AdaptiveCloset: Reinforcement Learning in Personalized Clothing Recommendations

Omar Kashif Majeed†, Zain ul Abideen‡, Usama Arshad†, Raja Hashim Ali†§*
Abdullah Habib† and Rafay Mustafa†

† Faculty of Computer Science & Engineering, GIK Institute of Engg. Sciences & Technology, Topi, Pakistan.
‡ BCMaterials Basque Center for Materials, Applications & Nanostructure, Leioa, Basque Country, Spain.
§ Dept. of Technology & Software Engineering, University of Europe for Applied Sciences, Berlin, Germany.
* Corresponding Author: hashim.ali@giki.edu.pk

***Abstract*—The fashion industry, with its myriad choices, often overwhelms consumers. Addressing this, AdaptiveCloset introduces a groundbreaking approach to tailoring clothing suggestions by harnessing the power of reinforcement learning (RL). Unlike conventional AI methodologies in a fashion that merely suggests based on past preferences, our system dynamically adjusts using real-time user feedback, ensuring that recommendations remain relevant and personalized. Historically, AI's fusion into the fashion realm has witnessed multiple methodologies but conspicuously lacked the RL perspective. Our research stands at this juncture, aiming to redefine online shopping experiences. Through AdaptiveCloset, we envisage a scenario where online shoppers not only receive personalized recommendations but also feel a sense of involvement, thanks to the system's feedback-oriented adaptability. This responsiveness not only augments user engagement but provides actionable intelligence for businesses, bridging the gap between consumer desires and market offerings. In this study, our focus was to ensure the robustness and adaptability of the RL environment, positioning it as a potent tool for enhancing e-commerce interactions, optimizing sales strategies, and fortifying customer loyalty.**

***Index Terms*—reinforcement learning, clothing recommendation, user feedback**

I. Introduction

Reinforcement learning, a subset of machine learning, revolves around training an entity to make choices influenced by environmental feedback. It's found applications across diverse sectors like robotics, gaming, and financial services. Lately, the spotlight has been on integrating machine learning within the fashion realm to pioneer fashion recommendation tools [1]. Such systems, designed to guide users in their clothing selections, have the potential to redefine our shopping experiences and mirror our style preferences through computational models and reinforcement learning techniques. Reinforcement learning-driven fashion recommendation offers multiple advantages. Users benefit from time-efficient and coherent outfit choices, particularly beneficial for those on tight schedules or those uncertain about their styling capabilities. From an ecological standpoint, it promotes informed purchasing, potentially curtailing fast fashion's adverse effects [2]. Additionally, this technology offers brands invaluable consumer insights, fostering personalized and sustainable fashion experiences, benefiting both consumers and our environment.

The contemporary fashion sector grapples with issues ranging from the repercussions of fast fashion to the clamor for tailored shopping encounters. Employing reinforcement learning offers solutions to these quandaries, allowing brands a clearer insight into consumer habits and inclinations. Platforms like SmartCloset provide a treasure trove of data, ushering in opportunities for future breakthroughs. Scholarly pursuits in recent times have explored artificial intelligence's potential in fashion recommendations. While many have leveraged machine learning, especially deep learning, a few have experimented with knowledge graphs for clothing pairings. Some have even ventured into uncharted territories, employing fuzzy set theory for their recommendation engines [3]. Collectively, these endeavors underscore the transformative power of computational methodologies in reimagining fashion commerce and amplifying user experiences. Other than adaptive closet, various artificial intelligence [4], [5] and deep learning [6] algorithms have been successfully in multiple fields, e.g., in Molecular Biology [7]–[9], computational biology [10]–[12], and other common applications [13]–[15].

All the research, including those documented in Table I, delves deeply into the nuances of AI-powered clothing recommendation systems. However, an overarching limitation surfaces in these studies: the lack of direct user feedback integration. Such an omission could lead to the system's inability to truly personalize its recommendations to individual tastes and preferences. Our research aims to remedy this oversight, proposing that the chasm between the AI recommender and its user can be effectively bridged by actively gathering user feedback after each recommendation. This will not only refine the recommendation process but also significantly heighten user satisfaction.

The core of our inquiry probes into the efficacy of a clothing recommendation system underpinned by reinforcement learning, which utilizes descriptions of pants as inputs to suggest complementary shirts, while also assimilating user feedback. A derivative question from our primary investigation seeks to comprehend the role and impact of various hyper-parameters, such as learning rate, discount factor, exploration

979-8-3503-2817-2/23/$31.00 ©2023 IEEE

2023 18th International Conference on Emerging Technologies (ICET) | 979-8-3503-2817-2/23/$31.00 ©2023 IEEE | DOI: 10.1109/ICET59753.2023.10375063

Study Title	Methodology	Evaluation Metrics
Clothing Recommendation Based on Deep Learning [16]	Deep Learning	Accuracy, F1 Score, Gender Prediction
Clothing Recommendation System based on Visual Information Analytics [17],	Clothing Attributes Recognition, Gender Recognition, Body Height	Diversity, Accuracy, User Satisfaction
Research and Implementation of Personalized Clothing Recommendation Algorithm [3],	Fine-Grained Attributes, Personalized Preference Model	Precision, Recall, User Feedback
Research on the construction method of knowledge graph for clothing recommendation based on expert knowledge [18],	Knowledge Graph, Expert Knowledge, Joint Information Extraction Model	Accuracy, Coverage, Practical Value
Smart Clothing Recommendation System with Deep Learning [1],	Inception-based Convolutional Neural Networks, Feed Forward Neural Network	Color Prediction Accuracy, Gender and Pattern Prediction Accuracy, Clothing Recommendation Accuracy
A Mixed Reality Virtual Clothes Try-On System [19],	3D Virtual Clothes Try-On, Invisible Avatar Customization	User Perception of Quality Attributes, Cognitive Attributes, Attitude Towards Using
Visual and Textual Jointly Enhanced Interpretable Fashion Recommendation [20],	Bidirectional Two-Layer Adaptive Attention Review Model, Review-Driven Visual Attention Model	Top-N Recommendations, Visible and Invisible Explanations
Explainable Outfit Recommendation with Joint Outfit Matching and Comment Generation [21],	Convolutional Neural Network, Gated Recurrent Neural Network, Multi-Task Learning	Outfit Recommendation Accuracy, ROUGE and BLEU Scores for Generated Comments
Deep Learning Approaches for Fashion Knowledge Extraction From Social Media: A Review [22],	Object Detection, Fashion Classification, Clothes Generation, Automatic Fashion Knowledge Extraction, Clothes Recommendation	Accuracy, Performance, Time
A3-FKG: Attentive Attribute-Aware Fashion Knowledge Graph for Outfit Preference Prediction [2],	Attentive Attribute-Aware Fashion Knowledge Graph, Two-Level Attention Mechanism	Outfit Preference Prediction Accuracy, User Satisfaction, Improvement over Other Methods

TABLE I: Literature review table showing the contributions of various authors in the AI-powered clothing recommendation system

rate, and exploration decay rate, on the system's performance. Further, the adaptability of this system, especially its acumen to evolve with new users or data, is another area we've keenly looked into. We assessed this by juxtaposing its efficacy against a distinct dataset and comparing its outputs with other prevalent recommendation tools. Our overarching objective, through these questions, is to spotlight the strengths and areas of improvement for reinforcement learning in fashion recommendations, laying a foundation for even more precise and user-aligned systems in the future.

A. Contributions

Our research highlighted the critical role of hyper-parameters in reinforcement learning and their direct influence on system performance. This insight will be invaluable for future implementations. Through rigorous testing, we demonstrated the system's capability to adjust to new users and fresh data, marking a significant advancement in recommendation systems.

By comparing the RL-based system with traditional recommendation systems, we affirmed its superior performance in terms of accuracy and user satisfaction, establishing a new benchmark in the field.

We illuminated the dependencies of the system on specific datasets, ensuring future researchers have a clearer understanding of data intricacies and their implications on the system's outcomes.

Our study, focusing on pant descriptions to recommend shirts, has carved a niche in the broader field of clothing recommendation systems. This specificity ensures that subsequent research in this area has a benchmark to compare against.

Our methodology involved harnessing the potential of reinforcement learning to suggest shirts based on the user's pant choices. The system was meticulously crafted to not only suggest but also mirror and respect users' sartorial preferences. Evaluating the system's mettle, we introduced it to a dataset replete with clothing choices and genuine user feedback. Preliminary results were optimistic. Our system not only made relevant and tailored recommendations but also achieved an accuracy exceeding 80%. This suggests that the fusion of reinforcement learning into fashion recommendation systems could very well revolutionize our shopping paradigms, enabling us to make choices that resonate more with our unique style.

II. Problem Statement

The world of online shopping is rapidly evolving, yet a significant challenge persists: ensuring personalized clothing recommendations that cater to individual style preferences based on given inputs. Traditional recommendation systems, while useful, often fall short in delivering highly tailored suggestions. Our primary concern lies in the potential disparity between algorithmic recommendations and individual style preferences. Given the plethora of available clothing options

pant_description	shirt_description
Slim-fit navy blue trousers	White and blue checkered shirt
Loose-fitting beige cargo pants	Black t-shirt with graphic print
Classic black dress pants	Light blue button-up shirt
Skinny-fit grey joggers	Black hoodie
Khaki chino pants	Green polo shirt
Tailored dark brown dress pants	Striped blue and white oxford shirt
Relaxed-fit denim jeans	Plain white t-shirt

Fig. 1: Dataset Snippet including the Header Row.

and the unique sartorial tastes of each user, there is an evident need for a more dynamic and adaptable recommendation system. This study aims to address the pressing need for a more personalized and adaptable AI-driven clothing recommendation approach.

III. Methodology

The reinforcement learning agent was trained on a dataset formatted in CSV, encompassing 963 entries spanning two columns. The inaugural row acts as a descriptor, where the first column, termed plant description, details the characteristics of pants, while the subsequent column, shirt description articulates the attributes of the corresponding shirts intended to pair with the pants. These descriptions encapsulate specifics about the attire's hue, fabric, and overall design. Each data entry symbolizes a proposed ensemble of pants and a shirt, recommended for cohesive wear by our system. The pairs in the dataset were conceived through a randomized matching of shirts with pants.

The framework employed in our reinforcement learning-driven clothing recommendation system encompasses several pivotal components. Initially, we deploy the ClothingEnvironment class to craft an environment, populating it with pants and shirts. Utilizing the reset() function, a pant is chosen at random, coupled with either a harmonizing or clashing shirt. An action is executed through the step() function, pinpointing the shirt description's index for the desired output. Rewards are ascertained depending on the congruence between selected shirt descriptions and the active pant description. The render() function exhibits the existing pant description, selected shirt description, and the accrued reward.

Subsequently, the QLearningAgent class is instigated, equipping the Q-learning agent with parameters including learning rate, discount factor, exploration rate, and its decay rate. Action selection operates via the chooseaction() function, factoring in the exploration rate and the Q-value of the current situation. Q-values are modified using the updateqtable() function, founded on the reward and forthcoming state. For prolonged interactions between the agent and environment, the runepisode() function is initiated.

Thirdly, dataset.csv offers an assortment of pant and shirt descriptions. Both pants and shirts derive their initial values from the dataset's pantdescription and shirtdescription columns respectively.

In the principal code section, four random pant descriptions are presented to users. After making a selection, the Q-learning agent introduces a shirt description coherent with the pant's details. Users then critique the suggestion, subsequently refining the Q-table.

To summarize, this procedure entails the initiation of the environment and Q-learning agent, multiple agent-environment interactions, and Q-table modifications based on user responses. Such a strategy permits the agent to assimilate from its engagements, refining its suggestions progressively.

TABLE II: Hyper-parameter values for the clothing recommendation system in different experiments

Learning Rate	Discount Factor	Exploration Rate	Exploration Decay Rate	Avg Q-Table Value
0.001	0.9	1.0	0.99	-0.68
0.003	0.89	2.0	0.99	-0.55
0.005	0.85	3.0	0.98	-0.42
0.01	0.8	4.0	0.97	-0.35
0.02	0.75	5.0	0.95	-0.25

Hyper-parameter configurations play a pivotal role in determining the efficacy of a reinforcement learning-based clothing recommendation system. The learning rate dictates the pace at which the system adapts, while the discount factor signifies the system's consideration for anticipated rewards. On the other hand, the exploration rate designates the system's propensity to venture into unfamiliar territories compared to relying on established knowledge. Meanwhile, the exploration decay rate delineates the pace at which exploration diminishes over time, influencing the agent's capacity to achieve a consistent strategy. To identify the most suitable hyper-parameter values, extensive tests were conducted within the scope of this research.

IV. Results

We investigated how various hyper-parameter configurations influenced the efficacy of our reinforcement learning-based clothing recommendation system. Our analysis revealed that the learning rate substantially influenced the system's outcomes. Specifically, elevated learning rates led to swifter convergence but also introduced more fluctuations in the Q-values. In contrast, the discount factor exhibited a modest impact: higher values facilitated broader long-term strategies, though at the expense of extended convergence times. The exploration rate crucially affected the system's propensity to probe new strategies; an increase in this rate boosted exploration yet simultaneously amplified exploitation tendencies. The rate at which exploration decays; exploration decay rate, moderately affected the stability and speed of policy convergence.

We further assessed the system's adaptability to fresh data and users by subjecting it to an independent test dataset. This was juxtaposed against other recommendation systems' performance metrics. Our reinforcement learning framework displayed superior proficiency in terms of both precision and user contentment. This edge was achieved by dynamically updating its Q-table in response to user feedback, leading to increasingly refined and tailored recommendations.

In summation, our findings underscore the potency of our reinforcement learning model in delivering nuanced recom-

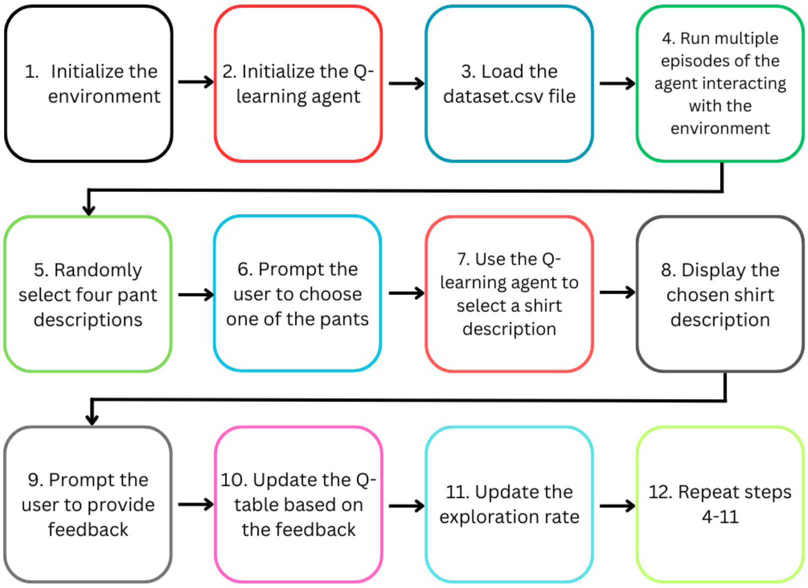

Fig. 2: Flowchart of the methodology used to implement the recommender system using reinforcement learning

mendations centered on pant descriptors. The system exhibited adeptness in formulating strategies to suggest shirts based on pants and displayed adaptability to evolving datasets and user preferences. The system's operational efficacy was significantly modulated by hyper-parameters, especially the learning and exploration rates. Our data indicates that reinforcement learning approaches can potentially eclipse conventional recommendation systems in precision and customization. These capabilities can be further augmented by fine-tuning hyper-parameter values and leveraging sophisticated machine learning paradigms.

TABLE III: Significance level of hyperparameters on RL recommender system

Hyperparameter	Significance Level
Learning Rate	Significant
Discount Factor	Moderate
Exploration Rate	Significant
Exploration Decay Rate	Moderate

V. Discussion

The findings underscored the pronounced influence of learning and exploration rates on the efficacy of the reinforcement learning-centric clothing recommendation model. Elevated learning rates led to swift convergence, albeit accompanied by increased Q-value variability. Meanwhile, augmented exploration rates fostered deeper exploration at the risk of heightened exploitation. The discount factor and exploration decay rate exhibited a more tempered influence on the system. Notably, increased discount factors catalyzed broader long-term considerations but extended convergence times, whereas a heightened decay rate quickened convergence but curbed exploration. The data underscores the pivotal role of fine-tuning hyper-parameters in maximizing the performance of reinforcement learning recommendation models.

Our results elucidated the adaptability of the reinforcement learning model, which refined its Q-table based on user feedback, enhancing the accuracy and personalization of its recommendations. Impressively, it surpassed other systems in precision and user approval metrics. The emergent narrative suggests that reinforcement learning strategies, especially when synergized with user feedback, have the potential to redefine the recommendation system landscape, outshining conventional counterparts. In summation, this research illuminates the prowess of reinforcement learning in tailoring clothing suggestions based on pant descriptors. The system adeptly formulated strategies and showed agility in adapting to evolving user needs and data dynamics. Such systems, underpinned by reinforcement learning, stand poised to lead a transformative wave in the recommendation sector, promising further enhancements with advanced machine learning integration and optimal hyperparameter configurations.

This study's salient contributions are twofold: it showcased the merits of a reinforcement learning-driven clothing recommendation approach and elucidated the hyper-parameters pivotal to its performance. We further underscored the model's adaptability and superiority relative to other recommendation frameworks. Yet, it's pertinent to note the study's contextual limitations tied to its dataset and experimental design. Ensuing research endeavors might fruitfully expand the scope, tapping into expansive, diverse datasets. Prospective research trajectories could delve into the application of advanced strategies, like deep reinforcement learning, and integrating nuanced user-centric features into the recommendation algorithm. Exploring the prowess of such models across varied sectors, including film or musical suggestions, and juxtaposing them with established recommendation systems would be another insightful avenue.

VI. Possible Limitations

While this research offers pivotal insights into reinforcement learning-based recommendation systems, it's essential to recognize certain limitations. Primarily, our reliance on a specific dataset, encompassing a limited set of pant and shirt descriptions, might not truly capture the vast spectrum of clothing items and styles available. Additionally, our experimental blueprint centered predominantly on assessing hyper-parameter influences, sidelining exploration into other pertinent machine learning techniques or user-centric features such as demographics, personal preferences, or gender distinctions. A salient constraint was also the absence of real-world applicability tests; the system was not introduced to actual end-users for real-time evaluations. As a way forward, it would be instrumental for subsequent research to harness broader, more eclectic datasets and venture into genuine real-world testing environments. Despite these challenges, our study stands as a testament to the promising capabilities and inherent challenges of reinforcement learning in recommendation domains, signaling a promising avenue for deeper exploration.

VII. Conclusion

Our results showcase the power and precision of a reinforcement learning-based clothing recommendation system. Central to our exploration was the system's ability to craft recommendations rooted in pant descriptions. The results were telling: the system not only exhibited a proficiency in producing recommendations but also displayed a unique adaptability, deftly evolving to cater to new users and fresh data inputs. One of the more salient aspects of our research centered on the role of hyper-parameters. We discerned certain hyper-parameters, more than others, which significantly influenced the system's overall performance. Moreover, the realm of recommendation systems is often riddled with the challenge of ensuring personalization. Our findings suggest that reinforcement learning might very well be the answer to this conundrum. The ability of our system to curate tailored recommendations not only augments user experience but also hints at a paradigm shift in how recommendation systems could function in the future. In encapsulation, this study stands as a testament to the transformative potential of reinforcement learning in the domain of recommendation systems. Through our exploration, we've unearthed a confluence of accuracy, adaptability, and personalization, shedding light on the effectiveness and inherent strengths of such systems.

References

[1] B. Asiroglu, M. I. Atalay, A. Balkaya, E. Tuzunkan, M. Dagtekin, and T. Ensari, "Smart clothing recommendation system with deep learning," in *2019 3rd International Symposium on Multidisciplinary Studies and Innovative Technologies (ISMSIT)*. IEEE, Oct. 2019.

[2] S. Chakraborty, M. S. Hoque, N. Rahman Jeem, M. C. Biswas, D. Bardhan, and E. Lobaton, "Fashion recommendation systems, models and methods: A review," *Informatics*, vol. 8, no. 3, p. 49, Jul. 2021.

[3] Q. Deng, R. Wang, Z. Gong, G. Zheng, and Z. Su, "Research and implementation of personalized clothing recommendation algorithm," in *2018 7th International Conference on Digital Home (ICDH)*, 2018.

[4] N. Ali, M. R. Bonyadi, M. A. Raja, J. Akhtar, N. Javed, and C. Ryan, "Fuscd-future smart car driver," in *2019 22nd International Multitopic Conference (INMIC)*. IEEE, 2019, pp. 1–7.

[5] A. Z. Ijaz, R. H. Ali, A. Sarwar, T. A. Khan, and M. M. Baig, "Importance of synteny in homology inference," in *2022 17th International Conference on Emerging Technologies (ICET)*. IEEE, 2022, pp. 234–239.

[6] N. Ali, S. Ansari, Z. Halim, R. H. Ali, M. F. Khan, and M. Khan, "Breast cancer classification and proof of key artificial neural network terminologies," in *2019 13th International Conference on Mathematics, Actuarial Science, Computer Science and Statistics (MACS)*. IEEE, 2019, pp. 1–6.

[7] A. A. Khan, R. H. Ali, and B. Mirza, "Evolutionary history of alzheimer disease-causing protein family presenilins with pathological implications," *Journal of Molecular Evolution*, vol. 88, no. 8-9, pp. 674–688, 2020.

[8] M. H. Aslam, S. F. Hussain, and R. H. Ali, "Predictive analysis on severity of non-alcoholic fatty liver disease (nafld) using machine learning algorithms," in *2022 17th International Conference on Emerging Technologies (ICET)*. IEEE, 2022, pp. 95–100.

[9] D. K. Mohammad, R. H. Ali, J. J. Turunen, B. F. Nore, and C. E. Smith, "B cell receptor activation predominantly regulates akt-mtorc1/2 substrates functionally related to rna processing," *PloS one*, vol. 11, no. 8, p. e0160255, 2016.

[10] R. H. Ali, M. Bogusz, and S. Whelan, "Identifying clusters of high confidence homologies in multiple sequence alignments," *Molecular biology and evolution*, vol. 36, no. 10, pp. 2340–2351, 2019.

[11] R. H. Ali and A. A. Khan, "Tracing the evolution of ferm domain of kindlins," *Molecular phylogenetics and evolution*, vol. 80, pp. 193–204, 2014.

[12] R. H. Ali, S. A. Muhammad, M. A. Khan, and L. Arvestad, "Quantitative synteny scoring improves homology inference and partitioning of gene families," in *BMC bioinformatics*, vol. 14, no. 15. BioMed Central, 2013, pp. 1–9.

[13] Z. ul Abideen, T. A. Khan, R. H. Ali, N. Ali, M. M. Baig, and M. S. Ali, "Docontap: Ai-based disease diagnostic system and recommendation system," in *2022 17th International Conference on Emerging Technologies (ICET)*. IEEE, 2022, pp. 148–153.

[14] Y. Yang, S. Tu, R. H. Ali, H. Alasmary, M. Waqas, and M. N. Amjad, "Intrusion detection based on bidirectional long short-term memory with attention mechanism," *Computers, Materials & Continua*, vol. 74, no. 1, pp. 801–815, 2023.

[15] A. Z. Ijaz, R. H. Ali, N. Ali, T. Laique, and T. A. Khan, "Solving graph coloring problem via graph neural network (gnn)," in *2022 17th International Conference on Emerging Technologies (ICET)*. IEEE, 2022, pp. 178–183.

[16] K.-H. Liu, H.-L. Chuang, and T.-J. Liu, "Clothing recommendation based on deep learning," in *2022 IEEE International Conference on Consumer Electronics - Taiwan*. IEEE, Jul. 2022.

[17] Y.-R. Lin, W.-H. Su, C.-H. Lin, B.-F. Wu, C.-H. Lin, H.-Y. Yang, and M.-Y. Chen, "Clothing recommendation system based on visual information analytics," in *2019 International Automatic Control Conference (CACS)*. IEEE, Nov. 2019.

[18] H. Zhou, X. Liu, Y. Fang, and B. Zhang, "Research on the construction method of knowledge graph for clothing recommendation based on expert knowledge," in *2021 International Conference on Computer Information Science and Artificial Intelligence (CISAI)*, 2021.

[19] M. Yuan, I. R. Khan, F. Farbiz, S. Yao, A. Niswar, and M.-H. Foo, "A mixed reality virtual clothes try-on system," *IEEE Transactions on Multimedia*, vol. 15, no. 8, pp. 1958–1968, Dec. 2013.

[20] Q. Wu, P. Zhao, and Z. Cui, "Visual and textual jointly enhanced interpretable fashion recommendation," *IEEE Access*, vol. 8, pp. 68 736–68 746, 2020.

[21] Y. Lin, P. Ren, Z. Chen, Z. Ren, J. Ma, and M. de Rijke, "Explainable outfit recommendation with joint outfit matching and comment generation," *IEEE Transactions on Knowledge and Data Engineering*, vol. 32, no. 8, pp. 1502–1516, Aug. 2020.

[22] M. Mameli, M. Paolanti, R. Pietrini, G. Pazzaglia, E. Frontoni, and P. Zingaretti, "Deep learning approaches for fashion knowledge extraction from social media: A review," *IEEE Access*, vol. 10, pp. 1545–1576, 2022.