontology alignment activities could also benefit from better tools to enhance semantic interoperability among different ontologies conceptualizing the same domains. Some recent approaches in the field of automatic alignment seem to be promising [64]: however, the matching between entities belonging to different models is still a time-consuming and difficult task [108], which often requires the ontologists' manual intervention. Alignment activities are usually conducted on ontologies that are maintained and updated over time. However, the results of this study show that maintenance is another neglected area. This is an ontology engineering issue of the final phases of the process: OEMs should dedicate more effort to supporting ontologists in uploading, sharing, and discussing their ontologies with stakeholders to acquire new information (so that ontology updates are possible) and to increase the model's shareability. In this regard, agile approaches –more focused on decentralized and collaborative approaches – could serve as a promising starting point [57,85].

Making ontologies "smarter". Finally, ontology engineering could benefit from Ontology Learning – a discipline supporting data-driven ontology engineering [109], to reduce the costs and the time devoted to this activity. Natural Language Processing (NLP) and Machine Learning techniques have significantly contributed to this discipline in the past 10 years; however, human intervention is still fundamental to verifying and validating the learned ontologies. Considering the challenges related to Ontology Learning (among them: a lack of reference framework to compare different extraction models, scarcity of dedicated tools, and lack of quality assessment frameworks for learned ontologies), ontology engineering could benefit from the role of domain experts for the assessment of learned models and validation [110].

7. Conclusions and limitations of this work

This work reviewed the scientific literature to retrieve articles describing ontology-based recommender and decision support systems devoted to nutrition therapy for diabetes. The results illustrated that most works are dedicated to helping patients identify the food items they can consume to control blood glucose levels or manage their diet. Most of the investigated systems privileged the adoption of local guidelines for diabetes management rather than international standards, focusing the attention also on the representation of foods. From an ontology engineering perspective, the reuse of existing ontologies is scarcely attested, while the cooperation with clinical domain experts in ontology engineering activities becomes more evident after 2018.

The discussion of the results highlighted that domain experts' role is still pivotal – particularly for rule development and to strengthen recommendations' tailoring. The use of domain ontologies for such systems may suffer from some challenges inherited from ontology engineering, maintenance and update, and alignment. Although many significant advancements in such areas are registered, their efficient adoption in developing domain ontologies for diabetes nutrition therapy is still lacking. Undertaking the research directions implied by these challenges may enable ontology-based recommender and decision support systems to cover a central role in explainable AI applications for diabetes nutrition therapy.

The results reported in this review should be interpreted cautiously since they present potential limitations. The first limitation consists of the unavailability of most of the ontologies retrieved in the included articles: these domain ontologies are no longer accessible, and, thus, the sole possible validation for them must rely on the ontology's descriptions provided by the articles. A second limitation concerns the sample of works addressed in this review. It may be plausible that diabetes nutrition therapy could be the secondary focus of papers primarily devoted to drug recommendation.

CRediT authorship contribution statement

Daniele Spoladore: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Visualization, Writing – original draft, Writing – review & editing. **Martina Tosi:** Conceptualization, Investigation, Methodology, Writing – original draft, Writing – review & editing. **Erna Cecilia Lorenzini:** Conceptualization, Data curation, Investigation, Methodology, Writing – original draft, Writing – review & editing.

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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