EXPLORING THE INTEGRATION OF PERSONALIZED PRODUCT RECOMMENDATIONS IN OMNICHANNEL STRATEGIES IN THE INDIAN BUSINESS-TO-CONSUMER E-COMMERCE MARKET

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Abstract

The growth of the Indian Business-to-consumer e-commerce market has intensified competition, prompting businesses to seek innovative strategies for customer engagement and retention. Notably, the integration of personalized product recommendations within the omnichannel framework has become a focal point for businesses aiming to enhance customer engagement and satisfaction. This research delves into the multifaceted impact of personalized recommendations, aiming to assess their effectiveness in augmenting customer engagement, ensuring cross-channel consistency, and improving overall satisfaction levels. Additionally, the study probes into the challenges associated with data collection, real-time integration, and data security implications inherent in the implementation of personalized recommendations. Utilizing a quantitative research methodology and structured questionnaires as the primary data collection tool, the survey aims to quantify the factors that influence the acceptance of personalized recommendations to provide comprehensive insights and recommendations for refining personalized recommendation strategies in omnichannel e-commerce settings, particularly within the unique context of India's diverse and rapidly evolving digital market.

Keywords: Business-To-Consumer, E-Commerce, Omnichannel Strategy, Personalized Product Recommendations.

1. INTRODUCTION

The digital transformation of the global business landscape has ushered in a paradigm shift in consumer engagement strategies, with a particular emphasis on the integration of omnichannel frameworks in the e-commerce sector. This shift is even more pronounced in emerging markets like India, where rapid technological advancements and burgeoning internet penetration have catalyzed the growth of the business-toconsumer (B2C) e-commerce market. One of the pivotal shifts in this domain is the adoption of omnichannel strategies, which aim to provide a seamless and enriched shopping experience across various touchpoints, between online and offline retail channels. Central to the success of omnichannel strategies is the integration of personalized product recommendations, which have emerged as a potent tool for redefining customer engagement, driving sales, and fostering brand loyalty (Chen et al., 2020; Gupta and Kim, 2020). Personalized product recommendations represent a confluence of data analytics, machine learning algorithms, and consumer behaviour insights aimed at delivering tailored shopping experiences to individual consumers. These recommendations leverage vast datasets to predict and present products that resonate with consumers' preferences, purchase history, and browsing behaviour. thereby enhancing engagement, driving conversions, and fostering brand loyalty (Chen et al., 2020; Gupta & Kim, 2020).

In the context of India's diverse and rapidly evolving B2C e-commerce landscape, the integration of personalized product recommendations within omnichannel strategies presents both unprecedented opportunities and intricate challenges. The vast and varied consumer base in India, characterized by varying demographic profiles, cultural nuances, and purchasing behaviours, adds layers of complexity to the deployment and optimization of personalized recommendation systems (Narayana & Ramesh. 2018). While personalized recommendations hold the promise of resonating with individual consumer preferences, thereby enhancing engagement, conversion rates, and customer loyalty, their successful implementation depends upon several critical factors. These include effective data collection methodologies, seamless real-time integration across multiple channels, and robust data security measures to safeguard consumer privacy. The effectiveness of personalized recommendations hinges on several critical factors, including but not limited to, data collection methodologies, algorithmic accuracy, real-time integration capabilities, and most critically, data privacy and security protocols. As personalized recommendation systems become increasingly sophisticated, the ethical considerations surrounding data usage, transparency, and consumer consent become paramount, particularly in jurisdictions with evolving data protection regulations like India (Smith & Telang, 2021).

Furthermore, the integration of personalized recommendations within omnichannel frameworks necessitates seamless coordination across various touchpoints, encompassing online platforms, mobile applications, physical stores, and customer service channels. This integration aims to provide a cohesive and enriched shopping journey, allowing consumers to transition effortlessly between channels while maintaining continuity in their shopping experience (Verhoef et al., 2015).

This research embarks on an in-depth exploration to assess the multifaceted impact of integrating personalized product recommendations within India's e-commerce ecosystem. The study would try to critically evaluate the effectiveness of personalized recommendations in enhancing customer engagement and driving sales within the omnichannel environment. Aims to gauge the broader impact of personalized recommendations on cross-channel consistency, customer satisfaction, and loyalty, shedding light on their role in shaping the overall customer journey. Also to rigorously scrutinize the challenges and implications associated with the seamless integration of personalized recommendations, focusing on privacy concerns, data security issues, and the evolving regulatory landscape governing data usage and consumer rights in India's digital economy. To achieve these objectives, the research adopts a quantitative research design, leveraging structured questionnaires as the primary instrument for data collection. By systematically analyzing the collected data, the study aims to furnish actionable insights and evidence-based recommendations. These insights are envisioned to serve as a strategic compass, guiding e-commerce stakeholders, including retailers, marketers, and technology providers, in calibrating their personalized recommendation strategies and navigating the complex terrain of data privacy and security in omnichannel e-commerce environments.

1.1 Purpose of the Study

The purpose of this study is to investigate the impact of integrating personalized product recommendations in the omnichannel framework in Indian e-commerce market. Additionally, the study explores challenges like privacy and data security

implications. Insights from this research aim to optimize personalized recommendation strategies in omnichannel e-commerce settings.

1.2 Research Gaps

The existing literature on the integration of personalized product recommendations as an omni-channel strategy in the Indian Business-to-consumer e-commerce market reveals several research gaps and scope for further research exploration. A few research studies from Western markets have examined the effectiveness of personalized product recommendations and omni-channel strategies, yet there is a need to investigate how these strategies adapt to the unique cultural and socioeconomic context of India (Verhoef, Kannan, and Inman, 2015). The Indian ecommerce market is marked by linguistic diversity, varying levels of internet literacy and diverse consumer behavior, making it essential to explore how omni-channel personalization strategies are received and adapted by Indian consumers. While large players in the Indian e-commerce market have the resources to implement sophisticated omni-channel strategies, there is a research gap concerning the adoption and impact of such strategies on SMEs (Narayana and Ramesh, 2018). Investigating how personalized recommendations can benefit or pose challenges to smaller e-commerce businesses can provide valuable insights for this segment. Cross-Border Dynamics: With the rise of cross-border e-commerce in India, there is a need to explore how omni-channel personalization affects international transactions and interactions with global customers (Jain and Palvia, 2020). This includes understanding how recommendations are tailored for cross-border customers and whether they enhance or hinder the cross-border shopping experience. An emerging research area is the examination of the relationship between omni-channel strategies. personalized recommendations, and sustainable consumption behavior in the Indian market (Gupta and Kim, 2020). Research could investigate how personalized recommendations can encourage eco-friendly shopping choices and contribute to sustainable e-commerce practices. While some studies have explored the impact of omni-channel strategies on customer retention and satisfaction, there's a research gap in understanding how personalized recommendations specifically influence customer lifetime value in the Indian context (Singh and Jain, 2019). Examining the long-term financial implications of such strategies can provide valuable insights for e-commerce companies. An area that warrants further exploration is the comparison of omnichannel e-commerce, including personalized recommendations, with traditional brickand-mortar retail in India (Dholakia and Zhang, 2014). Understanding how these strategies affect consumer preferences and choices between online and offline channels can be insightful. With technology continually evolving, research should investigate the role of emerging technologies such as artificial intelligence, augmented reality, and virtual reality in enhancing personalized recommendations within an omnichannel framework (Verhoef et al., 2015). As personalized product recommendations heavily rely on customer data, there is a critical research gap in understanding consumer attitudes and concerns regarding data privacy and security in the Indian ecommerce landscape (Bapna et al., 2008). Research should delve into how these concerns impact consumer trust and willingness to engage with personalized recommendations. These refined research gaps provide a comprehensive overview of areas where further investigation is needed in the context of personalized product recommendations and omni-channel strategies in the Indian Business-to-consumer ecommerce market.

1.3 Research Questions

- 1. How does integrating personalized product recommendations within the omnichannel framework affect the e-commerce customer experience?
- 2. What are the implications of personalized product recommendations on customer engagement and satisfaction in the omnichannel environment, considering challenges like privacy and data security?

1.4 Research Objectives

- 1. To investigate the effectiveness of integrating personalized product recommendations within the omnichannel framework in the Indian e-commerce context.
- 2. To assess the impact of personalized product recommendations on enhancing customer engagement, cross-channel consistency, and overall customer satisfaction within the omnichannel environment.
- 3. To explore the challenges and implications, including privacy and data security concerns, associated with the seamless integration of personalized product recommendations within the omnichannel framework, aiming to provide insights for optimizing the e-commerce customer experience.

2. LITERATURE REVIEW

The Indian e-commerce market has witnessed remarkable growth in recent years, emerging as one of the most vibrant and rapidly expanding sectors in a country's economy (Smith, 2021). This growth can be attributed to several key factors that have reshaped the digital landscape, including the proliferation of internet connectivity, accelerated smartphone adoption, and the continuous evolution of consumer preferences and behaviours (Kumar and Rahman, 2020). With an increasing number of consumers turning to online platforms for their shopping needs, e-commerce companies are navigating an increasingly competitive and dynamic environment (Singh and Gupta, 2019). The need to differentiate and provide value-added services has become paramount, prompting businesses to innovate and adopt new strategies to capture and retain customer attention (Verma and Gupta, 2021). In this dynamic landscape, e-commerce companies are actively seeking strategies to enhance customer engagement and drive sales. One such strategy that has gained prominence is the integration of personalized product recommendations within an omni-channel framework. The integration of personalized product recommendations within an omnichannel framework has emerged as a strategic imperative for e-commerce companies aiming to enhance customer engagement, drive sales, and foster longterm lovalty (Gupta and Kim. 2020: Sharma and Sheth. 2020). Omnichannel strategies enable businesses to create seamless and integrated customer experiences across multiple channels, bridging the gap between online and offline interactions (Choudhary and Sabharwal, 2021). Personalized product recommendations leverage advanced data analytics and machine learning algorithms to deliver tailored content and offers to individual customers based on their preferences, browsing history, and purchase behaviour (Jain and Singh, 2020; Patel and Patel, 2019). By providing relevant and timely recommendations, e-commerce companies can significantly enhance the shopping experience, increase conversion rates, and foster customer satisfaction and loyalty (Narayana and Ramesh, 2018; Verhoef et al., 2015).

2.1 Omni-channel Strategy in E-commerce

Omni-channel strategy is characterized by a multi-channel approach that aims to provide customers with a seamless and integrated shopping experience across various touchpoints, including online stores, mobile apps, physical stores, and social media platforms (Verhoef et al., 2019). Unlike traditional multichannel strategies that operate in silos, omnichannel personalization integrates various channels—online and offline—to create a cohesive and consistent customer journey (Lemon and Verhoef, 2016). This create a unified and cohesive customer journey, wherein each interaction is tailored to resonate with the customer's unique profile and expectations (Li et al., 2019; Chen et al., 2020). At its core, omnichannel personalisation embodies the convergence of technology, data analytics, and customer-centricity, aimed at fostering deeper connections and enhancing engagement with customers (Wang et al., 2021; Gupta and Kim, 2020). It acknowledges the dynamic nature of customer preferences and behaviours, advocating for agile and adaptive strategies that evolve in tandem with shifting market dynamics and consumer expectations (Huang et al., 2019; Jannach et al., 2015). Furthermore, omnichannel personalisation underscores the importance of consistency and coherence across all customer touchpoints, reinforcing brand identity and trust by delivering consistent messaging, offers, and experiences (Liu et al., 2018). This integrated approach not only enhances customer satisfaction and loyalty but also drives business performance by maximising conversion rates and fostering long-term customer relationships (Gupta and Kim, 2020). Omnichannel personalization represents a transformative approach to customer engagement, encompassing the integration of data analytics, technological advancements, and customer-centric strategies to deliver personalized and cohesive experiences across various channels (Narayana and Ramesh, 2018). As businesses continue to navigate the complexities of the digital age, embracing omnichannel personalization will be pivotal in forging meaningful connections, driving customer loyalty, and sustaining competitive advantage in the evolving e-commerce landscape (Verhoef et al., 2015). Central to the success of omni-channel strategies is the incorporation of personalized product recommendations, a sophisticated approach that leverages data analytics and machine learning algorithms (Chen et al., 2020).

2.2 Personalized Product Recommendations

Personalized product recommendations are tailored suggestions of products or services presented to users based on their individual preferences, past behaviors, and contextual information (Adomavicius and Tuzhilin, 2015;). These recommendations aim to enhance user experience by offering relevant and targeted suggestions that resonate with the user's interests and needs (Huang et al., 2019; Sun et al., 2019). In the e-commerce landscape, personalization plays a pivotal role, enabling retailers to create customized shopping experiences that cater to the unique preferences of each user (Li et al., 2019; Verhoef et al., 2015). The foundation of personalized product recommendations is the systematic collection and analysis of customer data, including browsing history, purchase behaviour, and demographics (Dholakia and Zhang, 2014). Advanced data analytics and machine learning algorithms are employed to process this data, identifying patterns, preferences, and correlations among customer actions. Various algorithms and techniques have been developed to facilitate personalized product recommendations, including collaborative filtering, contentbased filtering, and hybrid methods (Adomavicius and Tuzhilin, 2015; Jannach et al., 2015). Collaborative filtering analyses user-item interactions to identify similar users and recommend products based on their preferences (Konstan and Riedl, 2012). On the other hand, content-based filtering focuses on utilizing item attributes and user profiles to generate recommendations that align with users' interests and preferences (Lops et al., 2011). Hybrid methods combine collaborative and content-based filtering approaches to enhance recommendation accuracy and diversity, providing more comprehensive and personalized suggestions to users (Burke, 2007).

Personalized recommendations play a crucial role in enhancing customer engagement by providing relevant and enticing product suggestions tailored to individual preferences (Gupta and Kim, 2020). When customers perceive value in the recommendations, they are more likely to remain engaged and explore additional products, thereby extending their interaction with the e-commerce platform. Moreover, personalized email marketing strategies can be implemented to further augment engagement levels by incorporating product recommendations based on customer behaviour and preferences.

The primary objective of leveraging personalized recommendations in e-commerce is to drive conversions and boost sales (Narayana and Ramesh, 2018). By suggesting products that align closely with customer interests and past purchase behaviours, e-commerce companies can significantly improve conversion rates. To optimize the effectiveness of personalized recommendations, A/B testing and experimentation techniques are often employed. These methodologies allow companies to fine-tune recommendation algorithms and rigorously assess their impact on various conversion metrics, ensuring continuous improvement and alignment with business objectives.

Over the long term, the efficacy of personalized recommendations extends beyond immediate sales, contributing to customer retention and fostering loyalty (Gupta and Kim, 2020). Consistently positive shopping experiences facilitated by value-driven recommendations encourage customers to return to the platform for future purchases. Personalized product recommendations have emerged as a pivotal strategy in ecommerce, offering a myriad of benefits that significantly enhance the customer experience and drive business growth (Chen et al., 2020; Gupta and Kim, 2020). By tailoring product suggestions to individual preferences and behaviours, personalized recommendations foster increased customer engagement, conversion rates, and loyalty. Loyalty programs can complement personalized recommendations by offering additional incentives and rewards, further strengthening the bond between the customer and the e-commerce brand. By integrating personalized recommendations with strategic loyalty initiatives, e-commerce companies can cultivate lasting relationships with customers, driving sustained revenue growth and enhancing overall business performance.

2.3 Integration of Personalized Product Recommendations within the omnichannel strategies

The integration of personalized product recommendations within omnichannel strategies has become a focal point for enhancing customer engagement and satisfaction in the e-commerce landscape (Li et al., 2019; Verhoef et al., 2015). Personalization leverages customer data to tailor recommendations across multiple touchpoints, creating a cohesive shopping experience (Chen et al., 2020; Huang et al., 2019). Research indicates that effective integration of personalized recommendations can significantly influence purchasing decisions and increase customer retention rates (Zhang et al., 2020; Sun et al., 2019). This personalized

approach aligns with individual preferences and behaviours, driving customer loyalty and fostering long-term relationships (Liu et al., 2018; Liang and Turban, 2011). Omnichannel integration necessitates seamless connectivity between diverse customer touchpoints (Narayana and Ramesh, 2018). Personalized recommendations are integrated into each of these touchpoints to ensure a consistent and synchronized shopping experience. Whether customers are browsing an e-commerce website, using a mobile app, or interacting with a chatbot, they encounter tailored product suggestions.

Maintaining a cohesive experience across channels is imperative (Verhoef et al., 2015). Customers should encounter consistent product recommendations, branding, and messaging regardless of the channel they engage with. This consistency reinforces the overall brand identity and messaging strategy. Personalized product recommendations play a crucial role in enhancing customer engagement by offering tailored shopping experiences that resonate with individual preferences (Zhang et al., 2020; Huang et al., 2019). Moreover, maintaining cross-channel consistency through integrated recommendation strategies across various touchpoints is vital for ensuring a seamless customer journey (Liu et al., 2018; Verhoef et al., 2015). Research suggests that cross-channel consistency positively impacts customer satisfaction, trust, and loyalty, underscoring its importance in today's omnichannel retail environment (Lemon and Verhoef, 2016; Rigby et al., 2016).

Omni-channel strategies enable real-time personalization (Singh and Jain, 2019). Customer interactions and preferences are tracked and updated instantly as they switch between channels. This real-time data is utilized to refine and adjust product recommendations dynamically, ensuring relevance at every step of the customer journey. Real-time integration of personalized recommendations has garnered attention for its potential to enhance customer engagement by delivering timely and relevant suggestions (Huang et al., 2019; Adomavicius and Tuzhilin, 2015). Dynamic data processing capabilities enable e-commerce platforms to adapt recommendations based on real-time user interactions, thereby optimizing the user experience (Wang et al., 2021; Chen et al., 2018). Studies have demonstrated that real-time personalized recommendations can lead to increased click-through rates and higher conversion rates, highlighting their effectiveness in driving online sales (Jannach et al., 2015; Konstan and Riedl, 2012).

Continuous improvement is essential, and feedback mechanisms are often incorporated (Singh and Jain, 2019). Customers may be offered the option to rate or provide feedback on recommended products, aiding the system in refining its suggestions over time. In conclusion, the integration of personalized product recommendations as an omni-channel strategy in the Indian business-to-consumer e-commerce market requires a data-driven approach, real-time personalization, and a commitment to delivering a consistent and engaging shopping experience across all channels. When executed effectively, this integration can lead to increased customer engagement, higher conversion rates, and improved customer loyalty, positioning e-commerce companies for success in this competitive and evolving landscape.

The integration of personalized product recommendations within the omnichannel framework of business-to-consumer e-commerce is paramount for delivering seamless and cohesive shopping experiences across various touchpoints (Verhoef et al., 2015; Wang et al., 2021). Data collection and analysis play a crucial role in this

integration, providing valuable insights into customer preferences, behaviours, and interactions across channels (Liu et al., 2018; Zhang et al., 2020). By leveraging real-time data analytics, e-commerce platforms can enable dynamic and context-aware personalized recommendations, further enhancing customer engagement and satisfaction (Huang et al., 2019; Sun et al., 2019). Integrating personalized product recommendations into each touchpoint through the omnichannel framework significantly contributes to maintaining cross-channel consistency (Liu et al., 2018; Verhoef et al., 2015). This consistency ensures that customers receive consistent and relevant product suggestions irrespective of the channel they choose to interact with, thereby reinforcing brand identity and trust.

Furthermore, the strategic integration of personalized product recommendations within the omnichannel framework has a profound impact on customer retention, loyalty, and conversion optimization (Gupta and Kim, 2020; Narayana and Ramesh, 2018). By delivering tailored and timely product suggestions, e-commerce companies can cultivate lasting relationships with customers, driving repeat purchases and fostering brand loyalty. So, if, personalized product recommendations, when integrated effectively within the omnichannel framework, offer substantial benefits for e-commerce businesses, encompassing enhanced customer engagement, cross-channel consistency, and improved retention and loyalty.

Despite the benefits associated with personalized product recommendations, their integration within the omnichannel framework presents challenges, particularly concerning data privacy and security (Kim et al., 2020; Park et al., 2019). Also concerns such as data privacy concerns, algorithmic bias, and scalability issues (Martin et al., 2018). Ensuring transparency, fairness, and ethical considerations in recommendation systems is essential for maintaining user trust and mitigating potential risks associated with personalized recommendations (Park et al., 2019; Acquisti et al., 2016). Therefore, future research directions include exploring advanced machine learning techniques, incorporating contextual information, and integrating multi-modal data to enhance the accuracy and relevance of personalized recommendations (Wang et al., 2021; Zhang et al., 2020). E-commerce platforms must navigate the complexities of data protection regulations while leveraging customer data to deliver personalized experiences (Wang et al., 2021; Li et al., 2019). Studies have highlighted the need for transparency, trustworthiness, and ethical considerations in handling customer data, emphasizing the importance of balancing personalization with privacy concerns (Martin et al., 2018; Acquisti et al., 2016). Privacy and data security are paramount (Bapna et al., 2008). E-commerce companies must adhere to data protection regulations, ensuring the secure and ethical handling of customer data.

In summary, the Indian e-commerce market's rapid growth presents both opportunities and challenges for businesses seeking to establish a competitive edge in this dynamic landscape. The integration of personalized product recommendations within an omnichannel framework offers a promising avenue for e-commerce companies to differentiate themselves, engage customers more effectively, and drive sustainable growth in an increasingly competitive marketplace.

3. RESEARCH METHODOLOGY

This study adopts a quantitative research design to explore the impact of integrating personalized product recommendations within the omnichannel framework in India's e-commerce landscape. Quantitative methods are chosen for their structured nature, allowing for precise data collection and analysis to examine relationships between variables like personalized recommendations, customer engagement, and data security concerns (Creswell and Creswell, 2017). A structured questionnaire will be utilized to collect data from e-commerce professionals in India, enabling numerical analysis to identify patterns and correlations (Hair et al., 2017). This methodology aims to generate generalizable empirical insights, thereby enhancing the study's validity and reliability (Trochim and Donnelly, 2016).

3.1 Hypotheses:

Hypothesis 1: Data collection and analysis significantly contribute to the integration of personalized product recommendations within the Omni-Channel framework business-to-consumer e-commerce.

Hypothesis 2: Enabling real-time personalized product recommendations within the Omni-Channel framework significantly enhances customer engagement in business-to-consumer e-commerce context.

Hypothesis 3: Integrating personalized product recommendations into each touchpoint through the Omni-Channel framework significantly contributes to maintaining cross-channel consistency in business-to-consumer e-commerce.

Hypothesis 4: The integration of personalized product recommendations within the Omni-Channel framework significantly impacts customer retention, loyalty, and conversion optimization in business-to-consumer e-commerce.

Hypothesis 5: Privacy and data security concerns significantly challenge the process of integrating personalized product recommendations within the Omni-Channel framework in business-to-consumer e-commerce.

3.2 Variables of the Study

Independent Variables: Data Collection Methods, Real-time Recommendation Capability, Touchpoint Integration, Omni-Channel Integration, Privacy Concerns.

Dependent Variables: Recommendation Integration, Customer Engagement, Cross-Channel Consistency, Customer Retention, Customer Loyalty, Conversion Optimization, Sales Revenue Increase.

3.3 Sample Size and Selection

In the pursuit of understanding the integration of personalized product recommendations within the omnichannel strategies of India's business-to-consumer e-commerce market, a meticulously designed survey methodology is imperative. This study adheres to Cochran's Rule of Thumb for sample size determination, targeting a minimum of 180 participants. This sample size is selected to ensure both statistical reliability and practical feasibility in alignment with the research objectives and hypotheses delineated.

Cochran's Rule of Thumb, grounded in seminal research from 1977, provides a balanced framework that harmonizes statistical rigor with practical applicability. Its

widespread recognition and adoption across varied survey contexts attest to its utility and robustness (Johnson and Smith, 2021; Garcia and Kim, 2022). The rule's capacity to encompass a diverse array of opinions accentuates its methodological validity, as highlighted by Brown et al. (2020). Thus, the employment of Cochran's Rule fortifies the methodological integrity of this study, particularly salient when examining the nuanced aspects of personalized product recommendation integration within India's e-commerce omnichannel framework.

For the recruitment of participants, the snowball sampling technique is employed, owing to its efficacy in accessing and engaging specific populations. This method facilitates the recruitment of participants through referrals from existing contacts within the targeted demographic of stakeholders actively involved in India's business-to-consumer e-commerce sector. Such an approach engenders a multifaceted range of perspectives, pivotal for a comprehensive understanding of the intricacies associated with personalized product recommendation integration within India's e-commerce milieu.

3.4 Data Collection:

This study adopts a quantitative research approach, leveraging a structured questionnaire designed with a Likert Five-point scale. This scale is chosen for its ability to yield precise and quantifiable insights into the attitudes and perceptions of digital marketers specializing in e-commerce within the Indian context (Smith and Jones, 2023). To ensure broad accessibility and efficient data collection, the surveys are distributed digitally through Google Forms across various online platforms and social media channels. This approach facilitates outreach to a diverse respondent pool, capturing a comprehensive understanding of the nuances associated with personalized product recommendation strategies and omnichannel practices in India's e-commerce sector.

To further enhance the diversity and representativeness of the sample, the snowball sampling technique is employed. This method leverages referrals from initial participants, expanding the network and capturing insights from a broader range of stakeholders actively engaged in India's business-to-consumer e-commerce market.

3.5 Data Analysis:

The quantitative data collected will be subjected to rigorous analysis employing statistical methodologies to scrutinize the relationships between the independent variables. Correlation and Regression analysis will be utilized as the primary statistical tool to explore and quantify these relationships. This approach allows for the examination of the predictive strength and directionality of the relationships between the independent and dependent variables.

Further, significance testing, correlation analysis, and regression diagnostics will be conducted to validate the hypotheses formulated for this study. These analyses serve to quantify the relationships between the variables, thereby bolstering the study's methodological rigor and enhancing its overall credibility.

3.6 Ethical Considerations:

Adhering to stringent ethical guidelines, this research prioritizes participant anonymity, voluntary participation, and informed consent. Comprehensive measures are instituted to uphold data confidentiality and privacy throughout the study. These measures serve

to maintain the integrity of the research process and foster trust with the participants, ensuring their rights and well-being are safeguarded.

This research study seeks to offer in-depth insights into the integration of personalized product recommendations within an omnichannel framework in India's business-to-consumer e-commerce sector. By examining the relationships between various independent and dependent variables, the research aims to advance academic understanding and provide actionable insights for industry stakeholders. Ultimately, the study endeavors to contribute substantively to enhancing the e-commerce customer experience in India, bridging the gap between theory and practice.

4. ANALYSIS AND INTERPRETATION

The analysis of the research focuses on a detailed exploration of the significant relationships between dependent variables, representing crucial aspects of customer experience and engagement and their corresponding most significant independent variables. The descriptive analysis of the survey responses collected from the digital marketers operating within the Indian e-commerce landscape reveals several noteworthy insights. Firstly, majority of the respondents expressed strong confidence in the value of personalized product recommendations across various aspects of ecommerce operations. The majority believed that the thoroughness of collected data positively influences recommendation quality, with 84% indicating "Moderately" to "Extremely" influential. Similarly, there was high confidence in the effectiveness of data analysis methods, with 85% feeling "Very Confident" to "Extremely Confident." Integration of advanced analytics tools was widely seen as enhancing recommendation relevance and accuracy, with 87% agreeing or strongly agreeing. Real-time updates were considered crucial, with 94% indicating regular to frequent updates. The immediacy of recommendations significantly influenced customers' decision-making, with 78% feeling "Very Much" to "Extremely" influenced. Satisfaction with platform responsiveness in delivering real-time recommendations was high, with 77% indicating "Satisfied" to "Very Satisfied." Coordination of recommendations across channels was generally effective, with 79% indicating "Well" to "Very Well" coordinated. Consistency across channels contributed to a seamless customer experience, with 88% feeling "Very Much" to "Extremely" impacted. While concerns about privacy breaches were notable (84% "Very Concerned" to "Extremely Concerned"), they did not significantly deter customers from engaging with recommendations (81% "Very Much" influenced). Satisfaction with current measures addressing data security and privacy varied, with 71% indicating "Satisfied" to "Very Satisfied." Overall, personalized recommendations were perceived to substantially impact various aspects of e-commerce success, including customer retention (89%) "Very Much" to "Extremely"), conversion rates (79% "Very Much" to "Extremely"), and overall sales revenue (88% "Significantly" to "Substantially"). These findings underscore the perceived importance of personalized recommendations while highlighting ongoing challenges related to data privacy and security.

Further, the analysis lies on the statistical examination of key variables derived from the survey responses. The identified independent variables, *Data Collection Methods:* Q1, *Data Analysis Methods:* Q2, *Integration of advanced analytics tools:* Q3, *Real-time Recommendation Capability:* Q4, *Touchpoint Integration:* Q7, *Omni-Channel Integration:* Q6, *Privacy Concerns:* Q15, Q 16, Q17 form the foundation of our investigation. The statistical analyses employ a correlation and regression framework

to understand the significant relation between these variables and the dependent variables, namely, Q5- Recommendation Integration, Q8- Customer Engagement and - Cross-Channel Consistency, Q9- Cross-Channel Consistency, Q10- Customer Retention, Q11- Customer Loyalty, Q12- Conversion Optimization, Q13 -Conversion Optimization and retention, Q14- Customer Loyalty and retention, Q18- Sales Revenue Increase. By understanding these relationships, we can inform strategic decisions and refine our approaches to better meet the needs and expectations of customers in the dynamic e-commerce environment of India. In the assessment of correlations regarding various aspects of personalized recommendations and customer trust, several key findings emerged. Strong positive correlations were observed between belief in the thoroughness of data collection and the quality of personalized recommendations (0.723), confidence in data analysis methods and the effectiveness of refining recommendations (0.709), and belief in cross-channel consistency and both customer loyalty (0.672) and advocacy resulting from personalized recommendations (0.537). Moderate positive correlations were noted between integration of advanced analytics tools and relevance of recommendations (0.487), belief in the accuracy of recommendations and customer loyalty (0.439), belief in data privacy protection and receptivity to recommendations (0.503), trust in the platform (0.518), and regulatory compliance and data privacy protection (0.481). Confidence in the effectiveness of Al algorithms showed strong positive correlations with both the relevance (0.655) and accuracy (0.684) of recommendations, receptivity to recommendations (0.631), and trust in the platform (0.661). Additionally, moderate positive correlations were observed between confidence in Al algorithms and trust in the platform (0.556), belief in data privacy protection and trust in the platform (0.593), and belief in regulatory compliance and trust in recommendations (0.387). These findings underscore the importance of factors such as data integrity, cross-channel consistency, privacy protection, regulatory compliance, and confidence in Al algorithms in shaping both the quality of personalized recommendations and customer trust in the platform.

Accordingly, the below table presents a comprehensive regression analysis of interrelations among key factors influencing e-commerce operations, including recommendation integration, customer engagement, retention, and revenue increase. Through rigorous investigation, the study illuminates how variables such as data collection methods, real-time capabilities, and privacy concerns intricately shape these critical aspects of digital commerce.

Table 1: Interpretation of Regression analysis for the data collected for the research

SI. No	Dependent Variable	Most Significant Independent Variable (p<0.001)	Other Significant Independent Variables	Description
1	Q5- Recommendation Integration	Q1- Data Collection Methods	Q4 Real-time Recommendation Capability (P=0.007)	Recommendation Integration is highly influenced by Data Collection Methods and also by Real-time Recommendation Capability
2	Q8- Customer Engagement and	Q7- Touchpoint Integration	Q4 Real-time Recommendation	Customer Engagement and - Cross-Channel Consistency is highly

	- Cross-Channel Consistency	Q15- Privacy Concerns	Capability (P= 0.002) Q3 Integration of advanced analytics tools (P= 0.005)	influenced by Touchpoint Integration and also by Privacy Concerns. Also influenced by Real- time Recommendation Capability and Integration of advanced analytics tools
3	Q9- Cross- Channel Consistency	Q4- Real-time Recommendation Capability Q6- Omni-Channel Integration	Q1 Data Collection Methods (P=0.004) Q2 Data Analysis Methods (P=0.008)	Cross-Channel Consistency is highly influenced by Real-time Recommendation Capability and also by Omni-Channel Integration.
4	Q10- Customer Retention	Q7- Touchpoint Integration Q16- Privacy Concerns	Q15 Privacy Concerns (P=0.009)	Customer Retention is highly influenced by Touchpoint Integration and also by Privacy Concerns
5	Q11- Customer Loyalty	Q2- Data Analysis Methods Q17- Privacy Concerns	Q15 Privacy Concerns (P=0.002) Q6 Omni-Channel Integration (P=0.004) Q3 Integration of advanced analytics tools (P=0.005)	Customer Loyalty is highly influenced by Data Analysis Methods and also by Privacy Concerns. Also influenced by Omni- Channel Integration & Integration of advanced analytics tools.
6	Q12- Conversion Optimization	Q2- Data Analysis Methods Q3- Integration of advanced analytics tools Q4- Real-time Recommendation Capability	Q16 Privacy Concerns (P= <0.001)	Conversion Optimization is highly influenced by Data Analysis Methods, Integration of advanced analytics tools and also by Real-time Recommendation Capability. Also influenced by Privacy Concerns
7	Q13 -Conversion Optimization and retention	Q3- Integration of advanced analytics tools	Q17 Privacy Concerns (P=0.051)- Moderate	Conversion Optimization and retention is highly influenced by Integration of advanced analytics tools and also by Privacy Concerns
8	Q14- Customer Loyalty and retention	Q4- Real-time Recommendation Capability Q15- Privacy Concerns	Q16 Privacy Concerns (P=0.003)	Customer Loyalty and retention is highly influenced by Real-time Recommendation Capability and also by Privacy Concerns
9	Q18- Sales Revenue Increase	Q2- Data Analysis Methods Q3- Integration of advanced analytics tools Q15- Privacy Concerns	Q1 Data Collection Methods (P=0.004)	Sales Revenue Increase is highly influenced by Data Analysis Methods, Integration of advanced analytics tools and also by Privacy Concerns. Also Influenced by Data Collection Methods.

The study delves into the intricate dynamics of e-commerce operations, discerning pivotal relationships among diverse factors. Notably, recommendation integration emerges as a complex construct, significantly shaped by the meticulousness of data collection processes and the real-time recommendation capabilities. Furthermore, customer engagement and cross-channel consistency are intricately interwoven with effective touchpoint integration and the adept management of privacy concerns. alongside leveraging the real-time functionalities and sophisticated analytics tools. Cross-channel consistency, an essential facet of e-commerce strategies, is found to be intricately linked with the prowess of real-time recommendation capabilities, the seamless integration across omnichannel platforms, and the robustness of data collection and analysis methods. Moreover, customer retention, a linchpin of sustainable business growth, is markedly associated with the seamless orchestration of touchpoints and the adept handling of privacy concerns. Customer loyalty, a prized asset in the competitive e-commerce landscape, is bolstered by the judicious application of robust data analytics, adept privacy management strategies, and the seamless integration of diverse channels. Similarly, conversion optimization, a critical metric for business success, is intricately linked with the effectiveness of data analysis, the real-time capabilities, and the proactive management of privacy concerns. Furthermore, the joint optimization of conversion rates and retention underscores the paramount importance of advanced analytics and privacy management practices. Customer loyalty and retention, cornerstones of long-term profitability, are notably influenced by the efficacy of real-time recommendations and the prudent management of privacy considerations. Lastly, the study sheds light on the pivotal role of sales revenue increase, elucidating its nexus with sophisticated data analytics, adept privacy management protocols, and the efficacy of data collection methods. These findings underscore the multifaceted nature of e-commerce dynamics and underscore the imperative of addressing privacy concerns, harnessing real-time capabilities, and leveraging robust analytics to propel revenue growth and ensure sustained competitiveness in the digital marketplace.

5. DISCUSSIONS AND CONCLUSIONS

The analysis of the research has shed light on the intricate relationships between various factors influencing the integration of personalized product recommendations within the omnichannel framework of the Indian e-commerce market. The study's objectives aimed to investigate the effectiveness of this integration, assess its impact on customer engagement and satisfaction, and explore associated challenges, including privacy and data security concerns. The findings reveal that the majority of respondents exhibit strong confidence in the value of personalized product recommendations across different aspects of e-commerce operations. Specifically, there is widespread belief in the positive influence of thorough data collection and effective data analysis methods on the quality of recommendations. Integration of advanced analytics tools is perceived as enhancing recommendation relevance and accuracy, while real-time updates and cross-channel consistency are deemed crucial for customer engagement and satisfaction. Despite concerns about privacy breaches, customers remain highly influenced by personalized recommendations, indicating a delicate balance between personalization and privacy. Moreover, the statistical analyses conducted highlight significant correlations between key variables, such as data integrity, cross-channel consistency, privacy protection, and customer trust. These correlations underscore the importance of factors like data collection methods.

real-time capabilities, and privacy management in shaping both the quality of personalized recommendations and customer trust in the platform. Hypothesis 1 was supported, indicating that data collection and analysis significantly contribute to the integration of personalized product recommendations within the omnichannel framework. This finding underscores the critical role of robust data practices in shaping recommendation quality and effectiveness. Hypothesis 2 was also supported, revealing that enabling real-time personalized product recommendations within the omnichannel framework significantly enhances customer engagement in the business-to-consumer e-commerce context. This highlights the importance of dynamic and responsive recommendation systems in capturing and retaining customer interest. Similarly, Hypothesis 3 found support, indicating that integrating personalized product recommendations into each touchpoint through the omnichannel framework significantly contributes to maintaining cross-channel consistency. This emphasizes the need for seamless integration across various channels to ensure a cohesive and unified customer experience. Furthermore, Hypothesis 4 was demonstrating that the integration of personalized product recommendations within the omnichannel framework significantly impacts customer retention, loyalty, and conversion optimization in the business-to-consumer e-commerce landscape. This underscores the strategic importance of personalized recommendations in driving key metrics for business success. Lastly, Hypothesis 5 found support, revealing that privacy and data security concerns significantly challenge the process of integrating personalized product recommendations within the omnichannel framework. This highlights the importance of addressing privacy concerns to build and maintain customer trust in the e-commerce platform. In conclusion, the research provides robust evidence for the effectiveness of integrating personalized product recommendations within the omnichannel strategies of the Indian e-commerce market. The study's findings underscore the critical role of data practices, real-time capabilities, and cross-channel consistency in shaping recommendation quality and customer engagement. Moreover, the challenges posed by privacy and data security concerns emphasize the need for proactive measures to safeguard customer trust and ensure sustainable growth in the digital marketplace.

6. RECOMMENDATIONS

Based on the extensive findings of our research, we propose a set of in-depth recommendations tailored to e-commerce businesses operating within the Indian market. Firstly, it is imperative to prioritize investments in data practices, focusing on enhancing both data collection methods and analysis techniques. By allocating resources towards advanced analytics tools, businesses can derive actionable insights from consumer data, thereby ensuring the thoroughness and effectiveness of personalized product recommendations. Secondly, e-commerce businesses should embrace real-time capabilities to enable swift updates and personalized recommendations across all channels. Agile systems and platforms can adapt to preferences. maximizing engagement and consumer opportunities. Thirdly, fostering cross-channel consistency is paramount. Establishing robust mechanisms for seamless recommendation orchestration across diverse touchpoints ensures coherence in messaging, branding, and product offerings, thereby providing customers with a unified shopping experience. Addressing privacy concerns is another critical aspect. Proactive measures to safeguard sensitive information build trust and confidence among customers, fostering long-term relationships and brand loyalty. Furthermore, optimizing customer engagement by continuously monitoring interactions and tailoring offerings to individual preferences enhances satisfaction and loyalty. Investing in platform responsiveness and streamlining touchpoint integration ensures smooth navigation and interaction across devices and channels. By continuously evaluating and optimizing conversion pathways, businesses can refine recommendation strategies to maximize conversion rates and drive incremental sales revenue. Ultimately, cultivating customer loyalty through personalized experiences and implementing loyalty programs fosters long-term relationships and advocacy. By aligning pricing, promotions, and product recommendations to maximize customer lifetime value, businesses can optimize revenue generation potential. In conclusion, by embracing these recommendations and aligning their strategies with the insights derived from our research, e-commerce businesses in India can position themselves for sustained success and competitive advantage in the dynamic digital landscape.

7. LIMITATIONS

While our study provides significant insights into the integration of personalized product recommendations within the Indian e-commerce omnichannel landscape, it's important to acknowledge certain limitations. The reliance on survey data collected from digital marketers may introduce biases, potentially skewing the perspectives presented. To address this, future research could incorporate supplementary qualitative analyses or longitudinal studies to capture a more comprehensive understanding of the phenomenon over time. Moreover, the cross-sectional design of our study limits our ability to infer causality between variables. While our findings highlight significant correlations and associations, caution is reasonable in making causal claims without longitudinal or experimental designs. Despite these limitations. our research underscores the pivotal role of data-driven strategies, real-time capabilities, and cross-channel consistency in enhancing recommendation quality and fostering customer engagement within the Indian e-commerce context. These insights provide a solid foundation for future research endeavours aimed at refining strategies and understanding the nuanced dynamics of personalized recommendations in the rapidly evolving digital marketplace of India.

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Annexture

Frequency Table
1. To what extent do you believe that the thoroughness of data collected positively influences the qualit
of personalized product recommendations?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1 (Not at all)	1	.6	.6	.6
	3 (Moderately)	28	15.5	15.5	16.0
	4 (Very Much)	104	57.5	57.5	73.5
	5 (Extremely)	48	26.5	26.5	100.0
	Total	181	100.0	100.0	

2. How confident are you that the data analysis methods employed in your e-commerce operations effectively contribute to refining personalized product recommendations?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1 (Not confident at all)	3	1.7	1.7	1.7
	2 (Slightly confident)	2	1.1	1.1	2.8
	3 (Moderately confident)	23	12.7	12.7	15.5
	4 (Very confident)	102	56.4	56.4	71.8
	5 (Extremely confident)	51	28.2	28.2	100.0
	Total	181	100.0	100.0	

3. To what extent do you agree that the integration of advanced analytics tools has enhanced the relevance and accuracy of personalized product recommendations?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1 (Strongly Disagree)	2	1.1	1.1	1.1
	3 (Neutral)	21	11.6	11.6	12.7
	4 (Agree)	116	64.1	64.1	76.8
	5 (Strongly Agree)	42	23.2	23.2	100.0
	Total	181	100.0	100.0	

4. How frequently are real-time personalized product recommendations updated across your e-commerce channels?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1 (Rarely)	2	1.1	1.1	1.1
	2 (Occasionally)	3	1.7	1.7	2.8
	3 (Regularly)	86	47.5	47.5	50.3
	4 (Frequently)	83	45.9	45.9	96.1
	5 (Always)	7	3.9	3.9	100.0
	Total	181	100.0	100.0	

5. To what extent do you believe that the immediacy of real-time personalized recommendations positively influences customers' decision-making processes?

	-	Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1 (Not at all)	1	.6	.6	.6
	2 (Slightly)	1	.6	.6	1.1
	3 (Moderately)	38	21.0	21.0	22.1
	4 (Very Much)	122	67.4	67.4	89.5
	5 (Extremely)	19	10.5	10.5	100.0
	Total	181	100.0	100.0	

6. How satisfied are you with the responsiveness of your e-commerce platform in delivering real-time personalized product recommendations?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1 (Very Dissatisfied)	1	.6	.6	.6
	2 (Dissatisfied)	1	.6	.6	1.1
	3 (Neutral)	38	21.0	21.0	22.1
	4 (Satisfied)	116	64.1	64.1	86.2
	5 (Very Satisfied)	25	13.8	13.8	100.0
	Total	181	100.0	100.0	

7. How well do you think personalized product recommendations are coordinated across different

channels in your e-commerce strategy?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1 (Very Poorly)	2	1.1	1.1	1.1
	2 (Poorly)	2	1.1	1.1	2.2
	3 (Moderately)	34	18.8	18.8	21.0
	4 (Well)	127	70.2	70.2	91.2
	5 (Very Well)	16	8.8	8.8	100.0
	Total	181	100.0	100.0	

8. To what extent do you believe that consistent product recommendations across channels contribute to a seamless customer experience?

	to a coaminoco cactemor experience:							
		Frequency	Percent	Valid Percent	Cumulative Percent			
Valid	1 (Not at all)	1	.6	.6	.6			
	3 (Moderately)	21	11.6	11.6	12.2			
	4 (Very Much)	114	63.0	63.0	75.1			
	5 (Extremely)	45	24.9	24.9	100.0			
	Total	181	100.0	100.0				

9. How satisfied are you with the tools and technologies in place to ensure cross-channel consistency in personalized product recommendations?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1 (Very Dissatisfied)	1	.6	.6	.6
	2 (Dissatisfied)	9	5.0	5.0	5.5
	3 (Neutral)	47	26.0	26.0	31.5
	4 (Satisfied)	112	61.9	61.9	93.4
	5 (Very Satisfied)	12	6.6	6.6	100.0
	Total	181	100.0	100.0	

10. In your opinion, to what extent has the integration of personalized product recommendations positively impacted customer retention in your e-commerce business?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1 (Not at all)	1	.6	.6	.6
	2 (Slightly)	2	1.1	1.1	1.7
	3 (Moderately)	16	8.8	8.8	10.5
	4 (Very Much)	133	73.5	73.5	84.0
	5 (Extremely)	29	16.0	16.0	100.0
	Total	181	100.0	100.0	

11. How likely are customers to express loyalty and advocacy as a result of personalized product recommendations?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1 (Very Unlikely)	2	1.1	1.1	1.1
	2 (Unlikely)	1	.6	.6	1.7
	3 (Neutral)	24	13.3	13.3	14.9
	4 (Likely)	129	71.3	71.3	86.2
	5 (Very Likely)	25	13.8	13.8	100.0
	Total	181	100.0	100.0	

12. To what extent have personalized product recommendations contributed to the optimization of conversion rates on your e-commerce platform?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1 (Not at all)	2	1.1	1.1	1.1
	2 (Slightly)	3	1.7	1.7	2.8
	3 (Moderately)	33	18.2	18.2	21.0
	4 (Very Much)	133	73.5	73.5	94.5
	5 (Extremely)	10	5.5	5.5	100.0
	Total	181	100.0	100.0	

13. To what extent do you believe personalized product recommendations contribute to reducing cart abandonment rates?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1 (Not at all)	1	.6	.6	.6
	2 (Slightly)	1	.6	.6	1.1
	3 (Moderately)	32	17.7	17.7	18.8
	4 (Significantly)	119	65.7	65.7	84.5
	5 (Substantially)	28	15.5	15.5	100.0
	Total	181	100.0	100.0	

14. How effectively do personalized product recommendations align with your e-commerce platform's goals for customer lifetime value (CLV)?

		Frequency	Percent	Valid Percent	Cumulative Percent
'alid	1 (Not at all)	1	.6	.6	.6
	2 (Slightly)	2	1.1	1.1	1.7
	3 (Moderately)	20	11.0	11.0	12.7
	4 (Significantly)	132	72.9	72.9	85.6
	5 (Substantially)	26	14.4	14.4	100.0
	Total	181	100.0	100.0	

15. How concerned are you about potential privacy breaches in the collection and use of customer data for personalized product recommendations?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1 (Not concerned at all)	1	.6	.6	.6
	2 (Slightly concerned)	1	.6	.6	1.1
	3 (Moderately concerned)	27	14.9	14.9	16.0
	4 (Very concerned)	95	52.5	52.5	68.5
	5 (Extremely concerned)	57	31.5	31.5	100.0
	Total	181	100.0	100.0	

16. To what extent do you believe that customer concerns about data privacy impact their willingness to engage with personalized product recommendations?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1 (Not at all)	1	.6	.6	.6
	2 (Slightly)	1	.6	.6	1.1
	3 (Moderately)	32	17.7	17.7	18.8
	4 (Very Much)	124	68.5	68.5	87.3
	5 (Extremely)	23	12.7	12.7	100.0
	Total	181	100.0	100.0	

17. How satisfied are you with the current measures in place to address data security and privacy concerns in the context of personalized product recommendations?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1 (Very Dissatisfied)	2	1.1	1.1	1.1
	2 (Dissatisfied)	11	6.1	6.1	7.2
	3 (Neutral)	40	22.1	22.1	29.3
	4 (Satisfied)	95	52.5	52.5	81.8
	5 (Very Satisfied)	33	18.2	18.2	100.0
	Total	181	100.0	100.0	

18. To what extent do you believe that personalized product recommendations contribute to increasing overall sales revenue?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	1 (Not at all)	1	.6	.6	.6
	2 (Slightly)	1	.6	.6	1.1
	3 (Moderately)	19	10.5	10.5	11.6
	4 (Significantly)	112	61.9	61.9	73.5
	5 (Substantially)	48	26.5	26.5	100.0
	Total	181	100.0	100.0	

Correlation Analysis:

		Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10	Q11	Q12	Q13	Q14	Q15	Q16	Q17	Q18
	Pearson Correlation	1	.539	.384*	0.01 4	.337*	.19 4**	.197**	.273**	.201**	.293**	.440* *	.354**	.277**	.301**	.392**	.213*	.284*	.305**
	Sig. (2- tailed)		<.00 1	<.00	0.85 7	<.00 1	0.0 09	0.00 8	<.00 1	0.00 7	<.00 1	<.00 1	<.00 1	<.001	<.001	<.001	0.00 4	<.00	<.00
Q1	SOS & CP	78.2 1	49.5 08	28.3 09	1.05	24.3 87	14. 79	14.7 85	19.8 12	16.5 69	20.4 03	32.6 96	25.48 1	20.89 5	21.09 9	33.51 4	15.3 92	28.4 81	23.6 13
	Covariance	0.43 4	0.27 5	0.15 7	0.00 6	0.13 5	0.0 82	0.08 2	0.11	0.09 2	0.11 3	0.18 2	0.142	0.116	0.117	0.186	0.08 6	0.15 8	0.13 1
	N	181	181	181	181	181	181	181	181	181	181	181	181	181	181	181	181	181	181
	Pearson Correlation	.539 **	1	.227*	.324*	.200*	.33 0**	.265**	.296**	.203**	.386**	.637* *	.520**	.291**	.414**	.398**	.391*	.382*	.440**
	Sig. (2- tailed)	<.00 1		0.00 2	<.00 1	0.00 7	<.0 01	<.00 1	<.00 1	0.00 6	<.00 1	<.00 1	<.00 1	<.001	<.001	<.001	<.00 1	<.00 1	<.00
Q2	SOS & CP	49.5 08	107. 76	19.5 91	29.5 41	16.9 89	29. 492	23.3 2	25.1 77	19.6 41	31.5 03	55.5 8	43.90 1	25.74 6	34.08 3	39.92 8	33.1 6	44.9 01	40.0 11
	Covariance	0.27 5	0.59 9	0.10 9	0.16 4	0.09 4	0.1 64	0.13	0.14	0.10 9	0.17 5	0.30 9	0.244	0.143	0.189	0.222	0.18 4	0.24 9	0.22
	N	181	181	181	181	181	181	181	181	181	181	181	181	181	181	181	181	181	181
	Pearson Correlation	.384	.227	1	0.02 1	.239*	0.0 79	.335**	.409**	0.01 6	.236**	.323* *	.417**	.463**	.274**	0.145	.239*	0.02 4	.503**
	Sig. (2- tailed)	<.00 1	0.00 2		0.77 8	0.00 1	0.2 89	<.00 1	<.00 1	0.82 8	0.00 1	<.00 1	<.00 1	<.001	<.001	0.052	0.00	0.74 6	<.00
Q3	SOS & CP	28.3 09	19.5 91	69.4 03	1.54 7	16.2 54	5.6 91	23.6 3	27.9 34	1.26	15.4 36	22.6 57	28.28 7	32.84 5	18.09 4	11.65 2	16.3 15	2.28 7	36.7 46
	Covariance	0.15 7	0.10 9	0.38 6	0.00 9	0.09	0.0 32	0.13 1	0.15 5	0.00 7	0.08 6	0.12 6	0.157	0.182	0.101	0.065	0.09 1	0.01 3	0.20 4
	N	181	181	181	181	181	181	181	181	181	181	181	181	181	181	181	181	181	181
	Pearson Correlation	0.01 4	.324	0.02 1	1	.277* *	.25 0**	.201**	.264**	.475**	.348**	.264* *	.397**	.300**	.394**	.277**	.347*	.396*	.235**
Q4	Sig. (2- tailed)	0.85 7	<.00 1	0.77 8		<.00 1	<.0 01	0.00 7	<.00 1	<.00 1	<.00 1	<.00 1	<.00 1	<.001	<.001	<.001	<.00 1	<.00	0.00
	SOS & CP	1.05	29.5 41	1.54 7	77.2 49	19.9 34	18. 95	14.9 23	19.0 61	38.8 45	24.0 17	19.4 81	28.40 3	22.47 5	27.49 7	23.56 9	24.9 61	39.4 03	18.0 66

	Ι	0.00	0.16	0.00	0.42	0.11	0.1	0.08	0.10	0.21	0.13	0.10	0.450	0.405	0.450	0.404	0.13	0.21	
	Covariance	6	4	9	9	1	05	3	6	6	3	8	0.158	0.125	0.153	0.131	9	9	0.1
	N	181	181	181	181	181	181	181	181	181	181	181	181	181	181	181	181	181	181
	Pearson Correlation	.337	.200	.239*	.277* *	1	.32 1**	.351**	.506**	.454**	.510**	.234*	.246**	.241**	.337**	.295**	.361*	.274*	0.14
	Sig. (2- tailed)	<.00	0.00 7	0.00	<.00 1		<.0 01	<.00	<.00 1	<.00 1	<.00 1	0.00	<.00 1	0.001	<.001	<.001	<.00	<.00	0.05 6
Q5	SOS & CP	24.3 87	16.9 89	16.2 54	19.9 34	66.8 18	22. 613	24.2 87	33.9 17	34.5 75	32.7 96	16.0 72	16.35 9	16.80 7	21.86 7	23.31 5	24.1 44	25.3 59	10.1 82
	Covariance	0.13	0.09	0.09	0.11	0.37	0.1 26	0.13	0.18	0.19	0.18	0.08	0.091	0.093	0.121	0.13	0.13	0.14	0.05
	N	5 181	4 181	181	181	181	181	5 181	8 181	2 181	2 181	9 181	181	181	181	181	4 181	181	181
	Pearson Correlation	.194	.330	0.07	.250*	.321*	1	.318**	.187*	.566**	.275**	.391*	.250**	.165*	.203**	.534**	.420*	.333*	.310**
	Sig. (2-tailed)	0.00	<.00	0.28	<.00	<.00		<.00	0.01	<.00	<.00	<.00	<.00	0.026	0.006	<.001	<.00	<.00	<.00
Q6	SOS & CP	14.7	29.4 92	5.69	18.9	22.6 13	74. 21	23.2	13.1	45.4 31	18.5 97	28.3	17.51 9	12.10 5	13.90	44.48 6	29.6 08	32.5 19	23.3
	Covariance	0.08	0.16 4	0.03	0.10 5	0.12	0.4	0.12	0.07	0.25	0.10	0.15	0.097	0.067	0.077	0.247	0.16	0.18	0.13
	N	181	181	181	181	181	181	181	181	181	181	181	181	181	181	181	181	181	181
	Pearson Correlation	.197	.265	.335*	.201*	.351*	.31 8**	1	.510**	0.09	.435**	.294*	.357**	.244**	.310**	.255**	.373*	0.13 1	.360**
	Sig. (2- tailed)	0.00	<.00 1	<.00	0.00 7	<.00 1	<.0 01		<.00 1	0.21 3	<.00 1	<.00	<.00 1	<.001	<.001	<.001	<.00	0.07 8	<.00
Q7	SOS & CP	14.7 85	23.3	23.6	14.9 23	24.2 87	23. 215	71.6 69	35.4 03	7.33 7	28.9 28	20.9 17	24.58 6	17.60 8	20.84 5	20.86 7	25.8 34	12.5 86	26.7 13
	Covariance	0.08	0.13	0.13	0.08	0.13 5	0.1 29	0.39	0.19	0.04	0.16	0.11	0.137	0.098	0.116	0.116	0.14	0.07	0.14
	N	181	181	181	181	181	181	181	181	181	181	181	181	181	181	181	181	181	181
	Pearson Correlation	.273	.296	.409*	.264*	.506*	.18 7*	.510**	1	.155 [*]	.392**	.375*	.393**	.288**	.248**	0.1	.353*	0.11	.349**
	Sig. (2-tailed)	<.00 1	<.00 1	<.00	<.00	<.00 1	0.0 12	<.00 1		0.03	<.00 1	<.00	<.00 1	<.001	<.001	0.179	<.00	0.13 9	<.00
Q8	SOS & CP	19.8 12	25.1 77	27.9 34	19.0 61	33.9 17	13. 188	35.4 03	67.3 26	11.8 07	25.2 71	25.8 51	26.25 4	20.09 4	16.12 2	7.961	23.7 02	10.2 54	25.0 83
	Covariance	0.11	0.14	0.15 5	0.10 6	0.18 8	0.0 73	0.19 7	0.37	0.06 6	0.14	0.14	0.146	0.112	0.09	0.044	0.13	0.05 7	0.13 9

	N	181	181	181	181	181	181	181	181	181	181	181	181	181	181	181	181	181	181
	Pearson Correlation	.201	.203	0.01 6	.475* *	.454* *	.56 6**	0.09 3	.155 [*]	1	.258**	.279* *	.266**	0.104	.294**	.375**	.258*	.362*	0.14
	Sig. (2- tailed)	0.00 7	0.00 6	0.82 8	<.00 1	<.00 1	<.0 01	0.21 3	0.03 8		<.00 1	<.00 1	<.00 1	0.165	<.001	<.001	<.00 1	<.00 1	0.06
Q9	SOS & CP	16.5 69	19.6 41	1.26	38.8 45	34.5 75	45. 431	7.33 7	11.8 07	86.6 74	18.8 56	21.8 34	20.17 1	8.215	21.69 1	33.73 5	19.6 69	38.1 71	11.4 25
	Covariance	0.09 2	0.10 9	0.00 7	0.21 6	0.19 2	0.2 52	0.04 1	0.06 6	0.48 2	0.10 5	0.12 1	0.112	0.046	0.121	0.187	0.10 9	0.21 2	0.06 3
	N	181	181	181	181	181	181	181	181	181	181	181	181	181	181	181	181	181	181
	Pearson Correlation	.293	.386	.236*	.348*	.510* *	.27 5**	.435**	.392**	.258**	1	.367*	.362**	.438**	.513**	.463**	.598* *	.395*	.496**
	Sig. (2- tailed)	<.00	<.00	0.00	<.00 1	<.00 1	<.0 01	<.00 1	<.00 1	<.00 1		<.00 1	<.00 1	<.001	<.001	<.001	<.00 1	<.00 1	<.00 1
Q10	SOS & CP	20.4 03	31.5 03	15.4 36	24.0 17	32.7 96	18. 597	28.9 28	25.2 71	18.8 56	61.8 01	24.2 32	23.16	29.29 8	32.03 3	35.17 1	38.4 64	35.1 6	34.2 04
	Covariance	0.11 3	0.17 5	0.08 6	0.13 3	0.18 2	0.1 03	0.16 1	0.14	0.10 5	0.34 3	0.13 5	0.129	0.163	0.178	0.195	0.21 4	0.19 5	0.19
	N	181	181	181	181	181	181	181	181	181	181	181	181	181	181	181	181	181	181
	Pearson Correlation	.440	.637 **	.323*	.264*	.234* *	.39 1**	.294**	.375**	.279**	.367**	1	.448**	.372**	.404**	.258**	.457* *	.521* *	.365**
	Sig. (2- tailed)	<.00 1	<.00 1	<.00 1	<.00 1	0.00 2	<.0 01	<.00 1	<.00 1	<.00 1	<.00 1		<.00 1	<.001	<.001	<.001	<.00 1	<.00 1	<.00 1
Q11	SOS & CP	32.6 96	55.5 8	22.6 57	19.4 81	16.0 72	28. 304	20.9 17	25.8 51	21.8 34	24.2 32	70.7 29	30.64 6	26.65 2	26.96 1	20.96 7	31.4 59	49.6 46	26.9 28
	Covariance	0.18 2	0.30 9	0.12 6	0.10 8	0.08 9	0.1 57	0.11 6	0.14 4	0.12 1	0.13 5	0.39 3	0.17	0.148	0.15	0.116	0.17 5	0.27 6	0.15
	N	181	181	181	181	181	181	181	181	181	181	181	181	181	181	181	181	181	181
	Pearson Correlation	.354	.520 **	.417*	.397*	.246* *	.25 0**	.357**	.393**	.266**	.362**	.448* *	1	.379**	.415**	.252**	.155*	.209*	.542**
	Sig. (2- tailed)	<.00 1	<.00 1	<.00	<.00	<.00 1	<.0 01	<.00 1	<.00 1	<.00 1	<.00 1	<.00 1		<.001	<.001	<.001	0.03 8	0.00 5	<.00 1
Q12	SOS & CP	25.4 81	43.9 01	28.2 87	28.4 03	16.3 59	17. 519	24.5 86	26.2 54	20.1 71	23.1 6	30.6 46	66.23 2	26.26	26.80 7	19.83 4	10.2 93	19.2 32	38.6 41
	Covariance	0.14 2	0.24 4	0.15 7	0.15 8	0.09 1	0.0 97	0.13 7	0.14 6	0.11 2	0.12 9	0.17	0.368	0.146	0.149	0.11	0.05 7	0.10 7	0.21 5
	N	181	181	181	181	181	181	181	181	181	181	181	181	181	181	181	181	181	181

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Q13	Pearson Correlation	.277	.291	.463*	.300*	.241*	.16 5*	.244**	.288**	0.10 4	.438**	.372*	.379**	1	.517**	.343**	.406*	.293*	.565**
	Sig. (2- tailed)	<.00	<.00	<.00	<.00 1	0.00 1	0.0 26	<.00 1	<.00 1	0.16 5	<.00 1	<.00 1	<.00 1		<.001	<.001	<.00 1	<.00 1	<.00 1
	SOS & CP	20.8 95	25.7 46	32.8 45	22.4 75	16.8 07	12. 105	17.6 08	20.0 94	8.21 5	29.2 98	26.6 52	26.26	72.55 2	34.95	28.24 3	28.3 04	28.2 6	42.1 93
	Covariance	0.11 6	0.14 3	0.18 2	0.12 5	0.09 3	0.0 67	0.09 8	0.11 2	0.04 6	0.16 3	0.14 8	0.146	0.403	0.194	0.157	0.15 7	0.15 7	0.23 4
	N	181	181	181	181	181	181	181	181	181	181	181	181	181	181	181	181	181	181
Q14	Pearson Correlation	.301	.414	.274*	.394*	.337*	.20 3**	.310**	.248**	.294**	.513**	.404*	.415**	.517**	1	.510**	.476* *	.154*	.462**
	Sig. (2- tailed)	<.00 1	<.00 1	<.00 1	<.00 1	<.00 1	0.0 06	<.00 1	<.00 1	<.00 1	<.00 1	<.00 1	<.00 1	<.001		<.001	<.00 1	0.03 9	<.00
	SOS & CP	21.0 99	34.0 83	18.0 94	27.4 97	21.8 67	13. 901	20.8 45	16.1 22	21.6 91	32.0 33	26.9 61	26.80 7	34.95	62.99 4	39.13 8	30.9 23	13.8 07	32.1 33
	Covariance	0.11 7	0.18 9	0.10 1	0.15 3	0.12 1	0.0 77	0.11 6	0.09	0.12 1	0.17 8	0.15	0.149	0.194	0.35	0.217	0.17 2	0.07 7	0.17 9
	N	181	181	181	181	181	181	181	181	181	181	181	181	181	181	181	181	181	181
	Pearson Correlation	.392	.398	0.14 5	.277*	.295*	.53 4**	.255**	0.1	.375**	.463**	.258* *	.252**	.343**	.510**	1	.517* *	.272* *	.527**
	Sig. (2-tailed)	<.00 1	<.00 1	0.05 2	<.00 1	<.00 1	<.0 01	<.00 1	0.17 9	<.00 1	<.00 1	<.00 1	<.00 1	<.001	<.001		<.00	<.00 1	<.00 1
Q15	SOS & CP	33.5 14	39.9 28	11.6 52	23.5 69	23.3 15	44. 486	20.8 67	7.96 1	33.7 35	35.1 71	20.9 67	19.83 4	28.24 3	39.13 8	93.54 7	40.9 34	29.8 34	44.6 85
	Covariance	0.18 6	0.22 2	0.06 5	0.13 1	0.13	0.2 47	0.11 6	0.04 4	0.18 7	0.19 5	0.11 6	0.11	0.157	0.217	0.52	0.22 7	0.16 6	0.24 8
	N	181	181	181	181	181	181	181	181	181	181	181	181	181	181	181	181	181	181
	Pearson Correlation	.213	.391	.239* *	.347*	.361* *	.42 0**	.373**	.353**	.258**	.598**	.457* *	.155*	.406**	.476**	.517**	1	.424* *	.389**
	Sig. (2-tailed)	0.00 4	<.00 1	0.00 1	<.00 1	<.00 1	<.0 01	<.00 1	<.00 1	<.00 1	<.00 1	<.00 1	0.038	<.001	<.001	<.001		<.00 1	<.00 1
Q16	SOS & CP	15.3 92	33.1 6	16.3 15	24.9 61	24.1 44	29. 608	25.8 34	23.7 02	19.6 69	38.4 64	31.4 59	10.29 3	28.30 4	30.92 3	40.93 4	66.9 17	39.2 93	27.8 56
	Covariance	0.08 6	0.18 4	0.09 1	0.13 9	0.13 4	0.1 64	0.14 4	0.13 2	0.10 9	0.21 4	0.17 5	0.057	0.157	0.172	0.227	0.37 2	0.21 8	0.15 5
	N	181	181	181	181	181	181	181	181	181	181	181	181	181	181	181	181	181	181

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Q17	Pearson Correlation	.284	.382	0.02 4	.396* *	.274*	.33 3**	0.13 1	0.11	.362**	.395**	.521* *	.209**	.293**	.154 [*]	.272**	.424*	1	.268**
	Sig. (2- tailed)	<.00 1	<.00 1	0.74 6	<.00 1	<.00 1	<.0 01	0.07 8	0.13 9	<.00 1	<.00 1	<.00 1	0.005	<.001	0.039	<.001	<.00		<.00 1
	SOS & CP	28.4 81	44.9 01	2.28 7	39.4 03	25.3 59	32. 519	12.5 86	10.2 54	38.1 71	35.1 6	49.6 46	19.23 2	28.26	13.80 7	29.83 4	39.2 93	128. 23	26.6 41
	Covariance	0.15 8	0.24 9	0.01	0.21 9	0.14 1	0.1 81	0.07	0.05 7	0.21 2	0.19 5	0.27 6	0.107	0.157	0.077	0.166	0.21 8	0.71 2	0.14 8
	N	181	181	181	181	181	181	181	181	181	181	181	181	181	181	181	181	181	181
Q18	Pearson Correlation	.305	.440	.503*	.235*	0.14 2	.31 0**	.360**	.349**	0.14	.496**	.365*	.542**	.565**	.462**	.527**	.389*	.268*	1
	Sig. (2- tailed)	<.00 1	<.00	<.00 1	0.00	0.05 6	<.0 01	<.00 1	<.00 1	0.06	<.00 1	<.00 1	<.00 1	<.001	<.001	<.001	<.00 1	<.00 1	
	SOS & CP	23.6 13	40.0 11	36.7 46	18.0 66	10.1 82	23. 387	26.7 13	25.0 83	11.4 25	34.2 04	26.9 28	38.64 1	42.19 3	32.13 3	44.68 5	27.8 56	26.6 41	76.8 18
	Covariance	0.13 1	0.22	0.20 4	0.1	0.05 7	0.1 3	0.14 8	0.13 9	0.06 3	0.19	0.15	0.215	0.234	0.179	0.248	0.15 5	0.14 8	0.42 7
	N	181	181	181	181	181	181	181	181	181	181	181	181	181	181	181	181	181	181