Reviewer 1:

Question: Please provide the latest updates on this work, specifically any industrial A/B testing results to validate its practical effectiveness.

Response:

Thank you for your valuable feedback. When researching recommendation algorithms for traditional existing products, we can easily conduct tests of practical effects in industrial scenarios on the JD.com platform. However, this work focuses on developing disruptive integrated new products, for which there are no existing market counterparts available for research team testing in industrial settings. Moreover, relying solely on the current algorithms is insufficient to complete the entire process from product design to production; it also requires coordination with supply chain management, product pricing, and other stages. Therefore, waiting to test in industrial scenarios after successful product development is impractical. Unfortunately, at this stage, we cannot provide any industrial A/B testing results to verify its practical effectiveness.

Regarding the latest progress of this work, our research primarily concentrates on a joint forecasting model for pricing and sales volume of personalized integrated products. This model aims to provide a scientific basis for pricing integrated products by deeply analyzing the comprehensive attribute value of products and the interaction between price and sales volume. Specifically, the model targets utilizing purchasing data from users within specific market segments to analyze the interactions among product attributes, prices, and sales volumes, predicting the optimal price points and sales volumes based on a new set of product attributes. This framework includes three levels: firstly, the data layer, which collects information on product attributes, prices, and sales volumes from segmented groups, serving as the foundation for model learning; secondly, the multi-task feature extraction layer, which converts product attributes into feature vectors of functional and non-functional attributes (through embedding or one-hot encoding), and further extracts features for predicting price points and sales volumes; and finally, the optimization layer, which involves constructing an overall objective function aimed at minimizing the error between price and sales volumes while maximizing total profit. This model not only explores the direct connections between integrated product attributes and their prices and sales volumes but also reveals the complex dynamic relationship between price and sales volume, offering insights for maximizing profit through pricing of integrated products. Additionally, considering that the new products being developed have no precedents in the market and all training data come from existing products, there is a significant domain shift problem. Therefore, we are committed to building an unsupervised domain adaptation regression model to enhance the framework's performance, currently engaging in related experiments through techniques like adversarial training. If this research is accepted by KDD and we obtain valid experimental results before the final submission, we will update these contents in the final version.

Question: Could you elaborate on JD.com's strategy for utilizing this work in real-world applications?

Response:

JD.com's strategy for applying this work in practical scenarios is divided into two main aspects:

Collaboration with Enterprises for Product Innovation: JD.com provides comprehensive support to partner companies in product design and marketing strategies. This includes insights from this work on the target consumer groups, necessary product features and specific attributes, as well as pricing and recommendation strategies currently under research. Based on these recommendations, the partner companies will complete the specific development and production of the products. Subsequently, JD.com will provide testing (such as trial distribution, feedback collection, etc.) and sales channels for these products to achieve mutual profitability.

Independent Design, Development, and Production Organization: Through its own brand "JD Jingzao" (JD Jingzao, a lifestyle brand by JD.com, launched on Jan 17, 2018, meets consumer needs with a one-stop shop for quality products across categories like appliances, kitchenware, home decor, personal care, beauty, food, and fresh produce, including production, sales, distribution, and after-sales), JD.com independently manages the entire cycle from product design and development to production. With a vast supply chain network, JD Manufacture is capable of independently completing the entire process from design to production, ensuring a smooth transition of products from concept to end-users and maximizing brand value.

Question: Kindly clarify if this work is publicly available for validating the claimed offline results.

Response:

Thanks for your comment. Below is the GitHub repository link:

https://github.com/bjtu19113032/code-for-Uncovering-Personalized-and-Integrated-Demands

The provided GitHub repository contains the source code and supplementary materials for the project "Uncovering Personalized and Integrated Demands." This repository offers the necessary tools and instructions for interested parties to replicate and validate the offline results presented in the study. By making the code and data publicly accessible, the authors facilitate transparency and encourage further research and verification by the scientific community. We also include this link in the paper as well.

We hope the above response meets your satisfaction. You can review the revised content in the latest manuscript, with the modifications highlighted in yellow (The revised paper and source code you can view at the following link: https://github.com/bjtu19113032/code-for-Uncovering-Personalized-and-Integrated-Demands). If you could increase the score, we would be immensely grateful.

Reviewer 2

Question: The methodology section (Section 3) lacks clarity. In Section 3.1, the authors delve into "user behavior sequence", "embedding of discrete features", "encoding and decoding", and a clustering algorithm with an outlier removal mechanism. These concepts are well-known. Most importantly, how these concept are tied to the concept of "Deep Customer Segmentation" left untouched. In Section 3.2, the authors discuss the second core component of their framework, "extracting integrated preferences", but the technical details remain vague.

Response:

Thanks for your valuable comment. We apologize for the confusion caused by the methods section. The essence of Deep Customer Segmentation is to cluster user behavior sequences. Therefore, "user behavior sequence," "embedding of discrete features," "encoding and decoding," and a clustering algorithm with an outlier removal mechanism are all designed to achieve suitable clustering results for this work. "User behavior sequence" and "embedding of discrete features" aim to convert user actions into information that deep learning models can understand. "Encoding and decoding" are used to obtain a low-dimensional representation suitable for traditional clustering algorithms (usually, deep learning needs to be combined with traditional clustering algorithms to complete deep clustering). A clustering algorithm with an outlier removal mechanism can cluster the low-dimensional representations of user behavior sequences, thus dividing users into multiple groups to achieve customer segmentation. The overall process is what constitutes Deep Customer Segmentation. We describe the roles of each component in Deep Customer Segmentation before section 3.1.1 in the latest article. To make it easier for readers to understand our article, we have provided a detailed model framework (Figure 1 in the latest manuscript) to illustrate the roles of each component in Deep Customer Segmentation. In addition, we have also provided pseudocode for Deep Customer Segmentation (Algorithm 1 in the latest manuscript). We hope the latest section 3.1 meets your satisfaction.

Regarding the lack of technical details in Section 3.2, we have supplemented the calculation principles in Subsection 3.2.1 in the latest submitted manuscript. Additionally, we have provided pseudocode for the technical execution processes for both Sections 3.2.1 and 3.2.2. Please refer to the latest manuscript for details. Furthermore, we have also provided GitHub link to the source code in the article. These additions are intended to help readers obtain more technical details and facilitate the replication of the methods. We hope these contents will meet your satisfaction.

Question: In the experiments (Section 4), the information seems jumbled, making it difficult to comprehend. The authors should provide a clear explanation of their methodology settings. For instance, the statement, "To ensure consistent variable control throughout the comparison, we kept the integrated product and attribute mining method unchanged," needs clarification. If space is a constraint, consider moving the implementation details to the appendix.

Response:

Thank you for your valuable comment. We apologize for the lack of clarity in Section 4 of our writing. To improve the readability of the article, we have done the following: 1) We have assigned third-level headings to Section 4 to make the purpose of each comparative experiment more clear. 2) After each third-level heading, we describe the specific settings of the comparative experiments in the experiment, such as which components in the proposed framework were changed to benchmarks, and which components were ablated for the ablation experiments. We hope that this work can enhance the readability of the article. You can review the revised content in the latest manuscript, with the modifications highlighted in yellow. The revised paper and source code you can view at the following link: https://github.com/bjtu19113032/code-for-Uncovering-Personalized-and-Integrated-Demands.

Question: Lastly, the paper does not appear to adhere to the KDD template. The references are disorganized; for example, [13] should be [22], [20] should be [25], [26] should be [4], etc.

Response: We apologize for the elementary errors in the literature citations. We have rechecked all the references and ensured that every citation is correctly formatted. Thank you for your diligent peer-review work. The revised paper and source code you can view at the following link: https://github.com/bjtu19113032/code-for-Uncovering-Personalized-and-Integrated-Demands. We hope that all our revisions significantly improve the quality of the article and meet your approval. If you could increase the score, we would be immensely grateful.

Reviewer 3

Question: No ablation study was conducted regarding the different components used.

The term "outlier" was frequently mentioned in the paper, but no results were shown with outliers included.

Response: Thank you for your valuable feedback. We have included additional ablation study results in the latest manuscript (Section 4.4). This section now features comparative results from the ablation experiments on the outlier removal mechanism in clustering, the clustering loss function, the preference loss function, and the mechanism for eliminating the shared sequence modes.

The paper lacked a detailed figure illustrating the methodology. Figure 1 is very general, making it difficult to follow the verbose methodology without a helpful figure.

Response: Thank you for your valuable feedback. We have re-provided Figure 1, and the current version of Figure 1 contains more technical details. In addition, we have provided a pseudocode for Section 3.1 and Section 3.2, respectively, please refer to Algorithm 1 and Algorithm 2. We hope that this content can help you and other readers to follow our article more easily.

All baselines are much weaker and simpler than the model. Is is due to the fact that this task is new?

Response: We are very grateful for your in-depth feedback. To effectively address the problem we have posed, this study has developed a multi-stage integrated framework that incorporates several key components, including deep clustering, sequential pattern mining, and attribute selection. As you have pointed out, due to the innovative nature of our research task, there are no readily available benchmark methods in the existing literature specifically designed for this kind of task. Therefore, the baseline models we have selected only implement part of the functionality of our framework and must be used in conjunction with other components to complete the entire task, which makes their structural design relatively simple. Furthermore, our evaluation process needs to consider multiple performance indicators, including clustering effectiveness and the probability of user attribute selection, which is extremely challenging for baseline models. As a result, all baseline models are weaker when dealing with this specific task.

I think the paper is in the right direction. Technical figures and verbosity are the main issues I faced.

Response: We hope that the modifications can address the issues related to the technical figures and verbosity, thereby enhancing the quality of this paper. You can review the revised content in the latest manuscript, with the modifications highlighted in yellow. The revised paper and source code you can view at the following link: https://github.com/bjtu19113032/code-for-Uncovering-Personalized-and-Integrated-Demands. If you could increase the score, we would be immensely grateful.