Exploring Recommendations for Circular Supply Chain Management through Interactive Visualisation

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Abstract

The new era of circular supply chain management (CSCM) produces a new complex decision area for process managers. Part of it can be attributed to green procurement, in which a large number of potential ideas need to be reviewed that can sustain business. Such a large amount of data can quickly lead to information overload, especially without the presence of appropriate decision support tools. While there exists a range of visualization methods that can aid the exploration of recommendations, there is a lack of studies that illustrate how these exploration techniques can facilitate the identification of CSCM activities. This paper showcases a study on how to ease the identification of new sustainable business opportunities through visual data exploration. Following the design science methodology, we have designed and evaluated a recommender system prototype (the *IS Identification App*) that supports sector-based identification of industrial symbiosis. The interactive visualization enhances users with more control over recommendations and makes the recommendation process more transparent. Our case study results indicate that the interactive visualization technique is a viable, fast and effective approach for exploring recommendations that increase the sustainability of the supply chain.

Keywords: Circular Supply Chain Management, Circular Economy, Industrial Symbiosis, Recommender Systems, Exploration, Set Visualisation

1. Introduction

A key component for realizing sustainability is to incorporate circular thinking, the essence of the Circular Economy (CE), into a product's life-cycle, which is well manifested in the definition of Circular Supply Chain Management (CSCM) by Farooque et al. [1, p. 884]. While the integration of CE

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principles in supply chains are proposed as an effective means to contribute to sustainability, they also produce a new complex decision area for process managers, for example, in green procurement, product design, production, logistics, sales, product use and information management [1, 2]. A major issue for firms is searching reliable CE partners that can supply or consume material and waste flows in matching quality and quantity to form a circular network [3]. Now data are produced at a rapid pace that enables firms to analyze the effectiveness of potential CE relationships between firms, we are motivated to study how information systems can also facilitate circular decision making. In particular, as these enabling information technologies play a crucial role in driving sustainable development [4]. The key problem is that many of today's circular supply chain activities are reliant on multiple industry actors recognizing the value of ecosystem convergence [5], that is, combining the knowledge, technologies, and markets of multiple industries to identify unique value propositions requiring many of the actors in the supply chain [6]. In particular, since there is a lack of tools that enable multiple actors to explore circular business opportunities in supply chains.

The value of information visualisation is immense to these problems, as humans are used to visual thinking for solving problems [7]. For example, Park et al. [8] show that spatial and visual representations together with intuitive interaction techniques can amplify the ease of decision-making processes. In addition, Speier [9] points to the importance of the structural representation format of information as support for decision making. We, therefore, propose to utilize the promising aspects of visual data exploration techniques for exploring the circular business opportunities in supply chains.

Motivated by the use of existing visualisation techniques to address exploration in recommender systems, we designed an interactive visualisation to enable transparent exploration of recommendations for CSCM. We demonstrate an interactive visualisation tool named the *IS Identification App* that offers industrial operation managers an exploration interface that provides suggestions of the potential industrial symbiosis opportunities. Its key contribution is demonstrating how visualisation can support exploration in the upcoming and promising data-oriented area of CSCM. The paper's theoretical contribution is to demonstrate the potential usefulness of set visualisation (visualising sets and set-typed data [8]) as a means to yield data insights that facilitate unique value propositions in CSCM.

The rest of this paper is organized as follows. Section 2 explains the relevant conceptual background. Section 3 explains the research method. Sections 4.1-4.4 present the case study results, consisting of the data collection (Section 4.1), artefact design (Section 4.2), an implemented prototype, i.e., the *IS Identification App* (Section 4.3) and an expert-panel evaluation (Section 4.4). Section 5 discusses all results followed by conclusions in Section 6.

2. Background

2.1. Circular Supply Chain Management

The introduction of CE principles in supply chain management confronts firms with new considerations in product design, procurement, manufacturing, logistics, sales, product use and information management. For example, a firm's product design may now be reviewed in terms of product lifetime (extension), product/component reuse guidelines and other circular redesign strategies [1]. Furthermore, a firm's material procurement in a CE requires firms to keep track of component properties and their inventories (e.g., material passports) which in turn necessitates an organized data collection and exchange across the supply chain (e.g., defining the degree of transparency and accuracy of data) [10]. The general practice for manufacturing is to make wastes available as substitutes of inputs, which may involve assessing: (a) processing techniques needed (waste treatment or waste processing), (b) the mismatch in both quantity and the quality of produced wastes since these are not produced upon demand, (c) the economic viability of the synergy, and (d) the contractual clauses [3]. From the perspective of logistics, this may require changes and additions in distribution networks (e.g., pipelines to facilitate heat exchange, recycling networks, or reverse logistics in case of extended producer responsibility) [11]. Sometimes the integration of CE principles may even affect sales and requires a business model transformation [1]. Furthermore, consumption patterns of consumers may also be affected. Supply chain actors or governmental agencies, responsible for minimizing impacts due to product use, may coordinate awareness campaigns and sustainability education to influence consumer behaviour [1]. Finally, a firm's information management is affected. For example, by the need to manage the new logistics, or by the need to keep track of the environmental impacts of product components [11, 2, 10], where there is often a duality between the benefit of information sharing and protecting a firm's competitive advantage. [2]

These circular developments in supply chains are often the result of convergence activities of firms [5], i.e., identifying new opportunities in which the unique value proposition is delivered through a collaboration of multiple stakeholders typically from different sectors (e.g., integration of products or shared knowledge creation) [6]. These convergent activities are increasingly intertwined with the software industry [12], partly because of the important role ICT plays in identifying problems that require a common strategy, which is also visible in the era of CSCM. However, there is still a lack of decision support for many problems in CSCM. A particular problem area exists in the first step of procurement concerning the firm's task of finding symbiotic partners relevant for waste exchanges, which is a prerequisite to implement and sustain a circular supply chain [13, 3, 14, 15].

2.2. *Industrial Symbiosis*

The increasing procurement of waste material, energy and services to create circular networks is also known as industrial symbiosis (IS). IS entails the identification and utilization of a company's secondary outputs, generally considered as waste, to substitute (part of) primary resources, possibly after pre-processing, in the production process of another company, usually representing a different industrial sector [16]. This implies that the potential business partners are from traditionally disengaged sectors. Among others, new IS opportunities are often identified during facilitated industry workshops [17], by using specific IS identification systems [14], and through the exploration of items in IS marketplaces [18]. A typical example of opportunity identification is that a company states that it wants to find a sustainable and circular solution for the use of large amounts of a particular waste sludge produced daily instead of discharging it into the environment (specific details typically intentionally omitted). While the company currently disposes the waste to landfill, it is interested in learning which IS opportunities can be discovered in the geographic proximity. Thus, it searches which companies can be the potential (local) IS partners from different industry types to construct the symbiotic transfer of the waste sludge'. Once the IS-based business is implemented, then, the sludge is not considered as waste any more but a resource used sustainably and circularly. This reduces waste discharge costs for the waste producer and traditional input purchase costs for the waste user, thus, environmental achievements are accompanied by economic achievements. However, there are thousands of wastes with different technical characteristics and this leads us to ask how one can identify that a certain waste type can offer IS opportunities.

Existing IS identification systems struggle with analyzing data because of the high level of implicit knowledge in IS, which is a burden to the development of techniques that help to identify IS exchanges [14]. This is also reflected in the tools that currently facilitate IS, of which many require the exchange of resource information as a prerequisite for revealing IS opportunities [13, 15].

2.3. *Recommender Systems*

Recommenders, because of their capacity to increase item explorations and to reduce the search costs for identifying relevant IS opportunities can support areas experienced as a resource-intensive process. The purpose of the recommender system is to predict the preference of an item for a user [19]. Thereby, recommenders facilitate the exploration of available options while also filtering a set of items in an attempt to decrease the users' information load [20]. Traditionally, recommender system research has focused on different aspects, including (hybrid) algorithm design, evaluation mechanisms, recommender goals, data issues, context-awareness, solicitation techniques and more recently also address concerns around transparency, explanations and user-system interactivity, interface design and security [21].

A branch of recommender systems more recently also aims to improve circular thinking, including works on recommenders for energy-saving [22], finding sustainable products [23], discovering sustainable waste exchanges or industrial symbiosis [24, 25, 26], and achieving environmentally sustainable mobility [27, 28]. While in the field of information retrieval various methods exist for visualizing large data, exploration support through visualisation in recommender systems is relatively a new paradigm [29, 21, 30]. The visualisation techniques support the explanation of the provenance of recommendations in a transparent way [31] while the interaction techniques increase user-control over the recommendation [31, 29], and overcome display limitations associated with large data volumes and high multi-dimensional data [32] and provide structure to reduce cognitive efforts [33]. Xu et al. [34] suggests that there exists a relationship between the perceived value of a recommender agent and the degree of transparency of the algorithm. In addition, Jugovac and Jannach [29] show that systems in which users can select the list of recommendations that are perceived to be of interest improve the effectiveness and user experience of the recommender due to the increased control over the recommender and transparency provided. This transparency helps users understand why a recommendation is provided, which increases the consideration of accepting the recommendation [35].

2.4. Techniques for visual exploration of set-based recommendations

One of the key advantages of visual browsing is the positive effect on item discovery (i.e., the novelty of item recommendation) attributed to the function that provides a quick scan of a large number of items [36]. There exists literature that addresses the challenges with concerning the visual exploration of set-based recommendations.

Studies on visual exploration interfaces for recommender systems research include the use of graph-based interfaces (e.g., Peerchoser [37], Smallwords [38], Tasteweights [39] and CNvis) [40]. These graphs can illustrate relations between data that the algorithm uses to deduce preference, for example, in social networks. Another group of studies addresses recommender systems with a set-based result view in addition to a visual component for exploring sets from multiple perspectives (e.g., IntersectionExplorer in which a user-controlled exploration view determines which mixed set of recommendations is presented based on the data source that is used to make the predictions [41] and TalkExplorer which uses clusters to reveal the origin of the filtering algorithm [42]). Also, interactive Venn diagrams (e.g., SetFusion) are used to visualize relationships among recommendations [43]. Some visualisation techniques focus on intertwining set-based recommendation and search-based interfaces (e.g., the uRank [44] and ExplorationWall system [45] which utilizes topic-oriented charts to indicate which keywords are important for a result. Another popular visualisation technique is a word cloud, employed in the FaceTag system to structure tag recommendations [46] and in the Pharos system to show the most prominent latent concepts in key-word clouds [47]. Recent studies (SFVIz [48], Intent Radars or topic maps [49, 50], ECHO (Explorer of Collection Histories) [51]) also illustrate how circular layout visualisation can facilitate exploration. These systems, supported by radial space-filling techniques, are strong among others in showing clustered latent concepts and the relationships between different topics, users, preference. The technique employed in MOOCex shows recommendations placed into Voronoi cells that correspond to distinct topics [52]. Finally, geographic maps are used to visualize clustered topics of video content as well as the relations between the topics [53] and *tree maps* are used for the visualisation of news recommendations, in which clusters, size and colours indicate distinct relevance and similarity [54].

3. Research design

3.1. Methodology

The overall aim of the paper is to illustrate how interactive set visualisations can amplify and augment circular decision making by facilitating the exploration of recommendations. Therefore, this study's design theory can best be classified as exaptation [55], i.e., extending known techniques to a new area of problems. Our case investigation focuses on studying a prototype built for identifying industrial symbiosis in which a waste taxonomy and an industry classification system play a key role. The design of our approach to explore recommendations, the prototype development, and its evaluation follow the design science research approach [56] and are guided by the principles from [57].

3.2. Design goals, artefact and evaluation

The problem domain is formulated in the wider area of CSCM literature [1, 4], but exhibits an artefact in ongoing project work on industrial symbiosis recommenders [25, 24]. We formulate the key design problem for this paper as *How can one explore recommendations in a recommender system to identify circular supply chain opportunities?*. For the context of industrial symbiosis, our recommender design aims to support four main business functions. These functions cover two potential users: (a) a waste providing industry and (b) the waste receiving industry, that either seeks support in finding a partner or a competitor either in their industry or in the industry of their counterpart.

1. Industries producing waste and therefore searching for potential waste receivers may receive recommendations on which type of industries may absorb their particular wastes.

2. Industries producing waste and therefore searching for potential waste receivers may receive recommendations on which type of industries are potential collaborators or competitors for similar waste production.
3. Industries receiving waste and therefore searching for potential waste producers may receive recommendations on which type of industries may produce their particular wastes.
4. Industries receiving waste and therefore searching for potential waste producers may receive recommendations on which type of industries may be potential collaborators or competitors for similar waste production.

The first business function is the most common use case and is, therefore, the selected use case scenario in all design specification and demonstrative figures presented in this paper. The other business functions are supported in the prototype and are merely a variant of the same retrieval problem, algorithm and exploration interface. We explicitly transform the problem into system objectives related to the case example. The design should conform to the following requirements:

- Recommendations should support the identification of industrial symbiosis.
- The interface should enable the exploration of recommendations.
- The recommender should operate on the current characteristics of industrial symbiosis data for reasons of conformity with industry standards and the considerable efforts concerned with IS data collection. This implies that data characteristics are key to modelling the recommender design.
- The recommendations should not reveal any sensitive information that can be traced to the original transaction in the knowledge base, hence, the need to protect the specified confidential information.

Our design is presented using two key formalizations: (1) a formal description of the prediction algorithm used to generate recommendations (that is mainly developed for IS recommendation), and (2) a formalization of the visualisation method for hierarchical exploration of recommendations (applied to the IS identification problem) (see Section 4.2). The design focuses on illustrating the exploration capability of the node-link diagram. The purpose of the prediction algorithm design is solely to act as a simple content-based filtering algorithm. We implement the recommender algorithm and the interactive visualisation algorithm as a stand-alone web-based application, named the *IS Identification App*. Its user interface is based on the JavaScript library ReactJS [58]. ReactJS allows us to manage the state of our application and enables custom interactions with the visualisations. The interactive node-link visualisations are realized through Vega, a declarative language for describing visualisations in JavaScript [59].

We perform a preliminary evaluation of the exploration viability to amplify identification of CSCM opportunity recommendation in the context of the *IS Identification App*. Our prototype was evaluated by an expert panel (IS facilitators and research specialists) and a focus group (industry representatives). These experts and focus group members were consulted in a workshop setting to understand the usefulness of the prototype for the exploration of industrial symbiosis recommendations. The participants belonged to various European organizations and represented different sectors and different roles. Table 1 provides more detail on the composition of the expert and focus groups. The evaluation consisted of a qualitative analysis based on a short post-study questionnaire of five questions (see Section 4.4) conducted among the 23 participants and resulted in 18 filled-out forms. In addition to the survey, we held short discussions with the participants on the prototype.

4. Case Study Results

This case highlights a prototype built to support the initial discovery phase of IS, in which organizations identify the most promising areas and synergies to be turned into a business case. This stage is characterized by industries that are often not yet convinced to provide detailed data and are not yet committed to investing substantial resources for investigating potential business opportunities. This is where we observe the potential for industries to explore existing symbiotic relationships from other industries which may help in generating ideas that can lead to active participation in an IS market-

Table 1: Composition of the focus group and expert panel that participated in the workshop and post-study questionnaire. In the *Expertise* column the number in the brackets indicates the number of participants belonging to that category.

Role	Expertise	Experience	Persons	Forms
Industry representatives (Cluster managers (3), material R&D technicians (2), procurement engineers (3), health and safety engineers (2))	Raw material distributor (2), ceramics cluster (4), chemical cluster (1), automotive cluster (1), mixed clusters (2) (e.g., aviation industry, train industry, renewable energies, steel industry, chemicals, pharmaceuticals, biotechnology, and bio-resources).	20-30 years	10	8*
IS facilitator	Industrial symbiosis (2)	20+ years	2	2
Research specialists	Chemical processing (1), processing technology (2), fluids and energy (2), environmental software engineering (3), industrial symbiosis (3).	10-30 years	11	8**

* One group filled out a form together. ** Two groups filled out a form together.

place or IS network. Our recommender design suggests which IS activities to pursue.

4.1. Data collection

We use two data sets in our research. The first data set K_A represents the *Waste Profile Knowledge Base* (see Table 2), i.e., the statistical proportion of various wastes produced by an industry sector with which an end-user organization may identify itself. This waste profile is extracted from a data set composed of waste statistics collected by Rijkswaterstaat[1]. The data set K_A is a result of two regulations: (1) the European Regulation EVOA[2], and (2) the Dutch environment regulation[3]. The data set contains monthly aggregated waste statistics reported along two dimensions: (1) industry sectors (using the classification system 'Standaard BedrijfsIndeling' (SBI) [62], a derivative of The International Standard Industrial Classification of All Economic Activities (ISIC) system [63] and sibling of the Statistical Classification of Economic Activities in the European Community (NACE) system [64]), and (2) types of waste (using the European Waste Catalogue (EWC) [65]). The SBI, NACE and ISIC are all systems for statistical classifications of economic activities. However, "NACE is derived from ISIC, in the sense that it is more detailed than ISIC. ISIC and NACE have the same items at the highest classification levels, where NACE is more detailed at lower levels" [66]. SBI is the Dutch derivative which uses the first four digits of NACE. Finally, the EWC is a statistical classification system used to report wastes in the European Union in a concise manner. An example of the hierarchical structure of NACE is illustrated in Table 4 and an example of the hierarchical structure of EWC is illustrated in Table 5.

The second data set K_B represents the *Recommender Knowledge Base* (see Table 3). It consists of a set of symbiotic implementations specifying the waste items, classified by EWC, and the industry sector, classified by NACE, that consider these items for developing into a potential industrial symbiosis. We populated the prototype with data originating from industrial symbiotic workshops that were part of the EU-funded SHAREBOX project [67], serving as exemplary IS data as one of many the prototype can be potentially fed with (e.g., databases such as the IS data project [68], or the Library of Industrial Symbiosis case studies and linked exchanges published by the University of Cambridge [69]).

[1] Rijkswaterstaat is part of the Dutch Ministry of Infrastructure and Water Management and responsible for the design, construction, management and maintenance of the main infrastructure facilities in the Netherlands

[2] The abbreviation EVOA stands for "Europese Verordening betreffende de overbrenging van afvalstoffen" (Regulation (EG) 1013/2006). The EVOA provides the procedures to be followed when transferring wastes between EU-member states and the import to and export from EU-member states to non-EU-member states [60]

[3] Article 10.40(1) and article 10.38(3) of 'Wet Milieubeheer'. Data is registered in 'Landelijk Meldpunt Afval (LMA)' [61]

Table 2: Example of data in the *Waste Profile Knowledge Base* K_A. (Data are figurative)

NACE supplier	NACE receiver	EWC	Waste volume (yearly, reported per 10^3 kg or m3 or L)
C.24	<empty>	03 01 04	650.000
C.25	<empty>	03 01 04	40.000
C.24	<empty>	03 01 05	123.000

Note that K_A has no data on the NACE receiver as this is not registered in our data set. These receivers are typically processing, recycler or land filling companies. This data are not required for demonstrating the primary use case; the user in the role of waste supplier. However, when a user is in the role of a waste receiver, the app can theoretically derive a waste input profile either through the yet unregistered NACE receiver in K_A or through analyzing transactions in K_B.

Table 3: Example of data in the *Recommender Knowledge Base* K_B. (Data are figurative)

NACE supplier	NACE receiver	EWC	Frequency of occurance	Abstracted symbiosis details
C.24	G.46	03 01 04	5	Details how Symbiosis A is implemented.
C.25	G.46	03 01 04	2	Details how Symbiosis B is implemented.
C.24	M.71	03 01 05	1	Details how Symbiosis C is implemented.

4.2. Design

4.2.1. Item prediction

A prerequisite for generating recommendations is an algorithm that predicts the preference of an industry user u for each symbiotic relation i in the *Recommender Knowledge Base* K_B. We developed a simple content-based prediction model based on the present item features relevant to symbiotic transactions. The predictions appear in a ranked list of recommendations. The notation for both the knowledge bases equal those defined in Section 4.1, being the *Waste Profile Knowledge Base* denoted as K_A and the *Recommender Knowledge Base* as K_B. Furthermore, with respect to the prediction algorithm, a user u takes one out of two $roles$, being *a supplier of waste* ($u = u_{sup}$) or *a receiver of waste* ($u = u_{rec}$). This role is crucial for which NACE code (NACE supplier or NACE receiver) is selected from either knowledge base K_A and K_B. The NACE code that is selected depends on whether the role in the knowledge base should be similar to the role of the user or opposite to the role of the user. In what follows, we restrict ourselves to the similarity case.

Our prediction model considers four aspects to be included as weighting factors. Firstly, there should be a match between an EWC code from the waste profile of a user u in K_A and the potential recommendable transaction in K_B. Secondly, if the NACE code (concerning the selected role of the user) for a potential recommendable transaction i matches then weight is attributed (e.g., more weight is attributed to an existing symbiotic transaction for which the supplying industry sector (NACE) is

Table 4: Sample illustrating the structure of the industry classification system NACE [64]

Section	Division	Group	Class	Description
C	25	25.9	25.91	Manufacture of steel drums and similar containers
	28	28.1	28.11	Manufacture of engines and turbines, except aircraft, vehicle and cycle engines
		28.2	28.24	Manufacture of power-driven hand tools
		28.9	28.93	Manufacture of machinery for food, beverages and tobacco processing
			28.95	Manufacture of machinery for paper and paperboard production
G	46	46.1	46.14	Agents involved in the sale of machinery, industrial equipment, ships and aircraft
		46.6	46.61	Wholesale of agricultural machinery, equipment and supplies

Our algorithm design operates with NACE codes at division level because data in Table 2 and Table 3 are registered at division level. When source data are registered with more detail it could also operate with lower level codes.

Table 5: Sample illustrating the structure of the waste classification system EWC [65]

Chapter (Level 1)	Sub Chapter (Level 2)	Full Code (Level 3)	Description
03			Wastes from wood processing and the production of panels and furniture, pulp, paper and cardboard
	03 01		Wastes from wood processing and the production of panels and furniture
		03 01 01	Waste bark and cork
		03 01 04	Sawdust, shavings, cuttings, wood, particle board and veneer containing dangerous substances
		03 01 05	Sawdust, shavings, cuttings, wood, particle board and veneer other than those mentioned in 03 01 04
		03 01 99	Wastes not otherwise specified
	03 02		Wastes from wood preservation
		03 02 01	Non-halogenated organic wood preservatives

similar to that of the user in the role of waste supplier). The primary goal of this weighting factor is to support higher precision affecting negatively its support to novel IS explorations (i.e., to find symbiotic relationships between industries that formerly would never have considered each other). The reason for including this weighting factor is that it serves to bootstrap initial recommendations to industries often not yet convinced to provide detailed data and not committed to investing substantial resources. This way, a critical mass of industries can be reached that can form an IS market from which more IS explorations can follow that require stronger thrust and higher investigation costs. It is likely that, once the recommender system evolves (i.e., industries get engaged by the value the recommender provides), due to algorithm optimization the system develops more emphasis on item diversity, hence decreasing the effect of this weighting factor. Furthermore, the $volume$ of waste is considered as a weighting factor as it is known as an influential factor in the viability of a symbiotic business. This is because of an increased level of waste exchange gains typically in a proportionate saving in costs and has larger total business value, hence, positively affect the chances for sustainable symbiosis [70]. Finally, the frequency of occurrence of a particular symbiotic transaction seems to affect performance positively in IS algorithms [24], hence it is also included as a weighing factor.

The set of recommendations are generated using the prediction algorithm presented in Equation 1 using four weighting factors presented in Equation 2-5:

$$s(i|u) = w_{ewc\_match}(i|u) \cdot \frac{w_{nace\_match}(i|u) + w_{volume}(u) + w_{frequency}(i)}{3} \tag{1}$$

$$w_{ewc\_match}(i|u) = \begin{cases} 1, & \text{if } ewc_u = ewc_i \\ 0, & \text{otherwise} \end{cases} \tag{2}$$

$$w_{nace\_match}(i|u) = \begin{cases} 1, & \text{if } ewc_u = ewc_i \text{ and either} \\ & u = u_{sup} \text{ and } nace_{i,sup} = nace_u \\ & \text{or} \\ & u = u_{rec} \text{ and } nace_{i,rec} = nace_u \\ 0, & \text{otherwise} \end{cases} \tag{3}$$

$$w_{volume}(u) = \frac{(\log_{10}(volume_u)) - \min(\log_{10}(volumes))}{\max(\log_{10}(volumes)) - \min(\log_{10}(volumes))} \tag{4}$$

$$w_{frequency}(i) = \frac{frequency_i - \min(frequencies)}{\max(frequencies) - \min(frequencies)} \tag{5}$$

Equation 1 is the function that predicts the score that is the basis of preference estimation. The equation results a score $s(i|u)$ that represents the preference that an industry user in a specified role u has in an item i (i.e., the symbiotic relation to consider) considering four weighting factors, being:

1. $w_{ewc\_match}(i|u)$ (see Equation 2) the conditional weighting factor based on whether the ewc code is present or not in K_A,
2. $w_{nace\_match}(i|u)$ (see Equation 3) the conditional weighting factor determined by whether a symbiotic relation in K_B results from a similar NACE industry based on the role of the industry user u,
3. $w_{volume}(u)$ (see Equation 4) the weighting factor that considers the potential impact by valuing the normalized waste $volume$ of an EWC code in K_A, and

4. $w_{frequency}(i)$ (see Equation 5) as the weighting factor valuing the frequency of occurrence of the i-th record in K_B.

Equation 2 is the function that results the weighting factor $w_{ewc\_match}(i|u)$ with i as the item, u as the industry user in a specified role ($u = u_{sup}$ or $u = u_{rec}$), ewc_u as the EWC element user u is interested in, ewc_i as the EWC element that appears in at least one record of K_A. The equation expresses if there is a match between the EWC code of the user and any EWC in K_A. If not, then (due to the multiplication) the score equals zero and there is no need to proceed.

Equation 3 is the function that results the weighting factor $w_{nace\_match}(i|u)$ with i as the particular Industrial Symbiosis relation as listed in K_B, u as the industry user in a specified role ($u = u_{sup}$ or $u = u_{rec}$), $nace_{i,sup}$ the first NACE code in the i-th record (the i-th Industrial Symbiosis relation) as listed in K_B and $nace_{i,rec}$ the second NACE code in the i-th record in K_B. The result of the weighting factor is at scale $\{0,1\}$.

Equation 4 is the function that results the weighting factor $w_{volume}(u)$ with u as the industry user in a specified role, $volumes = \{volume_1, \ldots, volume_m\}$ denotes the array of volumes as they appear in K_A while $volume_u$ denotes the $volume$ of waste ewc_u that u is interested in. Each value in $volumes$ is log 10 transformed $log_{10}(\ volumes\ )$, likewise the value of $volume_u$ is 10 log transformed $log_{10}(\ volume_u\ )$. The result of the weighting factor is normalized at scale $\{0,1\}$. The normalization is based on classic min-max normalization, a simple method for rescaling features to scale the range in {0, 1} [71]. The minimum value of an array is calculated by

$min\ (log_{10}(\ volumes\ )) = \min_n\ log_{10}(volumes_n)$, and the maximum of the array is calculated by $max\ (log_{10}(\ volumes\ )) = \max_n\ log_{10}(volumes_n)$.

Although waste size is considered an important factor, the values form a heavy-tailed distribution (there are some waste streams accountable for a large proportion of the total waste stream size [61], but these are not by definition the most polluting resources in particular concerning the volumes these are produced [72, 73], e.g., sand). Therefore, a variance-stabilizing feature transformation, namely simple log transformation is applied [71].

Equation 5 is the function that results the weighting factor $w_{frequency}(i)$ with i as the item,

$frequencies = \{frequency_1, \ldots, frequency_k\}$ denotes the array of frequencies as they appear in K_B. Similar to Equation 4 the result of the weighting factor is normalized at scale $\{0,1\}$. The minimum value of an array is calculated by $min\,(frequencies) = \min_n (frequency_n)$ and the maximum of the array is calculated by $max\,(frequencies) = \max_n (frequency_n)$.

4.2.2. Hierarchical exploration

A search task in relational data aims to obtain an overview of a set, zoom in on items of interest, filter items, select an item group and receive details of the group, explore the relations among items, support historical refinement actions (undo, replay, progressive refinement), and extract sub-sets [74]. The key reasons for visualizing hierarchical relations (parent-child-sibling) in data are, to understand the structure of the data (e.g., understanding how organizations are distributed across sectors), to understand the data within the context of the structure (e.g., understanding whether organizations of different sectors employ similar populations), and to aggregate large amounts of data (e.g., to reduce information overload by showing the selected hierarchies, or report on an aggregated level) [75].

A hierarchical structure, such as taxonomies, can be visualized using different techniques, for which [76, 77] provides an overview of the most common tree visualisation techniques. We employ the classic node-link diagram to visualize the integration of two data sets with hierarchical structures (taxonomies EWC and NACE) as part of the *IS identification App* design. The characteristic element of the node diagram is that it breaks apart the breadth and depth of the hierarchical structure in a 2D space and then links the nodes by straight or curved lines. The advantage, as well as the support for the selection of a 2D node-link visualisation, is its intuitiveness, compactness, and its applicability for hierarchical-based search tasks. Moreover, they are very effective for smaller depth graphs [77]. However, traditional node-link diagrams have the drawback that they make poor use of the available display size [78] which affects broader graphs. Therefore, two design space reduction techniques are applied. Firstly, curvatures are used in the node-link diagram to optimize the design space [79]. Secondly, the interactive principle of hidden node-links is included, which means that nodes are only revealed once they have been selected on which the total diagram is reshaped to fit the frame boundaries, such as in [80]. These measures help to improve the reduction of visual clutter, the maximization of the display, reduction of cognitive loads, and aesthetic scalability [77]. The algorithm that provides a formulation of the hierarchical approach for exploring sets of IS recommendations generated by the prediction score presented in Equation 1 can be found in the supplementary material. It renders the interface components for *(1) industry profile view,* and *(2) the sectors interested view* in Fig. 1.

4.3. Prototype Demonstration

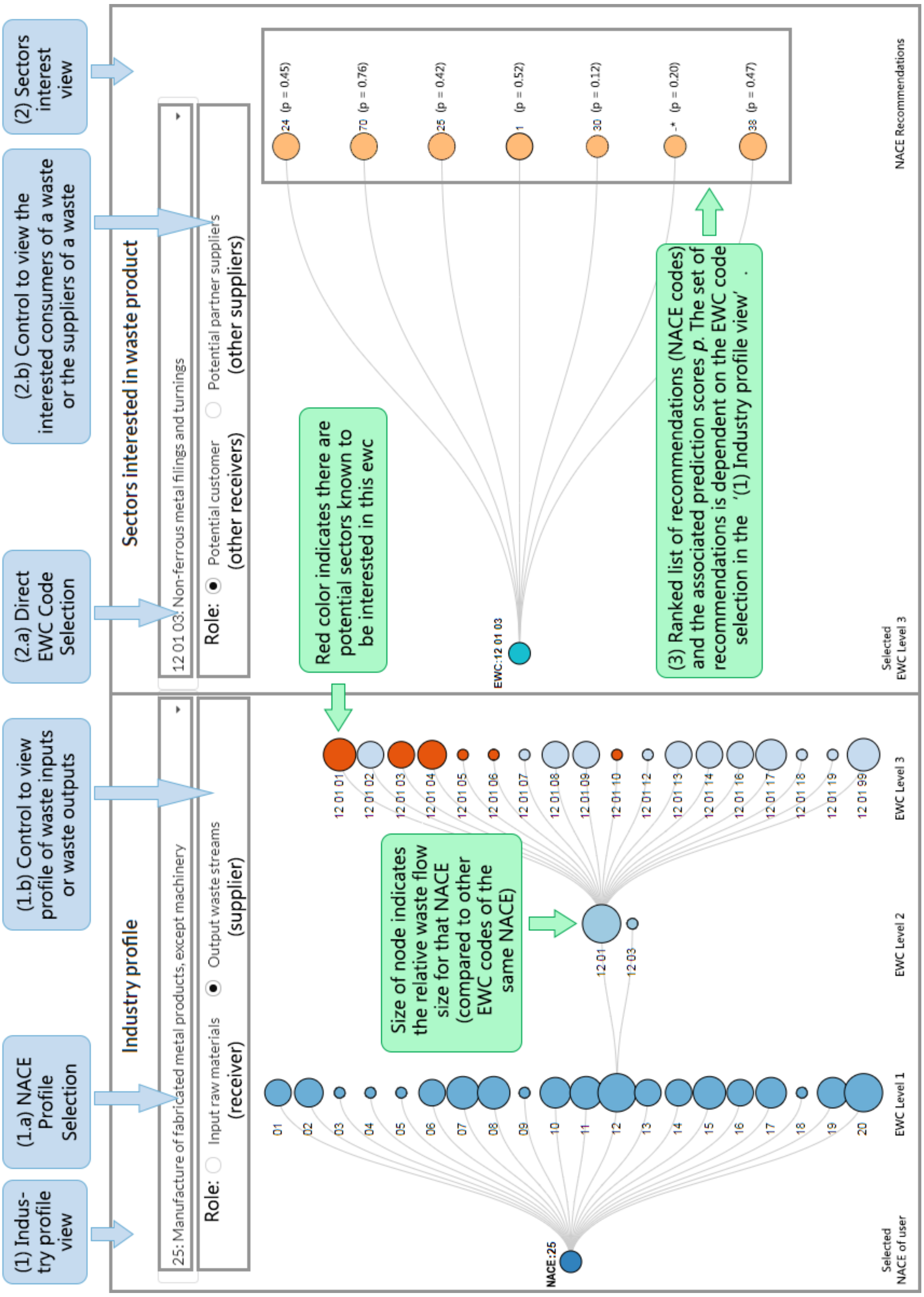
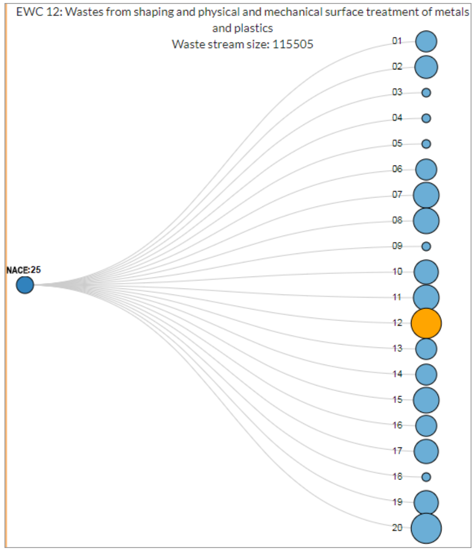
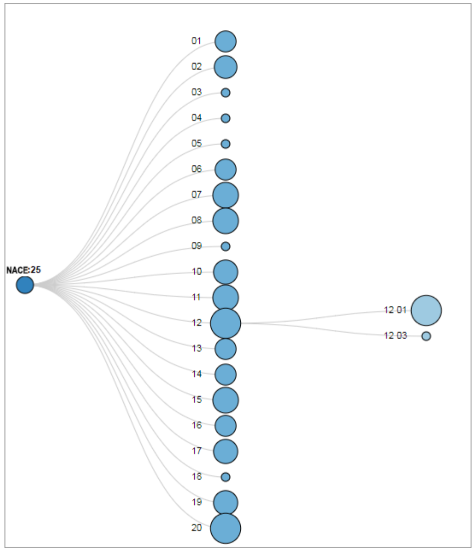


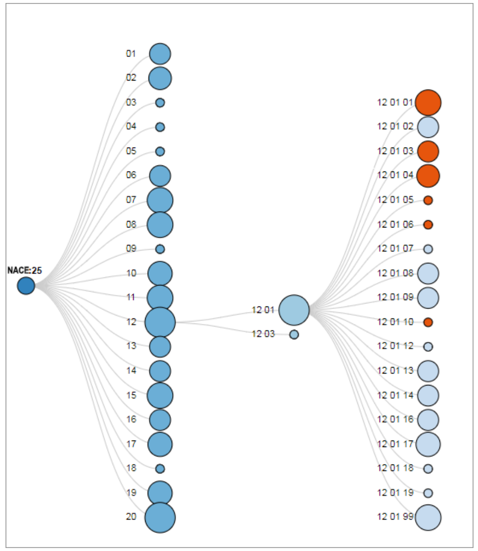
Figure 1: The *IS Identification App* - A full overview of the interface.



(a) Step 1: Select a NACE sector using the drop-down list at the top (see (1.a) NACE Profile Selection). The result is a list of first level EWC codes for which waste statistics are available (e.g., in the figure NACE sector is '25'



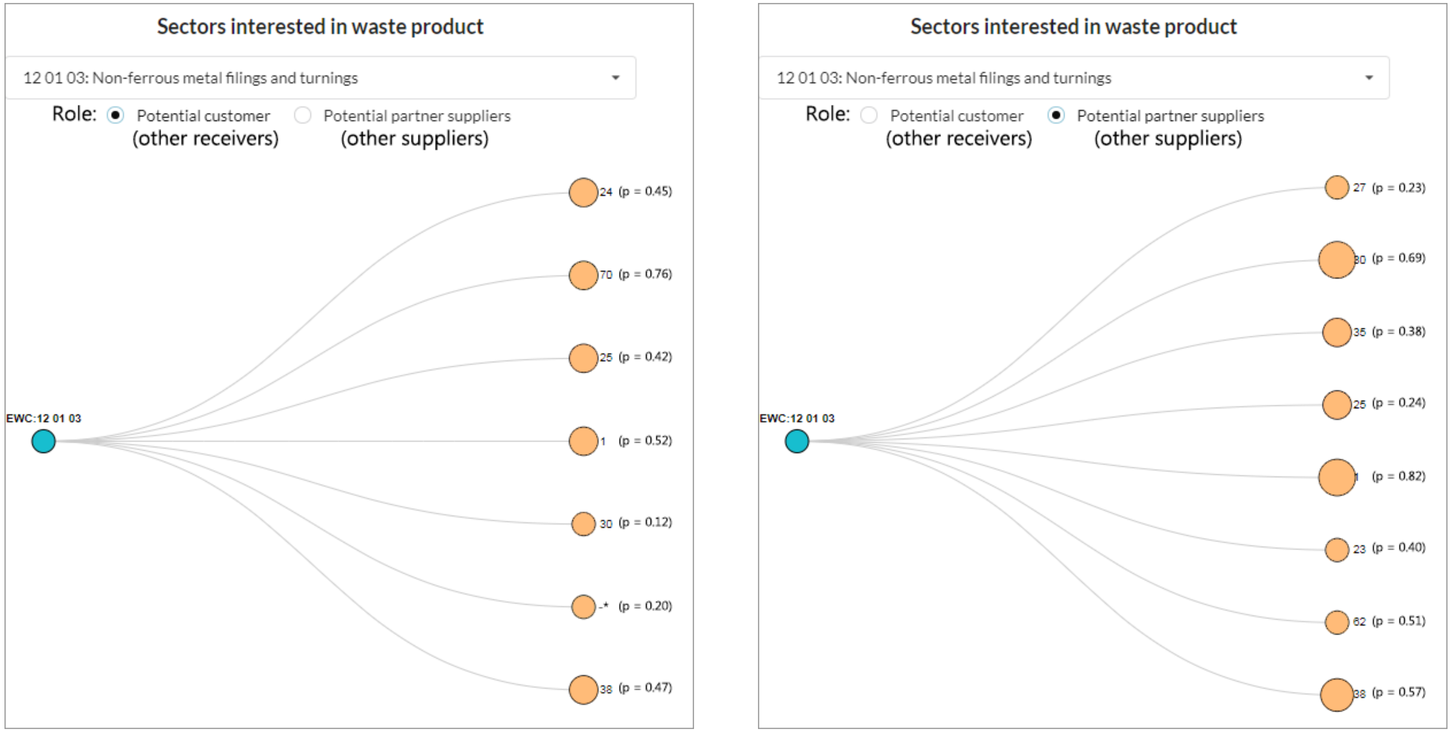
(b) Step 2: Explore the first level EWC code '12', by clicking the node labeled '12' a more detailed list of secondary level EWC codes for waste statistics of sector '25' reveals.



(c) Step 3: Explore the secondary level EWC code '12 01', by clicking the circle with label '01' a list of third level EWC codes for waste statistic of sector '25' reveals. Finally, select by clicking the node labeled with the third level EWC code '12 01 03'.

Figure 2: The *IS Identification App* - A detailed view of the *(1) Industry profile view* (see Fig. 1) showing three steps of the interactive drill-down of the EWC taxonomy for the user-selected NACE sector.

Accepted version: https://doi.org/10.1016/j.dss.2020.113431



(a) Exploration view of potential industry sectors that can take your waste to make industrial symbiosis waste

(b) Exploration view of potential industry sectors that compete over similar kinds of waste to make industrial symbiosis

Figure 3: The *IS Identification App* - A detailed view of the (2) Sectors interested view (see Fig. 1) showing the NACE sectors typically interested in a specific waste item flow, e.g., for EWC code '12 01 03' in either supplying this waste or receiving this waste.

The *IS Identification App* (see Fig. 1) interface is divided in two main sections, *(1) an industry profile view*, and *(2) a sector interest view*. The *(1) industry profile view* shows the waste input profile or the waste output profile for the associated NACE industry (based on its selection). The *(2) sector interest view* shows the industry sectors that are typically interested in a particular waste codified by the EWC code.

The interaction begins with selecting a NACE code in the *(1.a) NACE Profile Selection* and indicating whether to retrieve a NACE waste input profile or waste output profile using the *(1.b) Input/output control*. Once selected, a root node is plotted in the *(1) industry profile view*. The *(1) industry profile view* presents from left to right the NACE code by the user's selected industry, followed by a hierarchical node structure corresponding to the three levels of the EWC coding system. Users can navigate the tree by selecting (clicking) nodes upon which deeper level nodes appear in the *(1) industry profile view* (see Fig. 2). By hovering over a node (moving the cursor over the node), the node switches colour to orange and related node information appears right above the node-link tree visualisation. The node size is logarithmically proportional to the size of the waste stream to indicate the waste proportions in the users waste profile. Nodes with red colour indicate the presence of a set of recommendations for that waste code. A particular waste from the waste profile can be selected by clicking one of the red nodes. As a response, the *(2) sectors interest view* visualizes the set of recommendations for the selected EWC code (light orange coloured nodes). Whether the visualisation presents the *(3) ranked list of recommendations* for potential consumers of a waste code or potential partner suppliers or competitors of course from a different perspective is dependent on the selected option in *(2.b) consumer/supplier control* (see Fig. 3 for the different exploration views).

An additional feature of the application is to directly select a waste using the drop-down control *(2.a) direct EWC code selection*. By clicking a recommendation node a pop-up appears showing the related cases (transactions) used to compose the recommendation. The number of recommendations in the prototype is limited to a maximum of 10 recommendations (nodes). Which information is included, and to what extent the information is anonymized is open to the product owner of such an application (and less relevant to the study of item exploration in recommender systems). Therefore, no illustrative figure of this view is presented in this work but can be viewed in the additional online materials (e.g., the video).

4.4. Evaluation

We evaluated the *IS identification App* in terms of (1) the functional alignment with user expectations for the identification of IS, (2) whether the visual exploration interface supports the quicker exploration of IS recommendations, and (3) the user's experience of the prototype in general.

Overall, the respondents in our survey reported confidence (average 5.5 out of 7) that visual exploration of industrial waste profiles to explore a set of recommendations contributes to the early identification of synergies (indication of functional use). Furthermore, respondents indicated (average 5.8 out of 7) that the visual hierarchical exploration supports a quicker exploration process of relevant recommendations on industrial symbiosis (indication of time saving). Finally, respondents were moderately positive when asked if they would consider using the prototype based on its current functionality (average 4.8 out of 7) (indication of good general user experience).

Positive remarks were provided regarding the usefulness of the application and the understandability of the interface for exploring recommendations. Respondents called the prototype "*easy to use*", "*being visual and interactive*" and "*visually presenting the existing information in a more user friendly way*". One participant wrote about the usefulness: "*The system is automatically showing me areas I want to look deeper into*", referring to the provided reference cases in which other firms already have succeeded to implement a particular type of industrial symbiosis. Another participant wrote "*The prototype could succeed because it helps to identify new sectors of business opportunities within reasonable time*", which is an important point since sustainable procurement usually lies not within the core revenue model of a firm. Furthermore, a participant remarked that "*the issue of confidentiality and competitors is taken into consideration*" in the prototype, a key barrier of IS [17].

Still, some gentle scepticism was shown regarding the development of a knowledge base large enough to make the application attractive to businesses, but current initiatives show already promising growth [69]. Some users were interested in how the prototype operates in situations in which the waste supply-demand interest aligns but market sectors differ, and questioned "*if it was still possible to establish an industrial symbiosis relationship*" under these circumstances. Although these suggestions are included in this prototype, their prioritization is lower, but may re-evaluated over time. This is well explained in larger debate in recommender systems on how to successfully evolve recommender system goals over the lifetime of a system [19]. Furthermore, some experts suggested certain functionality to be added, e.g., tools for calculating the financial and environmental gain of the business opportunity. In particular, because the financial gain is typically "*the key motivation for pursuing a business opportunity*". A final remark was that the early detection approach may generate mostly broad recommendations, without considerations such as waste quality or costs, while sometimes more specific types of recommendations are also needed. For example, respondents wrote that the disadvantages of the prototype are that it "*will miss some possible synergies unrelated to the sector*" as "*identifying the profile can help sometimes but may not always be useful for identifying all possible synergies", and* *"highly different applications from those done before are not seemed to be taken into account"*.

Concerning the general user experience, respondents mentioned a few shortfalls considering the hierarchical visualization and the prototype in general. An issue experienced with the hierarchical visualization in its current form was that the end-users may not yet be familiar with the EWC coding structure. Hence, users indicated the need for a more prominent appearance of short text descriptions of the EWC codes (e.g., "12 01 01" or "12 01 01 - ferrous metal filings and turnings"). Furthermore, it was suggested to adapt the waste naming country-specific industry and waste classification systems, make use of icons, and to present more detailed information of the IS opportunities (i.e., transactions in the *Recommender Knowledge Base*) on which the recommendations were based. Some respondents indicated that the identification approach was fully based on existing transactions and cannot, therefore, suggest alternative resources which are not yet identified for a particular EWC category.

Although the sample for our evaluation is limited, our work outlines the steps one needs to take towards the implementation and field testing of our prototype. Longitudinal evaluation can provide further insights into the efficacy of the prototype under a firm's implemented conditions, which can strengthen the validity of how visual data exploration techniques play a crucial role in exploring the circular business opportunities in supply chains. This may be, in particular, useful because of the change in socio-contextual characteristics of the CSCM, which are driven by the transition to a circular economy (e.g., change of regulations, geographical material needs, etc.), and therefore motivate a continuous evaluation of the technology.

5. Discussion

Our results demonstrate the potential of interactive visual exploration of a set of recommendations as a useful technique for exploring new CSCM ideas. Moreover, the results indicate that the hierarchical exploration approach could fulfill its role as a provider of an effective exploration experience, particularly for sector-based IS identification. The most explanatory reason is found in the information retrieval problem, which is resolved by the integration of NACE and EWC coding systems to interact with industrial waste profiles. Regarding the data structure, we found that the presence of taxonomies in data aligned with and made the hierarchical exploration approach favourable. However, we endorse that the data structure and its modelling approach in the prediction algorithm should determine the particular exploration method, as demonstrated in other applications of exploration interfaces (e.g., graph-based interfaces [37, 38, 39, 40], multi-perspective approaches [41, 43, 42], search-based interfaces [81, 45], word-clouds [46, 47], circular layouts [48, 49, 50, 51], integration of time-line in Vonoroi cell structured presentations [52]), and map-based interfaces [53, 54]).

This development of an *IS identification App* provides a practical contribution in the form of a general approach for retrieving relevant IS cases to stimulate the development of other IS implementations, which can be used by industries, IS facilitators, and policymakers. The unique value of this approach for industries is that it enables either a quick consideration of known directions for IS development or supports the creation of new ideas for IS development. These are possible without the need for industries to make large research investments and reveal confidential process data [17]. Similarly, to IS facilitators, our prototype provides an exploration interface with quick access to a (personal) IS knowledge base, which can support consultancy services. Although the recommendation is dependent on having a knowledge base of existing symbiotic relations, which currently are mostly relatively small in size, there is growing attention worldwide for sustainable developments that are expected to accelerate the growth of IS databases (e.g., [69]). Finally, with few adjustments, the prototype may also support policymakers by providing insights into the common patterns of IS implementation (e.g., identifying IS markets with growth potential considering policy measures).

Our research has multiple theoretical contributions. This research provides both nomothetic and idiographic knowledge [82]. We create nomothetic knowledge from our interactive visualisation for CSCM convergence business activity identification, which is typically generalizable to the entire set of classes of this single case. On the other hand, the design of the *IS identification App* produces knowledge within an idiographic scope, as studying this artefact design over time provides explanation and theory on how to solve a particular problem, such as IS identification. We also provide a theoretical contribution for tackling the common data difficulties (e.g., having few explicit data) in IS tools that have been a burden in the development of techniques that help to identify IS exchanges [14]. We address the issue partly by removing the need for industries to provide detailed process data as a requirement for a recommendation. However, collecting explicit data from established IS implementations to populate the recommender knowledge base will remain a long-term challenge for scientists (e.g., projects [68, 69]), practitioners (e.g., facilitators building business models upon the knowledge base) and governmental bodies (e.g., governing waste registers).

Even though the *IS Identification App* was developed with scalability, controllability and transparency in mind, there are limitations to how recommendations can be explored through node-link visualization. For example, the visualization may still clutter or be overcrowded with items when unfolding many trees, or in cases where there are a considerable number of children. Concerning the set of recommendations presented, this list is likely to scale with the number of transactions in the *Recommender Knowledge Base*, hence, we applied a constraint of a maximum of ten items. Other interaction mechanisms (e.g., pagination) can be integrated here as well to deal with the issue of limiting display size. Furthermore, at this time, the design of the filtering algorithm only considers available item features while there is literature suggesting various other item features that are likely to be predictive in the identification of IS, e.g., location, technical characteristics, waste quality [3, 83]. A further limitation to the effective recommendation about both prediction accuracy and explorability is the shallow depth of the NACE coding system. Industry waste profiling could be more precise when waste registrations are captured at a more detailed level of industry codes. In the current application, we limited the search to NACE codings at the division level (as this is captured in our *Recommender Knowledge Base*), but it is not unlikely that two semi-different types of industries operate under the same NACE code, hence the aggregated waste profile of a higher level sector could diversify to some extent to those at lower levels (e.g., including group and class levels, see Table 4). Similarly, prediction algorithms benefit from more specific NACE codes when recording instances of IS implementations in any knowledge base. There are also several issues with the EWC classification system. For example, there is overlap between EWC codes addressing the same type of waste [84], and there are symbiotic transactions that cannot be classified with EWC (energy-related, capacity-related, and tools) [85]. Finally, through the survey, we received some suggestions for adding functionality related to the assessment of industrial symbiosis (e.g., business calculation tools). Although not addressed in our 'IS identification' prototype, such functionality can support the next step in developing IS.

Compared to the perspective of delivering recommendations for IS identification in our prior work (recommenders based on an association rule approach [24]), we observed in this study that visualization as a tool provides an advantage through its exploratory capability. These advantages can be traced to and explained by other works, such as [86], where users can visually explore association rules rather than observing the recommendations on demand. This can aid and support the user in making a decision, and stimulate user creativity leading to the creation of new ideas. Typically, the visualization methods also function as a way to increase the trustworthiness of recommendations [34, 87, 88].

While this work focused on demonstrating the value of exploration interfaces for revealing new circular business opportunities, further studies could aim for an in-depth validation and visualization method comparison on dimensions such as usability, exploration capacity and cognitive load. For example, a controlled user study can provide further insights into the strengths and weaknesses of different visualization methods and for various other aspects of exploring recommendations (e.g., in other user-domains, preferably less expert dependent, such that a larger user group can be reached in the study and study results may be analyzed quantitatively).

6. Conclusion

There exists a vast number of recommender systems that lead to a burgeoning call from users to gain more control over the recommendation process and effectuate transparency on how recommendations are provided. To address this issue, we discuss visualisation techniques as enablers, but these techniques need to be evaluated for their capacity to facilitate recommender exploration. This is especially relevant in the new era of CSCM development that prevails with a new set of decision problems for industrial process managers.

This paper demonstrates a representative example of how such a CE problem can be managed. Using the *IS Identification App*, a visual analytical prototype based on the interactive visualisation we have assessed and explained the potential of recommender exploration design. We find the *IS Identification App* to be a relatively fast and effortless application to navigate through a large set of potential IS opportunities for industries. Results of our preliminary evaluation with experts and a focus group emphasize two key observations. In line with other research, it suggests that a user interface enabling visual exploration of recommendations may increase user satisfaction. The study further indicates that the exploration interface of the prototype could support quicker identification of relevant business opportunities. The contributions of our study are multi-fold. To the best of the authors' knowledge, this paper is a first attempt to illustrate the relevance of exploration techniques for business opportunity exploration in the area of CSCM. Moreover, we propose an approach for exploring IS recommendations through potential hierarchical relationships in data sets and illustrate this design with the creation of our prototype. Our prototype has been evaluated by an expert panel and focus group to test the user experience of exploring recommendations through hierarchical structures. This evaluation revealed that IS exploration through interactive hierarchical structures aligns naturally with the predominant taxonomy used in the prediction algorithm and, therefore, provides a positive user experience.

In conclusion, our work illustrates that future designs of exploratory recommender systems can easily adapt node-link visualisation as an explorative approach. Environments characterized as taxonomy-rich may particularly benefit from this approach.

Acknowledgment

This research is funded by European Union's Horizon 2020 program under grant agreement No. 680843. We thank Rijkswaterstaat (The Netherlands) for providing waste statistics from 'Landelijk Meldpunt Afval (LMA)' to develop and populate the IS Identification App.

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