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RECOMMENDER SYSTEMS FOR PERSONALIZED OFFERS

Abstract: The development of information and communication technologies has forced companies to keep pace with technological innovations. This is referred to as digitalization, which leads to significant changes in companies' processes. It reshapes business environments, reconfigures business models and strategies, and enhances overall business performance and competitiveness. Compared to small and medium-sized enterprises, large companies tend to adopt digitization and digital transformation more quickly. However, their long-term survival in the market requires that small and medium-sized enterprises engage in digitization and digital transformation processes, as well. Digitalization is strongly linked to user experience, while personalization is the key to improved experience and satisfaction. It also influences sales and improves competitive position, while targeted advertising contributes to the optimization of the company's budget through more effective marketing campaigns that maximize return on investment. Concerning said, one of the challenges that small and medium-sized companies face is related to the application of information and communication technologies in the personalization of the product/service offer and targeted advertisement. As a limiting factor, the authors recognize insufficient knowledge and understanding of the possibilities and limitations of digital technologies, particularly artificial intelligence (AI), for improving the personalization of the offer and targeting customers by their preferences, habits, and aspirations. AI-driven product recommendation systems are key to improving customer experience and sales growth. To generate personalized recommendations that will align with individual preferences or behavior, recommendation systems utilize advanced machine learning algorithms and natural language processing techniques and process large amounts of customer and product-related data, both structured and unstructured. The paper aims to contribute to understanding the possibilities and benefits of applying AI-based recommendation systems in customer offer personalization through a review of current literature, with a closer look at the types of recommender systems and the possibilities and limitations of their functioning or implementation.

Keywords: recommender systems, personalization, customer experience, digitalization, digital transformation.

INTRODUCTION

The development of information and communication technologies has forced companies to keep pace with technological innovations. This is called digitalization, which leads to significant changes in companies' processes. It reshapes business environments, reconfigures business models and strategies, and enhances overall business performance and competitiveness (Ubiparipovic et al., 2020). Digitalization is strongly linked to user experience, while personalization is the key to improved experience and satisfaction. It also influences sales and improves competitive position (Grljević et al., 2024).

AI-driven product recommender systems are crucial for customer experience improvement and sales growth. They can guide users in a personalized way, providing suggestions the users will most plausibly use (Ricci et al., 2011; Burke, 2002). Recommender systems are used in various fields, such as e-commerce (Abdul Hussien et al., 2021), online marketing (Hwangbo & Kim, 2019; Guo et al., 2021), transportation (Quijano-Sánchez et al., 2020), healthcare (Tran et al., 2021; De Croon et al., 2021; Shaikh et al., 2022), tourism (Hamid et al., 2021; Sarkar et al., 2023), online articles (Raza & Ding, 2022; Feng et al., 2020), streaming platforms (Al-Ghossein et al., 2022), etc. If businesses utilize recommender systems in the right way, they can increase sales, personalize offers, reduce marketing costs, encourage passive customers to make purchases, attract new customers, help in the process of expanding into new markets, optimize the supply chain, etc. According to the research (Griesch, Rittelmeyer, & Sandkuhl, 2024), the financial benefits of AI-driven recommender systems are significant. Companies record 10-20% increase in conversion rates and revenues. These benefits can enhance the competitiveness of a business. On the other hand, consumers can reduce the duration of the decision-making process, discover new items or services, identify previously unknown preferences and desires, interact more with appealing and personalized content, reduce the overload of irrelevant information, and more.

Large-sized enterprises tend to adopt digitization and digital transformation more quickly than small and medium-sized enterprises (SMEs). However, their long-term survival in the market requires that SMEs engage in digitization and digital transformation processes. One of the challenges that SMEs face is related to the application of information and communication technologies in the personalization of the product or service offer. As a limiting factor, the authors recognize insufficient knowledge and understanding of the possibilities and limitations of digital technologies, particularly artificial intelligence (AI), for improving the personalization of the offer and targeting customers by their preferences, habits, and aspirations (Wang et al., 2023; Norveel et al., 2022; Steinlechner et al., 2021; Gong & Ribiere, 2021). This paper aims to answer the following research question in the context of the described research subject:

RQ1. How recommender systems enhance personalization of offerings?
RQ2. Which challenges SMEs might face during development of personalized recommender systems and how to overcome them?

The paper is structured as follows. The first section provides the literature review reflecting the importance of digitalization, digital transformation, and limitation for their adoption in SMEs. The following section details on how personalization is achieve in recommender systems. Section Fundamentals of Recommender Systems offers an overview of main types of personalized recommender systems, following the section on development challenges and approaches to overcoming them. Concluding remarks are presented in the section Conclusion.

1. DIGITALIZATION, DIGITAL TRANSFORMATION AND SMES

Modern digital technologies, such as AI, the Internet of Things (IoT), blockchain, cloud computing, augmented reality, chatbots, big data, and nanotechnology, are accelerating the digitization process in all industry sectors. Digitization enables organizations to improve efficiency, productivity, and sales. It facilitates product and service innovation, and the development of new forms of customer relationships. The digitization process also affects the change in market conditions and represents an important factor in securing a competitive advantage (Ubiparipovic et al., 2020).

Digitization is closely related to the digital transformation of organizations' operations. According to Ismail et al. (2017), the digital transformation of business is the process of applying various digital technologies, through which companies use the synergy of those technologies to achieve better business results and ensure a more favorable competitive position in the market. In essence, the digital transformation of business means the implementation of changes in the way the organization works, which are necessary due to the application and exploitation of the advantages of modern digital technologies (Matt et al., 2015).

The scope and content of the transformation depend on the industry branch and the degree of digitization. According to the authors Ismail et al. (2017), the digital transformation of business can include several business dimensions: business model, user experience during the use of digitized products and services, business processes and decision-making methods, simultaneously influencing the necessary skills and talents of people in the company, organizational culture, and the entire system of value creation. Also, the author Wade (2015) defined the "digitalization piano" framework presenting organizations with seven business categories that can be subject to digital transformation: the organization's business model, organizational structure, people, processes, IT capability, products and services, engagement model (with customers, suppliers, and other business partners). Both authors consider the business model the highest level and the most demanding dimension for transformation, as it includes all the elements necessary for the organization's operations (Ismail, Khater, & Zaki, 2017). According to Osterwalder and Pigneur (2010), a business model consists of nine elements: customers, value offered, key activities, key resources, key partnerships, distribution channels, customer relations, income streams, and costs. These business model elements point to the conclusion that the business model includes the entire chain of value creation in the organization, which is why it represents the most challenging aspect of digital transformation. The business model defines how the organization creates and delivers value to customers and partners, but also how part of that value is returned to the organization, in the form of income (Schallmo & Williams, 2017).

An important part of the business model that impacts other elements as well refers to customer relations. Digital transformation of customer relationships is centered on the improvement of customer experience and satisfaction (Ismail, Khater, & Zaki, 2017). Personalized offerings, tailored by individual preferences, increase customer satisfaction, and their overall experience, and impact companies' financial results (Singh, 2024; Plečko et al., 2023). The modern concept of personalization implies various user data processing, such as geo-location data, data collected through mobile applications, social media, or over-the-top technology (Pearson, 2019). The variety and volume of data exceed the possibilities of traditional approaches to their processing, and AI takes a central place in personalization processes, not only because of the possibility of processing and analyzing large amounts of data but also because of their ability to perform optimizations in real-time, such as the automated formation of consumer segments that are most likely to be more responsive to the upcoming campaign, based on the attributes that currently drive the desired response (Pearson, 2019). In addition to the current AI-driven-personalization chatbots and virtual assistants that contribute to the improvement of customer experiences across different types of businesses (Shafiquzzaman Bhuiyan, 2024), recommender systems are another AI-based technology that enables personalization of products and services. Personalized recommendation technology offers more accurate and diverse choices to consumers and, as authors (Yin, Qiu, & Wang, 2025) found such relevant, inspirational, and insightful experiences significantly promote consumers' clicking intention.

Although large organizations are leading the digitalization process, digitalization and digital transformation represent an equally important process for SMEs enabling business growth, competitiveness, and market survival. However, SMEs experience certain barriers on the path of digitalization. In addition to the lack of financial resources for investments in digital technologies (Favoretto et al., 2022; Ramachandran et al., 2023; Cirillo et al., 2023) and organizational barriers that are reflected in people's resistance, especially the introduction and application of new ways of managing innovations (Andersen et al., 2021; Caputo et al., 2023; Hewitt et al., 2020), the most prevalent barrier in the literature is the lack of digital competences and knowledge of capabilities of modern digital technologies and opportunities for their implementation in the business processes. Many authors believe that it is necessary for management to systematically work on the education of employees, but also for greater involvement of the academic community in assisting SMEs (Norveel et al., 2022; Steinlechner et al., 2021; Gong & Ribiere, 2021; Wang et al., 2023; Vuchkovski et al., 2023; Ramachandran et al., 2023; Dalenogare et al., 2023).

In this context, the authors of this paper aimed to increase the amount of knowledge needed by SMEs in terms of understanding the possibilities, limitations, and adequate application of AI-based technologies, with a special focus on recommender systems as a central technology that enables the personalization of companies' offers. In this way, the authors believe that they contribute to reducing this key barrier in the digital transformation process of SMEs.

2. PERSONALIZATION AND RECOMMENDER SYSTEMS

An abundant market supply affects both consumers and businesses. For businesses, it means increased competition and constant effort to reach customers. For consumers, the decision-making process is harder and requires more time to find a product or service with the best price-quality ratio. Recommender systems are a solution that can help both consumers and businesses to achieve their goals. They can be defined as software tools and techniques for providing item suggestions that users may wish to use (Ricci et al., 2011) or systems that can guide users in a personalized way to relevant items in a wide range of possibilities (Burke, 2002). The term „recommender system" is proposed by Resnick and Varian (1997) indicating they can recommend interesting items while identifying those out of interest scope that should be filtered out.

Personalization in information systems is a process in which the system is modified to correspond to user preferences (Blom, 2000). In order to provide personalized recommendations, recommender systems need to identify similar users or determine relevant items based on user interests. Over 35% of Amazon sales, 60% of movie interactions on Netflix, and 38% of reads on Google News are result of recommendations (Gulzar et al., 2018). Personalized recommender systems can encourage users to engage more with recommended content while also reducing the cognitive effort needed to choose specific items, allowing them to focus more on interacting with the content itself (Beam, 2014). The main reasons for implementing personalized recommender systems are increased sales, product and service diversification, enhanced user satisfaction, and repeated user interactions, which indicate user loyalty (Polatidis & Georgiadis, 2013). Personalization can help businesses target specific customers and their needs, while also enabling them to grow by recommending long-tail products, segmenting users, and monitoring their activities. Personalization recommender systems can be used in different areas like travelling (Renjith et al., 2020), education (Kundu et al., 2021; Gulzar et al., 2018), music (Han et al., 2010), social networks (Yu et al., 2011), tourism (Lim et al., 2018), e-commerce (Markellou et al., 2005), restaurants (Zeng et al., 2016), online news (Wu et al., 2023), etc.

The main challenges in these types of recommender systems are privacy concerns, social media integration, and enhanced role-based access control. Privacy issues arise when users are asked to share personal information, which can lead to negative behaviour. While collecting user data to personalize offers, recommender systems must prioritize user privacy and ensure it is protected with a high level of security (Li et al., 2020). Another consideration is the process of data collection and preparation in integration with social media, as it can be complex and security concerns may arise when implementing authentication with a role-based structure to determine user access to resources (Polatidis & Georgiadis, 2013).

3. FUNDAMENTALS OF RECOMMENDER SYSTEMS

Based on the underlying approach used to generate recommendations, Aggarwal (2016) classifies recommender systems on collaborative filtering, content-based filtering, knowledge-based filtering, and hybrid systems. Each utilizes specific approach to data and knowledge on user behavior and/or item characteristics to generate product/service recommendations that align most closely to the users' interests and current needs.

Collaborative filtering recommender systems are based on the opinions of other people, which are processed in real time to develop personalized and relevant suggestions for a particular user. Users' opinions can be presented in a user-item matrix (Table 1), often referred to as utility matrix, where the intersection of a row and a column represents the user's opinion about a particular item.

Table 1: User-item matrix example

	Item 1	Item 2	Item 3	Item4
User 1	5	3	-	4
User 2	-	3	1	1
User 3	2	-	3	5
User4	4	3	5	-

Source: (Schafer et al., 2007)

User opinions can be noted using a scalar, binary, or unary rating. Ratings can also be explicit (when a user provides an opinion) or implicit (when inferred from user actions) (Schafer et al., 2007). The goal of collaborative recommender systems is to suggest items that a user has not interacted with (marked as "-" in Table 1), based on the preferences of users with the most similar tastes who have interacted with those items and rated them with a high score. There are two types of collaborative filtering, memory-based and model-based (Aljunid et al., 2025). In memory-based collaborative filtering the system aims to generate recommendations based on identified similarities between users or items. If similarities are sought between users it is referred to as user-based collaborative filtering and item-based refers to the systems aiming to find similarities among items (products or services), (Aljunid et al., 2025). In model-based collaborative filtering ratings are obtained using advanced machine learning approaches, such as classification, regression, clustering, association rules, neural networks, matrix factorization, or other methods (Aljunid et al., 2025).

Content-based recommender systems suggest items similar to items a user previously liked (Balabanović & Shoham, 1997). These systems analyse the descriptions (metadata) of items that the user has rated in the past and build a model based on that information. The recommendation process relies on matching the attributes that user prefers with the descriptions of items they have not yet interacted with. Compared to collaborative filtering, content-based recommender systems offers advantages, such as user independence, transparency, and the ability to recommend new items that have not received any prior interactions. To achieve this, they utilize traditional classification and clustering techniques, including Support Vector Machines and Nearest Neighbour (Lops et al., 2011).

Knowledge-based recommender systems collect user preferences through dialog (e.g., conversational chatbot) and recommends items that correspond to user preferences based on the predefined set of recommendation rules (constraint-based approach) or based on similarity metrics that reveal similar items to users' preferences (case-based approach), (Uta et al., 2024). Knowledge-based recommender system are surpassing issues related to providing recommendations for new users or new products, referred to as a cold-start problem, and they do not require large datasets. However, the biggest challenge is to create a knowledge base which often requires expert knowledge in a particular domain. Two main components of knowledge-based recommender systems are knowledge base and user profile (Bouraga et al., 2014).

Hybrid recommender systems combine content-based and collaborative filtering approaches (Kulkarni & Rodd, 2020; Adomavicius & Tuzhilin, 2005), as well as knowledge-based and utility-based techniques, to overcome the limitations of individual methods (Fakhar et al., 2023). Authors Adomavicius & Tuzhilin (2005) categorize hybrid recommender systems based on the approach of combining collaborative and content-based filtering to enhance recommendation quality:

- Combining predictions. The system combines predictions obtained separately through collaborative filtering and content-based filtering to generate recommendations.
- Enhancing collaborative filtering system with features related to items.
- Enhancing content-based system with features obtained from collaborative filtering, such as user-item interactions data.
- Building a single model that combines features from both approaches.

4. RECOMMENDER SYSTEMS DEVELOPMENT CHALLENGES

Although recommender systems revolutionized personalization of products and services and contributed to the overall success of the companies that manage to implement them successfully, they face various limitations and challenges that jeopardize the quality of recommendations, such as cold-start problem, sparsity, scalability, explainability, diversity, novelty, and serendipity. These challenges are often surpassed by introduction of auxiliary data and innovative AI-based methods and techniques. Their introduction into recommender systems contributes to the enrichment of user profiles and items, going beyond data on user interactions with items or amounts of purchased products. The challenges are discussed in the remaining of the section with references on potential AI-based approaches to overcome them.

The ***cold-start*** problem occurs when new users or items appear in a system, which is common in collaborative filtering-based recommender systems. When there is no information about previous user ratings, it is hard to find similar users, and when there are no item ratings, it is difficult to recommend that particular item (Hasan & Khatwal, 2023; Shao et al., 2021). Solutions to this problem can be found in cross-domain recommender systems, enriching user profiles with association rules or clustering techniques, identifying demographic or other similarities among users, utilizing user browsing information, initiating user interactions to collect new data, incorporating content-based information into collaborative filtering, imputing missing values in the user-item matrix, and applying deep learning methods (Revathy & Anitha, 2019), etc.

The ***sparsity*** problem is common in collaborative filtering recommender systems and occurs when there is a large number of items and users, but only a small number of interactions between them. Users do not rate many items, leading to a sparse user-item matrix. For example, a single user will not consume every product offered on the e-commerce platform or will rate every product they consume. Those reasons make it difficult to find similar users because there are not enough historical records (F. Zhang et al., 2020). In this situation, sparsity problem can lead to unreasonable recommendations for users without ratings (Al-Bakri & Hashim, 2018). There are different approaches to solving this problem, such as dimensionality reduction techniques, hybrid recommender systems that use content-boosted algorithms or model-based algorithms, etc. (Su & Khoshgoftaar, 2009).

The scalability problem arises when the number of users and items grows (leading to high dimensionality), making it challenging for the model to process data efficiently and provide recommendations within an acceptable time (Singh, 2020). With the rise of big data, this problem has become increasingly common. Dimensionality reduction, cluster-based techniques, fuzzy logic, and unsupervised learning-based recommender systems are the most common strategies for solving this problem (Roy & Dutta, 2022).

The ***explainability*** problem occurs when the system does not provide explanation why a particular item was recommended, causing users to lose trust in the recommender system. If an explanation is provided, it helps system to improve transparency, effectiveness, trustworthiness, and user satisfaction (Y. Zhang & Chen, 2020). There are different ways to provide explanations in recommender systems, such as model factorization, topic modelling, graph-based and knowledge-graph models, deep learning or rule mining (Y. Zhang & Chen, 2020).

One of the challenges in recommender systems is ***diversification***. Even if a recommender system is accurate, diversity becomes a problem when recommendations are too similar. However, the goal of a recommender system should be to suggest items that are different, thereby expanding user preferences. Bradley and Smyth define diversity as the opposite of similarity (Bradley & Smyth, 2001). Diverse suggestions increase user satisfaction and help mitigate the overfitting problem in recommender systems (Kunaver & Požrl, 2017). Diversity metrics can be divided into three groups: collaborative (using user feedback), metadata-based (calculated based on domain-specific item attributes), and content-based (based on the unstructured content data of the items) (Dokoupil et al., 2024). There are many different approaches to increasing diversity (Kunaver & Požrl, 2017) including topic diversification (Ziegler et al., 2005), item ranking techniques (Adomavicius & YoungOk Kwon, 2012), hybrid approaches (Premchaiswadi et al., 2013), using only collaborative data (Bridge & Kelly, 2006), etc.

Novelty is a characteristic of recommender systems which enables them to suggest items with specific features that the user has not interacted with before (for example a new movie genre). The basic idea of these systems is to suggest items that users are likely to select in the future rather than in the present. Natural way to measure novelty is through experiment where we ask users were they aware of provided recommendation before (Aggarwal, 2016). A better understanding of the item space in an unbiased manner, along with considering how humans interact with new items until reaching a peak, can help design recommender systems that facilitate novelty attainment (Gravino et al., 2019).

Serendipity refers to a surprising recommendation that the users did not know they would like. Serendipitous recommendations are diverse and novel, leading to an unexpected and surprising experience for the user. Some authors believe that there is no controllable method to manage serendipity (Makri et al., 2014), while others argue that although this process cannot be fully controlled, there are possible ways to make progress and influence serendipity (Ziarani & Ravanmehr, 2021). There are various ways to enhance serendipity in recommender systems, such as using collaborative filtering with association rule mining (Khoshahval S. et al., 2018), deep learning (Deng et al., 2019), graph-based methods (de Gemmis et al., 2015), hybrid approaches combining Latent Dirichlet Allocation and Principal Component Analysis (Meng & Hatano, 2014), etc.

CONCLUSION

In today's digital world, all companies must follow the advancement of technology and adapt their business. One of the key elements of digital transformation is use of modern technologies for user experience improvement, which focuses on providing the consumer with a better and easier experience with products and service. A positive customer experience increases customer satisfaction, which can lead to an expansion of the customer base, stronger relationships with them thereby increasing their loyalty, and increased profitability.

The personalization of the offer, with the use of a recommender system, can further improve the user experience and satisfaction. These systems, based on artificial intelligence, help companies to better understand the needs of users and, based on that data, create personalized recommendations for products and services. This approach allows companies to build long-term relationships with customers and secure a stable income through the loyalty of their users.

Small and medium-sized enterprises face various challenges in the digitalization process. The biggest obstacle is the lack of knowledge and understanding of how modern technologies can be adequately applied in order to improve business. With deciphering their capabilities and development challenges, the paper can serve as a modest contribution to closing the identified barrier for SMEs' digitalization.

REFERENCES

Abdul Hussien, F. T., Rahma, A. M. S., & Abdul Wahab, H. B. (2021). Recommendation Systems For E-commerce Systems An Overview. *Journal of Physics: Conference Series*, *1897*(1), 012024. https://doi.org/10.1088/1742-6596/1897/1/012024

Adomavicius, G., & Tuzhilin, A. (2005). Toward the next generation of recommender systems: a survey of the state-of-the-art and possible extensions. *IEEE Transactions on Knowledge and Data Engineering*, *17*(6), 734–749. https://doi.org/10.1109/TKDE.2005.99

Adomavicius, G., & YoungOk Kwon. (2012). Improving Aggregate Recommendation Diversity Using Ranking-Based Techniques. *IEEE Transactions on Knowledge and Data Engineering*, *24*(5), 896–911. https://doi.org/10.1109/TKDE.2011.15

Aggarwal, C. C. (2016). *Recommender Systems*. Springer International Publishing. https://doi.org/10.1007/978-3-319-29659-3

Al-Bakri, N. F., & Hashim, S. H. (2018). Reducing Data Sparsity in Recommender Systems. *Journal of Al-Nahrain University Science*, *21*(2), 138–147. https://doi.org/10.22401/JNUS.21.2.20

Al-Ghossein, M., Abdessalem, T., & BARRÉ, A. (2022). A Survey on Stream-Based Recommender Systems. *ACM Computing Surveys*, *54*(5), 1–36. https://doi.org/10.1145/3453443

Aljunid, M. F., D.H., M., Hooshmand, M. K., Ali, W. A., Shetty, A. M., & Alzoubah, S. Q. (2025). A collaborative filtering recommender systems: Survey. *Neurocomputing*, *617*, 128718. https://doi.org/10.1016/j.neucom.2024.128718

Andersen, A. D., Frenken, K., Galaz, V., Kern, F., Klerkx, L., Mouthaan, M., Piscicelli, L., Schor, J. B., & Vaskelainen, T. (2021). On digitalisation and sustainability transitions. *Environmental Innovation and Societal Transitions, 41,* 96-98. https://doi.org/10.1016/j.eist.2021.09.013

Balabanović, M., & Shoham, Y. (1997). Fab. *Communications of the ACM*, *40*(3), 66–72. https://doi.org/10.1145/245108.245124

Beam, M. A. (2014). Automating the News. *Communication Research*, *41*(8), 1019–1041. https://doi.org/10.1177/0093650213497979

Blom, J. (2000). Personalization. *CHI '00 Extended Abstracts on Human Factors in Computing Systems*, 313–314. https://doi.org/10.1145/633292.633483

Bouraga, S., Jureta, I., Faulkner, S., & Herssens, C. (2014). Knowledge-Based Recommendation Systems. *International Journal of Intelligent Information Technologies*, *10*(2), 1–19. https://doi.org/10.4018/ijiit.2014040101

Bradley, K., & Smyth, B. (2001). Improving Recommendation Diversity. *12th National Conference in Artificial Intelligence and Cognitive Science*.

Bridge, D., & Kelly, J. P. (2006). Ways of Computing Diverse Collaborative Recommendations. *In: Wade, V.P., Ashman, H., Smyth, B. (eds) Adaptive Hypermedia and Adaptive Web-Based Systems.* AH 2006. Lecture Notes in Computer Science, vol 4018, 41-50. Springer, Berlin, Heidelberg. (pp. 41–50). https://doi.org/10.1007/11768012_6

Burke, R. (2002). Hybrid Recommender Systems: Survey and Experiments. *User Modeling and User-Adapted Interaction*, *12*(4), 331–370. https://doi.org/10.1023/A:1021240730564

Caputo, F., Cillo, V., Fiano, F., Pironti, M., & Romano, M. (2023). Building T-shaped professionals for mastering digital transformation. *Journal of Business Research, 154*, 113309. https://doi.org/10.1016/j.jbusres.2022.113309

Cirillo, V., Fanti, L., Mina, A., & Ricci, A. ({2023). The adoption of digital technologies: Investment, skills, work organisation. *Structural Change and Economic Dynamics, 66,* 89-105. https://doi.org/10.1016/j.strueco.2023.04.011

De Croon, R., Van Houdt, L., Htun, N. N., Štiglic, G., Vanden Abeele, V., & Verbert, K. (2021). Health Recommender Systems: Systematic Review. *Journal of Medical Internet Research*, *23*(6), e18035. https://doi.org/10.2196/18035

de Gemmis, M., Lops, P., Semeraro, G., & Musto, C. (2015). An investigation on the serendipity problem in recommender systems. *Information Processing & Management*, *51*(5), 695–717. https://doi.org/10.1016/j.ipm.2015.06.008

Deng, Z.-H., Huang, L., Wang, C.-D., Lai, J.-H., & Yu, P. S. (2019). DeepCF: A Unified Framework of Representation Learning and Matching Function Learning in Recommender System. *Proceedings of the AAAI Conference on Artificial Intelligence*, *33*(01), 61–68. https://doi.org/10.1609/aaai.v33i01.330161

Dokoupil, P., Boratto, L., & Peska, L. (2024). User Perceptions of Diversity in Recommender Systems. *Proceedings of the 32nd ACM Conference on User Modeling, Adaptation and Personalization*, 212–222. https://doi.org/10.1145/3627043.3659555

Fakhar, M. Z., Yalcin, E., & Bilge, A. (2023). A survey of smart home energy conservation techniques. *Expert Systems with Applications*, *213*, 118974. https://doi.org/10.1016/j.eswa.2022.118974

Favoretto, C., Mendes, G. H. S., Oliveira, M. G., Cauchick-Miguel, P. A., Coreynen, W. (2022). From servitisation to digital servitisation: How digitalisation transforms companies' transition towards services. *Industrial Marketing Management, 102,* 104-121. https://doi.org/10.1016/j.indmarman.2022.01.003

Feng, C., Khan, M., Rahman, A. U., & Ahmad, A. (2020). News Recommendation Systems - Accomplishments, Challenges & Future Directions. *IEEE Access*, *8*, 16702–16725. https://doi.org/10.1109/ACCESS.2020.2967792

Gong, C., & Ribiere, V. (2021). Developing a unified definition of digital transformation. *Technovation, 102,* 102217. https://doi.org/10.1016/j.technovation.2020.102217

Gravino, P., Monechi, B., & Loreto, V. (2019). Towards novelty-driven recommender systems. *Comptes Rendus. Physique*, *20*(4), 371–379. https://doi.org/10.1016/j.crhy.2019.05.014

Grljević, O., Marić, M., Gluščević, L., Horvat, D. (2024). Analyzing user experience from negative reviews: the Salesforce case stady. *Ekonomika*. (accepted).

Gulzar, Z., Leema, A. A., & Deepak, G. (2018). PCRS: Personalized Course Recommender System Based on Hybrid Approach. *Procedia Computer Science*, *125*, 518–524. https://doi.org/10.1016/j.procs.2017.12.067

Guo, L., Jin, J., Zhang, H., Zheng, Z., Yang, Z., Xing, Z., Pan, F., Niu, L., Wu, F., Xu, H., Yu, C., Jiang, Y., & Zhu, X. (2021). We Know What You Want: An Advertising Strategy Recommender System for Online Advertising. *Proceedings of the 27th ACM SIGKDD Conference on Knowledge Discovery & Data Mining*, 2919–2927. https://doi.org/10.1145/3447548.3467175

Hamid, R. A., Albahri, A. S., Alwan, J. K., Al-qaysi, Z. T., Albahri, O. S., Zaidan, A. A., Alnoor, A., Alamoodi, A. H., & Zaidan, B. B. (2021). How smart is e-tourism? A systematic review of smart tourism recommendation system applying data management. *Computer Science Review*, *39*, 100337. https://doi.org/10.1016/j.cosrev.2020.100337

Han, B., Rho, S., Jun, S., & Hwang, E. (2010). Music emotion classification and context-based music recommendation. *Multimedia Tools and Applications*, *47*(3), 433–460. https://doi.org/10.1007/s11042-009-0332-6

Hasan, S. N., & Khatwal, R. (2023). *Challenges and issues analysis in cold start recommendation system*. AIP Conf. Proc. 2930, 020017 (2023). https://doi.org/10.1063/5.0176685

Hewitt, R. J., De Boer, C., & Flacke, J. (2020). Participatory development of digital support tools for local-scale energy transitions: Lessons from two European case studies. *Global Transitions, 2,* 138-149. https://doi.org/10.1016/j.glt.2020.07.003

Hwangbo, H., & Kim, Y. (2019). Session-Based Recommender System for Sustainable Digital Marketing. *Sustainability, 11*(12), 3336. https://doi.org/10.3390/su11123336

Ismail, M. H., Khater, M., & Zaki, M. (2017). Digital Business Transformation and Strategy: What Do We Know So Far ?, *Cambridge Service Alliance 2017*. DOI: 10.13140/RG.2.2.36492.62086

Khoshahval S., Farnaghi M., Taleai M., & Mansourian A. (2018). *Geospatial Technologies for All* (A. Mansourian, P. Pilesjö, L. Harrie, & R. van Lammeren, Eds.). Springer International Publishing. https://doi.org/10.1007/978-3-319-78208-9

Kulkarni, S., & Rodd, S. F. (2020). Context Aware Recommendation Systems: A review of the state of the art techniques. *Computer Science Review*, *37*, 100255. https://doi.org/10.1016/j.cosrev.2020.100255

Kunaver, M., & Požrl, T. (2017). Diversity in recommender systems – A survey. *Knowledge-Based Systems*, *123*, 154–162. https://doi.org/10.1016/j.knosys.2017.02.009

Kundu, S. S., Sarkar, D., Jana, P., & Kole, D. K. (2021). Personalization in Education Using Recommendation System: An Overview. In: Deyasi, A., Mukherjee, S., Mukherjee, A., Bhattacharjee, A.K., Mondal, A. (eds) *Computational Intelligence in Digital Pedagogy. Intelligent Systems Reference Library*, vol 197, 85–111. Springer, Singapore. https://doi.org/10.1007/978-981-15-8744-3_5

Li, R., Lv, S., Zhu, H., & Song, X. (2020). Spatial-Temporal Topic Model for Cold-Start Event Recommendation. *IEEE Access*, *8*, 214050–214060. https://doi.org/10.1109/ACCESS.2020.3040778

Lim, K. H., Chan, J., Leckie, C., & Karunasekera, S. (2018). Personalized trip recommendation for tourists based on user interests, points of interest visit durations and visit recency. *Knowledge and Information Systems*, *54*(2), 375–406. https://doi.org/10.1007/s10115-017-1056-y

Lops, P., de Gemmis, M., & Semeraro, G. (2011). Content-based Recommender Systems: State of the Art and Trends. *In Recommender Systems Handbook* (pp. 73–105). Springer US. https://doi.org/10.1007/978-0-387-85820-3_3

Makri, S., Blandford, A., Woods, M., Sharples, S., & Maxwell, D. (2014). “Making my own luck”: Serendipity strategies and how to support them in digital information environments. *Journal of the Association for Information Science and Technology*, *65*(11), 2179–2194. https://doi.org/10.1002/asi.23200

Markellou, P., Mousourouli, I., Sirmakessis, S., & Tsakalidis, A. (2005). Personalized e-commerce recommendations. *IEEE International Conference on E-Business Engineering (ICEBE’05)*, 245–252. https://doi.org/10.1109/ICEBE.2005.95

Matt, C., Hess, T., & Benlian, A. (2015). Digital Transformation Strategies. *Business and Information Systems Engineering, 57*(5), 339–343. https://doi.org/10.1007/s12599-015-0401-5

Meng, Q., & Hatano, K. (2014). Visualizing Basic Words Chosen by Latent Dirichlet Allocation for Serendipitous Recommendation. *2014 IIAI 3rd International Conference on Advanced Applied Informatics*, 819–824. https://doi.org/10.1109/IIAI-AAI.2014.164

Norveel, J., Gonzalez, R., & Presthus, W. (2022). Basic digital competence in Norwegian banking. *Procedia Computer Science, 196,* 183-190. https://doi.org/10.1016/j.procs.2021.12.004

Osterwalder, A., & Pigneur, Y., (2010), *Business Model Generation*, Yohn Wiley, New Jersey.

Pearson, A. (2019). Personalisation the artificial intelligence way. *Journal of Digital & Social Media Marketing, 7*(3), 245–269. doi:10.69554/JJGR7331

Plečko, S., Tominc, P., & Širec, K. (2023). Digitalization in Entrepreneurship: Unveiling the Motivational and Demographic Influences towards Sustainable Digital Sales Strategies. *Sustainability*, *15*(23), 16150. https://doi.org/10.3390/su152316150

Polatidis, N., & Georgiadis, C. K. (2013). Mobile recommender systems: An overview of technologies and challenges. *2013 Second International Conference on Informatics & Applications (ICIA)*, 282–287. https://doi.org/10.1109/ICoIA.2013.6650270

Premchaiswadi, W., Poompuang, P., Jongswat, N., & Premchaiswadi, N. (2013). Enhancing Diversity-Accuracy Technique on User-Based Top-N Recommendation Algorithms. *2013 IEEE 37th Annual Computer Software and Applications Conference Workshops*, 403–408. https://doi.org/10.1109/COMPSACW.2013.68

Quijano-Sánchez, L., Cantador, I., Cortés-Cediel, M. E., & Gil, O. (2020). Recommender systems for smart cities. *Information Systems*, *92*, 101545. https://doi.org/10.1016/j.is.2020.101545

Ramachandran, H. J., Oh, J. L., Cheong, Y. K., Jiang, Y., Teo, J. Y. C., Seah, C. W. A., Y., M., & Wang, W. (2023). Barriers and facilitators to the adoption of digital health interventions for COPD management: A scoping review. *Heart & Lung, 59*, 117-127. https://doi.org/10.1016/j.hrtlng.2023.02.004

Raza, S., & Ding, C. (2022). News recommender system: a review of recent progress, challenges, and opportunities. *Artificial Intelligence Review*, *55*(1), 749–800. https://doi.org/10.1007/s10462-021-10043-x

Renjith, S., Sreekumar, A., & Jathavedan, M. (2020). An extensive study on the evolution of context-aware personalized travel recommender systems. *Information Processing & Management*, *57*(1), 102078. https://doi.org/10.1016/j.ipm.2019.102078

Resnick, P., & Varian, H. R. (1997). Recommender systems. *Communications of the ACM*, *40*(3), 56–58. https://doi.org/10.1145/245108.245121

Revathy, V. R., & Anitha, S. P. (2019). Cold Start Problem in Social Recommender Systems: State-of-the-Art Review. In: Bhatia, S., Tiwari, S., Mishra, K., Trivedi, M. (eds) *Advances in Computer Communication and Computational Sciences. Advances in Intelligent Systems and Computing*, vol 759, 105-115. Springer, Singapore. https://doi.org/10.1007/978-981-13-0341-8_10

Ricci, F., Rokach, L., Shapira, B., & Kantor, P. B. (2011). *Recommender Systems Handbook* (F. Ricci, L. Rokach, B. Shapira, & P. B. Kantor, Eds.). Springer US. https://doi.org/10.1007/978-0-387-85820-3

Roy, D., & Dutta, M. (2022). A systematic review and research perspective on recommender systems. *Journal of Big Data*, *9*(1), 59. https://doi.org/10.1186/s40537-022-00592-5

Singh, P. (2024). Beyond the basics: Exploring the impact of social media marketing enablers on business success. *Heliyon*, *10*(5), e26435. https://doi.org/10.1016/j.heliyon.2024.e26435

Schallmo, D., & Williams, C. (2017). Digital transformation of business models — best practice, enablers, and roadmap. *International Journal of Innovation Management, 21*(8):1740014, 1–17. DOI: 10.1142/S136391961740014X

Sarkar, J. L., Majumder, A., Panigrahi, C. R., Roy, S., & Pati, B. (2023). Tourism recommendation system: a survey and future research directions. *Multimedia Tools and Applications*, *82*(6), 8983–9027. https://doi.org/10.1007/s11042-022-12167-w

Schafer, J. Ben, Frankowski, D., Herlocker, J., & Sen, S. (2007). Collaborative Filtering Recommender Systems. In *The Adaptive Web* (pp. 291–324). Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-540-72079-9_9

Shafiquzzaman Bhuiyan, M. (2024). The Role of AI-Enhanced Personalization in Customer Experiences. *Journal of Computer Science and Technology Studies, 6*(1), 162-169. doi:https://doi.org/10.32996/jcsts.2024.6.1.17

Shaikh, S. G., Suresh Kumar, B., & Narang, G. (2022). Recommender system for health care analysis using machine learning technique: a review. *Theoretical Issues in Ergonomics Science*, *23*(5), 613–642. https://doi.org/10.1080/1463922X.2022.2061078

Shao, B., Li, X., & Bian, G. (2021). A survey of research hotspots and frontier trends of recommendation systems from the perspective of knowledge graph. *Expert Systems with Applications*, *165*, 113764. https://doi.org/10.1016/j.eswa.2020.113764

Singh, M. (2020). Scalability and sparsity issues in recommender datasets: a survey. *Knowledge and Information Systems*, *62*(1), 1–43. https://doi.org/10.1007/s10115-018-1254-2

Steinlechner, M., Schumacher, A., Fuchs, B., Reichsthaler, L., & Schlund, S. (2021). A maturity model to assess digital employee competencies in industrial enterprises. *Procedia CIRP*, *104*, 1185-1190. https://doi.org/10.1016/j.procir.2021.11.199

Su, X., & Khoshgoftaar, T. M. (2009). A Survey of Collaborative Filtering Techniques. *Advances in Artificial Intelligence*, *2009*, 1–19. https://doi.org/10.1155/2009/421425

Tran, T. N. T., Felfernig, A., Trattner, C., & Holzinger, A. (2021). Recommender systems in the healthcare domain: state-of-the-art and research issues. *Journal of Intelligent Information Systems*, *57*(1), 171–201. https://doi.org/10.1007/s10844-020-00633-6

Ubiparipovic, B., Matkovic, P., Marić, M., & Tumbas, P. (2020). Critical factors of digital transformation success: A literature review. *Ekonomika preduzeća, 5-6*(septembar-oktobar 2020), 400-415. doi:10.5937/EKOPRE2006400U

Uta, M., Felfernig, A., Le, V.-M., Tran, T. N. T., Garber, D., Lubos, S., & Burgstaller, T. (2024). Knowledge-based recommender systems: overview and research directions. *Frontiers in Big Data*, *7*. https://doi.org/10.3389/fdata.2024.1304439

Vuchkovski, D., Zalaznik, M., Mitrega, M., & Pfajfar, G. (2023). A look at the future of work: The digital transformation of teams from conventional to virtual. *Journal of Business Research, 163,* 113912. https://doi.org/10.1016/j.jbusres.2023.113912

Wang, K., Guo, F., Zhang, C., & Schaefer, D. (2022). From Industry 4.0 to construction 4.0: Barriers to the digital transformation of engineering and construction sectors*. Engineering, Construction and Architectural Management*. *31*(1), 136-158. https://doi.org/10.1108/ECAM-05-2022-038

Wade, M. (2015). Digital Business Transformation - A Conceptual Framework. *Global Center for Digital Business Transformation*, *15*, 1-15.

Wu, C., Wu, F., Huang, Y., & Xie, X. (2023). Personalized News Recommendation: Methods and Challenges. *ACM Transactions on Information Systems*, *41*(1), 1–50. https://doi.org/10.1145/3530257

Yin, J., Qiu, X., & Wang, Y. (2025). The Impact of AI-Personalized Recommendations on Clicking Intentions: Evidence from Chinese E-Commerce. *Journal of Theoretical and Applied Electronic Commerce Research, 20*(1), 21. doi:https://doi.org/10.3390/jtaer20010021

Yu, X., Pan, A., Tang, L.-A., Li, Z., & Han, J. (2011). Geo-Friends Recommendation in GPS-based Cyber-physical Social Network. *2011 International Conference on Advances in Social Networks Analysis and Mining*, 361–368. https://doi.org/10.1109/ASONAM.2011.118

Zeng, J., Li, F., Liu, H., Wen, J., & Hirokawa, S. (2016). A Restaurant Recommender System Based on User Preference and Location in Mobile Environment. *2016 5th IIAI International Congress on Advanced Applied Informatics (IIAI-AAI)*, 55–60. https://doi.org/10.1109/IIAI-AAI.2016.126

Zhang, F., Qi, S., Liu, Q., Mao, M., & Zeng, A. (2020). Alleviating the data sparsity problem of recommender systems by clustering nodes in bipartite networks. *Expert Systems with Applications*, *149*, 113346. https://doi.org/10.1016/j.eswa.2020.113346

Zhang, Y., & Chen, X. (2020). Explainable Recommendation: A Survey and New Perspectives. *Foundations and Trends® in Information Retrieval*, *14*(1), 1–101. https://doi.org/10.1561/1500000066

Ziarani, R. J., & Ravanmehr, R. (2021). Serendipity in Recommender Systems: A Systematic Literature Review. *Journal of Computer Science and Technology*, *36*(2), 375–396. https://doi.org/10.1007/s11390-020-0135-9

Ziegler, C.-N., McNee, S. M., Konstan, J. A., & Lausen, G. (2005). Improving recommendation lists through topic diversification. *Proceedings of the 14th International Conference on World Wide Web - WWW '05*, 22. https://doi.org/10.1145/1060745.1060754