sustainability

MDPI

Article

Crafting Taxonomies for Understanding Power Consumption in Industrial Kitchens: A Methodological Framework and Real-World Application

Miriam Ribeiro [1,†], Hugo Morais [1,2] and Lucas Pereira [1,3,*]

1 Instituto Superior Técnico—IST, Universidade de Lisboa, 1049-001 Lisboa, Portugal; miriam.ribeiro@usp.br (M.R.); hugo.morais@tecnico.ulisboa.pt (H.M.)
2 INESC-ID—Instituto de Engenharia de Sistemas e Computadores-Investigacão e Desenvolvimento, 1049-001 Lisboa, Portugal
3 ITI/LARSyS—Interactive Technologies Institute, 1900-319 Lisboa, Portugal
* Correspondence: lucas.pereira@tecnico.ulisboa.pt
† Current address: MasterCard, São Paulo 04730-090, Brazil.

Abstract: Although industrial kitchens consume significantly more energy than other commercial buildings and represent an important opportunity for sustainable energy systems, researchers have largely overlooked energy efficiency in these spaces. One of the main challenges is the diversity of kitchen configurations, complicating the characterization and generalization of research findings, including establishing a standardized methodology for assessing and benchmarking energy demand. To address this research gap, this paper proposes a methodological framework to develop taxonomies for understanding the electricity consumption in industrial kitchens. The proposed framework was developed following an extensive survey of the existing literature, and it is based on four main steps: identification of the knowledge domain, extraction of terms and concepts, data collection, and information analysis. To demonstrate the proposed framework, a case study was developed involving the participation of 50 restaurants located in Portugal. The proposed framework proved valid as it enabled the construction of a taxonomy that allows the classification of industrial kitchens according to different energy consumption-related concepts, such as costs with energy, the physical size of the kitchen, and the number of workers.

Keywords: taxonomy; industrial kitchen; restaurant; electricity consumption; classification; clustering

check for updates

Citation: Ribeiro, M.; Morais, H.; Pereira, L. Crafting Taxonomies for Understanding Power Consumption in Industrial Kitchens: A Methodological Framework and Real-World Application. *Sustainability* **2024**, *16*, 7639. https://doi.org/10.3390/su16177639

Academic Editors: Jack Barkenbus and Ocktaeck Lim

Received: 23 June 2024
Revised: 6 August 2024
Accepted: 30 August 2024
Published: 3 September 2024

Copyright: © 2024 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https://creativecommons.org/licenses/by/4.0/).

1. Introduction

Despite consuming large amounts of energy (five to seven times more per square meter than other commercial buildings [1]) and representing a multi-billion industry (set to reach USD 4651.03 billion by 2027 [2]), energy efficiency in Industrial Kitchens (IKs) has not been on the agenda of the research community [3]. A significant challenge reported by the few researchers in this area (e.g., [4–6]) is the diversity of restaurants and IK configurations, which makes it challenging to characterize the different IKs and, with that, generalize research findings.

A very good example of such challenges is the difficulty in defining a widely accepted methodology to assess and benchmark IKs in terms of energy demand [6,7]. For example, the Chartered Institution of Building Services Engineers suggests normalizing energy consumption with meals served or the kitchen area. Yet, recent studies show that energy use per pound turnover is more reliable, hence the most appropriate benchmark indicator for commercial kitchens [6]. Other good examples are the IK studies that focus on implementing lean strategies, inventory management, implementation of the supply chain, or customer satisfaction improvement [8,9], which are all very challenging to generalize and replicate due to the wide differences across IK configurations.

In this context, the definition of a taxonomy for IKs would provide a standardized and detailed framework for consistent data collection across key categories such as energy consumption, water usage, and waste production. By breaking down data into specific attributes like available equipment, operational practices, and time-space consideration, the taxonomy enables precise benchmarks against internal targets (i.e., within an IK) or industry standards (i.e., across IKs) and sharing best practices within and between kitchens to foster industry-wide advancements in energy efficiency and sustainable operations.

Taxonomies are crucial in automated information creation, extensively studied in Information Science, and used to structure information [10]. Terra defines taxonomy as "(. . .) a controlled vocabulary of a certain area of knowledge, and above all an instrument or element of structure that allows to allocate, retrieve and communicate information within a system, in a logical way" [11]. Additionally, taxonomies provide a structured way to classify items through hierarchical groups, facilitating identification, study, or location [12]. This classification groups similar items based on pre-established criteria, ensuring that each group shares at least one characteristic not found in other groups [13].

Taxonomies have been proposed in many domains besides biology [14], including the fields of information and communication technology [11,15]. However, to the best of our knowledge, it is not possible to find a systematic process to develop taxonomies independently of the application domain. Consequently, to define a taxonomy for IKs, it is first necessary to establish a modeling framework. In this sense, this paper makes the following original research contributions:

1. Proposes a new methodological framework to develop taxonomies for IKs, leveraging the main findings from a comprehensive survey of the background and state of the art concerning the definition and development of taxonomies in different domains. The proposed framework leverages concepts from corporate and faceted taxonomies. The former offers multiple entry points and dimensions (facets) to be analyzed. In contrast, the latter provides a structured and standardized vocabulary specific to the organization's business context, ensuring consistency and relevance of the facets.
2. Demonstrates the proposed methodology through a case study that uses data collected from 50 restaurants in Portugal. This case study evaluates the effectiveness of the proposed methodology. It provides some insights into the organizational (e.g., size, number of workers) and energy-related aspects (e.g., predominant appliances and costs with electricity) of the Portuguese industrial kitchen sector in light of the developed taxonomy.

The remainder of this paper is organized as follows. The background and state of the art on taxonomies are presented in Section 2. Section 3 presents the proposed methodology for developing taxonomies. A case study is developed in Section 4, presenting the tools used and the results obtained. The paper concludes in Section 5 with a discussion of the main findings and limitations and an outline of possibilities for future work.

2. Background and Related Works

To the best of the authors' knowledge, there is no systematized set of consolidated knowledge on the taxonomy of restaurants or any other similar subject. Thus, a thorough study and analysis of existing concepts in the literature on taxonomy was carried out.

2.1. Types of Taxonomies

Taxonomies can be classified according to their elaboration process: A faceted taxonomy divides the classification space into independent facets [16], where a facet is a specific classification category or criterion. A multidimensional taxonomy considers several dimensions [17], where a dimension corresponds to a particular aspect of the items under consideration. Unlike the faceted taxonomy, the dimensions may not be independent and may have more complex relationships. A subject taxonomy classifies the subjects based on concepts and themes. Finally, a relational taxonomy focuses on the relationships between items [18].

Likewise, taxonomies can also be classified according to their organizational use: corporate taxonomy is used to organize resources and information within an organization [19]; data management taxonomy focuses on organizing data in management systems; functional taxonomy categorizes information based on business functions; business taxonomy organizes information according to business activities and areas; finally, navigational taxonomy is used to facilitate navigation and location of information in digital systems [20].

Lastly, a taxonomy can also be classified according to its origin: Aristotelian taxonomy is an old approach based on observing the visible characteristics of living things, while scientific taxonomy is a modern, science-based approach that uses various information to classify organisms. Classical taxonomy can refer to both Linnaean taxonomy and a traditional approach based on morphological characteristics. On the other hand, plant taxonomy is a specific branch dedicated to classifying plants according to the rules established by the International Code of Botanical Nomenclature [20].

2.2. Modeling Taxonomies

There are several methods for modeling a taxonomy. The deductive reasoning method, for example, requires that the context of the taxonomy be considered first and only then its elements and relationships [21]. Thus, it is necessary to (1) understand the context and objectives, (2) identify the categories that represent the key aspects of the domain, and (3) establish hierarchies between the categories and their relationships.

Another method is based on Ranganathan's Theory of Faceted Classification (1967), the pillar of faceted taxonomies. This method allows the modeler to start by identifying the broader subject and, subsequently, the more restricted information [22]. Faceted taxonomy differs from traditional classification methods due to its flexibility in the use of facets: in traditional classifications, facets are stuck in rigid and enumerative tables, whereas in faceted classifications they gain freedom from relationships between terms and subjects [23]. In this method, some of the procedures adopted are the following: (1) identification of the purpose and target audience, (2) definition of the language used and the level of specificity of the subjects, (3) establishment of hierarchical relationships, (4) ordering and grouping subjects and survey of facets giving rise to sub-facets, and (5) structure validation and adjustment, if necessary.

Thesaurus development is another methodology that provides some principles for grouping concepts of the same nature into facets through the following steps: (1) establishment of general categories; (2) collection of terms; (3) analysis of selected terms; (4) control of the diversity of meaning; and (5) construction of semantic relationships [24].

Finally, there is also corporate taxonomy, based on the model for building corporate taxonomies by Aganette [25]. This method consists of 11 steps: (1) definition of the knowledge domain, (2) analysis of collected information, (3) collection of terms, (4) analysis of collected terms, (5) establishment of general taxonomy categories, (6) construction of semantic relationships, (7) taxonomy validation, (8) definition of the taxonomy mode of presentation, (9) definition of supporting technologies, (10) taxonomy publication, and (11) taxonomy management.

2.3. Related Works on Taxonomy Definition

While it was not possible to find any literature related to the definition of taxonomies for IKs, there are works developed for other domains, including biology [14], pedagogy [26], technology [11], management [27], development of product [23], information and communication technology [15], distributed storage technologies [28], and machine learning [29].

For example, in [27], Rohrich and Cunha proposed a taxonomy to analyze Environmental Management in industrial organizations, analyzing the profile of industrial organizations about product and process technologies about the environmental management standard adopted. For this, a cluster analysis was carried out that divided 37 companies into three groups, assembled in increasing order of concern and effective action concerning the environment. This analysis made it possible to understand the different behaviors of the companies in terms of management policies, applied resources, and environmental management control instruments.

Batista [13], on the other hand, developed a faceted taxonomy for requirement elicitation techniques so that the techniques were classified according to a list of parameters, or facets, that can help developers choose the ones used in elicitation. The relevance of the taxonomy in this work was mainly due to the difficulty of discovering what a user needs when developing software. From the facets, terms were created, ordered by their interrelationship, i.e., their conceptual proximity.

The surveyed related works are summarized in Table 1.

Table 1. Studies related to taxonomy, analyzed in the literature review stage.

Title	Year	Summary
A Faceted Taxonomy for Requirement Elicitation Techniques [13]	2003	Propose a taxonomy for the techniques used in the requirements elicitation phase through a faceted classification scheme.
The Proposition of a Taxonomy for the Analysis of Environmental Management in Brazil [27]	2004	Propose a taxonomy to analyze Environmental Management in industrial organizations with a formalized environmental management system and analyze the profile of industrial organizations regarding product and process technologies in relation to the adopted environmental management standard.
Taxonomy: a fundamental element for Knowledge Management [11]	2005	Introduce different types of taxonomy as well as their development. The study focuses on Knowledge Management, so numerous IT tools are presented.
Constitutive elements of the taxonomy concept [30]	2010	Search in the literature, in different areas of knowledge, the semantic understanding of the term taxonomy, in addition to identifying and analyzing different definitions of taxonomy.
The taxonomy as classificatory structure: an application in the domains of interdisciplinary knowledge [14]	2010	Present the method used in structuring the taxonomy of Environmental Geochemistry. Demonstrate the steps for modeling domains, based on the Theory of Faceted Classification and on the principles of the Theory of Integrative Levels, pointing to the conceptual map as a graphical form of representation.
Bloom's taxonomy and its adequacy to define instructional objective in order to obtain excellence in teaching [26]	2010	Present Bloom's Taxonomy and the changes that have occurred in recent years, as well as clarify how it can be used within the context of engineering teaching.
Taxonomy for creative techniques applied to the design process [23]	2011	Classify the creative techniques used in the process of product development through a faceted taxonomy.
Methodology for construction of faceted corporate taxonomies [15]	2021	Systematize the procedures for building corporate taxonomies, to reframe and characterize them as faceted.
A taxonomy for Blockchain-based distributed storage technologies [28]	2021	Propose a categorization and taxonomy of blockchain-based distributed storage technologies.
Lexicon annotation in sentiment analysis for dialectal Arabic: Systematic review of current trends and future directions [29]	2023	Present a taxonomy of data annotation methods in sentiment analysis for dialectal Arabic research.

2.4. Summary

In the papers analyzed, there is a lack of papers related to IKs or in the energy domain. In addition, this review reveals that the content on taxonomy available in the literature is not very systematic since it has several classifications (related to its elaboration, organizational use and origin); it is used in many areas of knowledge (biology, pedagogy, technology, management, product development, information and communication technology) and can be built using different methods (Deductive Reasoning Method, Ranganathan's Faceted Classification Theory, Thesaurus Elaboration, Corporate Taxonomy). Figure 1 shows a diagram that organizes various taxonomy-related classifications.

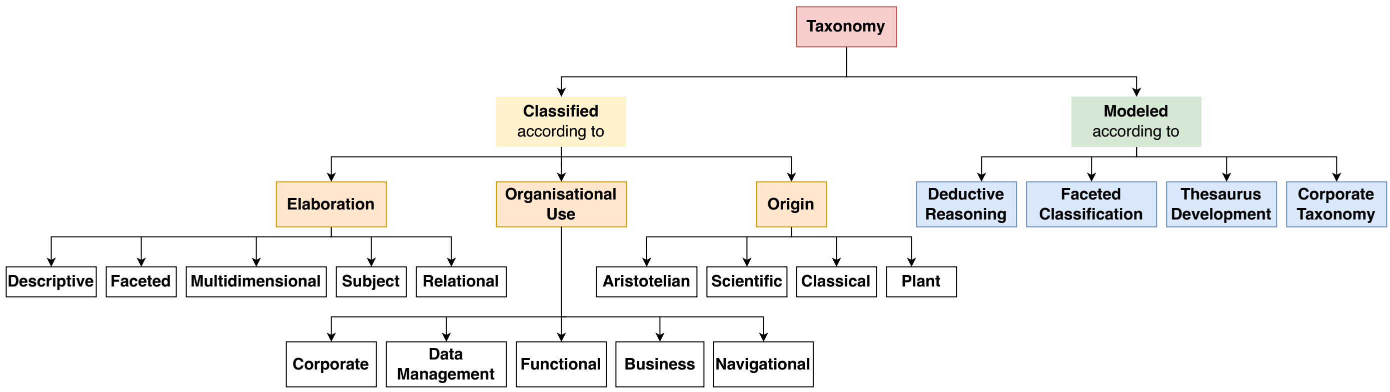

Figure 1. Different taxonomy-related classification strategies.

The deductive reasoning method emphasizes the abstract understanding of the domain before considering specific elements. Faceted Classification Theory, on the other hand, emphasizes flexibility in using facets to represent information. Thesaurus Development emphasizes semantic organization and control of related terms. Finally, Corporate Taxonomy emphasizes the organization of information. To conclude, the differences between taxonomy methods are related to the focus, approach, scope, objective, and context adopted.

Since this work aimed to classify restaurant kitchens by power consumption, grouping similar concepts that enable the coordination of IK-related issues at different levels, concepts from the faceted taxonomy were mainly used. In addition, concepts from the corporate taxonomy were also used extensively due to the organization of the resources and information that were collected from restaurants in Portugal. Ultimately, combining faceted taxonomy with corporate taxonomy creates a more powerful and flexible system for managing and retrieving information related to IKs. More precisely, this integrated approach enhances search and navigation by providing a structured and standardized vocabulary specific to the organization's business context (corporate taxonomy), ensuring consistency while allowing detailed filtering and discovery (faceted taxonomy). The combined taxonomy also offers greater flexibility and scalability, adapting to new attributes and dimensions that can be found, for example, different resources (e.g., water consumption) and legislation available in different countries.

3. Methodological Framework

In the face of the lack of a widely accepted methodology to develop taxonomies, it was necessary to establish a methodology for the concrete case of IKs. To state the objective more precisely, since the primary goal of this research was to classify IKs by grouping similar concepts that allow the coordination of IKs-related challenges at different levels, concepts from the faceted taxonomy were mainly employed. Furthermore, due to the inherent corporate organization of such spaces, it was also necessary to employ concepts from the corporate taxonomy.

After analyzing the procedures adopted by several authors, the methodology depicted in Figure 2 was elaborated, leveraging aspects from the faceted and corporate taxonomies. More precisely, the proposed methodological framework to define taxonomies follows the four steps detailed next: the definition of the knowledge domain, the definition of terms and concepts, data collection, and data analysis.

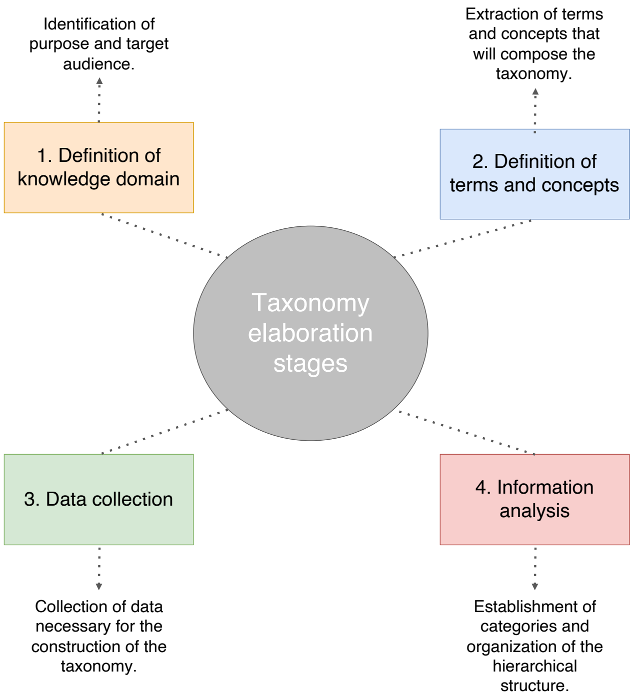

Figure 2. Four stages of the proposed methodology for taxonomy development.

3.1. Stage 1: Definition of Knowledge Domain

In the taxonomy elaboration, it is essential to set the stage in which the environment where the taxonomy is implemented so that the abstraction mechanisms are elaborated to think first in the context, independent of the elements and their relationships. In this regard, the proposed methodology applies the Faceted Classification Theory, requiring the specification of the taxonomy's purpose and the target audience [31].

3.2. Stage 2: Definition of Terms and Concepts

Some of the characteristics of a taxonomy are the following: (a) the existence of a structured list of terms, (b) hierarchically organized terms, and (c) enabling the navigation through structured terms [32]. Thus, this step in elaborating the taxonomy is the basis of its structure and consists of extracting the terms and concepts that are organized into hierarchical categories, starting from a more general subject to a more specific one. According to Ramsden, as the terms need to make sense to the group of users who use them, the specialized literature validates the selected terms [24]. Therefore, some suggested activities for collecting terms and concepts involve using an existing taxonomy and searching for information in the related literature [15].

3.3. Stage 3: Data Collection

In the literature, there is little information regarding how terms are collected, and the information regarding this step is superficially described [24]. However, conducting interviews with users and experts on the subject [15] and consulting the related literature is suggested. The work by Vital, for example, uses the content analysis technique for data collection [24]. The work by Batista [13], in turn, raises the question of the cost of data collection, especially in the case of interviews, which require considerable preparation from the interviewer. Finally, Viana [15] indicates two ways of collecting terms and concepts: manual (intellectual) and automatic. The manual one occurs with the reading of existing documents in the literature, and the automatic one occurs with the submission of a textual file in software for the automatic identification of candidate terms.

3.4. Stage 4: Information Analysis

After establishing the categories and collecting the data, the information is analyzed to organize the data hierarchically.

In a faceted taxonomy, for example, the terms are grouped in a structured way, identifying the facets of a subject, that is, the different aspects contained in it. Thus, facet analysis coordinates concepts such that a subject can be represented by synthesizing more than one facet, each indicating different concepts [15]. In this way, the facets (or categories) and subfacets of the taxonomy in question can be organized and related in a conceptual map [14].

In a conceptual map, the similarities and differences between the facets and subfacets of the taxonomy are explicit through their hierarchical relationships. Thus, in the relationship construction step, relationships are established between the defined terms to carry out the grouping of terms.

In the literature, there are several ways to analyze the information for the construction of the taxonomy, including statistical tests, content analysis, or even prior knowledge from a specialist in the subject. Rohrich, for example, uses factorial analysis techniques, the Kruskal–Wallis statistical test, and cluster analysis to develop its taxonomy to form groups of companies with common properties [27].

4. Case Study: A Taxonomy of Portuguese Industrial Kitchens

This section presents a case study that demonstrates the application of the proposed methodology. This case study is inserted in the context of the nexIK project: exploring the Human–Water–Energy Nexus in Industrial Kitchens, which aims to set itself as a one-of-a-kind real-world test bed for conducting exploratory research in IKs to understand how the Water–Energy–Food (WEF) Nexus can be leveraged to promote responsible resource consumption and cleaner energy [3]. One of the project's key objectives is to understand the energy efficiency/flexibility opportunities to evaluate the behavior of successful sustainable solutions.

4.1. Knowledge Domain

4.1.1. Purpose

The purpose of the nexIK project's taxonomy is to group similar terms and concepts that allow exploration of IK-related topics. Ultimately, at the end of the study, it will be possible to identify and develop abstract models of IKs according to the classification carried out.

4.1.2. Target Audience

The target audience comprises managers and members of IKs located in Portugal who answered a questionnaire with several questions that are the basis of the taxonomy. This same public has access to the results of this project component, such that they can compare the data of their restaurants with others around the country. This information can be helpful for them to gain a better understanding of the efficiency of their establishments in terms of energy consumption.

Another relevant target group is the scientific community, which can use the results to guide new lines of research. Sustainability agencies, such as energy, can also use the results to understand better an area that has been overlooked and few studies developed.

Still, it is possible that policymakers use this study to define new policies and rules, such as creating legislation that obliges restaurants to install renewable energy or offset carbon depending on IKs classification. Finally, there are also utilities, such as electricity companies, which may see this study as an opportunity to provide service with flexibility in energy contracts so that companies could move the high energy consumption on the most advantageous days.

4.2. Terms and Concepts

The terms and concepts present in this study were extracted by characterizing industrial kitchens concerning their infrastructure (e.g., devices) and processes (e.g., type of gastronomy). The following terms were extracted: location; type of gastronomy; spending (in euros) on energy; number of employees in the kitchen; size (in m^2) of the kitchen; time (in years) of the establishment's existence; amount of specific equipment present in the kitchen; how cooking equipment works (electricity or gas); and challenges related to the kitchen's energy consumption. Most of these terms resulted from the literature research on the topic, mainly works on establishing benchmark methodologies [5–7]. The list of appliances most commonly found in IKs was completed based on a survey of the website of IK equipment manufacturers (e.g., [33].)

The terms were then organized into three main sections: one with information about the establishment (such as name, registration number, number of employees, energy expenditure, etc.); another section with quantitative information like the type of equipment; and a third section with the qualitative terms.

4.3. Data Collection

The collection of the necessary data for the construction of the taxonomy was carried out by a Market Research company, which operates both at the level of qualitative and quantitative studies. To this end, the terms identified in the previous stage were organized in a questionnaire format, which the market research company later encoded into their platform. An overview of the encoded questionnaire is provided in Appendix A.

The data collection was conducted via telephone interviews with 50 restaurants located in Portugal. The interviews were conducted in Portuguese. The following restrictions applied to select the restaurants that were contacted: all restaurants participating in the survey must be located in Portugal; only restaurant managers and owners are eligible to answer the questionnaire; the survey can only be conducted with establishments that serve at least lunch or dinner.

All the interviews were conducted in four weeks, and the whole process (from the creation of the questionnaire to the final delivery of the data) was supervised by the nexIK project research team.

Preliminary Data Analysis

Figures 3 and 4 provide an overview of the answers given by the 50 interviewed restaurants. The data are color-coded using a semaphore-style heatmap, where dark red indicates the lowest number of occurrences and dark green highlights the highest.

	Portuguese	Fast Food	Indian	Italian	Chinese	Burger	BBQ	Steakhouse	Japanese	Asian	Other
Type of Cuisine	34	1	1	1	0	1	3	0	0	0	9

	< 500	501 to 750	751 to 1000	1000 to 1500	> 1500	Don't Know
Euros Spent in Electricity	11	10	11	7	10	1

	< 1	1 to 4	4 to 8	8 to 12	> 12
Years of Existence	3	8	10	2	27

	1 to 3	4 to 5	6 to 10	> 10
Workers in the Kitchen	23	14	9	4

	0 to 30	31 to 60	61 to 100	> 100
Square Meters	30	14	4	2

	Electricity	Gas	Don't Know
Predonomiant Equipment	25	24	1

Figure 3. Responses to general questions about the interviewed restaurants.

With respect to the general characteristics of the restaurants (Figure 3), the following observations can be made. First of all, as expected, the majority of the restaurants offer Portuguese gastronomy (34 out of 50). Concerning the costs of energy, there is no clear pattern since it is possible to find a similar number of restaurants in each category. This aspect becomes more interesting when considering that 30 of the 50 IKs are smaller than 30 square meters. Ultimately, this corroborates with existing literature where it is discussed that the size of the kitchens is not a good feature to normalize energy consumption. The small size of the kitchens also helps explain the relatively small number of kitchen operators—almost 50% of the kitchens are operated by 1 to 3 people. Finally, most restaurants are over 12 years old.

	Number of Units			
	0	1	2	> 2
Air Conditioning	5	18	10	16
Bain-Maries	32	13	2	3
Blast Chillers	24	20	4	2
Boilers	27	20	3	0
Braziers	31	15	1	3
Buffet Stand	49	1	0	0
Chicken Rotisseries	41	6	2	1
Cutters or Choppers	22	22	3	3
Deep Fryers	4	20	17	9
Dishwasher	1	21	24	4
Griddle	48	2	0	0
Kettles	38	9	1	2
Microwave	8	27	13	2
Oven	1	31	15	3
Plate Warmer	36	9	4	1
Plate Warmer Carts	46	4	0	0
Proofing Chambers	49	1	0	0
Refrigerator	0	5	5	40
Refrigerated Showcase	13	19	10	8
Salamander	39	10	1	0
Smoke Extractor	1	35	9	5
Stove	1	31	15	3
Water Heater	32	16	1	1

Figure 4. Responses to electric devices in each IK.

With respect to the electric devices available in each IK (Figure 4), the refrigerator is by far the most common device, with 40 restaurants indicating the presence of more than two units. Other common appliances are Air Conditioners (ACs), smoke extractors, cooking appliances (deep fryers, microwaves, stoves, and ovens), and dishwashers. In contrast, there are several appliances that are very uncommon, particularly very specific appliances such as plate warmers, proofing chambers, and rotisseries.

4.4. Information Analysis

4.4.1. Data Analysis Methodology

An iterative methodology was followed for the data analysis, as depicted in Figure 5. The different steps are described next.

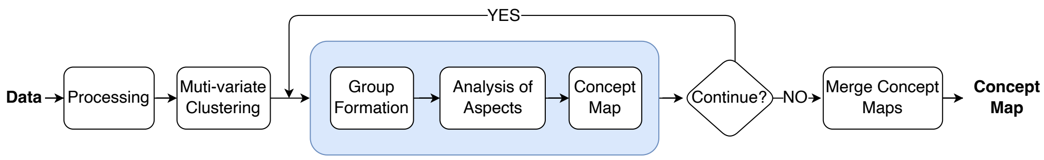

Figure 5. Process followed to carry out the analysis of the information.

In the first step, the data are processed such that they can be interpreted by the statistical software, which in the case of this work is the Minitab [34]. This step is not mandatory if the data are already in the desired format. However, it is necessary at least to describe the most relevant data arrangements for replicability purposes.

For the second step, since there is no a priori hypothesis about the structure or behavior in the data, it was decided to rely on hierarchical clustering to learn relationships from the data automatically. This decision is especially relevant since it avoids the need to re-establish the number of clusters, which is a required hyperparameter in most clustering algorithms. Instead, the only required hyperparameters are the dissimilarity (i.e., distance) and linkage functions. The former is used to quantify the distance between two clusters, and it was set to the Euclidean distance, the most widely used and recommended in the literature [35]. The latter is used to join the different pairs of clusters and was set to the ward method, which creates clusters by minimizing the intra-cluster variance.

This is followed by an iterative process that is composed of the following three steps:

1. Group Formation: all the possible cluster arrangements were organized and displayed using dendrograms, and the clusters were formed by slicing the distance axis (y-axis) at different values based on visual inspection.
2. Analysis of Aspects: Various aspects were analyzed based on the answers obtained from the questions asked to the restaurants interviewed. These questions included the type of gastronomy, the energy cost in euros, the number of employees in the kitchen, the size of the kitchen in square meters, the time of existence in years, and the equipment source of energy. The possible answers for each question are available in Appendix A. The percentage of responses for each alternative was then calculated in order to draw conclusions about each group formed. This made it possible to determine which type of gastronomy was predominant in a given group, as well as to identify trends in relation to energy expenditure, number of employees, and other aspects.
3. Concept Map Creation: The taxonomy structure is usually represented graphically through conceptual maps, making the hierarchical relationships between the taxonomy elements more visible. In this work, the software used to create the conceptual map was Cmap Tools [36]. As a tool for organizing the concepts, this software uses a hierarchical diagram, presenting the information in descending, with the most general information at the beginning of the hierarchical chain.

Finally, in the last step, the concept maps were merged following the temporal order in which they were developed in the previous steps.

4.4.2. Results and Discussion

Clustering

In the clustering step, the devices available in each of the 50 surveyed restaurants were used as input for the clustering algorithms. The resulting clusters are depicted in Figure 6, where the y-axis represents the Euclidean distance and the x-axis represents the observations (i.e., the 50 restaurants that participated in the interview).

After visual inspection of the dendrogram, it was decided to slide it at a distance of 12.71, resulting in three clusters (blue, green, and red). Following the structure of the survey, these clusters were then analyzed based on six different aspects: type of gastronomy, expense (in euros) with energy, number of employees working in the kitchen, kitchen size (in m^2), time (in years) of the existence of the restaurant, and way of working of the cooking equipment (gas or electricity).

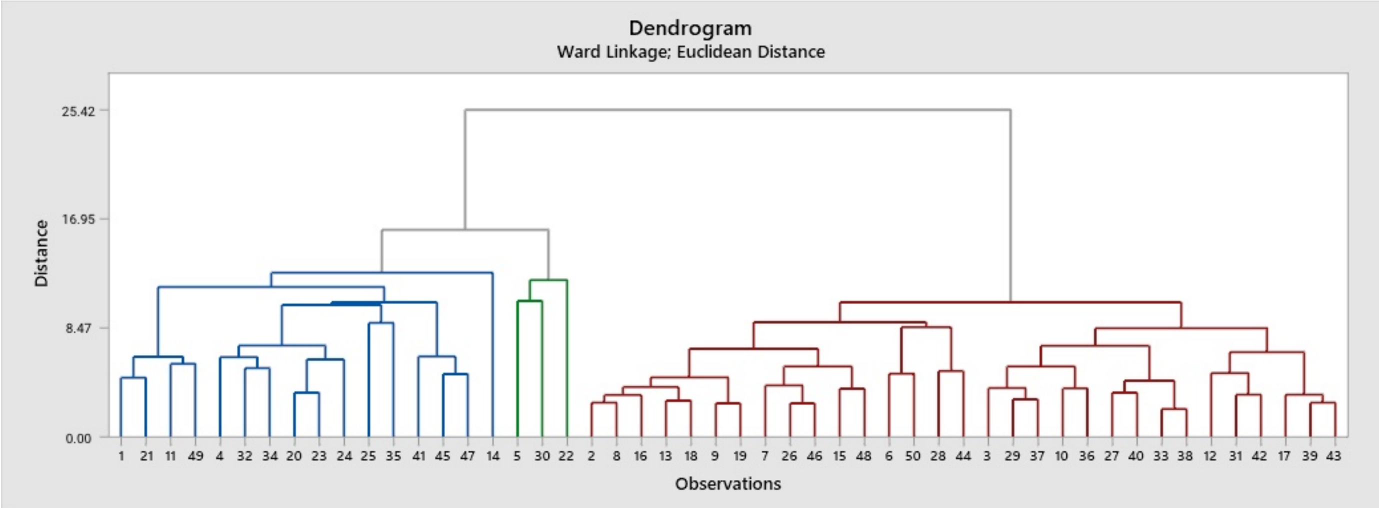

Figure 6. Cluster that divides the 50 restaurants that participated in the interview into three groups with similar characteristics.

Iteration 1

In the first iteration, the following criteria were defined for each different aspect:

- Energy Cost: The blue and green groups were classified as high because most restaurants spend from EUR 1000 to over EUR 1500 on energy (56.25%).
- Number of employees: The blue group was classified as inconclusive because the answers were well distributed between each of the categories presented, so there was no predominance. On the other hand, the green group was classified as high, at 66.67%.
- Kitchen Size: The blue and red groups were classified as small because most of the restaurants in these groups had a maximum of 60 m^2 in their kitchens (75% of the restaurants in the case of the blue group and 100% of the restaurants in the case of the green group). On the other hand, the green group was classified as inconclusive because there was no pattern in this aspect, as each restaurant in this group answered a different alternative for the size of its kitchen.
- Time of existence: All the groups were classified as high because, in all the groups, most of the restaurants have been in existence for more than 12 years: 75% of the restaurants in the case of the blue group, 100% in the case of the green group, and 38.71% in the case of the red group.
- Equipment operation: All the groups were considered inconclusive because, in all of them, the distribution between restaurants using gas and those using electricity was balanced, resulting in percentages close to 50% in all cases.

A summary of the analysis is presented in Table 2. The details of this analysis are provided next.

The gastronomy type variable was considered irrelevant for the analysis since all groups presented a predominance of traditional Portuguese gastronomy (66.67% for the blue and green group and 67.74% for the red group). The remaining percentages are divided between different types of gastronomy, but none of the others had a predominance, which was already expected since the field research was conducted in Portugal. The form of equipment operation was also not relevant at this stage since all groups presented inconclusive results, i.e., approximately half of the restaurants in each group used predominantly gas and the other half electricity, not having a pattern or a predominance. Similarly, the time of existence of the restaurants was not a relevant criterion in this step of the analysis because all groups presented a long time of existence, i.e., most restaurants in all groups have existed for more than 12 years.

Table 2. Summary of the analysis realized in Iteration 1.

Criteria/Group	Blue	Green	Red
Type of gastronomy	Portuguese traditional	Portuguese traditional	Portuguese traditional
Energy costs (EUR)	High	High	Low
Number of employees in the kitchen	Inconclusive	High	Low
Kitchen size (m^2)	Small	Inconclusive	Small
Time of existence of the restaurant	High	High	High
Equipment operation	Inconclusive	Inconclusive	Inconclusive

Concerning the remaining aspects, the blue group presented high energy costs, with most restaurants in this group spending from EUR 1000 to over EUR 1500 per month on energy (56.25%.) Regarding the number of employees working in the kitchen, the result is inconclusive because it is not possible to say whether the amount is high or low since the data are well distributed: 25% had one to three employees, 31.25% had four to five employees, 31.25% had six to ten employees, and 12.5% had more than ten employees in the kitchen. Moreover, most of the restaurants that make up the blue group had a small kitchen space, i.e., the kitchen size was smaller than 60 m^2 in most cases.

The green group, in turn, stood out for its high energy costs and the large number of employees in the kitchen since most restaurants in this group had more than ten employees. The size of the kitchen, on the other hand, was considered inconclusive, as the green group is formed only by three restaurants, and each of them provided a different size for its kitchen: the first one presented a size between 31 and 60 m^2, the second between 61 and 100 m^2 and the last one has more than 100 m^2 in its kitchen.

Finally, the red group showed low energy spending (most restaurants in this group spend less than EUR 750 per month on energy). Furthermore, this group had a low number of employees in the kitchen (less than six employees) and also a small amount of space (less than 60 m^2).

In summary, in this first analysis, the most important criteria were the energy cost and the number of employees in the kitchen. In this sense, it can be concluded that the red group presents characteristics of smaller restaurants with fewer employees and lower energy costs. In contrast, the kitchens in the green group have many employees and a high cost of energy, possibly representing large restaurants. Finally, the kitchens in the blue group tend to be in between the red and green groups, presenting higher energy costs but an inconclusive number of employees working in the kitchen. This group also has the smallest kitchens in m^2, suggesting that this group represents restaurants with many requests. Ultimately, this analysis made it possible to create the conceptual map presented in Figure 7.

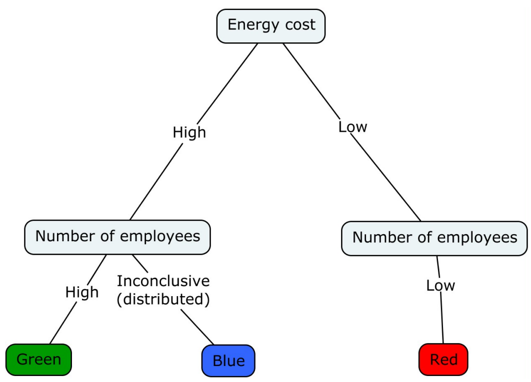

Figure 7. Conceptual map built at the end of Iteration 1.

Iteration 2

Since the green group comprises only three restaurants, its analysis ended in the first iteration. However, a second iteration was performed for the blue group (composed of 16 restaurants) and the red group (composed of 31 restaurants). To this end, these clusters were divided into smaller groups: the blue group was cut in the Euclidian distance at 9.32, whereas the red group was sliced at a distance of 8.47. The resulting clusters are depicted in Figure 8, dividing the blue group into five subgroups, and the red groups into three. Since the fifth subgroup in the blue category comprises only one restaurant, it was excluded from this analysis.

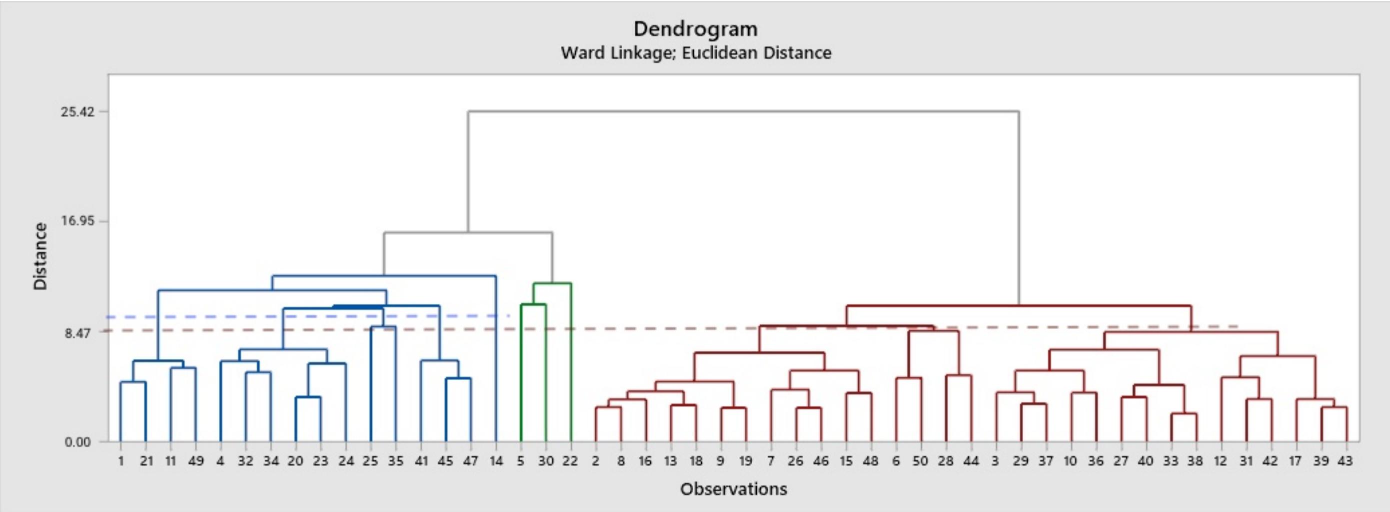

Figure 8. Cluster that subdivides the blue and red groups.

The analysis was conducted the same way as in the previous iteration (except for the criterion of type of gastronomy, which was disregarded since it proved irrelevant, as most of them are traditional Portuguese). The results of this iteration are compiled in Table 3.

Table 3. Summary of the analysis performed on the blue and red group subgroups.

Criteria / Group	B1	B2	B3	B4	R1	R2	R3
Energy costs (EUR)	High	High	Low	High	Low	Inconclusive	High
Number of employees in the kitchen	Low	Low	Low	Inconclusive	Low	Low	Low
Kitchen size (m^2)	Small	Small	Small	Small	Small	Small	Small
Time of existence of the restaurant	High	High	Low	High	Low	High	High
Equipment operation	Electricity	Gas	Inconclusive	Gas	Electricity	Gas	Electricity

In both groups, the variable kitchen size was not relevant for this analysis stage since, in all cases, most restaurants had few square meters (in all cases, the majority of restaurants in each subgroup had a kitchen smaller than 60 m^2. Regarding the analysis of the four subgroups of the blue group, the B3 is the one that differs mostly from the general characteristics of the blue group since most restaurants in this group had a short time of existence (3 to 4 years) and lower energy expenditure (although higher if compared to the red group). This is why this subgroup was assigned "average" and not "high", as with the blue group and subgroups B1, B2, and B4. In addition, the predominant use of electricity in the equipment of subgroup B1 separates it from subgroups B2 and B4, which predominantly used gas. Finally, the low number of employees (less than six) present in most restaurants of subgroup B2 separates it from subgroup B4, which has an inconclusive number of employees. More precisely, this subgroup comprises three restaurants, each with a different number of employees: the first had one to three employees in the kitchen, the second had six to ten, and the last had more than ten employees. These conclusions are represented in the conceptual map presented in Figure 9.

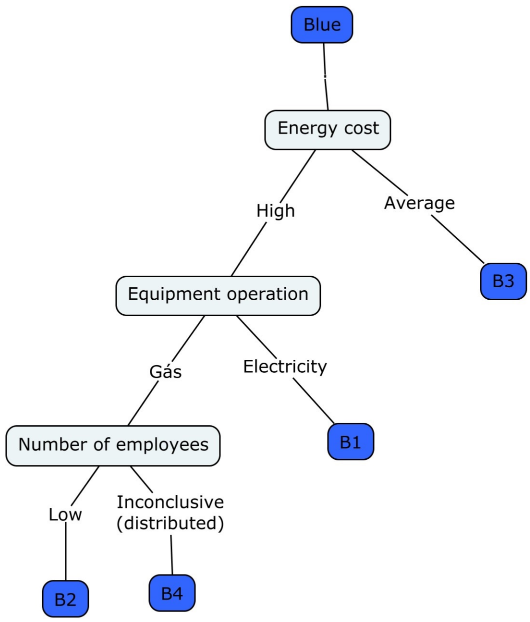

Figure 9. Conceptual map built based on analyzing the variables of the restaurants that compose the blue group.

Concerning the analysis of the red group, Subgroup R1 differs from the usual behavior regarding the time of operation since the restaurants that make up this subgroup have been open predominantly for a short time, i.e., from 1 to 8 years. Subgroup R2, on the other hand, differs from the usual pattern found in the red group in the energy consumption aspect, as it presented medium cost (from EUR 751 to EUR 1000) and not low cost (less than EUR 750), as most of the restaurants in the red group. The aspects analyzed in this case were the way of functioning of the equipment and the time of existence of the restaurants. In the first case, the gas operation separated R2 from the subgroups that work primarily with electricity, while the short time of existence separated R1 from R3, a subgroup composed mostly of restaurants that have existed for more than 12 years. The concept map in Figure 10 schematically represents this analysis.

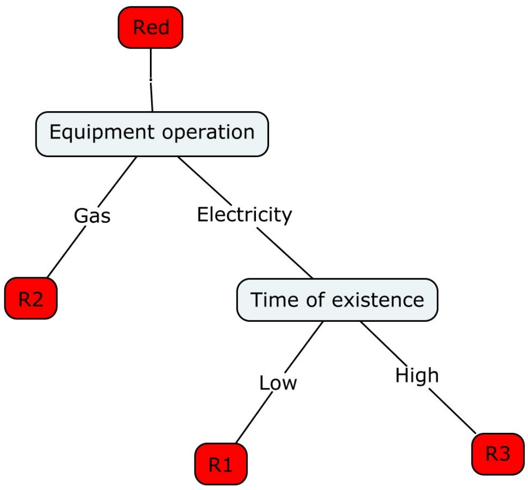

Figure 10. Conceptual map built based on analyzing the variables of the restaurants that compose the red group.

Merging

At this stage, because of the number of restaurants in each subgroup, it was not necessary to proceed with a third iteration. Hence, the three conceptual maps from Figures 7, 9, and 10 were merged to form the overall taxonomy depicted in Figure 11.

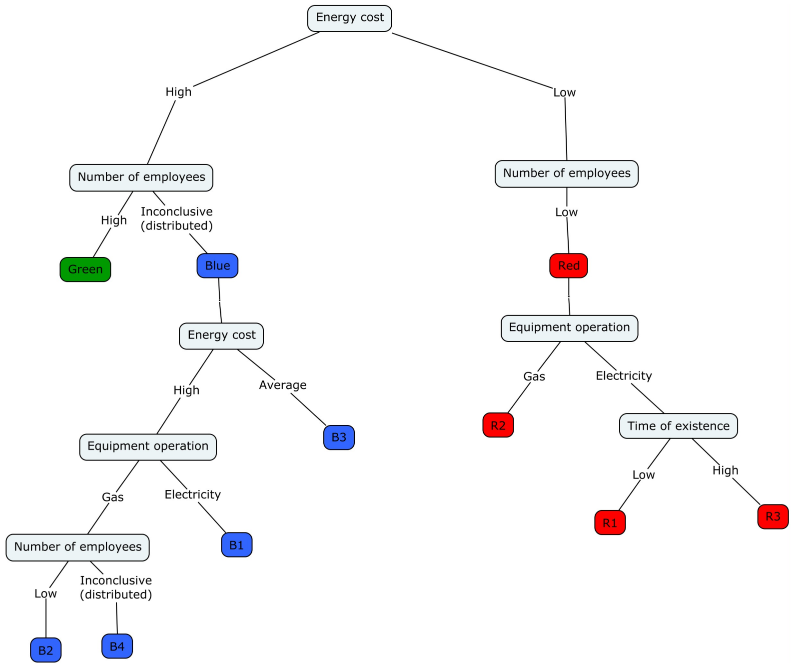

Figure 11. Conceptual map representing the final taxonomy.

On the right, it can be seen that the kitchens in the blue group belong to the group with high energy expenditure in the first stage of the analysis. However, in the second iteration, it is noted that B3 was classified as "medium". This happened because in the first iteration, restaurants from all groups were considered, and restaurants with high energy expenditure were predominated. In the second iteration, on the other hand, the analysis took into account only the restaurants belonging to the blue group, making the analysis more granular. Similarly, in the first stage of the analysis, the result for the number of employees in the kitchen was inconclusive since the numbers were well distributed, contrasting the second stage, in which the restaurants that make up the B2 subgroup predominantly presented a lower number of employees in their kitchens.

5. Conclusions

The present paper proposed a methodological framework for developing taxonomies for IKs. Given the lack of literature concerning a generalized method for developing taxonomies, the framework development was grounded on a survey of the existing literature focusing on the development of taxonomies for different fields, in particular information sciences and librarianship. The proposed framework borrows concepts from two well-established types of taxonomies, namely faceted and corporate taxonomies. Using this framework, it is possible to develop taxonomies following a four-step procedure: (1) definition of the knowledge domain, (2) definition of terms and concepts, (3) data collection, and (4) information analysis.

To illustrate the frameworks' applicability, a real-world case study was presented, where a taxonomy is developed for Portuguese IKs considering 50 restaurants spread across Portugal. Ultimately, it was shown that using this framework, it is possible to systematically build taxonomies of IKs based on their characterization, i.e., by analyzing facets such as the equipment that exists in them and their mode of operation.

In this regard, the initial exploratory analysis revealed that most restaurants offer Portuguese cuisine, with no clear pattern in energy costs, and most kitchens are smaller than 30 square meters. This aligns with the literature indicating that kitchen size is not a reliable energy consumption indicator. Common appliances include refrigerators, AC units, and various cooking devices, while very specific appliances (e.g., proofing chambers) are rare. Most restaurants have been operational for over 12 years, indicating established businesses and nearly half have one to three kitchen operators, reflecting the efficiency required in smaller kitchens. The balanced use of gas and electricity for equipment operation demonstrates flexibility in energy sourcing. This balance may also stem from the fact that most restaurants are at least 12 years old, as older establishments often retain their original gas setups due to the high cost and disruption associated with retrofitting. Over time, these restaurants gradually integrate electric appliances as technology advances and becomes more efficient.

The methodology-specific insights derived from Step 4 highlighted that combining corporate and faceted taxonomies enables a detailed and standardized analysis. Energy costs emerged as a significant criterion, with distinct differences in operational expenses among the restaurant groups, providing a basis for targeted energy efficiency measures. The cluster analysis further revealed the heterogeneity within groups, with the blue group showing higher energy costs but varied staffing and small kitchens, while the green group indicating large operations with high staffing and energy costs. On the other hand, the red group represented smaller, cost-efficient operations with lower energy expenditure and fewer employees. This granular analysis underscores the importance of benchmarking best practices and suggests that smaller, cost-efficient operations could benefit from the insights of higher-cost counterparts.

Limitations and Future Work

There are, however, some improvements that should be considered for future iterations of this work. More precisely, the information analysis (Step 4) follows a purely manual process, which can be subject to modeler bias, for example, when selecting where to split the clusters. Furthermore, each facet is analyzed and interpreted manually. In this sense, an important future research direction is to adopt different data mining techniques to automate this process. Association Rule Mining, for example, is a data analysis technique used to discover interesting and frequent patterns in transactional or relational datasets by identifying meaningful associations or relationships between frequently co-occurring items in a dataset [37]. Another technique is Ant Colony Optimization, a probability-based heuristic created for solving computational problems involving pathfinding in graphs [38]. Both techniques can be used to extract rules from the data automatically, which can later be translated into concept maps and assessed by the human modeler(s).

Ultimately, while not the main focus of this paper, the development of taxonomies for IKs can have significant practical implications for energy managers and researchers. For example, having such a framework, it should be possible to study and compare industrial kitchens within and across countries, considering different facets, organizational procedures, and business models such as virtual restaurants [39]. For instance, analyzing the interplay between location, type of food served, and energy costs can reveal whether these factors influence the energy expenditures of an IK. Furthermore, it should be possible to leverage the developed taxonomies to build abstract models of industrial kitchens, ultimately enabling the simulation of different energy efficiency measures. The importance of developing abstract models is centered on the difficulty of instrumenting a large number of kitchens since the costs of equipment and even human resources are very high.

Author Contributions: Conceptualization, M.R., H.M. and L.P.; methodology, M.R., H.M. and L.P.; software, M.R. and L.P.; validation, M.R., H.M., and L.P.; formal analysis, M.R., H.M. and L.P.; investigation, M.R.; resources, H.M. and L.P.; data curation, M.R.; writing—original draft preparation, M.R. and L.P.; writing—review and editing, M.R., H.M. and L.P.; visualization, M.R. and L.P.; supervision, H.M., and L.P.; project administration, H.M. and L.P.; funding acquisition, H.M. and L.P. All authors have read and agreed to the published version of the manuscript.

Funding: Lucas Pereira received funding from the Portuguese Foundation for Science and Technology (FCT) under grants CEECIND/01179/2017 and projects 10.54499/LA/P/0083/2020; 10.54499/UIDP/50009/2020 & 10.54499/UIDB/50009/2020. Hugo Morais received funding from FCT under project UIDB/50021/2020. This research was funded by FCT under the Exploring the Human-Water-Energy Nexus in Industrial Kitchens (nexIK) project (EXPL/CCI-COM/1234/2021).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The raw data supporting the conclusions of this article will be made available by the authors on request.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

AC	Air Conditioning
IK	Industrial Kitchen

Appendix A. Questionnaire Used in the Interviews with the 50 Restaurants

Table A1. Structure of the Questionnaire Used in the Interviews with the 50 Restaurants.

Content	Reference	Text	Type/Range
Question	[. . .]	**Registration number**	Quantity
Variables	Registration		[9 to 306]
Values			
Question	[. . .]	**Accepts recording**	Single
Variables	P0		1 to 2
Values	1	Yes	1 to 1
	2	No	2 to 2
	1		
Question	[. . .]	**Date of interview**	Open
Variables	Date	open-ended verbatim	
Values			
Question	[. . .]	**Interview time**	Open
Variables	Time	open-ended verbatim	
Values			
Question	[. . .]	**Name of establishment**	Open
Variables	Name_Cont	open-ended verbatim	
Values			
Question	[. . .]	**Location**	Open
Variables	Location	open-ended verbatim	
Values			

Table A1. *Cont.*

Content	Reference	Text	Type/Range
Question	[. . .]	**Q.1) What type of cuisine does your restaurant offer?**	Single
Variables	P1		1 to 98
Values	1	Traditional Portuguese	1 to 1
	2	Fast-Food	2 to 2
	3	Indian	3 to 3
	4	Italian	4 to 4
	5	Chinese	5 to 5
	6	Burger restaurant	6 to 6
	7	Churrascaria	7 to 7
	8	Steakhouse	8 to 8
	9	Japanese	9 to 9
	10	Asian	10 to 10
	98	Other	98 to 98
Question	[. . .]	**Q.1) What type of cuisine does your restaurant offer?—Other**	Open
Variables	P1_Out	open-ended verbatim	
Values			
Question		**Q.2) How much do you spend on energy in your restaurant (in euros)?**	
	[. . .]		Single
Variables	P2		1 to 99
Values	1	Less than 500 euros	1 to 1
	2	501 to 750 euros	2 to 2
	3	751 to 1000 euros	3 to 3
	4	1000 to 1500	4 to 4
	5	Maior que 1500 euros	5 to 5
	99	(Do Not Read) NS/NR (No Response/Not Reported)	99 to 99
Question	[. . .]	**Q.3) How many people work in the kitchen?**	Single
Variables	P3		1 to 4
Values	1	1 to 3	1 to 1
	2	4 to 5	2 to 2
	3	6 to 10	3 to 3
	4	More than 10	4 to 4
Question	[. . .]	**Q.4) How many square meters is the kitchen?**	Single
Variables	P4		1 to 4
Values	1	0 to 30	1 to 1
	2	31 to 60	2 to 2
	3	61 to 100	3 to 3
	4	More than100	4 to 4

Table A1. *Cont.*

Content	Reference	Text	Type/Range
Question	[. . .]	**Q.5) How long has the establishment been in existence?**	Single
Variables	P5		1 to 5
Values	1	Less than 1 year	1 to 1
	2	1 to 4 years	2 to 2
	3	4 to 8 years	3 to 3
	4	8 to 12 years	4 to 4
	5	More than 12 years	5 to 5
Question	[. . .]	**[. . .]**	Matrix
Variables	P6A_1	Temperature controllers	1 to 4
	P6A_2	Plate warmer	1 to 4
	P6A_3	Air conditioning	1 to 4
	P6A_4	Refrigerator	1 to 4
	P6A_5	Chicken rotisseries	1 to 4
	P6A_6	Bain-maries	1 to 4
	P6A_7	Braziers	1 to 4
	P6A_8	Electric buffet	1 to 4
	P6A_9	Boiler	1 to 4
	P6A_10	Proofing chambers	1 to 4
	P6A_11	Plate warmer carts	1 to 4
	P6A_12	Electric kettles	1 to 4
	P6A_13	Cutters or choppers (of meat, chicken, etc.)	1 to 4
Values	1	Does not exist	1 to 1
	2	1	2 to 2
	3	2	3 to 3
	4	More than 2	4 to 4
Question	[. . .]	**[. . .]**	Matrix
Values	P6B_1	Crepe makers/Waffles	1 to 4
	P6B_2	Electric water heater	1 to 4
	P6B_3	Extractor	1 to 4
	P6B_4	Stove	1 to 4
	P6B_5	Oven	1 to 4
	P6B_6	Fryer	1 to 4
	P6B_7	Dishwasher	1 to 4
	P6B_8	Microwave	1 to 4
	P6B_9	Salamander/Grill	1 to 4
	P6B_10	Refrigerated display case	1 to 4
Values	1	Does not exist	1 to 1
	2	1	2 to 2
	3	2	3 to 3
	4	More than 2	4 to 4

Table A1. *Cont.*

Content	Reference	Text	Type/Range
Question	[. . .]	**P.7) Equipment such as ovens, stoves and water heaters work predominantly at:**	Single
Variables	P7		1 to 98
Values	1	Electricity	1 to 1
	2	Gas	2 to 2
	98	Other	98 to 98
Question	[. . .]	**Q.7) Equipment such as ovens, stoves and water heaters work predominantly at: - Other**	Open
Variables	P7Out	open-ended verbatim	
Values			
Question	[. . .]	**[. . .]**	Multiple
Variables	P8_1	P.8) To conclude. What are the main challenges related to the energy consumption of your establishment's kitchen: High consumption, but I don't know how to save	0 to 1
	P8_2	P.8) To conclude. What are the main challenges related to the energy consumption of your establishment's kitchen: Difficult to promote the adoption of more efficient behaviors among the employees of the establishment	0 to 1
	P8_3	P.8) To conclude. What are the main challenges related to the energy consumption of your establishment's kitchen: Difficult to promote the use of equipment in a more efficient way	0 to 1
	P8_4	P.8) To conclude. What are the main challenges related to the energy consumption of your establishment's kitchen: I don't know which equipment consumes the most energy	0 to 1
	P8_5	P.8) To conclude. What are the main challenges: The kitchen's structure/organization does not allow for a layout that enables the intelligent use of equipment	0 to 1
	P8_6	P.8) To conclude. What are the main challenges related to the energy consumption of your establishment's kitchen: Lack of information on how to manage equipment for more efficient consumption	0 to 1
	P8_7	P.8) To conclude. What are the main challenges related to the energy consumption of your establishment's kitchen: The equipment in the establishments is not very efficient	0 to 1
	P8_8	P.8) To conclude. What are the main challenges related to the energy consumption of your establishment's kitchen: Difficult to maintain equipment in a way that keeps them efficient	0 to 1
	P8_9	P.8) To conclude. What are the main challenges related to the energy consumption of your establishment's kitchen: More efficient equipment has a high cost	0 to 1
	P8_10	P.8) To conclude. What are the main challenges related to the energy consumption of your establishment's kitchen: I don't encounter any difficulties	0 to 1
Values	0	No	0 to 0
	1	Yes	1 to 1
Question	[. . .]	P.9) **Confirm location of establishment**	Single
Variables	P9		1 to 2
Values	1	Yes	1 to 1
	2	No	2 to 2
Question	[. . .]	**P.9) Correct locality**	Open
Variables	P9A	open-ended verbatim	
Values			
Question	[. . .]	**Interviewee's email**	Open
Variables	Email	open-ended verbatim	
Values			

References

1. EnergyStar. *ENERGY STAR for Small Business: Restaurants*; EnergyStar : Washington, DC, USA, 2017.
2. *Food And Beverage Services Global Market Report 2023*; Technical Report 6193681; The Business Research Company: Hyderabad, India, 2023.
3. Oliveira, A.; Ribeiro, M.; Martins, R.; Morais, G.; Morais, H.; Pereira, L. On the Role of Industrial Kitchens in Sustainable Energy Systems: The nexIK Vision. In Proceedings of the 27th International Conference on Electricity Distribution (CIRED 2023), Rome, Italy, 12–15 June 2023; Volume 2023, pp. 686–690. [CrossRef]
4. Paillat, E. Energy Efficiency in Food-Service Facilities: The Case Of Långbro Värdshus. Master's Thesis, KTH Royal Institute of Technology, Stockholm, Sweden, 2011.
5. Hearnshaw, S.A.; Essah, E.A.; Grandison, A.; Felgate, R. Energy Reduction and Benchmarking in Commercial Kitchens. In Proceedings of the Technologies for Sustainable Built Environments, Reading, UK, 3 July 2012 ; p. 8.
6. Mudie, S. Energy Benchmarking in UK Commercial Kitchens. *Build. Serv. Eng. Res. Technol.* **2016**, *37*, 205–219. [CrossRef]
7. Hedrick, R.; Smith, V.; Field, K. *Restaurant Energy Use Benchmarking Guideline*; Technical Report NREL/SR-5500-50547, 1019165; National Renewable Energy Laboratory: Golden, CO, USA, 2011.
8. Lehtinen, U.; Torkko, M. The lean concept in the food industry: A case study of contract a manufacturer. *J. Food Distrib. Res.* **2005**, *36*, 57–67.
9. Keyser, R.S.; Marella, V.K.; Clay, K. Lean restaurants: Improving the dining experience. *J. High. Educ. Theory Pract.* **2017**, *17*, 67–79.
10. Beydoun, G.; García-Sánchez, F.; Vincent-Torres, C.M.; Lopez-Lorca, A.A.; Martínez-Béjar, R. Providing Metrics and Automatic Enhancement for Hierarchical Taxonomies. *Inf. Process. Manag.* **2013**, *49*, 67–82. [CrossRef]
11. TERRA, J.C.; Schouerl, R.; Vogel, M.; Franco, C. *Taxonomia: Elemento Fundamental Para a Gestão do Conhecimento*; Biblioteca Terra Fórum Consultores: Paraná, Brazil, 2005.
12. Graef, J. Managing taxonomies strategically. *Montague Inst. Rev.* **2001**, *41*, 1–41.
13. Batista, E.A.; Carvalho, A.M.B.R. Uma Taxonomia Facetada para Técnicas de Elicitação de Requisitos. In Proceedings of the Workshop em Engenharia de Requisitos (WER), Piracicaba-SP, Brazil, 27–28 November 2003 2003; pp. 48–62.
14. Novo, H.F. A taxonomia enquanto estrutura classificatória: Uma aplicação em domínio de conhecimento interdisciplinar. *PontodeAcesso* **2010**, *4*, 131–156. [CrossRef]
15. Viana, J.Q. Metodologia para a construção de taxonomia corporativa facetada. Master's Thesis, Universidade Federal de Minas Gerais, Belo Horizonte, MG, Brazil, 2022.
16. Wei, B.; Liu, J.; Zheng, Q.; Zhang, W.; Fu, X.; Feng, B. A survey of faceted search. *J. Web Eng.* **2013**, *12*, 041–064.
17. Tezanos Vázquez, S.; Sumner, A. Revisiting the meaning of development: A multidimensional taxonomy of developing countries. *J. Dev. Stud.* **2013**, *49*, 1728–1745. [CrossRef]
18. Zedeño, M.N. Animating by association: Index objects and relational taxonomies. *Camb. Archaeol. J.* **2009**, *19*, 407–417. [CrossRef]
19. Gilchrist, A. Corporate taxonomies: Report on a survey of current practice. *Online Inf. Rev.* **2001**, *25*, 94–103. [CrossRef]
20. Lima, R.A.; de Souza Saldanha, L.; Cavalcante, F.S. A importância da taxonomia, fitoquímica e bioprospecção de espécies vegetais visando o combate e enfrentamento ao COVID-19. *S. Am. J. Basic Educ. Tech. Technol.* **2020**, *7*, 607–617.
21. Campos, M.L.d.A. Modelização de domínios de conhecimento: Uma investigação de princípios fundamentais. *Ciência da Informação* **2004**, *33*, 22–32. [CrossRef]
22. Lopes, P.T.D.; Aganette, E.C.; Maculan, B.C. Taxonomia corporativa e taxonomia facetada: Usos e aplicações na ciência da informação no Brasil. *Investig. Bibl.* **2020**, *34*, 159–173. [CrossRef]
23. PLENTZ, S.S. Taxonomia para técnicas criativas aplicadas ao processo de projeto. 2011. Ph.D. Thesis, Dissertação (Mestrado)–Universidade Federal do Rio Grande do Sul, Programa, Rio Grande, RS, Brazil, 2011.
24. Vital, L.P.; CAFe, L.M.A. Práticas de elaboração de taxonomias: Análise e recomendações. *Encontro Nac. Pesqui. Cienc. Inf.* **2007**, *8*, 28–31.
25. Aganette, E.C. Taxonomias corporativas: Um estudo sobre definições e etapas de construção fundamentado na literatura publicada. *Perspect. Cienc. Inf.* **2010**, *15*, 222. [CrossRef]
26. Ferraz, A.P.d.C.M.; Belhot, R.V. Taxonomia de Bloom: Revisão teórica e apresentação das adequações do instrumento para definição de objetivos instrucionais. *Gest. Prod.* **2010**, *17*, 421–431. [CrossRef]
27. Rohrich, S.S.; Cunha, J.C.d. A proposição de uma taxonomia para análise da gestão ambiental no Brasil. *Rev. Adm. Contemp.* **2004**, *8*, 81–97. [CrossRef]
28. Cangir, O.F.; Cankur, O.; Ozsoy, A. A Taxonomy for Blockchain Based Distributed Storage Technologies. *Inf. Process. Manag.* **2021**, *58*, 102627. [CrossRef]
29. Sherif, S.M.; Alamoodi, A.H.; Albahri, O.S.; Garfan, S.; Albahri, A.S.; Deveci, M.; Baker, M.R.; Kou, G. Lexicon Annotation in Sentiment Analysis for Dialectal Arabic: Systematic Review of Current Trends and Future Directions. *Inf. Process. Manag.* **2023**, *60*, 103449. [CrossRef]
30. Aganette, E.; Alvarenga, L.; Souza, R.R. Elementos constitutivos do conceito de taxonomia. *Inf. Soc.* **2010**, *20*, 1–18.
31. Maculan, B.C.M.; Aganette, E.C. A Teoria da Classificação Facetada na Construção de Taxonomias Facetadas. In Proceedings of the XI Seminar on Ontology Research in Brazil and II Doctoral and Masters Consortium on Ontologies, São Paulo, Brazil, 1–3 October 2018; Volume 2228. Available online: https://ceur-ws.org/Vol-2228/paper2.pdf (accessed on 1 September 2024).
32. Zeng, M.L. Knowledge organization systems (KOS). *KO Knowl. Organ.* **2008**, *35*, 160–182. [CrossRef]

33. WebstaurantStore. Cooking Equipment. Available online: https://www.webstaurantstore.com/cooking-equipment.html (accessed on 29 August 2024).
34. Alin, A. Minitab. *Wiley Interdiscip. Rev. Comput. Stat.* **2010**, *2*, 723–727. [CrossRef]
35. Wang, L.; Zhang, Y.; Feng, J. On the Euclidean distance of images. *IEEE Trans. Pattern Anal. Mach. Intell.* **2005**, *27*, 1334–1339. [CrossRef] [PubMed]
36. Cañas, A.J.; Hill, G.; Carff, R.; Suri, N.; Lott, J.; Gómez, G.; Eskridge, T.C.; Arroyo, M.; Carvajal, R. CmapTools: A Knowledge Modeling And Sharing Environment. In Proceedings of the First International Conference on Concept Mapping, Pamplona, Span, 14–17 September 2004; Volume 1.
37. Kotsiantis, S.; Kanellopoulos, D. Association rules mining: A recent overview. *GESTS Int. Trans. Comput. Sci. Eng.* **2006**, *32*, 71–82.
38. Dorigo, M.; Birattari, M.; Stutzle, T. Ant colony optimization. *IEEE Comput. Intell. Mag.* **2006**, *1*, 28–39. [CrossRef]
39. Cai, R.; Leung, X.Y.; Chi, C.G.Q. Ghost Kitchens on the Rise: Effects of Knowledge and Perceived Benefit-Risk on Customers' Behavioral Intentions. *Int. J. Hosp. Manag.* **2022**, *101*, 103110. [CrossRef]

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.