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Julian Staehle ✉; Wolfgang Ziegler

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Product Compatibility and Recommender Logics Using Open Data and Semantics: A Case Study in the Automotive Sector

Julian Staehle [a] and Wolfgang Ziegler [b]

Karlsruhe University of Applied Sciences, Faculty of Information Management and Media, 76133 Karlsruhe, Germany

[a] Corresponding author: research@julianstaehle.de
[b] wolfgang.ziegler@h-ka.de

Abstract. Consumers require concise information regarding the compatibility of products, and this paper demonstrates how knowledge model patterns can facilitate the provisioning of product compatibilities. Furthermore, it will be demonstrated how the variety of variants influences the complexity of the ontology used for semantically modelling and managing products as well as their compatibilities. For instance, the automotive sector was studied, as it has a high product variance in vehicles and accessory products. In this domain, manufacturers are obliged to ensure safe usage and recommendation of their products. They solve the problem of compatibility via design and instruction manuals. However, existing product domain standards predominantly emphasize the design aspect, while standards for compatibility information are largely absent in numerous areas. This deficiency hinders consumers' ability to verify product compatibility. In this paper, we propose concepts and implementations to determine compatible products based on interface knowledge. The developed and tested semantic model pattern, Product Compatibility Model (PCM), enables the storage of interface knowledge in a machine-readable and analyzable form. The PCM is publicly available and is intended to serve as a key interface for manufacturers, retailers, and distributors. At the organizational level, we will discuss implications for public product communication and the necessary modifications.

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INTRODUCTION

Modern online stores support potential customers with their purchases and guide them to the product they are looking for. A central technology called Recommender Systems (RS) has contributed significantly to this success in recent years [1]. The main focus of RS lies in the recommendation of products and many e-commerce implementations utilize RS, including those of Amazon, Netflix, and Prime [2], [3], [4]. Conventional RS recommend based on user interests and search behavior using techniques such as collaborative filtering or content filtering. While this conventional approach has proven to be generally effective, it is not without its limitations. Issues such as recommendation homogeneity [5] and erroneous recommendations [6] have been observed. In light of these challenges, a subarea of RS has emerged in recent years, focusing on product compatibility. The aim of this field is to prevent the recommendation of incorrect or inappropriate products and to ensure that purchases are compatible with the user's needs [5], [7].

PROBLEM STATEMENT

The conventional approach of RS entails the recommendation of products that bear similarities in their respective features. To illustrate, the system suggests alternative products based on a selected item, with consideration given to the purchasing patterns of users exhibiting analogous search behavior [2]. In instances where a user seeks a product compatible with another, this conventional methodology may result in erroneous recommendations. This may occur due to the absence of compatibility criteria within the algorithms [8]. A study has demonstrated that 8 to 10 percent of recommendations are inappropriate [6]. Wrong recommendations may impose risks [9], including improper use, property damage, or personal injury. With the expansion of the digital product range, these risks are likely to increase.

The extent of the impact depends on the respective use case and product domain [8]. The selection of an appropriate LED bulb for a specific lamp can be regarded as a rudimentary example. With a direct connection existing between the LED bulb and the lamp, the connection is predicated on a limited number of characteristics, such as thread and power. The standardized connection facilitates the selection of the appropriate product and mitigates the risk of an

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erroneous purchase. However, it is imperative to note that a standard does not ensure optimal recommendations. For example, a consumer portal recommends HDMI cables compatible with the PlayStation 5 that meet the standard 2.0 [10]. The RS does not mention that the standard 2.1 would be optimal for peak performance. While this recommendation may not pose a safety concern, it could potentially mislead consumers. This example underscores the notion that compatibility can encompass varying levels, such as technical fit and performance. It should be noted that the apparent simplicity in determining compatibility can be deceptive, as the recommendation might not encompass the entirety of relevant factors. To illustrate, the assertion "child seat fits to a car" appears straightforward when considering the identification of an appropriate child seat for a specific vehicle. However, this statement fails to address the complexity inherent in the compatibility of a child seat with various car seat positions. This recommendation engenders a substantial degree of complexity for the consumer, who must identify and ascertain the compatible car seat positions. Inaccurate recommendations stemming from such imprecise guidance can result in misuse and safety hazards.

GOALS AND METHODOLOGY

The objective of this research was to develop a knowledge-based RS approach that ensures the compatibility of products. The presented method combines the concepts of Knowledge Graph, Semantic Data, and Open Data. Three sub-goals were pursued:

1. Preventing wrong or incorrect product recommendations;
2. Avoiding inappropriate or incompatible product purchases;
3. Reducing Safety Risks and avoiding critical injuries.

These goals were achieved by the design of a product compatibility model pattern, which covers the basic concepts of principal entities, properties, and relations. Assuming that product compatibility is dependent on the product domain [8], a case study of one domain was performed. On the basis of the sub-goals, the following requirements were derived for choosing an appropriate domain for the case study:

- Wrong or incorrect product recommendations occur in the product domain.
- Customers are confronted with the problem that product purchases can be inappropriate or incompatible.
- The combination of products can result in safety risks and critical injuries.

To address these challenges, a case study was conducted within the product domain, focusing on the selection of compatible seating positions for a child seat within a vehicle. The knowledge about the products and their interfaces were extracted by the expertise of domain experts. To enhance the comprehensiveness of the analysis, the domain-specific interoperability was also examined and discussed. The findings of this study led to the development of a semantic model in the machine-readable format RDF, which was generalized to enable its application in other domains. Furthermore, a demonstrator was implemented in a Python programming environment, integrating a graph database to simulate compatibility queries and a centralized data provisioning system.

PREVIOUS WORK

In recent years, the potential application of semantic technology in the domain of technical communication was investigated [56]. The central aim of our research was to examine specific topics, including product knowledge services, intelligent content delivery, and logic-driven publishing. In the guided and supervised study, we examined the utilization of semantic technologies in this field. Furthermore, we defined and tested various model approaches to maintain a product knowledge graph [11]. Another research topic referred to the support of authors in minimizing erroneous cross-references in documents and streamlining the authoring process itself. This objective was achieved through the implementation of a semantic model that incorporated the cross-reference logic. Consequently, authors are no longer required to manually maintain cross-references, enabling them to focus on their primary editorial responsibilities [12]. In summary, these research topics encompassed the conceptualization of semantic and logical linking and subsequent processing. This has led to the question of linking products and product compatibility.

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RELATED WORK

Product Compatibility

A common approach to identifying the compatibility of products is to compare specific properties [8]. For example, the interface of car tires with a rim is regulated by a standard, and the rim's code indicates the appropriate tire to purchase. Depending on the product domain, different product properties and their combinations can derive a compatibility result. A substantial body of research has been dedicated to the extraction of knowledge from user reviews and product descriptions [7], [13], [14] or based on visual style information [15-17]. Another specific research area focuses on the storage and representation of the extracted knowledge, particularly about products and their interplay. The technology underlying this process is referred to as Knowledge Graphs [18-20] used in ontology modelling domains.

Knowledge Graph

Knowledge Graphs (KGs) represent a pivotal technology for e-commerce platforms and information systems, facilitating search, recommendation, and question-answering functions [18], [19]. A comprehensive overview of this technology is provided in [4], offering a detailed examination of the current state-of-the-art. Additionally, the paper illuminates the requirements for creating and maintaining KG. In essence, a KG can be regarded as a data-rich semantic model that captures knowledge that can be processed by machines. Numerous research endeavors center on the automated extraction of domain knowledge with the aid of artificial intelligence, leveraging approaches such as deep learning [8] or instruction tuning [21]. However, these automated approaches for KG generation are not applicable to specific scenarios, such as novel, innovative, or discontinued products [22]. The reasons for this include a lack of information and data, which makes it difficult to recognize and assign patterns.

Recent years have witnessed the emergence of a novel research domain, characterized by the integration of artificial intelligence (AI) and RS. The objective of this domain is to facilitate the delivery of precise and accurate information in real-time, a process that is crucial in counteracting the problem of information overload. A potential approach to achieving this objective involves the utilization of knowledge graphs (KGs) as a foundational framework, a strategy that has been shown to yield positive outcomes, including enhanced consumer satisfaction and increased sales [1].

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Recommender Systems

The conventional approach of RS entails the provision of recommendations for similar products (or items) based on user behavior or interests. Common techniques employed include collaborative filtering, content filtering, and hybrid systems [23]. However, this approach can result in consequences such as recommendations that are homogeneous. In cases where the consumer's objective differs from the identification of a similar item, the recommendations are likely to be unsatisfactory [5], [24]. To address this limitation, a comprehensive analysis of user intents was conducted, resulting in the identification of two distinct categories: substitute and complementary recommendations [8], [13]. Substitute recommendations are designed to facilitate the identification of a replacement product, catering to scenarios where the consumer seeks a substitute for the viewed or bought product. In contrast, complementary recommendations are intended to support the discovery of products that can be utilized in conjunction with the viewed product or products the consumer has previously purchased [5].

DOMAIN SPECIFIC MODEL PATTERN

The automotive child safety sector has been selected as the case study for this research, as it fulfills all of the necessary criteria. This field exhibits a high degree of variability in products, which can pose significant challenges when attempting to combine them. A comparison of the specifications of the car and the child seat is necessary, and the variants of both product types can be complex for consumers. Additionally, retailers may encounter difficulties in recommending combinations of products that align with consumer preferences and demands [25-28]. The purchase of child safety products online, without the guidance of a professional, poses a significant risk to consumers. The appearance of a product's fastening may be deceptive, and its combination with an incompatible car seat can result in

a substantial safety risk. In the simplest case, unauthorized use can lead to a reminder fee. In the worst case, it can lead to death without insurance cover.

Extraction of Knowledge (Use Case Analysis)

In order to construct the domain-specific semantic model pattern, it is necessary to identify the entities, properties, and relations involved. Various studies utilize the approach of analyzing key use cases for this identification task [29], [12], [30]. Following this method, the key use case, 'Show compatible seating positions of a car for a selected child seat', of the product compatibility question was examined. This use case can be used in both scenarios, before and after the purchase of a child seat. In most cases, consumers already possess an automobile and do not purchase a child seat specifically for it; rather, they select a child seat that will fit their existing vehicle. Prior to making a purchase, consumers must identify a compatible child seat. During its use, it is not uncommon for a child seat to be installed in other vehicles as well, given its generally long product life. The fundamental question of whether two products are compatible forms the core of this use case. For the user, the focal points are twofold: product identification and compatibility assessment.

Product Identification

In the realm of automotive identification, various approaches have been employed by accessory retailers. A prevalent method involves the integration of brand, model, type, and release year (see appendix A table 1) [31-37]. When additional identification is required, information regarding car compartments is also solicited. An alternative approach involves the utilization of identification codes to ascertain the vehicle and its characteristics. In Germany, the German Federal Motor Transport Authority (KBA) maintains two identification codes, HSN and TSN, which are used to identify the car manufacturer and the type of car, respectively [38]. The HSN includes details such as the model, the car body, and the motorization. The KBA makes decoding lists of HSN and TSN available on their website. Alternatively, the content is shared by the KBA at the Open Data Content Delivery called *Mobilithek*, which is founded to share data about German traffic [39]. Detailed information of configuration is not identifiable with this approach. A similar way of identification is the VIN (Vehicle Identification Number) code, which is used in Europe and USA and is regulated by ISO 3779:2009. With this, the car configuration can be identified exactly. While numerous digital services exist for decoding the European VIN, the NHTSA (National Highway Traffic Safety Administration) provides an official decoder for the United States [40].

The identification of a child seat is analogous to the identification of a car by the use of characteristics, even though to a lesser extent. Typically, this is accomplished by the model name of the product in conjunction with the brand. In certain instances, particularly in the context of product recalls, consumers are required to identify the product by its serial number. The interface to be checked is contingent upon the approval type of the child seat and the securing method.

Divers Compatibility Results

The primary factor contributing to the complexity of this domain is the wide range of product variants, predominantly attributable to the variety of automobiles. Once the method for securing the child seat has been ascertained, the selection of an appropriate car seat can significantly enhance safety. The compatibility outcome, contingent on the securing and equipment features of the child seat and the car seat, can range from simple compatibility to restricted compatibility (see figure 1).

The provisioning of compatibility information between child seats and vehicles is a practice exhibited by child seat manufacturers, distributors, and retailers. This compatibility information is typically disseminated through various channels, including product descriptions and dedicated compatibility paragraphs. The first approach entails the description of characteristics that are pivotal in determining compatibility. In this context, the interface component between a vehicle and a child seat is the car seat itself. Consequently, consumers are guided by the instructions of use to examine the characteristics of both the child seat and the vehicle to ascertain its compatibility.

A number of companies offer digital information services that are intended to reduce research effort and, consequently, the complexity for the consumer. Typically, such services provide guidance by identifying the vehicle and recommending a compatible car seat (see figure 2). The basis for these recommendations is not apparent to the consumer.

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In order to comprehend the functionality of this middleware, it is necessary to examine the developmental process of child seats. The compatibility of two products depends on the interface of both. Specific components are engineered with the primary function of enabling the interface, driven by regulated standards [41]. Child seat manufacturers develop and test products according to these regulations and for representative cars [42], [43]. Following the development phase, manual installation tests are conducted to provide compatibility information based on the combination of the child seat and vehicles with randomly selected configuration. These tests can also serve as a foundation for generic cross-model inheritance logic, facilitating the scaling of the range of possible connections. Consequently, two approaches exist for achieving compatibility results: explicitly or implicitly (see figure 3).

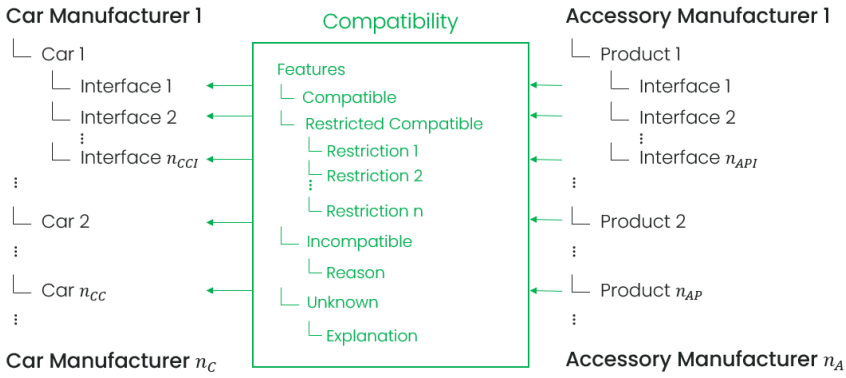

FIGURE 1. The compatibility of a vehicle with a child seat is typically dictated by the specific variant of the product in question. This variability arises due to the distinct product domain and the variety of available interfaces.

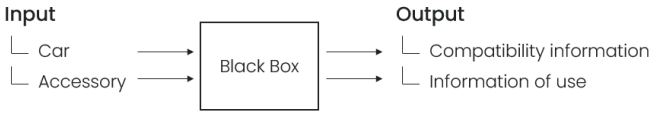

FIGURE 2. The abstract view of an RS as a black box involves the integration of the vehicle and the child seat as inputs. The resulting output encompasses both the compatibility information and the utilization information.

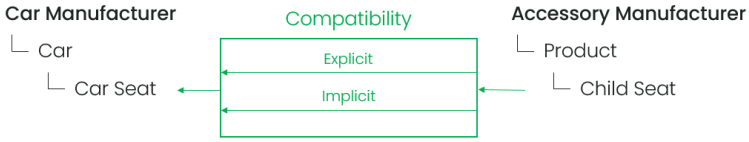

FIGURE 3. The compatibility relation between a child seat and a car seat can be either explicit or implicit.

Explicit Compatibility

As demonstrated in appendix B1, tables are utilized for the identification of vehicles, their respective car seats, child seats, and the establishment of compatible products. This approach exemplifies the method by which explicit compatibility information can be stored in a conventional table-based format. Adopting the semantic model-based approach, the outcome of a technical fitting test can be delineated, as illustrated in figure 4. A validation instance, in this case, a technical fitting instance, encompasses the tested products and their components. As the tested child seat employs a single securing method, its components were not combined, as their combination would be redundant. As previously mentioned, the car seat of the vehicle must be included in the validation instance, as it constitutes a critical component of the compatibility assessment. Each validation instance yields a result, and this example demonstrates *compatible* as the result.

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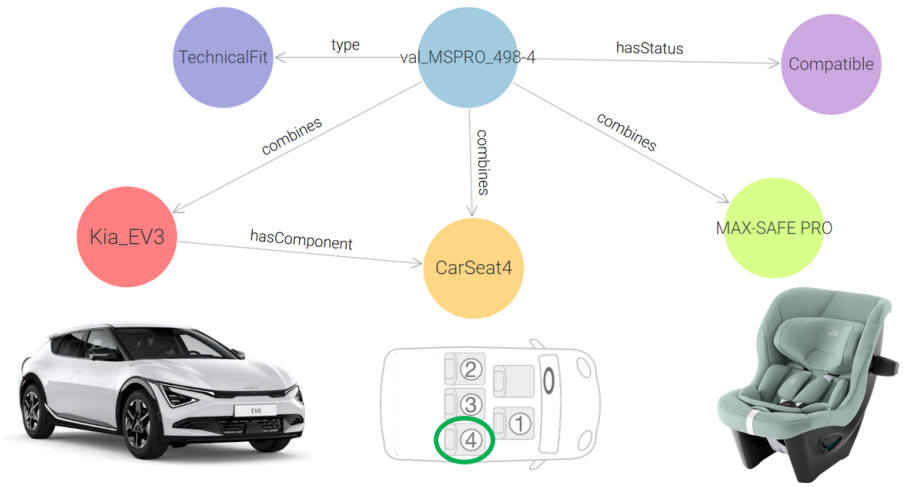

FIGURE 4. Result of a technical fitting test of the child seat called MAX-SAFE PRO in the car KIA EV 3. In this test scenario, the child seat was tested with the right outer car seat of the second row and resulted with the status compatible.

Implicit compatibility

In addition to technical fitting tests, compatibility results can be inherited and processed based on domain-specific knowledge of the technical interface. This knowledge was extracted with the assistance of domain experts, and compatibility rules were developed and implemented in the domain-specific model pattern. It was observed that two distinct types of rules could be grouped into clusters. Existing standardized interfaces, such as i-Size, ensure that two products are compatible with each other. If the child seat and the vehicle seat are certified according to the i-Size standard, no further tests are required. For the knowledge graph, this means that the i-Size feature creates the direct link between the product instances. The derived compatibility rule is characterized by simplicity and directness (see figure 5). The appendix B2 shows a table-based example.

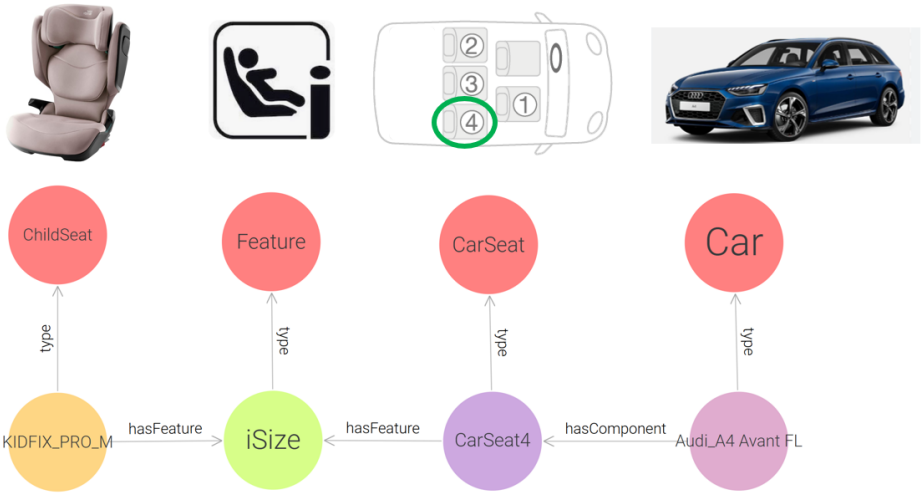

FIGURE 5. The feature i-Size serves as a direct connector of two product instances and reflects the compatibility of the products. In this example, no test result is required to determine compatibility.

The second cluster of rules was complex, containing a greater depth of knowledge and combinations of corresponding conditional dependencies (see figure 6). The compatibility of the system was dependent on the 3-point-belt component and the ISOFIX feature. Furthermore, the car seat under consideration had the constraint that the ISOFIX feature was optional. This means that some Audi A4 Avant vehicles were produced with the ISOFIX feature, while others were not. When formulating compatibility rules, it is imperative to consider potential constraints. In addition to technical requirements, the orientation and corporate philosophy of the child seat manufacturer influenced

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the development of these intricate rules. Variant drivers, such as various constraints, the level of recommendation detail, the explanation of recommendations, and the integration of subsequent information, such as instructions for use, allow for the design of the RS.

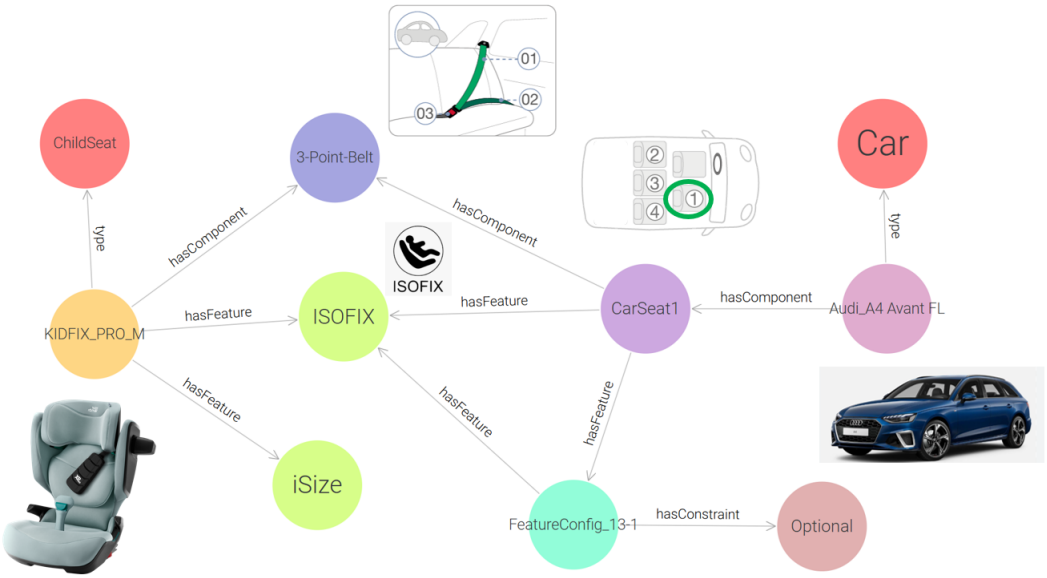

FIGURE 6. Conditional constraints can drive complexity of implicit compatibility rules.

KEY FINDINGS AND DISCUSSION

Product Identification

The analysis of the case study revealed several issues with regard to product identification. Given the wide variety of car configurations and the significant variability in child seats, consumers are confronted with an overwhelming amount of information. The distinguishing characteristics of cars and child seats allow for approximate identification. However, the possibility of configuration, existing variants, and versions contributes to the complexity of identification. In certain instances, the identification of a car and its corresponding child seat may require more precise characteristics, beyond the basic features, to ensure a precise match. This necessitates an assessment of the compatibility, which is determined by the interplay of relations between different compartment levels and their characteristics. For example, the car identification schema 'Audi A4' combines the characteristics of the brand 'Audi' and the model 'A4.' In some cases, this identification level is sufficient to recommend a compatible car seat. However, in certain instances, a more precise identification may be necessary. The Audi A4 model is available in various body types, including saloon, hatchback, and convertible. It is noteworthy that several child seats exhibit height-related compatibility issues with the convertible variant. Consequently, this identification level should be prioritized for child seats that are affected by these compatibility issues. Further identification levels were identified, including the year of production and serial numbers. As the identification process was pursued in greater detail, a mounting number of questions emerged. The annual data exhibited variations depending on the country under consideration, and the configuration of individual components could only be predicted with a certain degree of uncertainty. The feature approach entails a remaining risk of incompatibility between the products. At this juncture, a standardized identification and breakdown of the configuration is imperative. Achieving this standardization necessitates a paradigm shift within the automotive industry, as the proprietary nature of automotive equipment precludes external verification. Consequently, access to this information is typically restricted to vehicle manufacturers and their authorized service contract repair shops.

Compatibility Interface

As previously described, the compatibility of products depends on the components and their interconnection. In this study, we conducted an analysis of automotive components and features, with a particular focus on the product

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domain and use case. At certain points during the analysis, the determination of whether to model the connection based on components or features proved to be ambiguous. For instance, ISOFIX can be regarded as a feature that a child seat and a car seat may possess. Alternatively interpreted as components, the child seat can have ISOFIX arms and the car seat can be configured with ISOFIX anchors. Both modeling approaches have their advantages and disadvantages. Following the feature approach, the knowledge model is concise and straightforward. However, if different designs of the ISOFIX components are responsible for the incompatibility, modeling at the component level would be more feasible. The differentiation between components and features has been shown to be primarily driven by usability considerations of knowledge domain experts. Compatibility modeling is significantly more straightforward and unencumbered when utilizing an interface abstraction, which results in a single, unified entity. The type of parts that form the interface is irrelevant for modeling product compatibility. Consequently, these components can be modeled as instances of the *interface* entity.

Dimensions of Compatibility

In the course of conducting a comprehensive analysis of the test results and the data exchange process of the case study, three distinct dimensions of compatibility were identified. The initial dimension pertains to the physical compatibility of the products, which can be conceptualized as a *dimensional axis* within the broader compatibility information space. The subsequent dimension was determined through the investigation of various constraints. While the products exhibit physical compatibility, certain constraints may result in a state of incompatibility or, at the very least, necessitate the issuance of a recommendation against the utilization of the combination. For instance, a child seat, when installed in a car seat positioned behind the driver's seat, may require excessive forward adjustment of the driver's seat, potentially compromising the individual's ability to either sit comfortably or operate the vehicle safely. This phenomenon, characterized by the inability to adequately utilize the product due to physical constraints, is referred to as the *usability axis*. Constraints analysis further revealed a third axis, referring to the instructions for use of the product. These instructions, an integral component of the product, contain pivotal information regarding the compatibility of the product with other products. In certain instances, the instructions for use of a product may prohibit its usage, despite receiving positive results from both dimensional and usability validation. This third axis is referred to as the *information axis*. The integration of these compatibility dimensions, in conjunction with dimensions pertaining to user interests such as design, color, price, country of manufacture, and even brand preference, facilitates the development of a highly efficient, knowledge-based RS.

Interoperability

In light of the key findings, a transformation of the domain-specific model pattern to the generalized Product Compatibility Model (PCM) was undertaken. The publication of the PCM on GitHub has enabled manufacturers, retailers, and researchers to interoperate product compatibility data and knowledge (see figure 7). Consequently, the development of knowledge-based RS has become possible, enabling companies to collectively ensure safe, efficient, and effective use.

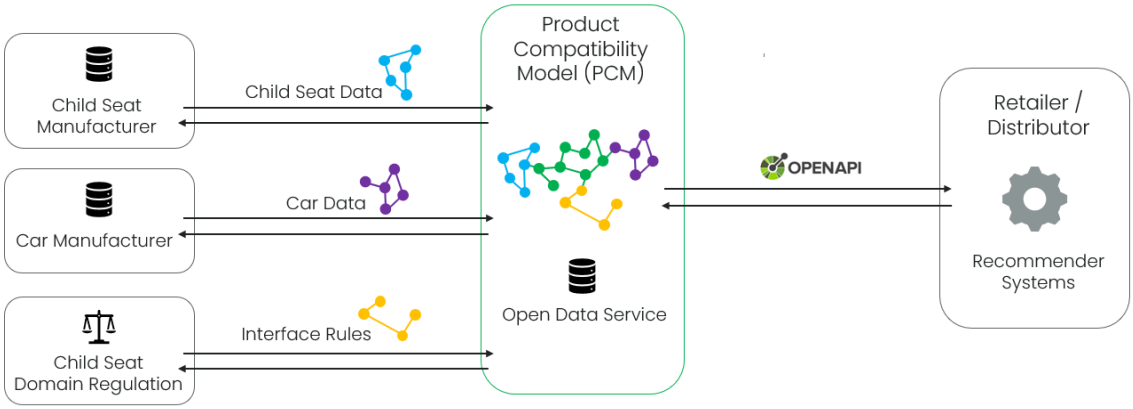

FIGURE 7. The interoperability schema under consideration is based on the Linked Open Data approach.

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DEMONSTRATOR OF PCM

We demonstrated the applicability of the Product Compatibility Model (PCM) to knowledge-based applications, with the implementation as a dialog- and knowledge-based RS application [24]. It should be noted that this is merely an example, as alternative forms of RS are also conceivable with the utilization of PCM as a backbone.

Knowledge Extraction

The extraction of knowledge should be automated to the greatest extent possible [4]. Various standards for knowledge extraction exist, including RDF Mapping Language (RML) [44], RDB to RDF Mapping Language (R2RML) [45], and CSV on the Web (CSVW) [46]. As the data source of our case study is a mixture of manually maintained CSV and CSV exports from relational databases, we tested several approaches for the extraction task. During the development of the PCM, case-specific Python scripts were created and utilized. Moreover, the pcsvw library was tested in accordance with the standard CSVW [47]. For a generic extraction from multiple CSV files with varying structures, it was decided to use the libraries pandas and rdflib [48], [49]. This approach permitted flexible adjustments to the circumstances and a combination of extraction and data pre-processing with corresponding data cleansing. The Use Case analysis yielded 16 key entities with seven relations to establish the connections. The essential properties for this product domain refer to the entities Product, Car, and CarSeat (see appendix C).

Application Structure

The design of the web application involved three layers (see figure 8). The front end and database layer constituted the foundation of the application. with the backend layer, which utilized the programming language Python, playing a central role. The Flask library facilitated RESTful communication with the front end, while the sparqlwrapper library enabled queries against the graph database GraphDB. Queries against the database were executed using the standardized semantic query language SPARQL [50].

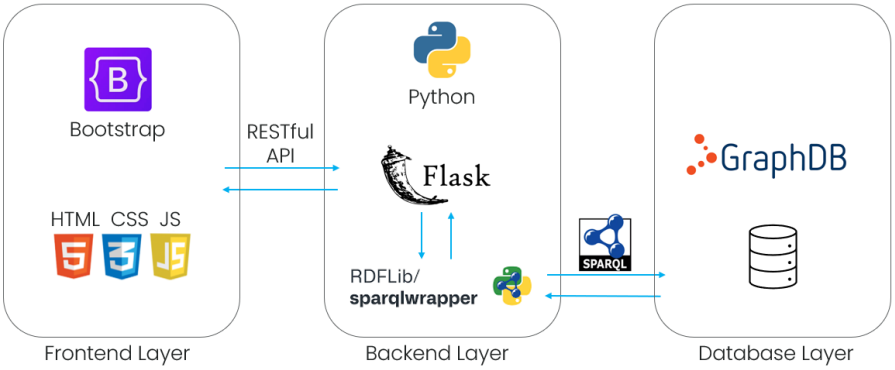

FIGURE 8. The application's structural design comprises three distinct layers: the Frontend, the Backend, and the Database.

Query Development

The queries were derived from the use cases of the product domain. Various use cases were translated into SPARQL queries and implemented in the application. One example is the use case "Find the compatible seating position of your child seat in your car" (see figure 9). In this use case, the user is guided through the application by answering key questions to identify their car. As a result, the user receives a list of possible car seats for securing the user's child seat.

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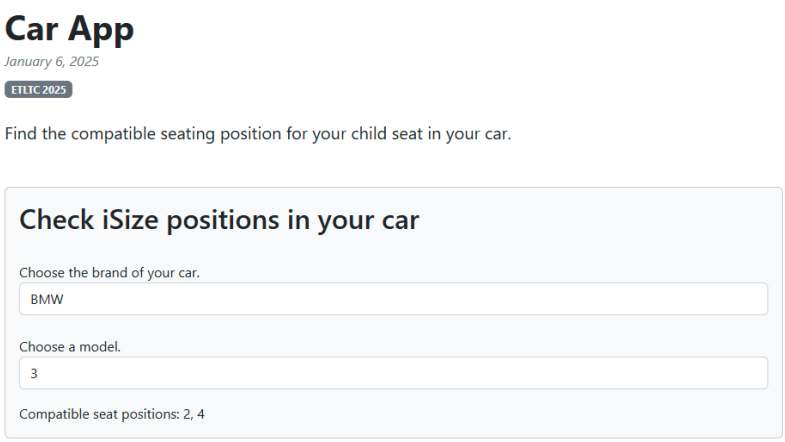

FIGURE 9. A particular component of the application suggests the utilization of car seats from a specific vehicle model for the purpose of accommodating a car seat equipped with the i-Size safety feature.

CONCLUSION

Recent studies have demonstrated that the compatibility of a pair of products can have different origins, depending on the product category. The products can be compatible based on specific components or features, such as dimensions, visual appearance, or performance limits [52], [8]. Our case study revealed a similar result, with key compatible drivers such as components and features. If no further logic is to be implemented in the graph, developers can dispense with the distinction between interface types as independent entities. Instead, all instances can be managed under the interface entity. The logic and knowledge of product compatibility can be captured with the PCM that has been designed and published [58].

In this particular case study, the child seat manufacturer is tasked with the challenge of managing the complex knowledge of various automotive vehicles. The import of cars into the knowledge graph has reached a total of 1,066, comprising 13,682 nodes and 103,688 edges. Based on estimated figures, the case study encompasses approximately 30 distinct car brands, with each brand having an average of 20 car models. Assuming that every two years, all car models undergo a facelift, it is estimated that over a decade, the system will need to maintain 6,000 car models. Given this requirement and the established benchmark results [51], the deployment in the field should be feasible.

Developers are able to use the PCM for creating a knowledge backbone and designing knowledge-based RS. For consumers, it is critical to get concise information about the compatibility of products. Given that product compatibility is contingent upon their interface, high variant-driven product domains are susceptible to information overload. A significant challenge faced by consumers is the presence of multiple product configurations under a single product name, which complicates the determination of consistent interface composition. Consequently, consumers must identify the interface configuration, a process that can be arduous and potentially lead to misjudgments, incorrect operation, and safety concerns. To avoid these challenges, it is essential to access precise, consumer- and product-specific information.

A potential solution to this problem is already available in the form of the Linked Open Data (LOD) approach [53], but this requires the manufacturers' support. Given their obligation to ensure product safety and unique identification, manufacturers attempt to address this issue through safe design and the publication of information materials such as instruction manuals [54], [55]. This approach is effective for products intended for individual use. However, when multiple products are combined, the issues previously mentioned can arise. One proposed solution is the utilization of open data, which necessitates that manufacturers share their product and configuration knowledge with others. However, it is not practical for manufacturers to directly share interface configuration with consumers. Instead, this data should be made available to retailers or third parties, who can implement it for intelligent services. The freely available PCM can be used to support and standardize the interoperability process. This approach has the potential to enhance consumer satisfaction and boost sales by leveraging knowledge-based RS [1]. From the perspective of retailers or distributors, compatibility information is important for products with restricted usage. They must have access to the necessary information or, at the very least, ensure that interested consumers are aware of how to acquire it. It stands to reason that the incentive for the seller to proactively share compatible products, as opposed to leaving the consumer to grapple with the issue independently, which may result in lost sales, should be substantial. From a research perspective, the PCM can be utilized for testing various applications with the objective of optimizing the

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model. However, there is still a need for research in other domains. Beyond that, implementations with Large Language Models (LLMs) promise positive effects. LLMs still face problems such as hallucination. Studies have shown that using an LLM with the Retrieval-Augmented Generation (RAG) approach can reduce these problems. The core element of RAG is to deliver the knowledge in the given context, avoiding wrong answers [57]. With the help of PCM, product compatibility issues can be provided to the LLM in a targeted manner, thus increasing the quality of the result.

OUTLOOK

To expand upon our approach, further research will be conducted, encompassing additional product domains, to validate or adapt the proposed model pattern PCM. Addressing quality assurance issues will prevent contradictory usage of the model. Best practices for development procedures and guides for implementing applications will facilitate the usage and dissemination of the model. Additionally, standardized interfaces and the integration of other model patterns and methods, such as Semantic Correlation Rules (SCR) [56], will be investigated. Furthermore, we will propose corresponding rules-based analytics using machine learning techniques to implement reporting mechanisms for the long-term quality assurance of the model and corresponding recommendations.

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APPENDIX

APPENDIX A

TABLE 1. Common ways of car identification

Company	Car identification
Walser GmbH	Brand, Series, Model or HSN with TSN
OMAC GmbH	Make, Model, Year
CYBEX Retail GmbH	Make, Model, Release Year, Phase Out
Maxi Cosi	Make, Model, Type, Release Year, Phase Out
Axkid	Make, Model, Type, Release Year, Phase Out
Britax Römer	Make, Model, Type, Release Year, Phase Out
BeSafe	Make, Model, Type, Release Year, Phase Out
Kfzteile24	Brand, Model, Type or HSN with TSN

Appendix B1

TABLE 2. Example of various cars and their characteristics.

Car Id	Brand	Model	Release Year	Phase Out Year	Body Type
c1	Audi	A3	2013	2020	Hatchback
c2	VW	ID.7	2024	-	Estate
c3	Kia	Soul EV	2014	2019	Estate

TABLE 3. Example of possible car seats.

Car Seat Id	Description
cs1	Passenger seat
cs2	Second row, left outer seat
cs3	Second row, middle seat
cs4	Second row, right outer seat

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TABLE 4. Example of various child seats and their characteristics.

Child Seat Id	Brand	Product Name
chs1	Britax Römer	MAX-SAFE PRO
chs2	Cybex	Anoris T2 i-Size
chs3	Maxi-Cosi	AxissFix

TABLE 5. Example of fitting test results.

Fitting Id	Car Id	Child Seat Id	Fitting information
f1	c1	chs1	cs2, cs4
f2	c2	chs2	cs1, cs2, cs4
f3	c3	chs3	cs2, cs4

Appendix B2

TABLE 6. Car seat features.

Car Id	Car Seat Id	Feature	Value
c1	cs2	ISOFIX	Yes
c1	cs2	Belt System	3-Point-Belt
c1	cs2	Allowed types of child seat	Universal belted, Universal ISOFIX
c2	cs1	i-Size	Yes
c2	cs3	i-Size	No

TABLE 7. Child seat features.

Child seat Id	Feature	Value
chs1	ISOFIX	No
chs1	Belt System	3-Point-Belt
chs1	Type of CRS	Semiuniversal Belted
chs2	i-Size	Yes

TABLE 8. Fitting rules.

chs feature	chs value	cs feature	cs value	Result
i-Size	Yes	i-Size	Yes	Compatible
ISOFIX	Yes	ISOFIX	Yes	Compatible
Footprop	Yes	Storage Compartment	Yes	Incompatible

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Appendix C

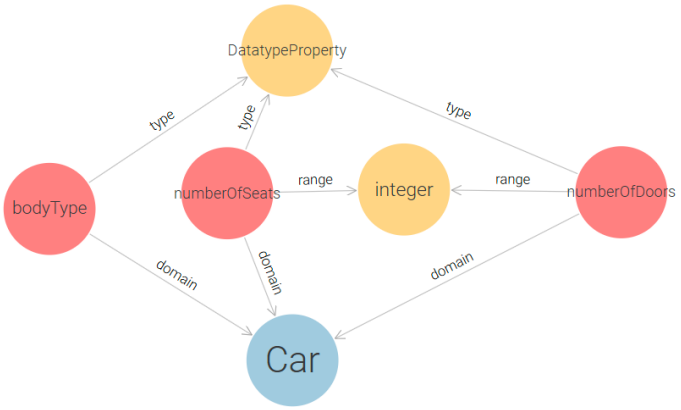

FIGURE 10. Car with its properties.

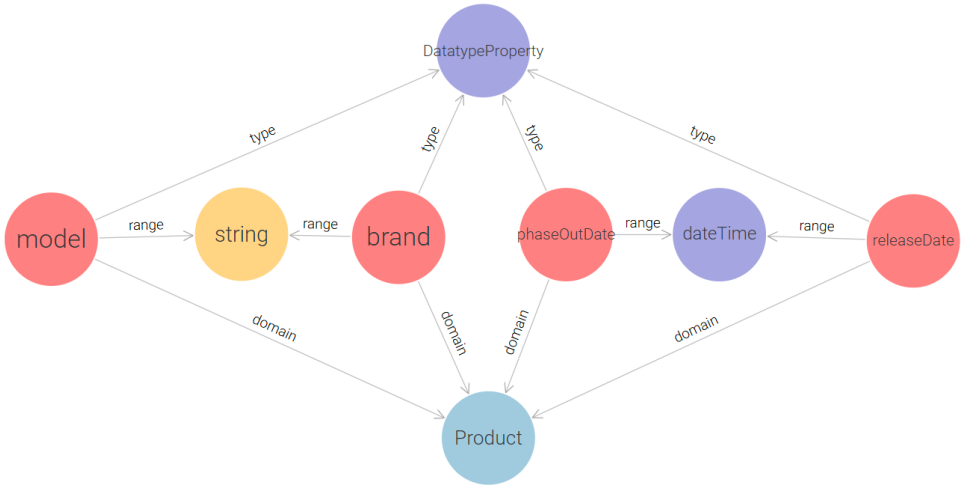

FIGURE 11. Product with its properties.

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FIGURE 12. Overview of relations.

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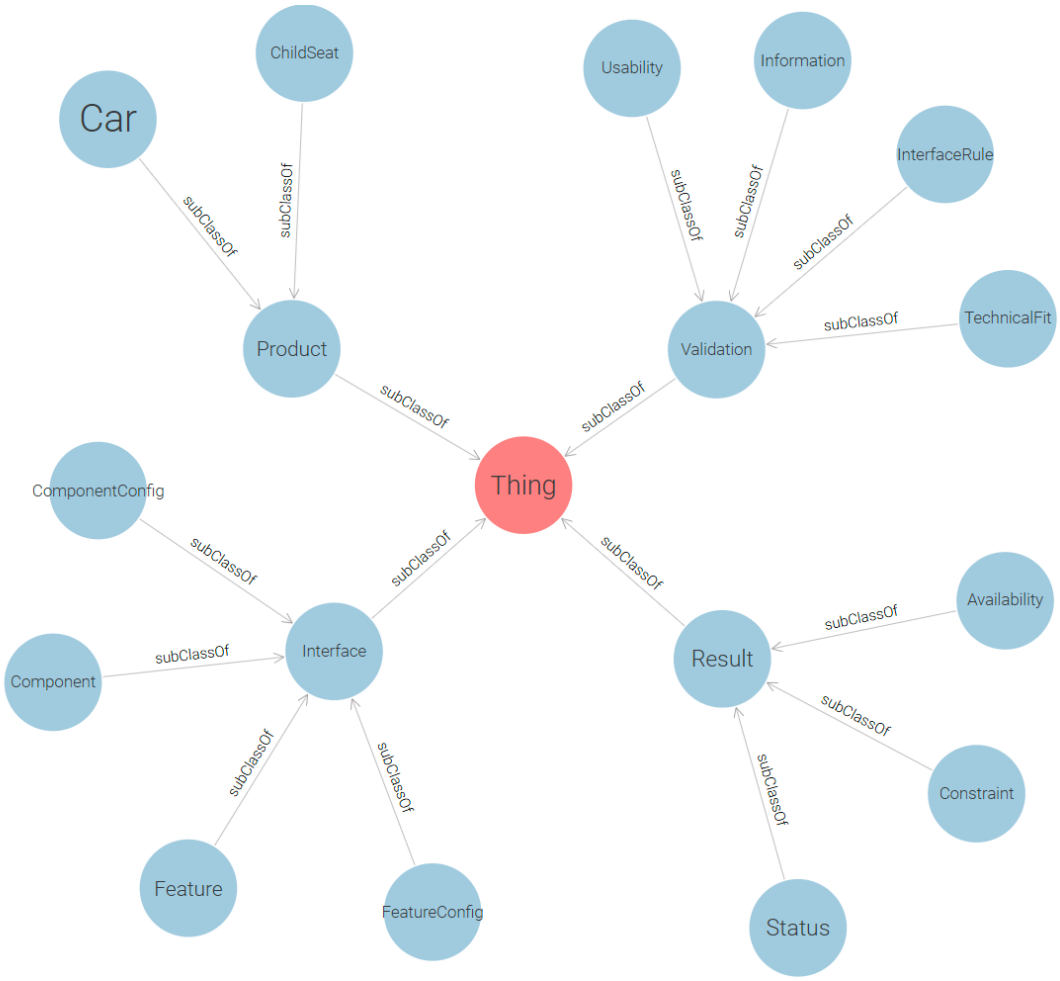

FIGURE 13. 16 key entities were found by the use case analysis of the specific domain.

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