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Enhancing Perceived Transparency and Purchase Decisions through Explanations in Personalized Product Recommendations

Ene U.M., Bakpo F.S., Ebem D.U., Udanor C.N. & Eneh A.H.
[1,2,3,4, 5] Department of Computer Science
Faculty of Physical Sciences
University of Nigeria, Nsukka
E-mail: [1]eneugochukwumaduka2@gmail.com, [2]francis.bakpo@unn.edu.ng,
[3] deborah.ebem@unn.edu.ng, [4]collins.udanor@unn.edu.ng, [5]agozie.eneh@unn.edu.ng
Phone: +2348037690890

ABSTRACT

The increasing adoption of artificial intelligence(AI) in financial services has raised concerns about the transparency of product recommender systems. This study investigates how explanations in personalized product recommendations influence users' perceived transparency and purchase decisions to help customers make informed decisions and improve product adoption. This research builds on concepts from Explainable Artificial Intelligence (XAI) and Dual-Process Theory. It draws from these theories to understand how users respond to financial product suggestions and how explanations support decision-making. The methodology adopted a comparative experimental design with a within-subject approach. Participants from different backgrounds interacted with the system versions. Structured questionnaires were administered to gather responses on perceived transparency and purchase decisions using a 5-point Likert scale. Statistical analysis included descriptive statistics and the Mann-Whitney U test. Results revealed that users perceived the Personalized Product Recommender (PPR) system with explanations as significantly more transparent ($U_1 = 2279.5$, $U_2 = 2837$, $U_3 = 3192$, $p < 0.05$) and were more likely to act on the recommendations ($U = 2889$, $p < 0.05$). Explanations improved transparency and trust, supporting informed purchase decisions. This research provides insight for designing transparent, user-aligned financial recommender models, which implies improved customer experience strategies and AI decision support. This study presents a working explanation framework with real user evaluation, revealing its value for advancing transparency in financial services.

Keywords: Personalized Product Recommender(PPR) System, Transparent explanations, Decision-making, Artificial Intelligence(AI) in Financial Services, Explainable Artificial Intelligence(XAI).

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1. INTRODUCTION

As of 2024, the number of active internet users worldwide stood at 5.52 billion, representing over two-thirds of the global population, a significant rise from 50.2% a decade ago (Petrosyan, 2024). Similarly, the number of adults with access to a bank account has increased by 50% worldwide over the past ten years (Degenhard, 2024). As digital banking adoption grows, financial institutions rely on intelligent applications to provide personalized recommendations for financial products, helping customers make informed decisions about banking products and improve their overall experiences. These applications utilize artificial intelligence (AI) to analyze user behaviours and preferences and recommend bank products such as credit and debit cards, loans, and investment options. The critical challenge in using these applications is the users' ability to understand the reason behind product recommendations due to lack of transparency in the process of arriving at suggestions.

Explainable AI (XAI) has emerged as a solution to address the "black-box nature" of these systems. XAI builds fair, transparent, and interpretable models, ensuring users understand the reason for specific recommendations. It helps users make informed decisions, empowers individuals to address the risks associated with automated decisions, boosts users' trust and confidence by developing reliable AI-recommended products, and upholds the right to explain AI decisions (Guidotti et al., 2018). Explainable AI is crucial in the financial services industry, where uninformed decisions can result in poor financial outcomes. Providing explanations in Personalized Product Recommender (PPR) systems can improve customers' perception of recommendation transparency, increasing their willingness to act on suggested financial products.

While research on recommender systems has explored personalization techniques and accuracy, researchers have not given much attention to the role of explanations in financial product recommendations and their impact on perceived transparency and purchase decisions. Personalized Product Recommender (PPR) Systems leverage data from users' interactions, such as ratings, demographics, and digital traces gathered during their daily activities (e.g., web searches, movement, social media activity, and transactions) - to provide product recommendations (Ricci et al., 2015; Rastogi & Vijendra, 2016). Despite their growing adoption in banking, users often struggle to trust recommendations due to the lack of transparent explanations. The lack of clarity affects decision-making and reduces engagement with the recommended products, portraying the need to include explanations in Recommender systems.

For financial institutions, integrating transparent explanations into PPR systems is essential for enhancing customer trust and decision-making. Customers need to understand the reason for recommending a product to make informed choices. This study investigates the impact of explanations on perceived transparency and purchase decisions in PPR systems, contributing to the knowledge of explainable AI in financial services. It focuses on two (2) key research questions: (1) How do explanations in a PPR system enhance customers' perception of recommendation transparency? (2) To what extent do explanations in a PPR system influence customers' decision-making and willingness to purchase financial products?

We examine the impact of explanations on perceived transparency and decision-making in financial product recommendation using live experimental evaluation with human subjects. Our findings contribute to the growing body of knowledge of personalized recommender systems in banking, offering valuable insights for financial institutions to enhance customer engagement and trust through personalized recommendations accompanied by explanations. Section 2 outlines the theoretical framework supporting the study. Section 3 details the methodology applied, including the evaluation approach. Section 4 presents a summary of the key findings. Finally, Section 5 concludes the study by summarizing its contributions, limitations, and directions for future research.

2. THEORITICAL FRAMEWORK

2.1 Recommender Systems

Recommender systems are software tools and methodologies that suggest personalized items to customers based on their interests and preferences (Ricci et al., 2015). The systems help customers discover products they might not have found independently, making them valuable in domains like finance with various products, but where customers are interested in only a fraction of them. Recommender systems are valuable in domains with a large variety of items, but the users are interested in a small fraction of the items. Products, also referred to as “items”, describe what the system recommends to users, while “users” or “customers” are the individuals who benefit from the recommendation process. The products are usually ranked based on the customers’ preferences.

2.1.1 Benefits of Personalized Recommender Systems

Personalized Recommender systems serve customers and organizations by improving customer satisfaction, sales process and volume. For customers, recommender systems offer high-quality, tailored product lists and highlight and sort valued products according to preferences. Organizations promote awareness, increase sales of unknown and underexplored products, build customer loyalty, and ensure a better understanding of customers’ needs. They assist customers in discovering products that match their preferences, ensuring credible recommendations, and enabling feedback on suggestions.

2.1.2 Recommendation Techniques

Recommendation tasks can be carried out in various ways, referred to as “techniques”. Recommendation techniques include content-based approaches, which identify product features similar to those a user has previously bought or liked, offering user independence, transparency and adaptability but experiencing challenges like overspecialization, limited content analysis, rating and extension capacity. Collaborative filtering recommends products based on preferences of similar customers or products, with easy-to-implement and efficient memory-based methods adopting existing customer-product data and more extensive model-based methods requiring predictive algorithms; however, it suffers from limited coverage and cold start problems, and the model-based approach requires more resources to train data. The demographic technique considers users’ demographics such as age, gender, occupation, or income, offering speed, cold-start problem resolution, enhanced user preference and real-time prediction but suffers less personalization when relying on shared attributes due to privacy and security concerns.

Knowledge-based systems generate recommendations by explicitly matching product features to the customers' needs and preferences without requiring previous ratings. However, they need up-to-date domain knowledge to be accurate. The community-based technique leverages social networks and friends' preferences to provide recommendations, notwithstanding data privacy concerns, data migration across networks, and complex handling of stream data. Hybrid techniques combine two or more approaches, leveraging the strength of one technique to overcome the disadvantage of another technique for better performance.

2.2 Recommender Systems in Banking

Recommender systems are used in the banking sector to suggest products, such as accounts, loans, investment plans, money transfer services and digital solutions. While Personalized Product Recommender(PPR) systems are gaining traction, their development in finance remains an evolving research area. These systems integrate various technologies to enhance customer decision-making and engagement. However, despite advancements in Machine Learning and Hybrid Recommender techniques, the role of explanations in enhancing transparency and purchase decisions remains an underexplored research area.

More studies have focused on optimizing recommendation accuracy in banking. Met et al. (2024) presented an ML-based SME recommender system that clusters customers in segments based on transaction patterns and provides specific recommendations, reducing customer churn. Nieves et al. (2020) proposed a fog computing solution integrating a predictive model with case-based reasoning(CBR) to enhance personalized recommendations. Oyebode and Orji (2020) adopted a hybrid approach that combines transaction data and demographic profiles to improve recommendation accuracy and support decisions. Gigli et al. (2017) applied clustering and network analysis to expand customer preferences by introducing new products based on clustering and network analysis, supporting investors' decisions. However, they did not measure how explanations can influence customer decisions. Nieves (2021) proposed a methodological framework to improve customers' decision-making by personalizing recommendations to user-specific profiles but did not explicitly discuss how transparency or explanations influence decision-making.

While prior research has explored personalization techniques, the impact of transparent explanations on perceived transparency and purchase decisions has received limited attention in financial product recommendations. Unlike domains such as healthcare and e-commerce, where explainable AI(XAI) has been integrated into recommender systems, the banking sector still lacks empirical studies showing how explanations influence customer decision-making and willingness to use the recommendation. This study addresses the gap by investigating the role of explanations in enhancing perceived transparency and purchase decisions in PPR systems.

2.3 Explaining recommendations

Explanations are pieces of information that clarify the recommendations made to users. These explanations make the decision-making process more understandable and transparent while addressing the "why" behind the recommendation (Zhang & Chen, 2020).

2.3.1 Importance of Explanations

Explanations bridge the gap between the systems' complex algorithms and the end-user's understanding. Explanations improve user satisfaction by making customers feel more informed and in control of their decisions. Explanations enhance transparency, enable scrutability, ensure validity, build trustworthiness, and educate customers. They support multiple objectives such as effectiveness, persuasiveness, efficiency, relevance, and satisfaction (Tintarev & Masthoff, 2015). For example, explanations can persuade customers to consider new products and consider trade-offs in decision-making for better choices. For system designers, explanations help with improved system debugging, model refining and identifying areas of improvement (Zhang & Chen, 2020).

2.3.2 Key Aspects of Explanations

Explanations should focus on key aspects of recommendations, such as product features matching user preferences and similar users' behaviour (Zhang & Chen, 2020). For the customers, transparent explanations should focus on product features and benefits (attributes or characteristics that define its functionality, aesthetics, outcome, value and appeal), justification (reason and rationale behind a recommendation showing its relevance, facts, preferences and transparency) and how to get the product (application process, eligibility, closing, requirements, support and other vital information on obtaining the product). It could include the internal workings of the system to assist system designers and analysts. Table 1 illustrates the Mortgage loan, showing the features, benefits, justification, and how to get the product.

Table 1 Features, Benefits, Justification

Category	Components	Explanation
Features and Benefits	Functionality	**Loan purpose:** Financing for outright purchase, refinancing or construction of residential properties. **Flexible repayment:** Maximum tenor of twenty (20) years, subject to retirement age. **Equity contribution:** Minimum equity contribution of 30% based on your location. **Loan disbursement:** Disbursed in tranches to align with project stages,
	Aesthetic	**Streamlined Process**: The Legal and documentation process is seamless and secure. **Location-based benefits:** The location determines the terms and benefits.

Features and Benefits	Components	Explanation
	Outcome	**Property ownership:** Your goal of owning a property can be achieved quickly. **Flexibility:** Existing mortgages can be refinanced with favourable terms.
	Value	**Affordable repayment:** The repayments are favourable and capped at 35%. No down payment is required for refinancing. **Large loan amounts:** You can obtain up to ₦50,000,000.
	Appeal	**Convenience**: You can consider location-based flexibility and refinancing options. **Fitness:** It demonstrates the target market the customer fits, such as “It is designed for individuals like you in paid employment.”
Justification	Relevance	It demonstrates why this product is fit for the customer, such as “It is suitable for first-time buyers like you.”
	Facts	It shows logical reasoning, such as “Customers with similar profiles and same location experienced a 92% approval rate.”
	Preferences	It is tailored to the customer’s specific needs and circumstances, such as “Your preference for affordable housing loan matched with this product.”
	Transparency	Clear Terms details the loan terms, fees, interest rates and policies. For example, “the mortgage includes a 15% annual interest rate with no hidden charges.”
How to get the product	Application process	It details how to apply for the loan.
	Eligibility	It defines the eligibility of the customers for the product.
	Requirements	It provides details of the requirements needed to apply for the product. For example, customers will need a certificate of good title, a survey plan, and a valuation report.
	Closing	It details how to close the process of obtaining the product.
	Support	It provides details of support to offer detailed walkthroughs of the process.

2.3.3 Explanation Styles

Recommendation explanations can be presented in different styles, such as textual explanations, which are explanations displayed in the form of sentences or phrases; visual explanations, which use text images and highlight features that portray the users' preferences on the image or product features visually using charts, graphs, and other images; feature-based explanations, which are based on product features that match customers' preferences; social explanations based on social connections with similar preferences in the same category or products subset and hybrid explanation style combining multiple explanation styles. Table 2 illustrates the different explanation styles for a Mortgage loan.

Table 2 Illustration of Explanation Styles for Mortgage Loan Recommendations

S/n	Explanation Style	Example
1	Textual	"We recommend a mortgage loan because it matches your income and preferred repayment term of 20 years."
2	Visual	"This bar graph shows that your monthly income of ₦500,000 can accommodate a mortgage loan of ₦48M with a maximum repayment of ₦200,000(40% of your income)."
3	Feature-based	"Based on your preferences, the mortgage loan offers flexible repayment options, allowing you to pay off the loan without penalties."
4	Social	"85% of first-time home buyers in your connection prefer flexible repayment options."
5	Hybrid	"This mortgage loan is recommended because of your interest in a mortgage. Also, the interest rate of 15% is lower than your current credit card debt rate of 25%."

2.3.4 Timing of Explanations

Explanations are provided before or during the decision-making process, such as when presenting recommendations, after or upon customer request, to ensure timely and accurate choices.

2.4 Decision-Making and Cognitive Processing

Decision-making is a cognitive process that influences how individuals evaluate and act on recommendations. The dual-process theory of cognition identifies two types of cognitive processing (Evans & Stanovich, 2013). Type 1 processing is fast, automatic, intuitive, and heuristics-based, allowing individuals to make quick decisions with minimal cognitive effort. This approach is used in everyday decision-making, where intuition plays a significant role, and the justification follows later. The post-hoc explanation approach adopts the type 1 process, which makes a recommendation and then offers an explanation independent of the recommendation mechanism. In contrast, type 2 interaction is slow, deliberate, rule-based, analytical, and can handle complex tasks. It includes detailed and logical reasoning, allowing individuals to make decisions based on careful logical reasoning, and showing step-by-step processes of arriving at those decisions. This interaction type corresponds to the model intrinsic approach in recommender systems, where the recommendations and explanations are interconnected.

Explanations integrated into recommender systems help users understand what is recommended, why it is relevant, how it aligns with their needs, and when to act on the recommendation. Overall, providing clear explanations can lead to improved adoption of personalized recommendations.

2.5.1 Explanation framework

The decision process begins with a task (e.g. a customer doing a transaction and a recommendation popping up or a customer asking for a recommendation). The PPR system with explanations, as shown in Figure 1, comprises a recommender model with an explanation module that generates recommendations and offers transparent explanations, enabling customers to make informed decisions. The customer's decision and evaluation are fed into the system to improve future recommendations and explanations.

3. METHODOLOGY

What follows is the methodology framework for this research.

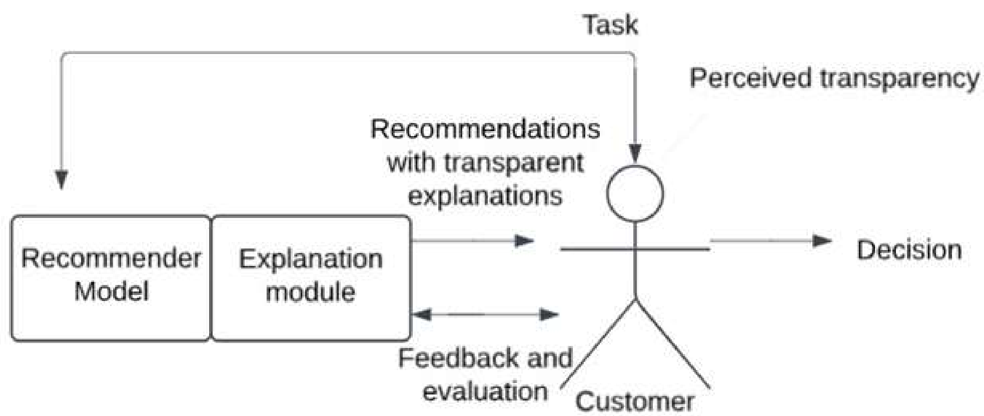

Figure 1: PPR System with A Transparent Explanation Framework

The methodology adopted for this research comprises a comparative experimental design aimed at evaluating the influence of explanations in a Personalized Product Recommender (PPR) system. The study involved a within-subject approach, where the same participants interacted with two versions of the system—one with explanations (PPRE) and another without (PPR). The survey was incorporated into the recommender system to perform an experimental evaluation. It was administered to both staff and customers of various financial institutions. A total of 170 invitations were sent, but 135 responses were received for the PPR system, and 148 responses were received for the PPR system with explanations. The respondents were 18-70 years old and represented various professional backgrounds, including 13% financial sector employees, 24% other professionals, 23% traders/entrepreneurs, 18% civil servants, and 22% students.

As part of the survey, respondents were provided with: (1) a description of the PPR system with details of onboarding and navigating the system. (2) a link to the system application. (3) a survey assessing the evaluation constructs of ‘perceived transparency’ and decision-making based on it. The participants assess two systems: the PPR system with transparent explanations and the PPR system without explanations. They are onboarded with a privacy data policy, which must be accepted before they can assess the system. Secondly, the participants are required to provide demographic information about themselves. The system automatically detects some information, like location. The system provides recommendations and offers transparent explanations. Lastly, participants are provided with survey statements on a 5-point Likert scale to evaluate the perceived transparency and the
impact on decision-making (See Table 3). This process is repeated for the PPR system without explanations.

Table 3: Survey items, Item measurement and literature references evaluating the recommender system from a user perspective

Item Number	Survey Item	Item measurement	Literature reference
1	The PPR system clearly explains the reasons behind its recommendations in a way that is easy to understand.	Perceived Transparency	(Hellmann et al., 2022)
2	I have been provided with sufficient and clear information about the product's pricing, features, and benefits	Perceived Transparency	(Hellmann et al., 2022)
3	The information the system provides is relevant to my preferences, needs and lifestyle.	Perceived Transparency	(Hellmann et al., 2022)
4	The information provided by the PPR system is precise and sufficient to make an informed decision.	Impact of perceived transparency on purchase decision.	

4. RESULTS AND DISCUSSION

Raw data were downloaded from the PPR systems in CSV format and uploaded to the Statistical Package for the Social Sciences (SPSS) platform for analysis. We first used SPSS to calculate the descriptive frequencies table (See Table 4).

Table 4: Descriptive statistics for the PPR systems

System	Transparency1		Transparency2		Transparency3		Purchase decision	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
PPR	2.61	1.016	2.70	0.972	2.93	0.878	3.01	0.763
PPR with explanation	4.38	0.936	4.26	0.999	4.26	0.970	4.34	0.953

The mean transparency and purchase decision scores show a clear trend where the PPR system with explanations scores higher than the PPR system (Figures 2 and 3). The standard deviations indicate that the scores are closely clustered around the mean for the PPR system, with explanations compared to the other system.

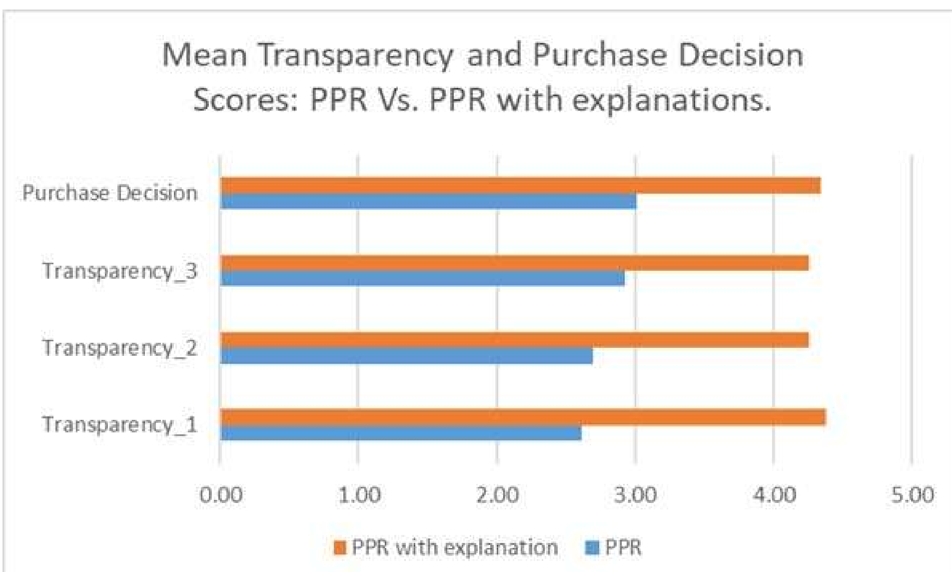

Figure 2: Mean transparency and purchase decision scores for the PPR systems

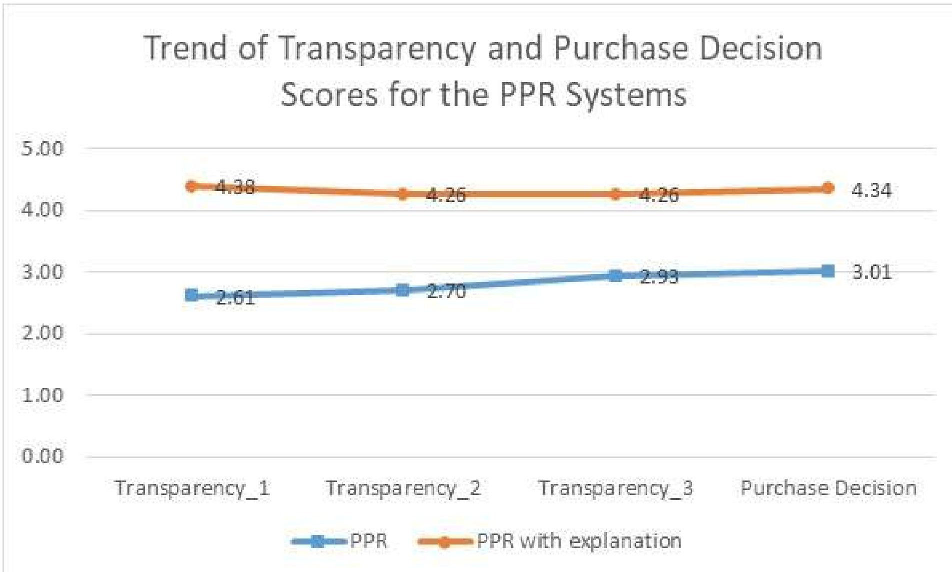

Figure 3: Trend of Transparency and Purchase Decision scores for the PPR systems

We performed a non-parametric Mann-Whitney U test to test our hypothesis, considering the ordinal nature of the Likert scale data, non-normal distribution, and unequal group sizes. The null hypothesis (H_0) is that there is no significant difference in perceived transparency and purchase decisions between users of the PPR system with explanations and those without explanations, while the alternative hypothesis (H_1) is that a higher proportion of users of the PPR system with transparent explanations will perceive the system as more transparent and make purchase decisions based on perceived transparency significantly more than those without explanations.

The results, as shown in Table 5, indicated that the perceived transparency in the PPR system with explanations (Median rank =194.10) was significantly higher compared to the PPR system without explanation (Median rank =84.89) for Transparency_1, $U = 2279.50$, $Z = -11.563$, $p < .001$. Similar significant differences were found for Transparency_2 ($U = 2837.00$, $Z = -10.713$, $p < .001$) and Transparency_3 ($U = 3192.00$, $Z = -10.216$, $p < .001$), indicating that users found the system more transparent when explanations were provided.

The purchase decisions were also significantly higher for users of the PPR system with explanations (Median rank = 189.98) compared to those of the PPR system without explanations (Median rank = 89.40), $U = 2889.00$, $Z = -10.799$, $p < .001$, indicating that transparent explanations positively influenced users' decisions to request the recommended product. The large z-values (-10.216 to -11.563) confirm substantial system differences. There are statistically significant differences between the p-values of the systems. Since $p<0.05$, we reject the null hypothesis and conclude that the system with explanations has significantly different scores than those without explanations.

Table 5 Comparison of User Perceptions Between PPR Systems using Mann-Whitney U Test

Variable	PPR system (N=135) Mean Rank	PPR system with explanations (N=148) Mean Rank	Mann-Whitney U	Wilcoxon W	z-score	p-value(2-tailed)
Transparency_1	84.89	194.10	2279.500	11459.500	-11.563	0.000
Transparency_2	89.01	190.33	2837.000	12017.000	-10.713	0.000
Transparency_3	91.64	187.93	3192.000	12372.000	-10.216	0.000
Purchase Decision	89.40	189.98	2889.000	12069.000	-10.799	0.000

5. CONCLUSION

The study examined the impact of transparency in a Recommender system by comparing user feedback between a Personalized Product Recommender (PPR) system and a PPR system enhanced with transparent explanations. The findings indicate that users who interacted with the PPR system with explanations perceived it as more transparent and were more likely to make a purchase decision based on this perceived transparency. The results highlight the relevance of incorporating transparent explanations into recommender systems, particularly in financial services, where trust and informed decision-making are critical for customer retention. While this study assessed users' perceived transparency and its influence on decision-making, future research will examine additional factors such as user satisfaction and persuasiveness. Understanding how explanations affect these factors will provide more insights into how recommender systems can enhance customer engagement and product adoption.

This work contributes fourfold. First, it provides a structured framework for incorporating transparent explanations into a Personal Financial Recommender System (PFRS), showing the key aspects that should be prioritized. The framework contributes to the existing body of knowledge on personalized product recommendations. Second, the study empirically validates how transparent explanations influence user perception and decision-making from a user perspective, specifically through the constructs of perceived transparency and purchase decisions. This validation extends the understanding of recommender systems within the domain of information systems. Third, unlike many studies that rely on simulated data, this research conducted a live experimental evaluation within an operational financial recommender system. This approach ensures the findings apply to real-world banking and financial service contexts. Lastly, this study bridges the gap between Artificial Intelligence(AI) research and financial services, showing how transparency mechanisms can be integrated into the Personal Finance Recommender (PFR) system without compromising efficiency and effectiveness.

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