Leveraging Action Knowledge from Product Reviews to Enhance Human-Centered Recommender Systems: A Knowledge Graph-Based Framework

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Abstract

Actions that people aim to do are considered one of the main drivers behind purchase decisions and uncovering people's needs in a human-centered manner. Such actions are often expressed by buyers in product reviews. However, most existing recommender system approaches still lack incorporating buyer-product action knowledge in the recommendation process. This limitation increases the gap between buyers' needs and the recommended products. This research proposes a knowledge graph-based framework to represent buyers' action knowledge from product reviews and integrate it in recommender systems to provide more human-centered and explainable recommendations. The framework is validated through a set of prototypes, which demonstrate the feasibility of buyers expressing their needs in the form of actions and recommending products accordingly. An initial evaluation revealed a promising 75% System Usability Scale score, with interview-based feedback that shed light on the capabilities of the proposed approach in supporting buyers in their online product selection experience.

Keywords: knowledge graph; human-centricity; recommendation systems; artificial intelligence; ontologies; product reviews

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1. Introduction

Putting people at the center of artificial intelligence (AI) research is gaining more attention. Related studies revealed that people don't only care about understanding the machine's behavior (e.g., through explainability and interpretability features in human centered artificial intelligence (HCAI) (Ehsan et al., 2021), but they also appreciate the machine understanding them (Bingley et al., 2023). Human-centricity is one of the core objectives of recommender systems (Konstan & Terveen, 2021). Today, product recommendation is an inherent feature of most online services and e-commerce platforms, assisting consumers with their online choices and purchase decisions. Aligning the recommended products with buyers' needs is a key aspect of recommender systems (Komiak & Benbasat, 2006; Xiao & Benbasat, 2007). Actions and analyzing what people do with the product are important to understand users' needs in human-centered design (HCD) (Norman, 2013), and for uncovering why people decide to buy a product (Christensen et al., 2016). Consider a person looking to buy a laptop. If this person needs to use the device for studying on the move, then the laptop selection would be different than a device that is mainly bought by designers for drawing. In other words, it is the potential need for studying or drawing—usually represented in the form of actions—that mainly drives purchasing a certain laptop, rather than its features.

Often buyers describe their experience with products in the form of text-based reviews, making product reviews left on e-commerce platforms (e.g., Amazon.com and BestBuy.com) a substantial reference for online shoppers in supporting their purchase decisions (Baek et al., 2012; Biswas et al., 2022; Lee et al., 2022; Park et al., 2007). With the value they bring to the product selection process, product reviews are being increasingly studied to advance recommender systems (Chen et al., 2015; Tang et al., 2017). However, related research that analyze product reviews for improving product recommendations mainly focus on buyers' sentiments and product aspects detected in the reviews (e.g., Elahi et al., 2023; Kamath et al., 2023). In addition, other efforts that provide action-based product recommendations aim at analyzing buyer-system actions such as where users are clicking and their browsing behavior, rather than the buyer-product actions (e.g., Kumar et al., 2024; Patro et al., 2022). Hence, we observe that little attention is given to the latter actions as a potential to understand buyers' needs for machines to provide more human-centered product recommendations. This limitation may contribute to increasing the mismatch between buyers' needs and the recommended products. To address this gap, this research follows the design science research methodology (A. Hevner et al., 2004; Peffers et al., 2007), with a focus on the following research question:

how can we leverage buyer-product action knowledge expressed in product reviews to provide more human-centered product recommendations?

This study proposes a novel framework that guides the development of a set of prototype artifacts. Building on the value of buyer-product action knowledge in the recommendation process, and on the advancements of semantic web and knowledge graph technologies in representing knowledge (Berners-Lee et al., 2001; Fensel et al., 2020; Hogan et al., 2021), the proposed framework provides explainable product recommendations aligned with user needs through explicit knowledge graph linkages, connecting actions identified in product reviews with the relevant related entities. This framework includes an *ontology* designed to guide the extraction and representation of knowledge graph data connections between actions expressed by buyers in product reviews and the contextual entities, such as product, environment, sentiment, and others; a *semantic annotator* to enable automatic semantic web data extraction from product pages, and the annotation of actions and their related entities from product reviews; and a *recommender engine and interface* layer that builds on the knowledge graph data, offering action-driven and explainable product recommendations.

The framework's main components are demonstrated through the development of a set of prototype artifacts that help with evaluating the feasibility of the proposed approach. The development is conducted in the context of electronic products available on BestBuy.com, a leading online consumer electronics store. 3,665 product reviews were annotated, with around one-third discovered to have at least one action expressed by the buyers in the review. An initial evaluation study of the developed prototype features with 32 participants revealed a promising 75% System Usability Scale (SUS) score, complemented with qualitative interview-based feedback that shed light on the capabilities of the approach in supporting buyers in their purchase decisions.

This paper contributes to the field at three levels: First, it offers online shops with a novel approach to modeling and computationally integrating buyer-product actions from product reviews in recommender systems to enable more human-centered product recommendations. Second, it provides a knowledge graph with openly accessible linked data used to further develop action-related features in recommender systems. Third, it lays the path for supporting emerging conversational AI personal assistants (e.g., Amazon's Alexa) (Lopatovska et al., 2019) that can rely on the knowledge graph created to better understand the needs of their users and recommend products accordingly.

The rest of the paper is organized as follows. The next section presents the theoretical background and related works in the field. Section 3 discusses the methodology and proposed approach details. Section 4 presents the validation and development of the artifact in the context of a consumer electronics use-case. Section 5 covers the system usability evaluation and users' feedback. The paper concludes with a discussion of the results, research limitations, and potential future research directions.

2. Theoretical Background and Motivation

Design science research (A. Hevner et al., 2004) has been increasingly shaping information systems (IS) research (Indulska & Recker, 2010; Peffers et al., 2007). One of the core aims of design science research in IS is the study of information technology artifacts with a focus on their application in organizational and human contexts (A. Hevner & Chatterjee, 2010). This study builds on the design science research methodology (DSRM) (Peffers et al., 2007), which provides a set of activities that guide the research process. DSRM starts with identifying a motivated research problem to address. Subsequently, the process involves specifying a set of objectives to be incorporated in a solution to tackle the problem at hand. The objectives are used to instruct the development of an artifact to demonstrate and validate the solution in a suitable context of use. The artifact contributes to the evaluation step to reflect on the suitability and effectiveness of the proposed approach.

We review in this part related efforts on human-centricity in recommender systems, with the importance of understanding buyers' needs in this context. Then we reflect on related recommender systems research efforts that incorporate product reviews and action related information in the recommendation process. We then explore existing efforts on representing data and knowledge that support recommender systems on the web, and conclude this part with the motivation and research questions to address.

2.1 Human-Centricity in Recommender Systems: Understanding Buyers' Needs through Product Reviews

Research on recommender systems has been on the rise since the early days of human-computer interaction. One of the first recommender systems, Grundy, aimed to understand and model users to recommend relevant books (Rich, 1979). From its inception, one of the quests in this domain is to understand people and recommend appropriate items that match their requirements. Beyond this scope, AI researchers from different disciplines are working on achieving more human-centered interactions with machines (Boy, 2017; Riedl, 2019). Explainability, understandability, and interpretability by users are key components for HCAI (Ehsan et al., 2021). While such components are important, Bingley et al. (2023) revealed that, from a user experience perspective, people care more about being understood by machines rather than understanding the machine. They found that "an increased focus on what people need in their lives is required for HCAI to be truly human-centered" (Bingley et al., 2023). In other words, human-centricity advocates for machines to better understand their users and their needs, a feature particularly relevant for product recommendations. Investigating such people-machine relationships is core to human-centered recommender systems, which focus on studying the characteristics of systems, their users, and the relationships between them (Konstan & Terveen, 2021).

Needs-based recommender systems are seen to provide a potential solution that goes beyond products' features and aspects, to better support consumers in their online purchases (Komiak & Benbasat, 2006; Xiao & Benbasat, 2007). Extensive research has been conducted on consumer behavior and what drives their shopping and purchase decisions (Chiu et al., 2014; Tauber, 1972). Understanding why customers decide to bring certain products to their lives is one of the motivations behind the jobs to be done concept (Christensen et al., 2016). Unlike traditional marketing metrics that measure the sales performance from a product or customer perspective, focusing on jobs or actions helps truly uncover how well a product helps certain customers perform their objectives. Such information is hard to identify from traditional customer satisfaction metrics (e.g., product ratings), and arguably provides a better understanding of product fulfillment of customer-specific needs. Christensen et al. (2016) performed several experiments by observing and interviewing buyers in the types of jobs they hired certain products to do. For example, they revealed that a consumer may hire a milkshake in the morning to stay entertained while commuting to work, while someone else may hire it to better connect with his kids and replace unhealthy snacks. This notion reflects a job usually articulated using action verbs and nouns in the context of what a customer performs through a product or service. Similarly, the focus on actions and what people are aiming to do is core for building empathy with users during the human-centered design process. HCD aims to develop products around well-defined human needs (Norman, 2013), and actions can support the identification of people's needs through observing users' behavior and what they do in certain contexts (Silva et al., 2022).

One substantial source of contextual buyers' feedback can be found in product reviews. Product reviews provide context and support consumers' purchase decisions from online stores (Baek et al., 2012; Biswas et al., 2022; Lee et al., 2022; Park et al., 2007). Research reveals that as much as 97% of consumers consult product reviews, and around 89% consider reviews essential for purchase decisions (Power Reviews, 2018). Reviews in free-form text enable previous buyers to voice their opinion on products they bought and help prospective buyers to understand the potential of the sought product to fulfill their needs. Product reviews text contain a wealth of information articulated by buyers to reflect what worked and what did not work for them when they hired a product to perform certain jobs (Christensen et al., 2016), and provide a substantial input for improving user-centered design (Han & Moghaddam, 2021). We illustrate this point in Figure 1 that shows some reviews of a 2-in-1 laptop left by customers online.[1]

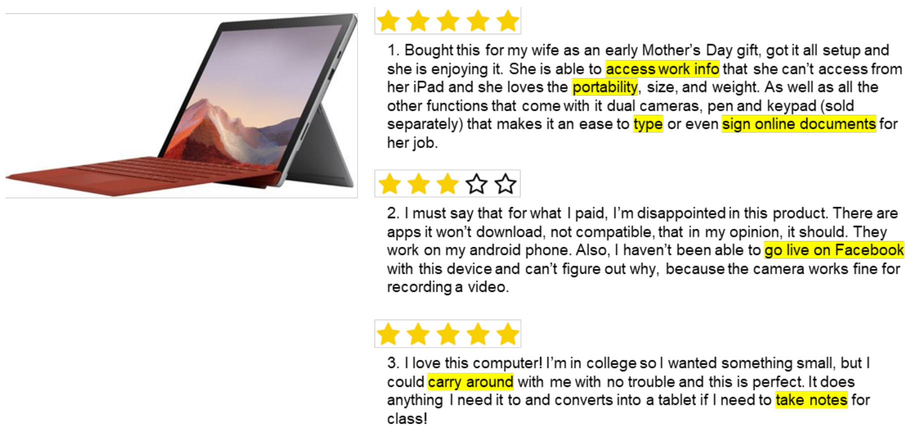

Figure 1 – Three customers describe their purchase experiences in sample reviews revealing one product fulfilling different needs

In the first review, the buyer expresses his satisfaction with the device as it succeeds in helping his wife, who is a working mother, to access work information, carry it, easily type, and sign documents. While the second reviewer was less satisfied due to his inability to go live and socialize on Facebook. A student left the third comment who seems to like the device that she can easily carry around, and is helping her take notes in class and study better. Those three reviews illustrate how the same product fulfills different actions for different buyers. To a busy working mother who needs to access her work on the go, or a student who needs to carry the laptop around campus and take notes in class, such a device might be attractive to fulfill those actions. Such actions, coupled with further information that connect the actions with additional contextual relations (e.g., product, environment of use, buyer sentiment, and others), are key to uncover buyers' needs. Hence, capturing and managing knowledge about the actions that previous buyers have performed on the products, or prospective buyers are aiming to perform provides

[1] The reviews were extracted from www.bestbuy.com for illustration purposes.

an opportunity to design recommender systems that could better understand buyers and recommend products that fulfill their needs.

2.2 Overview of Review and Action-Based Recommender Systems

With the increased sophistication of peoples' interactions with a wide range of computing platforms (e.g., web and mobile-based platforms), researchers have access to a wide variety of product and usage data that can be studied to advance the field of recommender systems in various domains (Lu et al., 2015). This data includes user feedback in the form of product reviews, as well as usage and action data performed by users on the platforms. We review in this part related works that focus on analyzing product reviews to support the recommendation process, and research efforts that investigate usage information for recommending products.

Product reviews enabled a substantial growth of online stores, driving more research attention to uncover insights for improving product recommendations. A literature review on the Scopus database using the relevant search keywords—recommender AND systems AND "product reviews"— reveals an increasing trend of related research on product reviews in the context of recommender systems. The unstructured and rich nature of text reviews provides researchers the opportunity to analyze product reviews based on a variety of elements (Chen et al., 2015). Elahi et al. (2023) proposed an approach that incorporates sentiments detected in product reviews, with product ratings to improve product recommendations. Similarly, several efforts investigate and propose means for improving the detection of sentiments and opinions from product reviews (Hung, 2020; Khanvilkar & Vora, 2019; Kim & Song, 2013). However, related research argued that sentiment analysis can be further extended to provide more concise views of what buyers are saying on particular product aspects and features (Kamath et al., 2023), such as the *battery*, *performance*, or *size* or a laptop (Da'u et al., 2020). In this context, one of the main research objectives is to analyze product reviews text to mine product features and integrate them in the recommendation process (Aldayel & Ykhlef, 2017; Baizal et al., 2016; Cao et al., 2019; Chen et al., 2015; Chen & Wang, 2017; Latha & Rao, 2024; Susmitha & Rajesh, 2023; Won et al., 2023).

Most of these approaches consider features described as a set of nouns and their corresponding descriptions in the reviews (Dong et al., 2013; M. Hu & Liu, 2004). For example, in a review that mentions "this tablet is small enough to pack, but the screen is the perfect size for watching movies on the plane when traveling, also, very budget friendly with good battery life" (Kamath et al., 2023), the features in focus are budget friendly, small size, and good battery. Tang et al. (2017) provided an approach for detecting usage context from product reviews. Their methodology aims to link product features to more usage context. They designed a solution that enables buyers to search for digital cameras by terms like beach, travel, and portrait, and revealed the advantages of relying on usage information in product selection by novice buyers, compared to only relying on product features (Tang et al., 2017). These approaches can be extended to semantically specify the elements of usage context, rather than treating usage as a set of freeform terms.

While product features and aspects are important elements around which buyers express their opinions, analyzing the actions that buyers perform has also been a focal research attention. Online platforms provide opportunities to store and analyze user actions. Such actions may infer opportunities to understand user preferences. A search on the Scopus database using a set of relevant keywords—recommender AND systems AND products AND action—also reveals an increasing trend in the number of research output. By focusing on actions, user behavior can potentially be derived by analyzing for example where buyers are clicking and which products they are buying (Alhadlaq et al., 2022; Bock & Maewal, 2020; Kumar et al., 2024; Kużelewska, 2022; O'Brien et al., 2021; Turgut et al., 2023; Wan et al., 2021; Xu et al., 2024; Yan et al., 2019). In this context, analyzing orders and click actions can reveal buyer preferences that can be integrated into recommender systems. Furthermore, web usage data and browsing history that provide traceability of page navigation and visits, enable uncovering buyer interests (Lopes & Roy, 2015; S. Sharma & Shakya, 2023; Zhang, 2014). Other approaches have incorporated more behavioral data from user-systems interaction to include for example dwell time, browsing patterns, and items ordered (Lin et al., 2010; Patro et al., 2020, 2022). We observe from this review that most actions analyzed in this stream of research focus on the buyer-platform interactions. More specifically, the recommendations are based on what people do on the platforms (e.g., clicking on a laptop product), and do not incorporate what they do (or are aiming to do) with the products they intend to buy (e.g., streaming movies on a laptop). Table 1 provides a summary of the related research.

We observe that most existing works that analyze product reviews text mainly focus on buyers' sentiments, product aspects, and usage terms. Additionally, most related works that investigate buyers' actions focus on the actions performed by the buyer on the system itself (e.g., clicking and browsing patterns). However, as discussed earlier, buyer-product action relationships can enable a better understanding of user needs and requirements. This paper extends existing efforts that leverage text product reviews, with a focus on analyzing the buyer-product actions revealed in the reviews, to better represent user needs and provide human-centered product recommendations. Referring back to the review example of the tablet that has a perfect screen to watch movies on the plane (Kamath et al., 2023), this study proposes focusing on buyer-product actions like *watching movies*, while capturing related contextual information when recommending products. Achieving this objective computationally requires attention to be paid to the following: the need for capturing action knowledge described by buyers in their purchase experiences that may be expressed in product reviews; connecting products, buyers, and action-related data required to drive the recommendation process; and processing the data to render product recommendations on e-commerce stores for buyers to access.

Reference	Type	Unit of Analysis
(Elahi et al., 2023), (Hung, 2020), (Khanvilkar & Vora, 2019), and (Kim & Song, 2013)	Review-Based	Buyer Sentiments
(Aldayel & Ykhlef, 2017), (Baizal et al., 2016), (Cao et al., 2019), (Chen et al., 2015), (Chen & Wang, 2017), (Da'u et al., 2020), (Kamath et al., 2023), (Latha & Rao, 2024), (Susmitha & Rajesh, 2023), and (Won et al., 2023)	Review-Based	Buyer Sentiments / Product Aspects
Tang et al. (2017)	Review-Based	Buyer Sentiments / Product Aspects / Usage Terms
(Lopes & Roy, 2015), (S. Sharma & Shakya, 2023), and (Zhang, 2014)	Action-Based	Clicks / Browsing
(Alhadlaq et al., 2022), (Bock & Maewal, 2020), (Kumar et al., 2024), (Kużelewska, 2022), (O'Brien et al., 2021), (Turgut et al., 2023), (Wan et al., 2021), (Xu et al., 2024), and (Yan et al., 2019),	Action-Based	Clicks / Orders
(Lin et al., 2010), (Patro et al., 2020), and (Patro et al., 2022)	Action-Based	Clicks / Orders / Browsing / Dwell Time
This work	Review-Based Action-Based	Buyer-Product Actions

Table 1 - Overview of related research that focus on review and action-based recommender systems

2.3 Knowledge Representation in Recommender Systems on the Web

The semantic web and knowledge graph technologies are facilitating the creation of seamless and more sophisticated knowledge representation and processing capabilities (Berners-Lee et al., 2001; Fensel et al., 2020; Hogan et al., 2021). Recommender systems increasingly rely on knowledge graphs and ontologies for performing several tasks (Sun et al., 2019). Middleton et al. (2004) proposed an ontology to profile users and recommend academic articles relevant to user context. They demonstrated how ontological inferencing can contribute to more accurate representation and user profile bootstrapping. Ontologies have also been increasingly used to model different domains and support context-aware recommender systems (Buriano et al., 2006). Tarus et al. (2018) reviewed approaches that use ontologies in education to recommend materials for learners. They discuss the advantages of knowledge-based recommender systems in terms of improving the recommendations by bridging the knowledge between users and recommended entities. Further studies investigated knowledge graph adoption to provide more personalized recommender systems (Sha et al., 2021; Sun et al., 2019; Zanon et al., 2022).

Graph-based recommender systems that rely on external knowledge from the Linked Open Data cloud have witnessed an increase in performance and feature selection (Musto et al., 2017), as well as improving the transparency in the recommendation process (Musto et al., 2019). Explainable recommender systems can provide buyers with an additional reasoning layer on why certain products are recommended. Such explanations have proven to improve user trust and recommender system effectiveness (Zhang & Chen, 2020). Hundreds of knowledge graph ontologies and vocabularies exist today that work on semantically interconnecting entities from different domains in an open way (Vandenbussche et al., 2017). Such efforts materialize when organizations agree on vocabularies that make data exchange seamless between content publishers and content consumers. For example, schema.org is a vocabulary initiated by Google, Microsoft, and Yahoo (and later joined by Yandex) to align and agree on how to represent entities (e.g., products, organizations, places, etc.) on the web. Statistics show this effort led to the wide adoption of existing content publishers on the web (Brinkmann et al., 2023; Guha et al., 2016). Brinkmann et al. (2023) have been tracking the evolution of online data published following schema.org since 2013. Their statistics reveal that *product* entities are among the most published data.[2] Schema.org also represents *potential actions* that can be performed with products.

From a high-level check of the published statistical data (Brinkmann et al., 2023),[3] we observe that most actions represented on websites focus on transactional actions, such as search, add to cart, and quote actions. This work studies the possibility of extending the current use of action entities covered by knowledge graphs, to represent buyer-product actions revealed in product reviews and support recommender systems. It also builds on the potential of knowledge graphs for providing explicit semantic connections for easier and more sophisticated manipulation of data for product recommendation tasks with transparency and explainability features, considered key ingredients in achieving human-centered AI solutions (Ehsan et al., 2021).

[2] To this date, around 2.5 million pay-level domains publish products information with schema.org annotations
[3] The statistical data is available on this link: https://data.dws.informatik.uni-mannheim.de/structureddata/

2.4 Motivation and Research Questions

In this theoretical background overview, first, we explored the importance of analyzing buyer-product actions detected in product reviews text to understand buyers' needs, and subsequently provide more human-centered product recommendations. Second, we realized that most recommender systems efforts that process product reviews and analyze actions do not incorporate buyer-product action knowledge in the recommendation process. Third, we recognized the potential of adapting knowledge graphs in creating meaningful data connections around contextual actions that could represent and align buyers' needs with products in recommender systems. This work aims to extend research efforts on recommender systems, with a focus on the following research question:

How can we leverage buyer-product action knowledge expressed in product reviews to provide more human-centered product recommendations?

More specifically, the following related sub-questions merit consideration:

How can we effectively represent and capture action knowledge conveyed by buyers in product feedback and reviews? and *how can we integrate action knowledge during buyer-system interaction to provide needs-based and explainable product recommendations?*

3. Methodology and Proposed Approach

3.1 Research Objectives

We recognize three objectives that should be handled to address the identified research questions. Firstly, with the value that actions bring to understanding user needs (Christensen et al., 2016; Norman, 2013), one objective is to conceptually connect and model products with their potential buyers' actions and related context detected in product reviews. The presence of a model aids with representing and capturing the buyer-product action information. Secondly, it is expected from typical recommender systems to require the specification of user preferences, preferably in an explicit way, for the system to match relevant products (Kramer, 2007; Xiao & Benbasat, 2007). Consequently, we need to investigate means for buyers to specify their needs in the form of actions to match and rank potential products accordingly. Thirdly, given the potential advantages introduced by explanatory aspects of systems in general (Zhang & Chen, 2020), and more specifically in supporting human-centricity in AI

(Ehsan et al., 2021), this research aims to investigate the potential of leveraging the modeled actions to provide product recommendation explanation and exploration capabilities.

3.2 Proposed Framework for Action Driven Product Recommendations

This study proposes a novel knowledge graph-based framework that fulfills the research objectives. The framework is designed to integrate buyer-product action knowledge from product reviews and provide more human-centered product recommendations. The proposed framework involves (a) a semantic web ontology designed to model the conceptual data-level connections around product-enabled actions and their related context, (b) a semantic annotator that follows the designed ontology to create the knowledge graph data based on existing product pages for online stores; and (c) recommender engine and interface functionalities to process the knowledge graph data and offer action-driven product recommendations. Figure 2 provides a high-level view of the framework components.

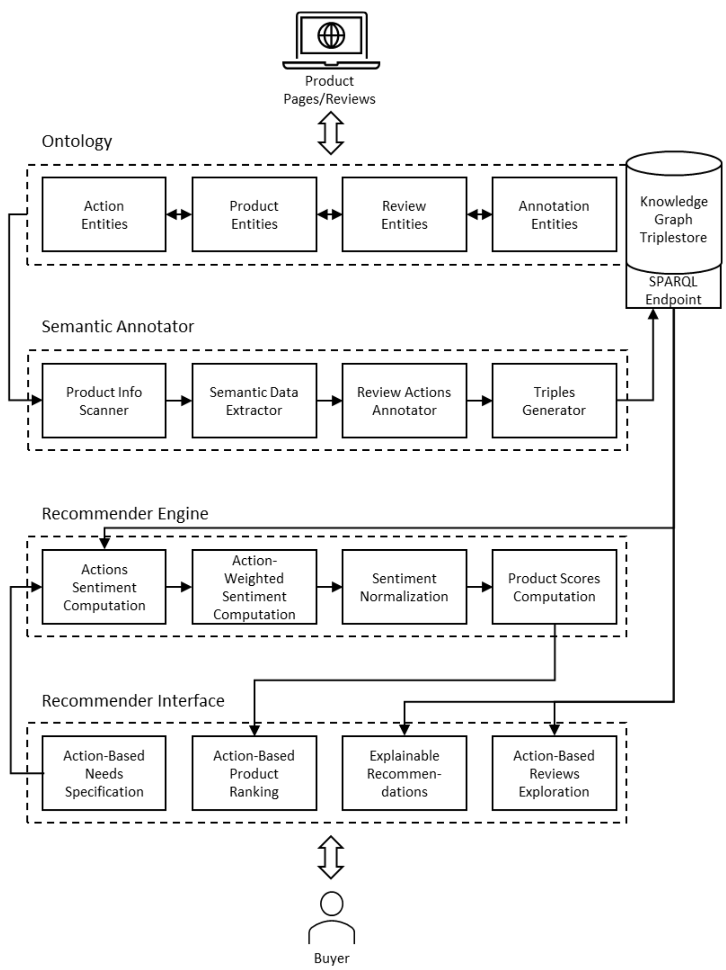

Figure 2 – Framework components overview

3.3 Ontology Design for Representing Contextual Action Knowledge

Drawing on the benefits of ontologies and knowledge graphs in supporting various recommender systems tasks (Sun et al., 2019), the framework includes an ontology proposed to model the semantic connections among the various knowledge graph entities of the products' enabled actions. The proposed ontology reuses and extends elements from other online ontologies to maximize interoperability and data exchange on the web. The major ontologies extended are schema.org[4] and the Web Annotation ontology.[5] The proposed ontology schema source files are available online.[6] The core ontology concepts include Action, Review, Product, and Annotation, with related entities described as follows. Figure 3 presents the ontology model diagram.

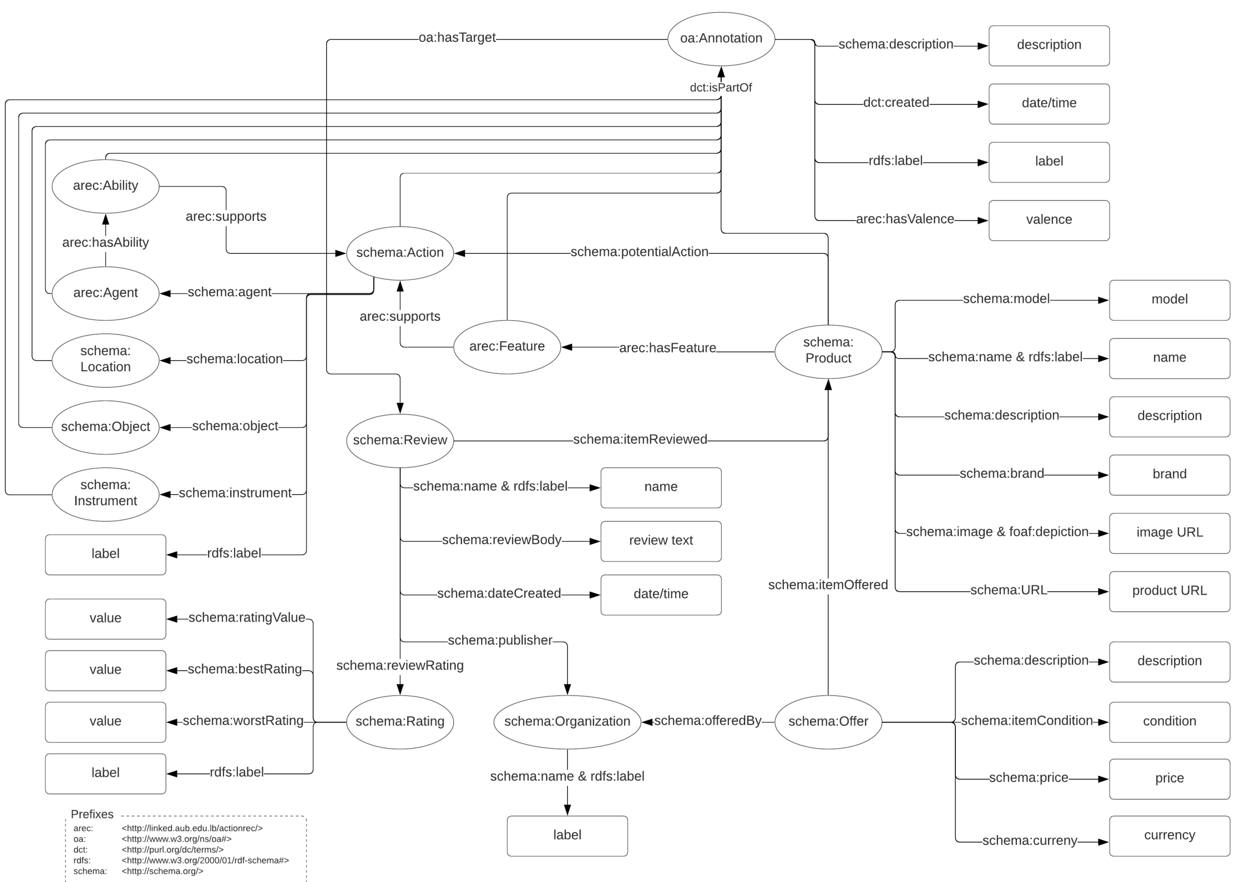

Figure 3 - Ontology schema to represent knowledge graph linkages around the action-related entities

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[4] The latest schema.org vocabulary is accessible at the following link: https://schema.org/
[5] The Web Annotation ontology is available at the following link: https://www.w3.org/ns/oa
[6] The ontology schema source file is accessible (in RDF Turtle format) at the following link: https://linked.aub.edu.lb/actionrec/ontology/ActionRec_Ontology_v01.ttl

3.3.1 Action Entities Representation

An *Action* entity is performed by an *Agent* who has a certain *Ability* to use a product *Feature*. Both the ability and feature *support* the execution of the action. While the schema.org vocabulary provides a *potentialAction* relation between a product and an action, the proposed ontology extends this connection by specifying an additional relation between a product's feature and an action. This design enables us to have a more granular understanding of which feature in a product becomes pertinent to a buyer's intended action. For example, if the buyer aims to *draw* on a tablet, then the writing device feature (e.g., digital pen) needed to perform this action is relevant, thus finding a compatible tablet for drawing. This notion also aligns with Chemero's (2003) view of action possibilities as relational between an agent's ability (e.g., drawing ability) and an environment feature (e.g., tablet's digital stylus). This can make product recommendations even more targeted based on the buyer's ability. For example, a buyer with no drawing ability would care less about having a tablet with a digital stylus recommended to them, compared, say, to designers and architects. The reasoning capabilities of the knowledge graph enable, for example, inferring common abilities of a *researcher* agent (e.g., writing ability) versus an *artist* (e.g., drawing). In addition, as defined in schema.org, an action (e.g., writing) has an *agent* (e.g., researcher), occurs in a *location* (e.g., train), results in an *object* (e.g., academic paper), and is performed using an explicit *instrument* (e.g., tablet). Based on this design, a product or feature can be considered an instrument to perform actions.

3.3.2 Review Entities Representation

A *Review* entity is another core concept of the designed ontology. It is represented following the schema.org vocabulary. It has an *itemReviewed* relation with products, an explicit *label* describing the review, a *review body* containing the review full text, a *dateCreated* property, and a *rating* that contains the *rating value*, *best rating*, *worst rating*, and *label* properties. A review has a *publisher* explicitly defined, which usually includes the *organization* running the online store that sold and published the product review.

3.3.3 Product Entities Representation

A *Product* entity has several properties reused from schema.org, including a product *model*, *name*, *description*, *brand*, *image*, and *URL*. Products also have links to explicit features that are relevant to support certain actions. Furthermore, the ontology captures the product *offers*, *offered by* certain organizations, and properties to capture the offer *description*, *condition*, *price*, and *currency*.

3.3.4 Annotation Entities Representation

An annotation serves as a description of a context of use identified in product reviews. It points to a certain part of the review where a certain action is articulated. Its purpose is to connect the different entities identified in a certain review, representing a buyer's expressed needs in the review. Such entities include an *Action*, *Product*, *Review*, *Feature*, *Agent*, *Ability*, *Location*, *Object*, and *Instrument*, which connect to an annotation through Dublin Core terms[7] *isPartOf* relation. An annotation entity has a *description*, *creation date* and *time*, *label*, and *valence* that reflects if the buyer's sentiment on the action described in the annotation is positive, negative, or neutral. Sentiments provide a potential source of data for ranking products. Following the Web Ontology Annotation, an Annotation uses the *hasTarget* relation to connect to a specific review.

3.4 Semantic Annotator for Creating Product Actions Data

A substantial number of websites publish their product information with semantically rich data (e.g., using schema.org) to increase the discoverability of their product by online services such as search engines (Mika, 2015). The *Product Info Scanner* component in the Semantic Annotator scans existing e-commerce product pages for potential semantic data markup, and passes the scanned data to the *Semantic Data Extractor* to extract the data for further processing. Such data cover different types that are pertinent to the recommender systems' tasks. Data types include (a) product information, such as model, name, description, brand, images, etc. (b) product offers that include information on the item condition, price, and currency, and (c) product reviews that include the review text, creation date, and ratings.

The *Review Actions Annotator* component enables annotating parts of reviews text with additional information needed for representing contextual action information eliciting the fulfilled buyers' needs. The designed ontology serves as a guide to the data type needed for the annotation process. Such data include, for example, the agents' type who performed the actions, their abilities, the valence, and the relevant product features. The annotated data is passed to the *URI and Triples Generator* component that transforms the data into knowledge graph data as per the designed ontology and stores it in a triplestore though a SPARQL (Prud'Hommeaux & Seaborne, 2008) endpoint as follows. Each data entity is referenced through a Unique Resource Identifier (URI) that serves as an anchor for linking the data points. For example, each action will have a URI that connects it to

[7] The Dublin Core Terms are available at: https://www.dublincore.org/specifications/dublin-core/dcmi-terms/

other entity URIs (e.g., review annotations, products, and reviews). The URIs stored in the triplestore form the nodes in the graph, connected through properties defined in the ontology. When the URIs are consistently created, the linkages in the graph enable a coherent traversal of the graph through a set of queries that can selectively extract elements needed by the recommender system. Knowledge graph linkages provide data traceability through established links at the data level. This traceability feature is key to explaining the reasoning behind recommendations. For example, tracing actions back to their source review comment and other related data can better explain the recommendation of certain products.

3.5 Recommender Engine

The *Recommender Engine* relies on a combination of product data and user needs as input to provide human-centered product recommendations. A novel feature of the framework provides buyers with the ability to express their needs in the form of actions through the recommender interface. We see the need to provide a function in the recommendation process to represent the buyers' needs through one or more actions with a relative degree of importance. Moreover, we need to consider that not all product actions captured from previous reviews are of equal importance, from a product perspective. For example, a device that was mentioned in several reviews that helped buyers with *drawing* will be more important for drawing than *streaming*, if streaming was mentioned by previous buyers relatively less than drawing. The framework aims to align the expressed prospect buyers' needs in the form of actions with the recommended products, considering the needs and actions' importance relative to both the buyer and the product. The recommender engine process is as follows.

The *Actions Sentiment Computation* step gets the product data needed as input from the knowledge graph SPARQL endpoint (sample SPARQL queries are available in Appendix A), and the buyers' needs in the form of actions and their importance weights. The product data includes product-related actions and valence information. The action sentiment score of a product is computed based on the ratio of the total positive valence annotations of the action performed on the product, to the total number of actions related to this product. Equation 1 provides the details of the computation of sentiments, where A is a certain action related to a product P in the knowledge graph, $POS(A,P)$ is the count of positive actions A related to the product P, NEG is the count of negative ones, and NTR is the count of neutral ones. The equation generates a sentiment value in the range of (0-1) for the action in the context of a certain product.

$$Sentiment(A, P) = \frac{POS(A, P)}{POS(A, P) + NEG(A, P) + NTR(A, P)}$$

Equation 1 - Calculation of the sentiment score of a product's action

The *Action-Weighted Sentiment Computation* step is tuned to give higher importance for actions that frequently occur for a product. This step enables the identification of cases in which product reviewers repeatedly mention the use of a product to perform specific actions. Equation 2 provides the details behind the computation, where *A* is a certain action related in the knowledge graph to product *P*, *Count(A)* computes the frequency of the action in the product, *TotalActions(P)* is the total number of actions performed using product *P*, and *Sentiment(A,P)* is the sentiment score of action *A* performed using product *P,* as computed in Equation 1.

$$WeightedSentiment(A, P) = \frac{Count(A)}{TotalActions(P)} * Sentiment(A, P)$$

Equation 2 - Calculation of the action-weighted sentiment score of products' actions

The *Sentiment Normalization* step normalizes the sentiment scores to enable an appropriate comparison among products. The normalization is applied as a two-step computation, starting with a Min-Max normalization applied to sentiment values between (0-1), followed by a normalization step applied to values between (1-5). The second normalization is applied to generate values that are aligned with the (1-5) review ratings scale commonly adopted on most review sites. Equation 3 shows the sentiment normalization computation of action *A* related to product *P*, *Min* and *Max* are the minimum and maximum weighted sentiments of actions in the context of product *P* respectively.

$$NormSentiment(A, P) = 4 * \frac{WeightedSentiment(A, P) - Min}{Max - Min} + 1$$

Equation 3 – Normalization of the sentiment scores of products' actions

Lastly the *Product Scores Computation* step computes the overall score of the product for the actions representing the prospect buyer's needs. Buyers may represent their needs through several actions with a varying degree of importance by assigning a certain weight to the corresponding action. Equation 4 provides the overall product score computation details, where *P* is a product, the set $\{(A_1,w_1), \ldots, (A_n,w_n)\}$ represents the needs expressed by the potential buyer in the form of actions A_i and their corresponding weights w_i and *NormSentiment* is the normalized sentiment computed in Equation 3.

$$ProductScore(P, \{(A_1, w_1), \ldots, (A_n, w_n)\}) = \sum_{i=1}^{n} \left(\frac{w_i}{\sum_{i=1}^{n} w_i} * NormSentiment(A_i, P) \right)$$

Equation 4 – Overall score computation of a product with respect to the weighted actions expressed by the potential buyer

To illustrate the application of the above recommender engine logic, let's consider the following scenario where a buyer is looking for a device that she will mainly use for *streaming* (with the highest weight of 1), and sometimes for *drawing* (with a weight of 0.5). Assuming we have two devices available online, Device X and Device Y. Device X has a total of 100 reviews, with a total of 150 actions mentioned having a weighted sentiment ranging between a minimum of 0.02 and a maximum 0.72 (noting that reviews may contain more than one action). In these reviews, 60 reviews have buyers reflecting on their streaming experience (35 positive, 20 negative, and 5 neutral), and 70 reviews mention drawing experiences (45 positive, and 25 negative). Device Y has a total of 130 reviews, with a total of 160 actions mentioned with a weight sentiment ranging between a minimum of 0.03 and a maximum of 0.84. The reviews have 80 mentions of streaming experiences (30 positive, 15 negative, and 35 neutral), and 50 reviews mentioning the drawing experience (35 positive and 15 negative). Table 2 shows the computations of the recommender engines' formula, resulting with Device A's better overall product score of 2.35, compared to Device B's overall score of 1.82, making it rank less than Device A with respect to the buyer's specified actions and weights.

3.6 Recommender Interface

The *Recommender Interface* component enables the interaction between a buyer and the recommender system. In addition to enabling buyers to specify their needs, this component performs an *Action-Based Product Ranking* function based on the scores computed by the recommender engine. The knowledge graph links can potentially provide traceable explanations on the products' related actions and their provenance from the processed reviews in the *Explainable Recommendations* function. The graph links can also be leveraged at the interface level to provide buyers with *Action-Based Product Exploration* features. Such features allow buyers to openly discover and explore additional products that may fulfill their needs.

	Recommender Engine Score Computation
Device X	$Sentiment(streaming, X) = \frac{35}{35+20+5} = 0.583$ $WeightedSentiment(streaming, X) = \frac{60}{150} * 0.583 = 0.233$ $NormSentiment(streaming, X) = 4 * \frac{0.233-0.02}{0.72-0.02} + 1 = 2.22$ $Sentiment(drawing, X) = \frac{45}{45+25} = 0.643$ $WeightedSentiment(drawing, X) = \frac{70}{150} * 0.643 = 0.3$ $NormSentiment(drawing, X) = 4 * \frac{0.3-0.02}{0.72-0.02} + 1 = 2.6$ $ProductScore(X, \{(streaming, 1), (drawing, 0.5)\}) = \frac{1}{1.5} * 2.22 + \frac{0.5}{1.5} * 2.6 = 2.35$
Device Y	$Sentiment(streaming, Y) = \frac{30}{30+15+35} = 0.375$ $WeightedSentiment(streaming, Y) = \frac{80}{160} * 0.375 = 0.188$ $NormSentiment(streaming, Y) = 4 * \frac{0.188-0.03}{0.84-0.03} + 1 = 1.78$ $Sentiment(drawing, Y) = \frac{35}{35+15} = 0.7$ $WeightedSentiment(drawing, Y) = \frac{50}{160} * 0.7 = 0.219$ $NormSentiment(drawing, Y) = 4 * \frac{0.219-0.03}{0.84-0.03} + 1 = 1.93$ $ProductScore(Y, \{(streaming, 1), (drawing, 0.5)\}) = \frac{1}{1.5} * 1.78 + \frac{0.5}{1.5} * 1.93 = 1.82$

Table 2 - Examples of the recommender engine scores computation applied on two devices

4. Validation: Computing Device Recommender Use-case

We validate the proposed framework through a use-case in the context of computing product recommendations on BestBuy.com, one of the leading online consumer electronics stores. The motivation behind the choice of this use-case is twofold. First, today's computing devices are used extensively in supporting people with performing a variety of actions (e.g., socializing, studying, entertaining, etc.), providing an interesting and information-rich scenario from a user-needs perspective. Second, BestBuy is one of many online stores that provide semantically marked-up product pages following the schema.org ontology, making it a good starting point to evaluate the framework. This scenario makes the approach easily transferrable to other online stores that increasingly enrich their products with semantic web data.

4.1 Artifact Development

Artifact development is a key component of design science research that can help with the evaluation of the approach, and draw additional insights and reflections from users (A. Hevner et al., 2004; Peffers et al., 2007). We discuss in this part the development of two prototypes—a semantic annotator and a web-based recommender system app—that implement the proposed framework components functionalities.

4.1.1 Semantic Annotator to Construct the Knowledge Graph Connecting Products, Reviews, and Related Action Entities

A semantic annotator prototype was developed to automatically extract semantic markup data from computing product pages, and enable human annotators to create connections between the products and the related actions identified from product reviews. BestBuy follows the schema.org vocabulary and embeds semantic metadata into their product pages. The semantic annotator is developed as a Google Chrome browser extension. When activated in the browser, the tool automatically scans the product pages to extract the relevant product and review information. Then the tool allows the data annotators to highlight on the review the identified actions and the related details, including, for example, description, valence, agent, and other details defined in the ontology. The generated data is pushed and stored in a knowledge graph triplestore. More details on the semantic annotator functionalities are available in Appendix B-1. Research assistants have been trained in using the Semantic Annotator and have annotated around 3,665 reviews of 11 computing products sold on BestBuy. 1,118 reviews contained at least one relevant action enabled by the reviewed product, reflecting that around one-third of the reviews contained potential action knowledge. This activity resulted in around 68,900 triples (i.e., in the form of subject-predicate-object format) that are added to the knowledge graph triplestore.

4.1.2 Web-based Action-Driven Product Recommendation Application

The scenario involves the development of a web-based action-driven product recommendation application with a set of features to demonstrate the designed framework's recommender engine and interface components. The features include functionalities to specify buyers' needs in the form of actions and matching products accordingly, list and rank the available products, provide explainable recommendations and action-based product exploration by levering the knowledge graph data linkages. Figure 4 shows a screenshot of the recommender app prototype that is available online.[8] We describe the application and the fulfilled tasks in more detail below.

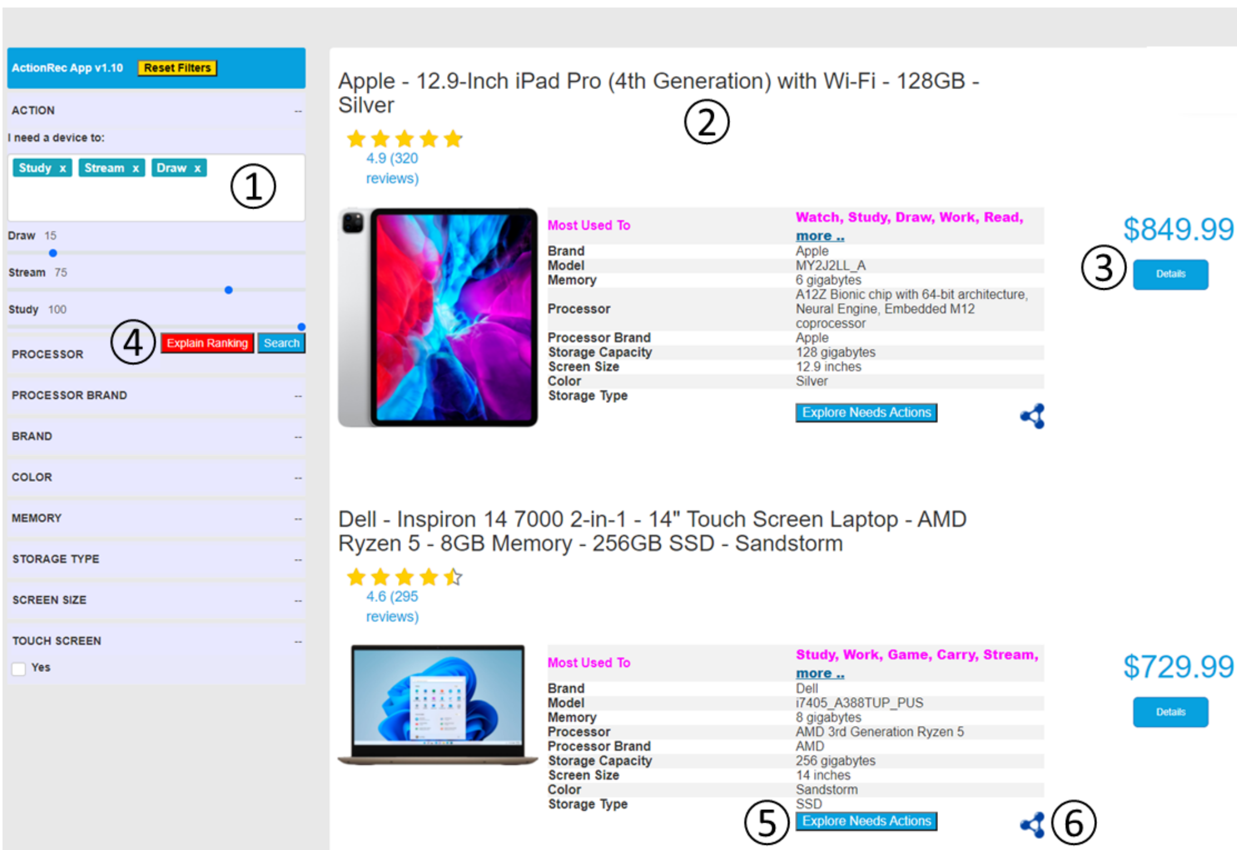

Figure 4 - Screenshot of the action-driven product recommendation prototype

[8] The web-based product recommender app is available at this link: https://linked.aub.edu.lb/apps/actionrec

Specifying Buyers' Needs in the Form of Actions

The developed web prototype enables prospect buyers to specify their needs in the form of actions that can be entered into a textbox. Their corresponding importance weight is specified using a slider. One or many actions can be entered on the interface, and changing the importance weight of each action will dynamically impact product rankings and therefore how they are displayed to the user. For example, the buyer may specify in the action-needs text box that they need a device to *study*, *stream*, and *draw* (part 1, Figure 4). While typing, the action-needs box provides automatic action completion available in the knowledge graph. This enables limiting the queries to the scope of data in the knowledge graph. In the same example, using the sliders below the actions box, the user specified this device will mostly be used for *studying* (reflected by the highest slider weight), followed by *streaming*, and then *drawing*.

Ranking and Matching Products Based on Buyers' Needs

In the proposed framework, listing product information on the recommender system can be applied through a set of SPARQL queries that extract data from the knowledge graph endpoint and render them on the application pages. The resulting data for such queries is used to render the information shown on the initial application page. For example, queries were designed to extract products information, rating, offer prices and other related entities from the knowledge graph (Queries 1-3, Appendix A). The listed products are displayed on the page (part 2, Figure 4).

Following the recommender engine process described in Section 3.4, the product ranking and matching, based on needs, initially involve extracting product data from the knowledge graph. The triplestore endpoint is queried to get the list of products, their related actions, valence, and count values (Query 4, Appendix A). The data is used to sequentially compute the product's actions sentiment, weighted sentiment, normalized sentiments, and the overall product scores (Equations 1-4). The result is a score given to each product for the actions entered by the buyer. Referring back to the needs example for a device for studying, streaming, and drawing, the top two recommended products are an iPad, followed by a Dell laptop (based on the available data of the eleven products that were annotated). Putting a higher weight on *drawing* would push other more expensive products (e.g., Microsoft's surface products) above the Dell laptop, due to their better position in fulfilling the *drawing* action. This level of flexibility in fine-tuning user-needs matching with products can bring to the users' attention products that were originally out of their feature-based search scope.

Explaining and Exploring Action-Based Product Recommendations

Unlike black-boxed algorithms, explicit knowledge graph connections provide data traceability features that can assist with providing explainable recommender systems. The recommender prototype implements the two functionalities of the proposed framework, providing explanatory and exploratory features around the action-based recommendations: first, a *product ranking explanation* to visualize the process of generating the products' scores according to the specified buyers' needs, second, an *action-based reviews exploration* that visualizes the actions enabled by the products and their source review text.

Product Ranking Explanation. The product ranking explanation is a feature that explicitly lays out to the buyers the algorithmic steps on how each product scored with respect to the actions they specified in the action-needs box. After entering the actions in the box on the recommender app and pressing the search button, the products are ranked based on how best they match the actions entered by the user. At the same time, an *Explain Ranking* button appears (part 4, Figure 4) for the buyers to understand how the score was computed for each product. Pressing the explain button opens a new window with visual boxes showing each step in the process. Details of the product ranking explanation features and computation details of the Apple iPad Pro versus the Dell are illustrated in Appendix B-2.

Action-Based Reviews Exploration. Another feature developed for this prototype is the action-based reviews explorer. This feature also builds on the explicit connections of the knowledge graph to provide further explanations and contextualize information that could help with purchase decisions. This was developed through two features: a needs-based reviews explorer, and a product actions dashboard.

The *need-based reviews explorer* provides buyers with the feature to explore reviews supporting their specified needs. It offers a visual view of the portion of positive, negative, and neutral reviews relevant to the buyers' needs. It is activated by pressing on the *Explore Needs Actions* button (part 5, Figure 4), which is only visible after performing an action-based product search. When activated, the needs-based reviews explorer shows a concentric view of positive, negative, and neutral reviews related to the actions query specified by the buyer. Appendix B-3 shows an example of the Dell Inspiron reviews related to the studying, drawing, and streaming actions denoted by the buyer. This feature may provide more context behind the product scores.

The *product actions dashboard* enables buyers to selectively explore all the actions and related reviews relevant to a certain product. It is activated by pressing the *Details* button next to a product (part 3, Figure 4), and a new window opens in the app (Appendix B-4 provides a dashboard example with additional details). Using the product as an anchor point, the action data extracted from the knowledge graph are limited to the selected product. This feature allows buyers to filter the actions based on sentiment (i.e., positive, negative, or neutral), to be able to investigate the frequency of actions supported by the product in the form of a bar chart. The bars are also interactive to enable drill-down functionalities to identify entities related to the selected action, including Agents, Environments, Features, and Reviews. This exploratory feature, aided by the preserved knowledge graph data connections, can potentially support buyers in discovering additional actions the products can support, beyond the scope of their specified needs.

5. Evaluation

5.1 Evaluation Setup and Data Collection

To our knowledge, currently no datasets exist that incorporate actions performed by buyers on products in the product recommendation process, to which this work can be quantitatively compared with respect to time, precision, recall or other measures. Hence, the evaluation focused on the recommender web application prototype that incorporated the main features enabled by the knowledge graph-based framework. The objective of the evaluation was to shed light on the usability of the proposed prototype features. The evaluation setup included a scenario for participants to rely on the proposed tools to find an appropriate computing product for their use. The evaluation sessions were designed to last for around 20-25 minutes, in which the participants were introduced to the tool features, then had the opportunity to use and experience the tools on their own. The participants were encouraged to think aloud while working on the tools to express their thoughts during the assessment sessions.

The assessment was split into two parts. First, a System Usability Scale (SUS) (Brooke, 1996; Lewis, 2018) questionnaire was used to provide a high-level overview of the usability of the proposed system. The SUS evaluation was chosen due to its high reliability with a small sample size (Lewis, 2018; Peres et al., 2013; Tullis & Stetson, 2006). The standard 10 SUS questions (Q1-Q10) were adopted, following the minor modification of question 8 in which the word “cumbersome” was replaced by “awkward” as proposed by Bangor (2008) and Finstad (2010). Table 3 in Appendix C presents the list of SUS questions used. Second, an open-ended interview-based discussion was conducted with the participants to elicit further qualitative feedback on the system’s key features. The questions focused on collecting participants’ feedback at two levels: (a) reflections on the potential of the studied recommender system app to find products that match the participants' needs; and (b) feedback on the explainability and exploratory features.

A total of 93 participants were invited to be part of the evaluation study. The target participants were mainly university employees and students (undergraduate and graduate) who have experience with online shopping. 32 participants voluntarily joined our usability study without any incentive offered. With the Institutional Review Board approval and participants' consent, computer screens and participants' voice were recorded to ensure a consistent capturing of the data across the sessions. A total of 10 hours and 52 minutes of recordings were captured.

5.2 Evaluation Data Processing and Analysis

The SUS questionnaire data were collected anonymously using an online form. The standard procedure for computing the SUS score was followed (Lewis, 2018). The first step is to adjust the score of the raw question items to a range from 0 (weakest score) to 4 (best score). This adjustment reflects subtracting the raw score of the even-numbered SUS questions from 5, while subtracting 1 from the raw score of the odd-numbered questions. Then the sum of the adjusted scores is computed, and multiplied by 2.5 to generate the SUS score for a participant *p* as per Equation 5. Then finally the overall SUS score of the recommender app is computed based on the average SUS of the 32 participants.

$$SUS_p = 2.5 * ((\mathrm{Q1}-1)+(\mathrm{Q3}-1)+(\mathrm{Q5}-1)+(\mathrm{Q7}-1)+(\mathrm{Q9}-1)+ \\ (5-\mathrm{Q2})+(5-\mathrm{Q4})+(5-\mathrm{Q6})+(5-\mathrm{Q8})+(5-\mathrm{Q10}))$$

Equation 5 – SUS score computation for each participant

The interview recordings were transcribed and glossed for further analysis. Text transcriptions were then split and classified based on the sentiment expressed by the participants (i.e., positive or negative) as a way to aggregate their opinions on the recommender system app in general, and the key features related to the action-driven product recommendations and explanations.

5.3 Results

Based on the participants' questionnaire feedback, the recommender app achieved a 75.16% overall SUS score. This score falls in the range between good and excellent systems (Bangor et al., 2008). This is a promising indicator reflecting potential usability of the developed application in this study. As we know, SUS scores cannot be treated as an absolute measure of usability, and having a high score does not guarantee high acceptability in the domain. Hence interviews help with further understanding the participants' opinions on the usability of the tools, and the potential improvements that can be introduced. Guided by the research objectives of the study, we observe below some of the key insights that emerged from the discussions with the participants.

5.3.1 Reflections on the Designed Recommender App in Meeting Buyers' Needs

On whether and how the studied product recommendation approach helped find products that match the buyers' needs, the majority of interviewees expressed positive feedback. One observation that emerged from the discussions with the participants is that it allows buyers to find products based on the objectives and purpose of the buyer's intention from purchasing the product. For example, a participant mentioned the following:

> Of course this website helps a lot! Because you can search for the purpose [*pointing to the actions search text box*] that you're buying the laptop or the tablet. And then you can use this option [*clicking to the Explore Needs Actions button*] to dig deeper and analyze the reviews related to the laptop you are interested in related to the purpose you are buying the laptop for. It's very creative, I like it, maybe only the UI [*user interface*] needs a bit of improvement. But other than this, it's nice, it's innovative.

Participants seemed to value the ability to identify products that fulfill certain purposes, coupled with the ability to explore and analyze the positive and negative reviews related to this specified purpose. This *purpose-driven* buying decision seems to have been enabled by the action search feature, which was perceived by participants as a potential alignment between buyers' needs and products recommended. Furthermore, the analysis of reviews that are within the scope of the specified needs was valuable to the users and was perceived as an innovative feature to further help in the recommendation process. One aspect that requires further attention is the interface design, which could benefit from further improvements as mentioned by several participants.

Another interesting pattern that emerged from the interviews is that participants seemed to have perceived the proposed recommender system as a way to better support non-expert buyers in their product choices. For example, one interviewee mentioned:

> I think this is a perfect way to help people look for devices that match their needs, especially people who are not…tech-savvy…who like understand specs in a detailed manner, processing speed, memory, resolution, etc. you name it. I feel there is a great potential to support like average day-to-day people who are just looking for a device to fulfill tasks, get the job done, work.

Another comment on supporting non-experts in their product selection:

> Definitely this website is more useful than other feature-based recommendations. It is rare to find a customer who knows what he wants in terms of the specifications of the device he is looking for. Because, usually, the way it happens, they go to an expert and say something like I want to *do* one, two, three. So, what do you recommend? This is somehow easily captured in this website, it makes me specify what I need and get recommendations based on that.

Those comments reflect the potential of the proposed application to act as a recommender system that better incorporates buyers' needs while focusing less on the product features that require experts' knowledge. Novice buyers are believed to have a lower ability to easily understand product attributes (Alba & Hutchinson, 1987; Tang et al., 2017). They usually seek help from friends and experts in finding an appropriate product based on their needs. This initial evaluation reveals the potential of the framework to support novice buyers in their product selection experience.

5.3.2 Reflections on the Recommendation Explainability and Exploratory Capabilities

We cover in this part an overview of the participants' feedback on the explainability features of the recommender system application.

Feedback on the Product Ranking Explanation

The product ranking explanation received mixed feedback from the participants. On the positive side, some participants saw value in better understanding the process behind the ranking of products. One interviewee mentioned the following:

> The ranking explanation is nice, as it gives you the logic behind the system. Because sometimes we always doubt that the ranking could be fake. Most of the time, when I see reviews and rankings, I see the scores in an aggregated form without further explanations. But this way, I can see exactly how the scoring was done.

The open aspect of understanding ranking has also seemed to provide more transparency and trust as articulated by this participant:

> I really like this feature. It makes it more transparent for the user to see that the ranking is legit, and not coming from a robot or fake reviews. This is very nice to make the person feels that, ah, this is real… this is from a trusted source.

The visualization of the numbers behind the product ranking generation offered a degree of confidence in the product recommendations. However, some participants revealed that this method of explaining the algorithmic logic of the system is not for everyone. For example, one participant mentioned the following:

> Honestly, I think this part of the website is not really interesting to the buyer who actually mainly would like to check a laptop to do X and Y, the price, and other details. I think this is a part that should not be shown to end users. Maybe it helps more developers and technical users who may be interested in knowing all these numbers and computations. I don't recommend displaying this to all users.

The aggregated feedback revealed that the average user may face difficulties in making sense of the diagram. The feature of explaining the details behind the algorithm using numbers and visual connections has clearly overwhelmed some participants. Further effort should be invested in better understanding how to make the product ranking explanation feature more user-friendly and acceptable to a wider audience.

Feedback on the Needs-based Reviews Explorer

The needs-centered reviews explorer feature was perceived valuable by several participants. Some participants compared it to the product ranking explanation feature as follows:

> I prefer to rely more on this visualization than the product ranking explanation. This one is more beneficial as it enables me to look at the pros and cons of each action. Like here [*pointing to a green positive review around the 'work' action*], I can see what worked for other users who bought this product. While the red parts provide me with negative reviews of things that didn't work for other buyers. This is very helpful as it kind of visualizes the reviews in a nice format around my specified needs.

It seems participants valued the ability to see the reviews contextualized in what they are aiming to use the product for. The knowledge graph connections enabled the construction of this innovative feature that brought the reviews around certain needs contexts. This feature was also perceived to help with faster decision-making, for example, one participant mentioned:

> This feature is very new, I never saw this on any other website. This is much more useful than buyers having to go through several reviews that could be irrelevant to them. This circular layout of reviews summarizes the positives and negatives of the laptop. It is easier. Now you can see this red part and you know this is something bad. More green means people were happy here. So it will help in making faster decisions on whether the laptop fits their purpose or not. I really like this, I never saw this before.

The visual layout in a summarized view, coupled with the color coding of sentiments contributed to supporting consumers in having an overview of the recommended product reviews around buyers' needs and a more informed purchase decision. Some participants offered some recommendations to improve this feature. For example, making this visualization fit on the screen can improve readability. Some have found the circular layout can be a bit confusing and proposed having a simple table option to improve legibility.

Feedback on the Product Actions Dashboard

The product actions dashboard was perceived useful by the participants at various levels. Some interviewees valued the way the data was integrated at this level around the product and its reviews. One participant commented:

> I love it, it is very nice because it goes into more detail compared to the previous parts of the website. It filters the customer type who performed a certain action that you can specify. So you can focus on a specific type of customers or organizations so you can get feedback from a source relevant to you, instead of getting feedback from a random person who is buying this laptop for regular use. You wouldn't get the same feedback from people who perform a different job than yours, for example from a graphic designer, while I am a university administrator with different needs. You would rather get feedback from someone who has the same work environment as you do, so you have a better understanding of their perspective of this type of device that you may be buying. That's what I think. So seeing this extra feature that I haven't

> seen on other websites before, actually makes it better for me to see more specific and relevant positive and negative feedback on this product and decide whether I should buy it or not.

This feature of the app provides additional information for prospective buyers derived from previous purchases by people who share a similar context of use. This also reflects the complexity and richness of information needed when performing purchase decisions. Such decisions are multi-dimensional, requiring buyers to combine information pertaining to the context of use, sentiments, and other relevant pieces of data. The fusion of various information types through the connections established in the knowledge graph enabled the creation of such features that support buyers in the analysis of products. This analysis is usually an extensive process that sometimes requires buyers to seek contextual help by asking friends and experts and going through substantial qualitative reviews beyond the quantitative scores. The information filtering features, combined with the visual charts were perceived to assist buyers in this process.

6. Discussion and Conclusion

While actions that people do or aim to do are considered one of the main drivers in purchase decisions and uncovering people's needs (Christensen et al., 2016; Norman, 2013), most recommender systems still lack taking them into account during the recommendation process. With the wealth of information left on product reviews where customers describe their purchase experience, actions that products helped them with performing can potentially be discovered from such reviews (Christensen et al., 2016). Following the design science research methodology (A. Hevner et al., 2004; Peffers et al., 2007), this article focused on investigating how to leverage buyer-product action knowledge expressed in product reviews to provide more human-centered product recommendations.

The proposed approach involves the design of a novel framework, which includes the following components. First, a semantic web ontology that aims to represent the actions expressed in product reviews with their related entities, such as products, environments, agent types, and others. Second, a semantic annotator that supports the extraction of semantic web data from product pages online, and the annotation of product reviews' action-related data that are stored in a knowledge graph triplestore. Third, a recommender system engine and interface components that build on the captured product action data with specific customer needs as input, processes the knowledge graph data to match customer needs with potential product actions, and renders the recommendations to the buyer on the application page with explanation and exploration features.

Following a scenario-based evaluation, the proposed framework was validated through a set of prototype artifacts in the context of a leading online consumer electronics store. First, the prototypes supported the potential of the proposed ontology design to connect the buyers' actions expressed in the reviews with contextual data relations. The ontology schema, which also builds on existing semantic web ontologies, aided in guiding the automatic extraction of product information from online product pages. The semantic annotator component in the implemented prototype enabled data creation that contextually links the actions identified in reviews to the relevant entities, such as environments, agents, and buyers' sentiments. The ontology contributed to transforming the needs implicitly buried in the reviews' text to an explicit data representation in a knowledge graph.

Second, the knowledge graph data enabled more sophisticated product recommendation tasks, such as matching products to prospective buyers' needs, one of the core objectives of this research. The prototypes included features implemented in a web-based product recommender application for shoppers to express their needs in the form of actions, with options to allocate different importance for each action. The recommender engine relied on ontology-based queries, to process product-related data and rank products according to buyer-specific needs. The needs-sensitive product ranking contributes to supporting the notion of bridging action-based needs with product recommendations.

Third, the knowledge graph linkages supported the prototypes to bring more visibility and explainability to the product recommendations. Unlike black-boxed algorithms, the preserved graph-based data connections that represent and hold buyers' needs elements, together with source reviews, provide traceability to the recommendations. Through the product ranking explanation feature in the prototype, buyers were able to see how each product's score was computed, based on the articulated action needs. Buyers were able to explore the connection between the product-enabled actions with source reviews around their needs, as well as around the product through a dynamic dashboard. The needs-based reviews explorer allows shoppers to explore the reviews related to their specified needs. This helps them better understand how the product is related to their needs giving additional context provided by the review text. The product actions dashboard supports the discovery of new potential actions that could go beyond the buyers' initial needs. This was achieved through ontology-driven connections between product-enabled actions, particular agent types, environment, product features, and related reviews. Such prototypes support the proposed research framework objective to provide more human-centered and explainable product recommendations.

A system usability evaluation was conducted with 32 participants. The results revealed a promising 75% system usability score, placing the recommender app prototype in a good to an excellent range of perceived usability. The usability test was complemented with a set of interviews to collect further qualitative feedback on the proposed recommender app features. One pattern that emerged from the participants' feedback is that the studied recommender app has the potential to meet buyers' needs with the recommended products. The qualitative feedback reflected that the participants valued how they could explore product reviews beyond the product features that are usually mainly understood by experts. This can also be related to previous studies that revealed how novice consumers, unlike experts, are usually negatively affected by reviews information overload (H. Hu & Krishen, 2019), and by the complexity of product features (Tang et al., 2017). The ability to exploit the data connections established in the knowledge graph offered a more transparent product recommendation process. Participants valued the ability to better navigate and analyze the abundant information of the substantial number of reviews in a contextualized manner relevant to the buyer's needs and jobs to be done, and assist in their purchase decisions.

It is worth mentioning some of this work's limitations. First, the manual annotation of product reviews can be a bottleneck when detecting additional needs and related data entities. Further work can be investigated on automating the annotation process and knowledge graph construction using, for example, a combination of Natural Language Processing and machine learning approaches. Second, our proposed approach's performance may be highly dependent on the number of reviews processed on the knowledge graph. This may introduce a bias in favor of the recommendation of products that have a higher number of reviews processed. This would require further studies on the impact of this bias and the means for addressing it. Third, the current data is limited to eleven products in the electronic domain. In this context, the products in focus have a variety of usage actions that can be performed on, while in other contexts, products may have less variety in the potential actions they can be used for. This limitation may hinder the performance of the approach and requires the investigation of additional action-related context elements to be integrated in the recommendation process. Furthermore, this work can benefit from the generation of additional data that includes additional products, which also belong to other domains. This can potentially open up new insights and domain-specific needs beyond the electronics domain.

As part of future work, this research can be extended to different dimensions. First, the needs-based product ranking tested in the current prototype relies mainly on actions specified. This needs specification mechanism can be extended to cater to more sophisticated needs representations. For example, the presence of SPARQL queries provides more flexibility in incorporating additional elements, such as environments, buyers' abilities, or other relevant information, to needs specifications. Second, further investigation can be conducted on connecting the needs captured in the knowledge graph to other knowledge graphs, such as Amazon's product knowledge graph, to study the degree to which product recommendations can be improved. Third, as highlighted by the qualitative feedback of our participants, this work can benefit from further research on improving the user interface and experience of the explainability features of the recommender system that cater to the needs of casual users. Fourth, it is worth investigating the combination of the proposed needs-based recommendations with other existing recommendation approaches (e.g., collaborative or content-based filtering), and assessing the impact of such hybrid approaches.

To conclude, we revisit this work's main contributions. First, it offers a novel framework for online shops to leverage product reviews and computationally process product-enabled actions to deliver human-centered product recommendations. Second, it provides an openly accessible knowledge graph that can be extended and used to provide action-driven data to support recommender systems features that can be used in other online platforms. Third, this research lays foundations for providing additional knowledge that can be used by conversational recommender systems to offer more sophisticated needs-based recommendations to its users.

Declarations

Ethics approval and participants consent

The usability study was evaluated and approved by the Institutional Review Board (IRB) at the American University of Beirut. The study was conducted with participants' consent to participate, collect data, and anonymously reuse interview extracts in the publication.

Availability of data and material

The data collected and used to develop the product recommendation tools are openly accessible on the web through the data repository referenced in the paper.

Competing interests

The author declares that he has no conflict of interest.

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Authors' contributions

The author confirms responsibility for the study conception and design, analysis and interpretation of results, and manuscript preparation.

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Appendix A – Knowledge Graph Queries

This appendix includes a sample of SPARQL queries used in the prototypes.[9]

Query 1 - SPARQL query to extract and rank product information based on their average review rating

```
PREFIX arec: <http://linked.aub.edu.lb/actionrec/>
PREFIX oa: <http://www.w3.org/ns/oa#>
PREFIX dcterms: <http://purl.org/dc/terms/>
PREFIX xsd: <http://www.w3.org/2001/XMLSchema#>
PREFIX rdf: <http://www.w3.org/1999/02/22-rdf-syntax-ns#type/>
PREFIX schema: <http://schema.org/>

SELECT ?product (AVG(xsd:integer(?rating)) as ?avg)
WHERE {
 ?product schema:potentialAction ?action .
 ?product dcterms:isPartOf ?annotation .
 ?annotation rdf:subClassOf oa:Annotation .
 ?annotation oa:hasTarget ?review .
 ?review schema:reviewRating ?review_rating .
 ?review_rating schema:ratingValue ?rating
}
GROUP BY ?product
ORDER BY DESC(?avg)
```

Query 2 - SPARQL query to select a product's related actions, agents, environments, features and reviews text

```
PREFIX oa: <http://www.w3.org/ns/oa#>
PREFIX dcterms: <http://purl.org/dc/terms/>
PREFIX xsd: <http://www.w3.org/2001/XMLSchema#>
PREFIX rdf: <http://www.w3.org/1999/02/22-rdf-syntax-ns#type/>
PREFIX schema: <http://schema.org/>
PREFIX arec: <http://linked.aub.edu.lb/actionrec/>

SELECT ?productName ?action ?agent ?environment ?feature ?reviewBody
WHERE {
 ?product schema:potentialAction ?action .
 ?product dcterms:isPartOf ?annotation .
 ?product schema:name ?productName .
 ?action dcterms:isPartOf ?annotation .
 ?agent dcterms:isPartOf ?annotation .
 ?environment dcterms:isPartOf ?annotation .
 ?feature dcterms:isPartOf ?annotation .
 ?action schema:agent ?agent .
 ?action schema:location ?environment .
 ?product arec:hasFeature ?feature .
 ?annotation oa:hasTarget ?review .
 ?review schema:reviewBody ?reviewBody .
 ?annotation rdf:subClassOf oa:Annotation .

 #filtering on a specific product
  FILTER(?product = <http://linked.aub.edu.lb/actionrec/Product/PUV_00001>)
}
```

[9] The SPARQL queries can be tested on the live SPARQL endpoint (https://linked.aub.edu.lb/actionrec/sparql).

Query 3 - SPARQL query to extract product price offers and conditions

```
PREFIX arec: <http://linked.aub.edu.lb/actionrec/>
PREFIX schema: <http://schema.org/>

SELECT ?product ?condition ?price
WHERE {
 ?offer schema:itemOffered ?product .
 ?offer schema:itemCondition ?condition .
 ?offer schema:price ?price
}
```

Query 4 - SPARQL query to select the products, their related actions, and valence from the knowledge graph

```
PREFIX oa: <http://www.w3.org/ns/oa#>
PREFIX dcterms: <http://purl.org/dc/terms/>
PREFIX xsd: <http://www.w3.org/2001/XMLSchema#>
PREFIX rdf: <http://www.w3.org/1999/02/22-rdf-syntax-ns#type/>
PREFIX schema: <http://schema.org/>
PREFIX arec: <http://linked.aub.edu.lb/actionrec/>

SELECT ?productName ?action ?valence (COUNT(?action) as ?count)
WHERE {
 ?product schema:potentialAction ?action .
 ?product dcterms:isPartOf ?annotation .
 ?product schema:name ?productName .
 ?action dcterms:isPartOf ?annotation .
 ?annotation rdf:subClassOf oa:Annotation .
 ?annotation arec:hasValence ?valence
}
GROUP BY ?productName ?action ?valence
ORDER BY ?action
```

Appendix B – Expanded View of Prototype Features

B-1 Semantic Annotator Feature

The semantic annotator prototype enables the creation of knowledge graph entities detected in product reviews. It is implemented as a Google Chrome Browser extension. Pressing the extension button activates the tool (part 1, Figure 5), which automatically scans and extracts the following data: product-related information, offers, and reviews as per the ontology's schema. It then displays the review text body in a popup window (part 2, Figure 5). The annotator person can highlight part of the review text where an action is detected, then add action-related details, including, for example, description, valence, agent, and other details defined in the ontology (part 3, Figure 5). The annotator is then asked to review the data triples (part 4, Figure 5), and finally presses the save button to push the data to the knowledge graph endpoint.

An openly accessible endpoint is deployed to store and serve knowledge graph data. The endpoint relies on the Apache Jena Fuseki Server[10] on the backend to store the data, with a YASGUI[11] package on the frontend to provide a user-friendly SPARQL interface. The endpoint with sample queries is accessible online[12]. Users can also browse the knowledge graph data using a custom-made semantic web data browser, with the possibility of downloading the data in different formats, such as JavaScript Object Notation (JSON), Comma Separated Values (CSV), or Resource Description Framework (RDF).[13] Part 5 in Figure 5 shows an example of the data resulting from this example.

---

[10] The Fuseki Server documentation and package is available at: http://jena.apache.org/documentation/fuseki2/
[11] The YASGUI package is available at the following link: https://yasgui.triply.cc/
[12] The link to the knowledge graph endpoint is: https://linked.aub.edu.lb/actionrec/sparql
[13] For example, the annotation data generated in Figure 5 can be accessed on the following page: https://linked.aub.edu.lb/actionrec/Annotation/03a762510ea9558b6506068056e1fab2
Another example is this product's data page: https://linked.aub.edu.lb/actionrec/Product/PUV_00001

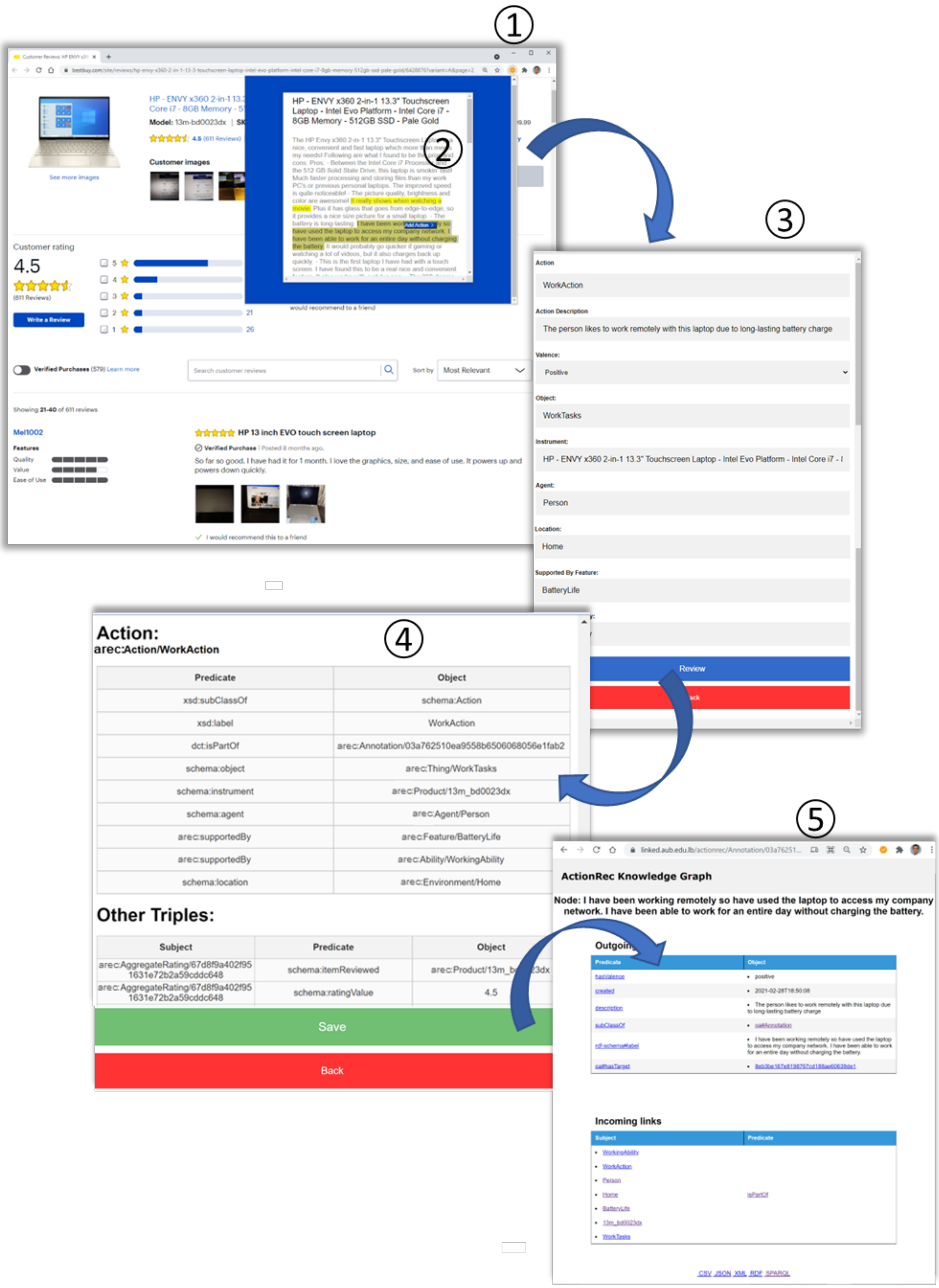

Figure 5 - Semantic annotator prototype screens applied on a laptop review page on BestBuy

B-2 Product Ranking Explanation Feature

The product ranking explanation functionality exposes the computational steps of the recommender engine (described in Section 3.4) applied to the knowledge graph data to generate each product's score concerning the buyer's specified action-based needs. Figure 6 shows how the first ranked product (Apple iPad Pro) scored 3.4/5, compared to the second product (Dell Inspiron) that scored 3.3/5 with respect to the need for *drawing*, *streaming*, and *studying*, with their importance weight specified in Figure 4. At this level, the user is in a better position to understand the reasoning behind the scores and make any necessary adjustments to the specified actions. This visualization is interactive, allowing the user to collapse and expand the nodes as needed.

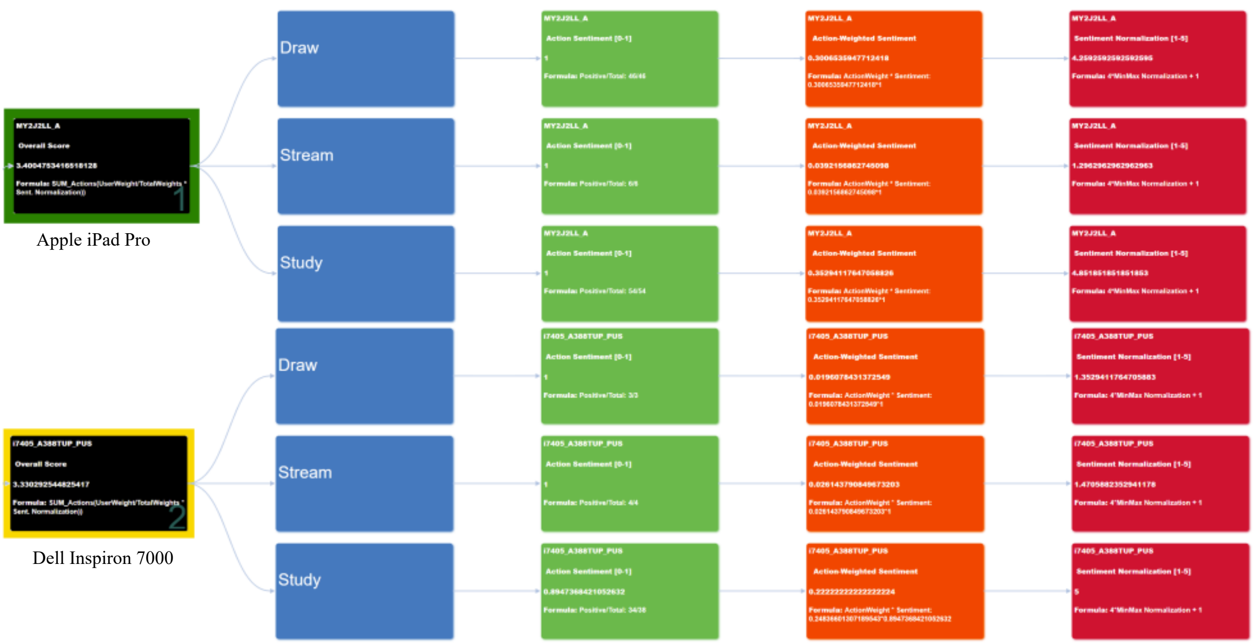

Figure 6 - Screenshot of the products ranking explanation based on the need for drawing, streaming, and studying

B-3 Explore Needs Actions Feature

The Explore Needs Actions feature activates the visualization shown in Figure 7. The Dell product (part 1, Figure 7) seems to support the *study*, *draw*, and *stream* actions (part 2, Figure 7). The size of the circular portion on the visual reflects the number of review annotations in which every action is covered. At this level, it becomes clearer to the buyer the higher frequency of study-related reviews compared to drawing and streaming. This results in a higher weight of studying for the Dell product, compared to the other two actions. The user can then see the related reviews' annotations where the actions were mentioned (part 3, Figure 7). The annotations are colored in green for the positive statements, red for negative, and yellow for the neutral ones. The users can hover over the annotation to see the full annotation text (part 4, Figure 7) to get a visual of the review: "issues started with video and sound after 2nd day of class." Such visual may help buyers to better understand the reason behind the relatively lower score of the Dell Inspiron product, with respect to their needs.

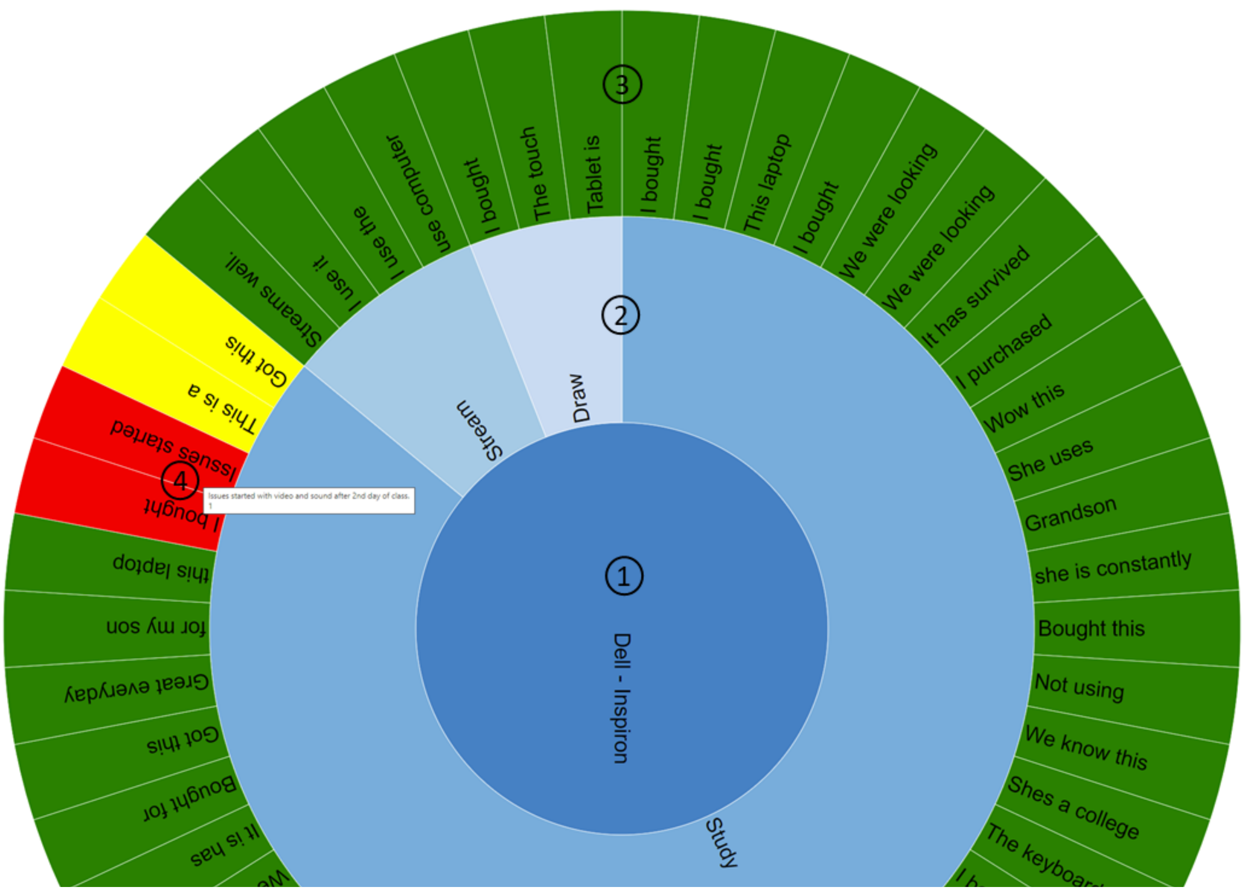

Figure 7 - Needs-centered reviews explorer view

B-4 Product Actions Dashboard Feature

Through the Product Actions Dashboard, the user can filter the actions based on sentiment (i.e., positive, negative, or neutral) by pressing the filter buttons (part 1, Figure 8). The actions supported by the product are listed as a bar chart (part 2, Figure 8) showing their frequency count. The bars are selectable and allow the user to click on them to further drill down the related entities. For example, Figure 8 shows that the action *work* is selected (light green highlight around the bar), and the interface automatically populates with the related Agents, Environments, Features, and Reviews. The user can filter the entities through the drop-down menu (part 3, Figure 8). The filters dynamically update based on user selection. For example, if the user selects the *Soldier* agent, only the environments and features related to soldier will be selectable. Those filters allow the user to browse the related reviews with their highlighted annotations in yellow at the bottom of the screen (part 4, Figure 8) to get further context on the action.

Figure 8 – Product actions dashboard

Appendix C – System Usability Scale Standard Version

		Strongly disagree	Disagree	Neutral	Agree	Strongly agree
Q1	I think that I would like to use this system frequently	○	○	○	○	○
Q2	I found the system unnecessarily complex	○	○	○	○	○
Q3	I thought the system was easy to use	○	○	○	○	○
Q4	I think that I would need the support of a technical person to be able to use this system	○	○	○	○	○
Q5	I found that the various functions in this system were well integrated	○	○	○	○	○
Q6	I thought that there was too much inconsistency in this system	○	○	○	○	○
Q7	I would imagine that most people would learn to use this system very quickly	○	○	○	○	○
Q8	I found the system very awkward to use	○	○	○	○	○
Q9	I felt very confident using the system	○	○	○	○	○
Q10	I needed to learn a lot of things before I could get going with this system	○	○	○	○	○

Table 3 - List of SUS questions used in the evaluation study