RECOMMENDER SYSTEM'S ECONOMIC IMPACT ON E-BUSINESS. A THEORETICAL REVIEW

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Abstract: *The rapid advancement of technology and the Internet led to an unprecedented abundance of information and data. Where too much information exists, the risk raises for that information to become irrelevant or too hard to handle; a phenomenon called information overload. Filtering vasts amounts of data and highlighting relevant information became a priority, especially for ecommerce business. Recommender Systems (RS) as a branch of Decision Support Systems were developed and implemented to help users handle information overload and access items based on relevancy. The financial returns RS have brought stimulated the spread of such referral systems to other business domains. As knowledge is a critical resource in nowadays economy, efficient knowledge production and management are a prerequisite for competitive advantage. E-businesses are concerned with online traffic on their platforms and with customer experience and impressions. The multitude of e-businesses facilitated by the Internet has created a highly competitive market in terms of gaining customers loyalty. New available frontier technologies might help online retailers enhance their customer pool and build a solid relationship with their existing ones. One major issue RS tackle is the information overload, meaning that vasts amounts of data might confuse the customer in making a purchase choice, paradoxically due to too many options. Information overload might lead to fatigue, purchase postpone and overall loss for the online retailers. RS have the power to gather data and transform it to valuable personalized knowledge; a feature that can add more revenue, build customer trust, build a personalized customer relationship and even influence the distribution value chain. In this paper we propose a theoretical overview on the RS and how they create value, their fields of implementation and how they are working. By doing so, we enhance both the RS and the e-commerce literature by analyzing tools and means of economic development provided by the DT.*

Keywords: *recommender-systems; decision support systems; e-commerce; content-based filtering; information-overload.*

JEL Classification: *L81; L86*

Introduction

Internet-based software applications have led to an unprecedented level of unlimited and effortless of network connectivity. Digital transformation (DT) technologies and the usage of Internet-facilitated online software challenge and shape traditional economic models, creating both opportunities and systemic threats Yanqing Duan, Edwards, and Dwivedi (2019); and Guven (2020). Businesses are being impacted in terms of innovation, knowledge, new potential revenues and the overall business model (Machado, Silvana, and Davide 2021).

The permeability of Internet-powered services let to the phenomenon of Internet of things and its adoption in production value chain let to the term Industry 4.0 (Guven 2020). Companies that will adopt Industry 4.0 feature would maximize their changes as a competitive advantage in highly globalized world. Machado, Silvana, and Davide (2021) identified four thematic areas on successful Industry 4.0 integration within the organization: a) digital enrichment of resources to leverage human performance; b) collaboration and networking; c) leadership and learning; and d) new forms of digitally enabled knowledge-intensive value creation. According to (Machado, Silvana, and Davide 2021) digital transformation could be structured in the following categories: the technological aspect of DT (devices, social media, analytics); the organizational perspective of DT (changes in the internal processes and structure of the company with focus on DT) and the social aspect of DT (improvement of customer experience, user interface). In the end, DT and Industry 4.0 goal is to raise productivity, efficiency and flexibility in terms of production and operation effort using emergent digital technologies.

In this technologically influenced era, knowledge is of primary importance for companies (Akhavan, Philsoophian, and Karimi 2019) and the capacity to extract and filter knowledge from information might determine the market’s winners. Knowledge management research have begun in the 1960’s and still continues. Early researchers were preoccupied on capturing or codifying knowledge and preserve it explicitly (Machado, Silvana, and Davide 2021). Today, knowledge is considered a critical resource in economic terms hence organizations that want to grow and benefit from digital changes, must find efficient ways to organize and create knowledge (Machado, Silvana, and Davide 2021).

In a digital ecosystem, digital tools enhance knowledge management process, creating a spiritual of business performance. The overall learning process and knowledge preservation techniques and mechanisms can benefit from DT adoption within organizations as software enhance codifying, storing, filtering and sharing of data as knowledge (Machado, Silvana, and Davide 2021).

The presence of vasts amounts of data led to the creation of filtering tools to better navigate through it. The rapid raise of IT and the use of online services have generated an unprecedented information availability regardless of the domain (Roetzel 2019). As a consequence, powerful technologies such as AI, cloud computing are used to create decision support systems. With knowledge being a critical resource and digital technologies available to manipulate it, AI powered decision support systems efficiently organize, identify patterns and make correlations in large data creating knowledge (Machado, Silvana, and Davide 2021).

What are Expert systems

Expert systems (ES) are informatic knowledge-based systems (KBS) (Yi Zhang et al. 2017; Liao 2005; do Rosário et al. 2015) designed as substitutes for human expertise in a given domain (Saibene, Assale, and Giltri 2021; Tavana and Hajipour 2019; Liao 2005; M. Radwan, Senousy, and M. Riad 2016; Alshare et al. 2019). Their role as decision support tools is to provide structured assessments, conclusions, or predictions by mimicking the human-expert advisory/decision-making process up to a certain possible degree (Kaklauskas 2015; Golini and Kalchschmidt 2015; Ravasan and Rouhani 2014; Atanasova 2019; Fait et al. 2019; Chatterjee et al. 2021; Al-Ebbini, Oztekin, and Chen 2016; Saibene, Assale, and Giltri 2021; Zerbino et al. 2018; Y. Duan, Edwards, and Xu 2005; Cortés Sáenz et al. 2015).

ES, as a branch of Artificial Intelligence (AI) field (Atanasova 2019; Bradac and Walek 2017; do Rosário et al. 2015; Nazari et al. 2018; Ikram and Qamar 2015) and together with similar terms (such as intelligent systems, informatic systems, recommender systems, warning systems or advisory systems) belong to the decision support systems (DSSs) umbrella term (Kaklauskas 2015; Belciug and Gorunescu 2020; Leo Kumar 2019). DSSs are computational tools that employ multiple disciplines and query vasts amounts of data, emulating the human decision-making process (Belciug and Gorunescu 2020; Arnott and Pervan 2008).

What are Recommender systems

Recommender System (RS) are knowledge-based systems that have derived from ES as separate branch or variant in mid-1990s. They are information processing systems that continuously gather specific data in order to build customized relevant suggestions for users (Ricci, Rokach, and Shapira 2011; Yalcin and Bilge 2021; Fernandes et al. 2020; Ahmadian et al. 2022; Tlili and Krichen 2021). By engaging specific algorithms, RS are able to query dynamically generated data (e.g., likes, dislikes, views, number of replays or other criteria) building a profile based on which valuable personalized items are highlighted and provided to individual users (Biswas and Liu 2022; Tlili and Krichen 2021).

Traditionally, RS have mostly present in e-commerce business, but recently successful applications have been developed in e-business, e-learning, e-tourism, etc. (Yi Zhang et al. 2017; Natarajan et al. 2020; R, Kumar, and Bhasker 2020). Increased interest from both the research community and the practitioners came as RS are being implemented in big tech companies like Amazon, Netflix, LinkedIn, eBay, Pandora, Meta, Google, Twitter, Quora etc. (Ricci, Rokach, and Shapira 2011). Such companies use RS to benefit from their pattern exploitation power and increase revenues as users are presented with new items to explore/purchase (Biswas and Liu 2022).

As the amount of Internet-available data is growing, users are facing more and more with information overload (IO) (Ricci, Rokach, and Shapira 2011; Ahmadian et al. 2022; K. Kim and Ahn 2017; Wu et al. 2022; Yang and Gao 2017; Silva et al. 2019). IO is a counterproductive state where users are exposed to too much data, rendering much of it as non-processable and inapplicable (S. Zhang et al. 2016; Terán, Mensah, and Estorelli 2018; Zhou et al. 2020; F. Zhang et al. 2020). (Roetzel 2019) shows that IO also has negative financial impacts and can induce users into a state of fatigue (S. Zhang et al. 2016). In this context, last decades have witnessed an increase in referral systems relevancy and usage (Ahmadian et al. 2022; Bogaert et al. 2019; Roetzel 2019; Terán, Mensah, and Estorelli 2018) as they help to cope with IO by screening, refining and personalizing data, providing rich user experience (K. Kim and Ahn 2017; Ricci, Rokach, and Shapira 2011; Alabdulrahman and Viktor 2021).

RS generate value for customers/users and companies that have implemented them, mostly in terms of time-savings and alternatives for the former and customer-knowledge for the latter (Wu et al. 2022; Scholz et al. 2017; Leo Kumar 2019). For companies, among the immediate effects RS have, is the revenue growth as more products are being recommended and (possibly) sold (Kumar and Thakur 2018; K. Kim and Ahn 2017). RS enable the trails users left from browsing the Internet to enhance or develop adjacent businesses (K. Kim and Ahn 2017) by creating personalized profiles. The knowledge captured and stored from the users' profiles help businesses to adapt to their customer's changing preferences, being up-to-date with the market demands and trends (Wu et al. 2022; Kumar and Thakur 2018).

For users, one of the most important attributes of RS is that it handles IO, helping detect relevant items, exempting the user from stressful factors such as the time-consuming searching or decision process (Kunaver and Požrl 2017; Kumar and Thakur 2018).

Methodology

Literature review

This section provides a brief background on how and where RS have been developed and implemented. Since RS have spread into multiple domains and have gained popularity in many areas, researchers have tried to address the challenges that have occurred over time and constantly update recommendation algorithms; an endeavour has led to a variety of RS approaches in multiple domains. The following literature review is intended to offer an informative context of RS applications.

Among the first most visible and profitable usage of RS had been in e-commerce and in the online services provided by the big tech companies (Biswas and Liu 2022; Cordero et al. 2020; Protasiewicz et al. 2016; Zhou et al. 2020). According to (Silva et al. 2019) in terms of ecommerce roughly 35% of Amazon’s sales are due to RS. For giant streaming platforms like Netflix, ⅔ of the watched movies are through recommendations and 38% of Google News are clicked thanks to existing referral system. (Zhou et al. 2020) offers the example of YouTube, saying that up to 60% of the videos are being watched through recommendations. For Netflix, they offer different statistics, attributing 80% of movie choices to RS.

Their efficiency in keeping the customers engaged, the potential returns generated, and the scalability capabilities, have motivated researchers and practitioners to study, develop and implement RS across various business domains, such as: tourism (Tlili and Krichen 2021; Binucci et al. 2017; Esmaeili et al. 2020); streaming platforms (Jakomin, Bosnić, and Curk 2020); music (Fernández-García et al. 2022; Ben Sassi, Ben Yahia, and Liiv 2021); movies (Walek and Fojtik 2020); recipes (Lei et al. 2021); hotels (Nilashi et al. 2021); hairstyle (Pasupa, Sunhem, and Loo 2019); news (Symeonidis, Kirjackaja, and Zanker 2021; Ulian et al. 2021); academia and research (Pradhan et al. 2021; Protasiewicz et al. 2016); peer to peer lending (Liu et al. 2021); recruitment services (Cardoso, Mourão, and Rocha 2021); medicine (Ferran Torrent-Fontbona, Massana, and López 2019); or additive manufacturing (Ying Zhang and Fiona Zhao 2022).

The literature acknowledges that regarding the domain, there is an unprecedented availability of information (Natarajan et al. 2020). The rapid advancement of the Internet and its adjacent technologies have generated the problem of too many options, or IO. Among RS main objectives is to help end-users handle IO and quickly filter through data for relevant personalized items (Lei et al. 2021; F. Zhang et al. 2020; K. Zhang et al. 2021; Kunaver and Požrl 2017; K. Kim and Ahn 2017; Yang and Gao 2017; Scholz et al. 2017; Biswas and Liu 2022; Guo, Deng, and Wang 2019; Ait Hammou, Ait Lahcen, and Mouline 2019; F. Zhang, Liu, and Zeng 2017; Zangerle and Bauer 2022; Heinrich et al. 2022; Khalid, Lundqvist, and Yates 2022).

In dealing with IO, RS researchers and developers engaged certain methodologies with different algorithms. In this respect, RS differ in terms of the used methodology. Since novel RS methodologies and algorithms are being constantly combined (Ali et al. 2020), there is not a rigid list of possible methodologies for developing an RS. But although RS permit flexibility due to the need to adapt to a specific implementation-dependent niche (Tlili and Krichen 2021; Liu et al. 2021), certain traditional approaches are being highlighted (Ricci, Rokach, and Shapira 2011; Khusro, Ali, and Ullah 2016).

Two paradigms to create RS emerged as traditional or classic and a third one that derives and combines the first two: Collaborative Filtering (CF), Content-Based Filtering (CBF) and Hybrid approaches (Fernández-García et al. 2022; Khalid, Lundqvist, and Yates 2022; Natarajan et al. 2020). Most RS are built using the Collaborative Filtering (CF) approach that recommends items to a user/customer depending on the valuation or feedback provided by other users (e.g., in its most simple implementation, valuation, or feedback could mean likes or dislikes) (Kumar and Thakur 2018; Ricci, Rokach, and Shapira 2011; Scholz et al. 2017; Khalid, Lundqvist, and Yates 2022; Guo, Deng, and Wang 2019). CBF takes into consideration the user's past behavior and makes referrals based on user's historical pattern of preferences (Khalid, Lundqvist, and Yates 2022; Ricci, Rokach, and Shapira 2011; Bagher, Hassanpour, and Mashayekhi 2017).

There is a third category acknowledged by the literature called hybrid approach that mixes CF and CBF in order to secure stronger performance and relevancy of the recommended items (Ricci, Rokach, and Shapira 2011; Bagher, Hassanpour, and Mashayekhi 2017; Esmaeili et al. 2020; F. Zhang et al. 2020; Kumar and Thakur 2018).

The aforementioned hybrid approaches have tried to overcome CF and CBF weaknesses by combining the algorithms. Several new approaches have been developed in order to surpass the challenges traditional methodologies weren't able to handle completely. The literature is homogenous concerning what those limitations are, namely data sparsity and the cold-start problem (Esmaeili et al. 2020; Fernández-García et al. 2022; Tlili and Krichen 2021; Ali et al. 2020; Cordero et al. 2020; Ait Hammou, Ait Lahcen, and Mouline 2019; Zhou et al. 2020; Bogaert et al. 2019; Liu et al. 2021; Ricci, Rokach, and Shapira 2011; R, Kumar, and Bhasker 2020; Hong et al. 2019). In sum, data sparsity appears when there is no sufficient complete information in a dataset/database, hence making it difficult for the RS (especially CF) to make relevant referrals. The cold-start problem occurs for new users, where no sufficient data exists to either include the user in a similarity group or make predictions about their past preferences (Natarajan et al. 2020). An in-depth analysis of the Pure Cold-Start problem, its challenges and improvement scenarios is found in (Silva et al. 2019). Often times, those challenges are treated separately but (F. Zhang et al. 2020) regards the cold-start problem as the extreme stage of data sparsity. Besides these main issues, Ait Hammou, Ait Lahcen, and Mouline (2019) addressed expense computational time; and Kunaver and Požrl (2017) provided more details of other challenges such as the big data problem and over fitting or scalability to high dimensional data (Koohi and Kiani 2017). Also, a non-technical challenge for RS might be the users' trust in collecting cookies information for creating personalized profile; an issue described by Ardissono and Mauro 2020; Mazeh and Shmueli (2020).

Conclusions and further work

In trying to overcome the aforementioned challenges of RS, newer methodologies and RS design approach have been implemented in various domains with the goal of enhancing the recommendations relevancy and accuracy.

To reduce data sparsity and improve computational time Ait Hammou, Ait Lahcen, and Mouline (2019) have proposed FRAIPA v2, an RS that uses auto-tresholding, preference grouping and error estimations to pre-estimate the users' preferences based on past representation of the users and items. (Kumar and Thakur 2018) have taken into consideration the importance of context and preferred patterns in user activity to determine a meaning in the order of recommended items (Kumar and Thakur 2018).

Ali et al. (2020) have adopted deep neural networks in producing citation recommendations for research manuscripts on digital libraries. (Biswas and Liu 2022) developed a smartphone RS. Deep learning technique integration had been considered by various authors (Biswas and Liu 2022; Chambua, Niu, and Zhu 2019; R, Kumar, and Bhasker 2020).

Other studies have tried to compensate the cold-start problem with existing data the users leave on the internet, mainly in social media. (Ardissono and Mauro 2020) introduces a Multi-faceted Trust Model that integrates social links with public anonymous feedback received by user profiles and user contributions in social networks. He, Ai, and Wu (2021) have used a Social Bayesian Personalized Ranking algorithm, which utilizes social connections to improve the prediction of the ranking of items and users.

Bagher, Hassanpour, and Mashayekhi (2017) proposed an evolutionary user model that incrementally adapts with changes of user interest. This capacity of RS to adapt over time with users' changing behaviors and tastes is called time-aware, and it has been addressed by other authors as well (Ahmadian et al. 2022; Jakomin, Bosnić, and Curk 2020; F. Zhang, Liu, and Zeng 2017).

The location-dependent and travel RS employ specific algorithms for yielding recommendations based on points of interests (POI); users' current position (near or far from POI); fetching most-visited places from TripAdvisor (Binucci et al. 2017; Cai, Lee, and Lee 2018; Esmaeili et al. 2020; K. Zhang et al. 2021).

(Hong et al. 2019) proposed a crowdsourcing based RS that incorporates the knowledge and insights of crowd workers and neighboring items from human expertise into the recommendation of new items.

Some have included the functionalities and benefits of ES in RS design (Shojaei and Saneifar 2021) in group recommender systems (Castro, Yera, and Martínez 2018; Pujahari and Sisodia 2020; Seo et al. 2021; Yalcin and Bilge 2021); conversational RS (Cordero et al. 2020); intuitionistic fuzzy approach (Guo, Deng, and Wang 2019).

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