International Review of Management and Marketing

ISSN: 2146-4405

available at http: www.econjournals.com

International Review of Management and Marketing, 2026, 16(3), 491-500.

Adoption of Omnichannel Technology along with its Impact on Customer Experience from an FMCG Perspective

R. Sharmila, D. Janis Bibiyana*

Department of Commerce, Faculty of Science and Humanities, SRM Institute of Science and Technology, Ramapuram Campus, Chennai, Tamil Nadu, India. *Email: janisbid@srmist.edu.in

Received: 26 September 2025 **Accepted:** 27 February 2026 **DOI:** https://doi.org/10.32479/irmm.22275

ABSTRACT

The use of omnichannel technology is becoming more important in improving customer experience with the fast-moving consumer goods (FMCG) segment that enables customers to utilize captive channels seamlessly either online or offline. This study explored the effects of three dimensions of technology adoption i.e., Channel synchronization, personalized marketing and technology integration on customer experience in a metropolitan retail setting in Chennai, India. A cross-sectional study design was applied utilizing structured surveys and quantitative analysis was conducted to assess the direct association of technology adoption dimensions on customer experience. The results indicate that all three dimensions had a positive association with customer experience, with personalized marketing and technology integration having the most influence on customer experience, followed by channel synchronization. The study provides empirical evidence from an emerging market that reinforces the importance of aligned practices in technology adoption to enhance consumer engagement and offers implications for retailer managers in term of insights into technology investment allowing for the delivery of impactful customer experience.

Keywords: Omnichannel, Channel Synchronization, Personalized Marketing, Technology Integration, Customer Experience, Fast-Moving Consumer Goods
JEL Classifications: M31; O33

1. INTRODUCTION

Omnichannel retailing firms to integrate multiple channels and touch-points so customers experience a seamless, consistent journey regardless of entry point (Verhoef et al., 2015; Cai and Lo, 2020). In FMCG markets characterised by frequent, low-involvement purchases and varies retail formats (kirana shops, supermarkets. e-commerce) omnichannel technology can reduce friction, promote convenience and influence repurchase behaviour (Ailawadi and Farris, 2017). Chennai, a significant metropolitan city in India exhibiting a blend of modern retail and traditional trade, represents an appropriate empirical context to examine the extent to which technology adoption across channel transforming customer experience in FMCG.

In recent years, consumer expectations have changed dramatically: Shoppers now expect a seamless, contextually relevant experience in which transitions from online to offline channels are effortless and personalized. The profile-ration of mobile devices, rapid and reliable internet access and a variety of all digital payment systems in Indian metros like Chennai have hastened omnichannel adoption in FMCG, which has rendered the use of technology a necessary proposition, rather than a means of competitive differentiation. For instance, Indian FMCG brands are exploring fast commerce and hybrid formats that combine storefront and delivery models (Goel and Madan, 2025).

However, while many firms have invested in omnichannel capabilities, the precise mechanisms by which these technologies impact customer experience remain under-explored particularly FMCG, where purchase cycles are frequent and low-involvement. Chennai, with its mix of modern-retail chains, traditional grocery stores and rising e-commerce adoption, presents an ideal lab to test

how four specific technology adoption dimensions relate directly to overall customer experience. By empirically validating these relationships with data from 454 consumers, this study aims both theoretical and managerial contributions.

2. LITERATURE REVIEW AND THEORETICAL BACKGROUND

2.1. Omnichannel and Customer Experience

Omnichannel integrates online and offline channels to create an integrated experience and is known to influence customer satisfaction, loyalty and repurchase intention (Shankar and Kushwaha, 2020). Omnichannel retail integrates digital and physical points to provide a unified experience and consistent shopping experience to enhance satisfaction and loyalty (Verhoef et al., 2015). Recent research highlights that omnichannel features, including mobile apps and unified promotions create combined effects that enhance customer engagement (Beck and Rygl, 2015).

2.2. Channel Synchronization

Channel synchronization minimize uncertainty and assist seamless switching by consumers (Verhoef, 2021). The Channel synchronization develops consistent pricing, inventory information, and promotions across online and offline channels, which limits confusion for customer (Herhausen et al., 2015). A synchronized channel system allows for the ability for transparency and convenience for the consumers in the shopping process (Huré et al., 2017).

2.3. Personalized Marketing

Personalization across channels driven by consumer data and AI improves relevance, perceived value and engagement; top performers in personalization report higher revenue (Tyrväinen et al., 2020). Personalized marketing leverages big data and AI to deliver relevant offers and content tailored to individual customer preferences, significantly influencing satisfaction and loyalty (Lemon and Verhoef, 2016).

2.4. Technology Integration (Back-end and Front-end)

Integration of POS, CRM, inventory and analytics, emotional engagement and cognitive ease and is measured through validated scales (Cai and Lo, 2020). Integration also improves operational efficiency and enables true omnichannel coordination across logistics, marketing and service processes (Ailawadi and Farris, 2017).

2.5. Customer Experience

Customer experience is multi dimensional including functional convenience, emotional engagement and cognitive ease and its measured through validated scales (satisfaction, CES, overall experience). It construct encompassing emotional, cognitive, sensory and behavioral responses during interactions with a brand (Gentile et al., 2007)

Beyond the core dimensions, researchers have explored additional structural and behavioral frameworks supporting omnichannel experience. For example, the expectation disconfirmation theory has been applied to assess how consistency across online and offline experiences influences satisfaction and repurchase intention the customers dislike discrepancies in experience quality and favor alignment across channels. The channel expansion theory explains that over time, as user gain experience with a communication medium, they perceive richer communication through that medium; in omnichannel retail, repeated exposure to integrated systems enhances perceived richness and usability of channels.

3. HYPOTHESIS DEVELOPMENT

H_1: Channel synchronization has a positive effect on FMCG customer experience.

Consistent product information, inventory transparency and synchronized promotions across channels reduce search friction and expectation disconfirmation, improving perceived experience. Empirical omnichannel studies show that coordinated channels increase satisfaction and repurchase intentions (Verhoef et al., 2015).

H_2: Personalized marketing has a positive effect on FMCG customer experience.

Personalization increases relevance and perceived value; retail and marketing literature link personalization to stronger customer engagement and revenue gains. Personalized communications and recommendations across channels enhance the shopping experience (Tyrväinen et al., 2020).

H_3: Technology integration has a positive effect on FMCG customer experience.

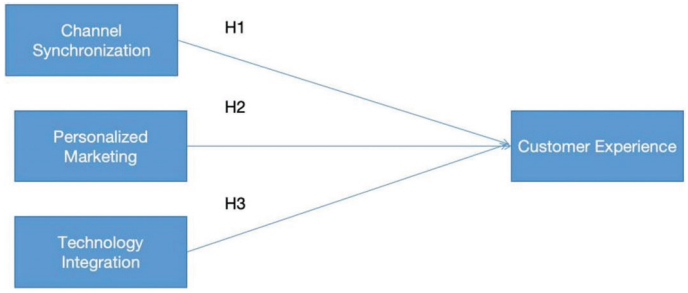
By linking back-end system (inventory, POS, CRM) with front-end applications (mobile interface, website interface, in-store systems) in real-time the fulfillment experiences will eliminate service failures and enhance the experience. In fact, it has been suggested that technology integration as a direct driver of omnichannel marketing effectiveness (Cai and Lo, 2020).

H_4: Overall omnichannel technology adoption has a significant and positive effect on FMCG customer experience.

Integration all omnichannel technology adoption dimensions are Channel synchronization, Personalized Marketing and Technology Integration collectively enhances the perceived customer experience in FMCG. The model suggests these components will all coexist together under a well-structured technology-influenced consumer experience to increase satisfaction and loyalty.

As articulated in the research hypothesis developed earlier, the research used the conceptual model design as an integral part of the methodological basis for this study (Figure 1).

Figure 1: Conceptual model and research hypothesis



Source: Own research

This conceptual design allows for examination of the relationships between technological and experiential variables, that systematic and empirically assess omnichannel technologies as a shaper of total consumer experiences. Each independent variable is a technological dimension of omnichannel adoption deemed to be salient in determining the effectiveness of customer engagement at digital and physical touch-points.

The primary aim of the constructs is to describe how technology integration provides benefits for consumer satisfaction, convenience and loyalty aimed at shifting consumer behaviours. There is a belief that advancements and synchronicity in omnichannel technologies would achieve superior and more synchronous customer experience in the FMCG retail case contexts. Therefore this framework facilitates testing the four hypothesis empirically and contributes to a theoretical and methodological experience and consumers in omnichannel retailing.

4. RESEARCH METHODOLOGY

4.1. Research Design

This study uses a cross-sectional quantitative research design to examine the role of omnichannel technology adoption on customer experience in the Indian FMCG retail context, in the city of Chennai. Data were collected for the study at a single point in time from a different FMCG shoppers types to measure the relationships proposed among the constructs. A structured, self-administered questionnaire using closed-ended questions asked consumers to respond using a five-point Likert scale (1-Strongly Disagree to 5-Strongly Agree), which is commonly used to capture consumer perception (Saunders et al., 2007; Hair et al., 2014). This research design allows for the simultaneous investigation of multiple relationship whilst controlling for measurement error and supports the generalizing of study findings across urban retail consumers.

4.2. Sampling Technique and Sample Description

The target demographic for the study were consumers of FMCG in Chennai experiencing different retail formats including model trade outlets, supermarkets, neighborhood grocery store or online orders either click-and-collect or home delivery. A stratified random sampling approach was employed to ensure proportional representation from main areas in Chennai: North, Central, South, East and West. Each stratum, the respondents were approached at stores and online randomly selected to incorporate diversity in demographic.

The study established representatives based on stratified sampling but convenience sampling for getting potential respondents surveying consumers who were readily available to participate, scope of work would be the cost of having workplace online retail and hybrid shoppers (Robson, 2002; Saunders et al., 2007; Zhao, 2020). Convenience sampling is widely used for matrix and behavioral studies the potential greater usefulness of this sampling approach is the lower cost and practical usefulness when studies are focused on surveying perceptual variables. Convenience sampling is not appropriate for the unconditional support of statistical generalizability; however articulated convenience sampling has validity for theory testing that consider time and costs (Fortin, 2009; Robinson, 2014).

A total of 454 usable responses were collected which exceed the recommendation for regression and PLS-SEM analysis (Hair et al., 2014). According to Stevens (1996), recommend at least 15 usable sampled responses per observed variable mean the study had 25 indicators meaning each observed user needed at least 375 respondents, with a total of 454 usable cases the sample size is sufficient (Fortin, 2009; Robinson, 2014).

4.3. Sample Size Justification

The sample size determination followed Cochran's formula (1997) for large population, with a 95% confidence level and ±5% margin of error:

$$n_0 = \frac{Z^2 \cdot p(1-p)}{e^2}$$

where Z = 1.96, p = 0.5 and e = 0.05

$$n_0 = \frac{(1.96)^2 \cdot 0.5(1-0.5)}{(0.05)^2} = 384.16$$

Accounting for a 15% expected non-response rate:

$$n_0 = \frac{384.16}{0.85} = 452$$

Although the minimum required sample size after adjustment was 452, the final target sample was increased to 454 respondents to ensure adequate data for PLS-SEM analysis.

4.4. Instrumentation and Measurement

The instrument comprised four constructs - channel synchronization, personalized marketing, technology integration and customer experience each measured using five items adapted from validated scales and prior omnichannel and customer experience. Each item was assessed using a 5-point Likert scale and demographic items were included to profile respondents. The full questionnaire is provided in Appendix for replication and SPSS data entry.

A pilot test (n = 30) confirmed clarity and content validity; minor rewording improved comprehension. The instrument's reliability was later evaluated using Cronbach's α, composite reliability and average variance extracted to ensure internal consistency and convergent validity (Nunnally and Bernstein, 1994; Mohajan, 2017).

4.5. Data Collection and Ethical Considerations

Data were collected between March and July 2025 through both field-administrated and online surveys. Field surveys were conducted in major retail hubs (T. Nagar, Velachery, Anna Nagar, Tambaram and Porur), while online links where distributed via WhatsApp and Chennai-based retail customer groups.

Table 1: Sample characterization

Demographic variable	n	Mean	Standard deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Standard error	Statistic	Standard error
Age	454	2.06	1.152	0.858	0.115	−0.256	0.229
Gender	454	1.45	0.528	0.520	0.115	−1.052	0.229
Educ	454	3.07	0.910	−0.171	0.115	−0.203	0.229
Occup	454	2.05	1.182	1.421	0.115	1.745	0.229
Income	454	2.57	1.099	0.251	0.115	−0.697	0.229
Retail_format	454	2.41	1.342	0.702	0.115	−0.767	0.229
Freq_purchase	454	2.27	0.941	0.277	0.115	−0.810	0.229
Valid N (listwise)	454						

Source: Own elaboration - SPSS data

All participants were informed about the research purpose and assured anonymity and confidentially. No personal identifiers were collected. Ethical producers followed University research ethics guidelines and standard academic research principles (Warrell and Jacobsen, 2014; Elmas, 2023).

4.6. Data Analysis Plan

Data analysis was carried out using SPSS 26.0 and SmartPLS 4.0 to examine the hypothesized relationships and ensure robustness of results. In SPSS, preliminary analysis were conducted to compute descriptive statistics for all constructs to assess data normality and distribution patterns.

4.6.1. Measurement model assessment

Outer loadings, Composite Reliability and Average Variance Extracted were computed to evaluate reliability and convergent validity. Discriminant validity was examined using both the Fornell-Larcker criterion and the Heterotrait-Monotrait ratio.

4.6.2. Structural model evaluation

The structural relationships among the constructs were analyzed through using path coefficients, P-values and the effect size indices (R^2, f^2, Q^2). It also determined if multicollinearity issues existed with the variance inflation factor values Variance using VIF <3.3. Bootstrapping with 5,000 resamples were employed to determine if the hypothesized paths were statistically significant.

This dual analytical approach integrated classic statistical validation with advanced structural modeling, which provided well-rounded understanding of the dataset's reliability, validity and predictive power (Hair et al., 2014).

4.7. Reliability and Validity Testing

Reliability and validity studies were conducted to determine if the measurement were accurate and consistent. Reliability for internal consistency was assessed using Cronbach's α and composite reliability, with values exceeding 0.70 indicating satisfactory reliability (Nunnally and Bernstein 1994).

Convergent validity was determined when the average variance extracted for each construct was >0.50. Discriminant validity was determined when the square root of each construct's AVE was greater than the inter-construct correlations. The HTMT ratio was applied, with all values maintained below the acceptable threshold of 0.85 (Henseler et al., 2015).

4.8. Statistical Tools Justification

The integration of SPSS and SmartPLS 4.0 form complementary analytical framework suited for both descriptive and inferential research purposes. SPSS facilitates strong preliminary analysis, including reliability tests and fundamental inferential tests, that provide an adequate premise for modeling.

Meanwhile, SmartPLS 4.0, is a variance-based structural equation modeling tool. This type of tool is best suited for systems that demonstrate predictive, exploratory and theory building research. SmartPLS works excellent for larger structural models with multiple predictors and smaller sample sizes, making it the preferred method for marketing and consumer behavior research.

Together, these tools facilitate a comprehensive, multi method analysis is accomplished using SPSS to provide accurate descriptive profiling in altering a measurement system, followed by SmartPLS to confirm casual relationship and predictive statistical outcome hypothesis (Hair et al., 2014; Brereton, 2019; Bollen, 1989).

5. RESULTS

The analysis of the results obtained from the consumer questionnaire began with the description of the sample, followed by descriptive statistics, assessment of a measurement model and an assessment of a structural model. This sequence was intentional so that several variables of internal consistency, hypothesis testing, reliability and validity could all be analyzed with SPSS 26.0 and SmartPLS 4.0.

5.1. Sample Characterization

The total number of valid respondents served for this study is 454 in Table 1. The mean age of the respondents was 2.06 (SD = 1.152) with slight positive skewness (0.858) and near normal kurtosis (−0.256), indicating that there were slightly more younger respondents. The mean of Gender was 1.45 (SD = 0.528) indicating that there was moderate positive skewness (0.520) and negative kurtosis (−1.052) suggesting that there were slightly more males than females or gender non-conforming, which were either did not mark the gender box or did not identity as male or female. The mean educational attainment was 3.07 (SD = 0.910) with a slight negative skew (−0.171) and a near-zero kurtosis (−0.203) suggesting there was a balanced distribution across educational attainments. The mean for occupation was 2.05 (SD = 1.182) with high positive

skewness (1.421) and kurtosis (1.745) suggesting that there were also a few ethnic groups concentrated in other occupational groups. The mean monthly household income was 2.57 (SD = 1.099) with a mild positive skew (0.251) and negative kurtosis (−0.697). The respondents' preferred retail formats for purchasing FMCG was mean of 2.41 (SD = 1.342) with positive skew (0.702) and slight negative kurtosis (−0.767). Lastly for purchase frequency of FMCG weekly or monthly the mean was 2.27 (SD = 0.941) with a modest positive skew (0.277) and negative kurtosis (−0.810). Overall, the data suggest a majority of respondents are younger, female, moderately educated and show variation in occupation, income, retail preferences and FMCG purchase frequency.

5.2. Assessment of Measurement Models

5.2.1. Assessment of reliability and convergent validity

Indicator reliability is the proportion of variance in each item accounted for by its underlying construct. Factor loading or outer loading, represent the contribution of the given item to its respective context. The loading should be >0.70, while (Chin, 1998), notes that values above 0.50 or 0.60 are more acceptable. The results from Table 2 indicate that all items exceeded the value of 0.50, with the majority exhibiting >0.70, demonstrating appropriate indicator reliability. In the customer experience (CE) construct, loadings for CE item 1-5 ranged from 0.899 to 0.915. Loading for the channel synchronization (CHA) items CHS1-CHS5 ranged from 0.853 and 0.886. For personalized marketing (PM) items PM1-PM5 ranged from 0.861 to 0.899 for loadings, with technology integration (TI) having loadings from TI1-TI5 ranging from 0.867 to 0.895. Therefore, each item appropriately represents its underlying construct and convergent validity is high.

Cronbach's alpha and composite reliability (rho_a and rho_c) to measure internal consistency of the constructs and average variance extracted (AVE), to assess convergent validity. The results indicate strong reliability for all constructs. Customer experience (CE) showed a Cronbach's alpha of 0.946, composite reliability rho_a = 0.947, rho_c = 0.959 and AVE = 0.823. Channel synchronization (CHS) exhibited Cronbach's alpha = 0.919, rho_a = 0.920, rho_c = 0.939 and AVE = 0.756. Personalized marketing (PM) had Cronbach's alpha = 0.924, rho_a = 0.930, rho_c = 0.942 and AVE = 0.780. Technology integration (TI) showed Cronbach's alpha = 0.930, rho_a = 0.932, rho_c = 0.947 and AVE = 0.780. Table 3 presents Cronbach's alpha and composite reliability values exceed the recommended threshold of 0.70 and AVE values are above 0.50, confirming strong internal consistency and convergent validity of the measurement model.

5.2.2. Discriminant validity

To verify whether each construct is empirically distinct from others, discriminant validity was assessed following the Fornell-Larcker criterion (Fornell and Larcker, 1981). According to this approach, the square root of the average variance extracted (AVE) for each construct should be greater than its correlation with any other construct. As shown Table 4, the square roots of AVE for customer experience (0.907), channel synchronization (0.869), personalized marketing (0.875) and technology integration (0.883) are all higher than their corresponding inter-construct correlations. This indicates that each construct shares more variance with its own indicators than with other constructs, thereby confirming satisfactory discriminant validity.

Nonetheless, (Henseler et al., 2015) assert that the evaluation of discriminant validity may not always be satisfactorily established with the Fornell-Larcker criterion when factor have similar loadings across constructs. Thus, the Heterotrait-Monotrait ration (HTMT) was also assessed as a secondary measure. Table 5 presents the HTMT ratios, demonstrating that all HTMT values fall below

Table 2: Outer loadings

Indicator	Customer experience	Channel synchronization	Personalized marketing	Technology integration
CE1	0.914			
CE2	0.899			
CE3	0.915			
CE4	0.905			
CE5	0.904			
CHS1		0.863		
CHS2		0.886		
CHS3		0.853		
CHS4		0.877		
CHS5		0.869		
PM1			0.864	
PM2			0.861	
PM3			0.877	
PM4			0.899	
PM5			0.874	
TI1				0.887
TI2				0.881
TI3				0.895
TI4				0.867
TI5				0.887

Source: PLS-SEM

Table 3: Internal consistency reliability and convergent validity results

Construct	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted
CE	0.946	0.947	0.959	0.823
CHS	0.919	0.920	0.939	0.756
PM	0.924	0.930	0.942	0.766
TI	0.930	0.932	0.947	0.780

Source: PLS-SEM

Table 4: The assessment of discriminant validity using the Fornell-Larcker critertion

Construct	CE	CHS	PM	TI
CE	0.907			
CHS	0.408	0.869		
PM	0.374	−0.006	0.875	
TI	0.365	0.000	0.016	0.883

Source: PLS-SEM

Table 5: Heterotrait-monotrait ratio (HTMT) correlations

Construct	CE	CHS	PM	TI
CE				
CHS	0.437			
PM	0.396	0.032		
TI	0.389	0.039	0.038	

Source: PLS-SEM

0.90, with the highest ratio 0.437 being reported for customer experience and channel synchronization. These comparably low ratios which are below the suggested threshold indicate that each construct is empirically distinct and provide further evidence of discriminant validity in the measurement model.

To evaluate potential collinearity among the indicators in Table 6, the variance inflation factor (VIF) was used, as suspected multicollinearity bias would violate the conclusions on the measurement model results. Researches typically consider VIF values below 5 as not indicative of critical multicollinearity. Moreover, values <3.3 are considered ideal. To this end, the VIF varies across the indicators between 2.491 and 3.982, including for the customer experience (CE) indicators (CE1 to CE5 = 3.489-3.982), Channel synchronization (CHS) indicators (CHS1 to CHS5 = 2.491-2.970), personalized marketing (PM) indicators (PM1 to PM5 = 2.655-3.148) and technology integration (TI) indicators (TI1-TI5 = 2.725-3.124). All VIF estimates fall well below the threshold for critical multicollinearity, providing assurance that multicollinearity is not an issue and further support that the collinearity estimates are centres for the measurement construction.

5.3. Structural Model Assessment and Hypothesis Test

The structural model was evaluated to examine the relationships among the constructs and to test the proposed hypothesis. The assessment included the analysis of correlations, coefficient of determination (R^2), effect size (f^2), predictive relevance (Q^2) and path coefficients with corresponding significance levels (P-values).

Table 7 presents the correlation matrix among the constructs. The relationships between customer experience (CE) and the predictors - channel synchronization (CHS) (r = 0.408), personalized marketing (PM) (r = 0.374) and technology integration (TI) (r = 0.65) suggest moderate positive relationships. The independent variables exhibited low inter-correlations, indicating that multicollinearity is not an issue, therefore showing the strength of the model.

The R^2 value of customer experience (CE) was 0.438 in Table 8 shows, which indicates that CHS, PM and TI explain 43.8% of the variation in CE. The observed is adjusted R^2 value of 0.434 supports this finding and indicates that the structural model has a high degree of explanatory power as defined by Cohen (1998), where R^2 values above 0.26 represent a substantial effect.

The f^2 value (Table 9) was used to evaluate the contribution of each exogenous construct to the endogenous variable. The result show medium to large effect sizes for CHS (f^2 = 0.300), PM (f^2 = 0.245) and TI (f^2 = 0.230) on CE, suggesting that each predictor construct makes a meaningful contribution to explaining customer experience.

The Q^2 value obtained through blindfolding (Table 10) was 0.428, indicating model predictive relevance for the endogenous construct since the value is >0. To support acceptable predictive accuracy of the PLS-SEM model, the RMSE (0.76) and MAE (0.601) values were also consider.

Table 6: Collinearity assessment (VIF)

Construct	VIF
CE1	3.913
CE2	3.489
CE3	3.982
CE4	3.569
CE5	3.597
CHS1	2.648
CHS2	2.970
CHS3	2.491
CHS4	2.753
CHS5	2.697
PM1	2.772
PM2	2.655
PM3	2.852
PM4	3.148
PM5	2.685
TI1	3.013
TI2	2.949
TI3	3.124
TI4	2.725
TI5	3.091

Source: PLS-SEM

Table 7: Correlation

Construct	CE	CHS	PM	TI
CE	1.000	0.408	0.374	0.365
CHS	0.408	1.000	−0.006	0.000
PM	0.374	−0.006	1.000	0.016
TI	0.365	0.000	0.016	1.000

Source: PLS-SEM

Table 8: R-square

Endogenous construct	R-square	R-square adjusted
CE	0.438	0.434

Source: PLS-SEM

Table 9: F-square

Relationship	CE	CHS	PM	TI
CE				
CHS	0.300			
PM	0.245			
TI	0.230			

Source: PLS-SEM

Table 10: Q-square

Endogenous construct	Q^2predict	RMSE	MAE
CE	0.428	0.76	0.601

Source: PLS-SEM

As presented in Table 11, the path coefficients demonstrate hat channel synchronization (β = 0.41, t = 12.138, P < 0.001), personalized marketing (β = 0.371, t = 10.468, P < 0.001) and technology integration (β = 0.36, t = 10.49, P < 0.001) have significant positive effects on customer experience. All path coefficients are statistically significant at the 0.001 level, supporting the proposed that CHS, PM and TI positively influence CE.

6. DISCUSSION

In this section, hypothesis H_1-H_4 were tested using PLS-SEM. The significance level for this study was set at $P < 0.05$, meaning hypothesis are supported when the P = value is below this threshold. The analysis revealed that channel synchronization (CHS), personalized marketing (PM) and technology integration (TI) have a statistically significant and positive effect on customer experience (CE) within the FMCG omnichannel context.

Hypothesis 1 (H_1), customer experience ($\beta = 0.41$, $t = 12.138$, $P < 0.001$, $f^2 = 0.300$). This indicates that customer believe their interactions are smoother and more convenient across the online and offline channel when FMCGs successfully align their channel operation. This supports H_1 and is consistent with previous findings (Verhoef, 2021) that registered both physical and digital channel alignment preferences ease the customer effort aspect of the interaction and consumer convenience. The moderate effect size ($f^2 = 0.300$) confirms that operationally aligned channels are a prerequisite for increasing customer satisfaction and perceived value in omnichannel retailing.

Hypothesis 2 (H_2), The path coefficient between personalized marketing and customer experience was both positive and statistically significant ($\beta = 0.371$, $t = 10.468$, $P < 0.001$, $f^2 = 0.245$). This supports H_2, and demonstrates that personalized marketing communications, such as personalized promotions, recommendations and customer messaging, improve the customer's interactions and enhance satisfaction. This is consistent with prior studies (Lemon and Verhoef 2016) which found a personalized marketing communication deepen an emotional bond and loyalty because a marketers attempts to pair offers with customer expectations. The moderate effect size ($f^2 = 0.245$) signifies that personalizing marketing communication remains a strong driver of perceived omnichannel facilitation and enhanced customer experience in the FMCG context.

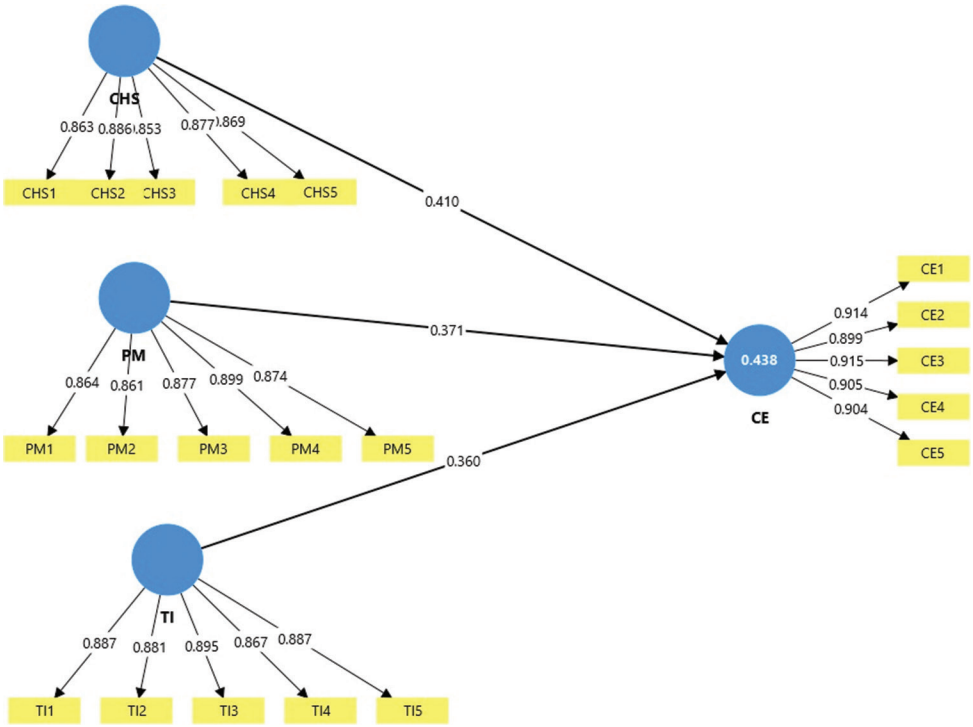
Hypothesis 3 (H_3), The structural analysis revealed that technology Integration has a positive and significant influence on customer experience ($\beta = 0.360$, $t = 10.490$, $P < 0.001$, $f^2 = 0.230$). Hence, confirm H_3 which suggesting that integrated technological solutions inclusive of single unified consumer relationship technology CRM systems, artificial intelligence computing analytical functionality and multi-channel inventory visibility, enhance customer convenience and service consistency. These results are supported by previous research (Beck and Rygl, 2015) who suggest that seamless technology integration fosters an integrated journey that drives satisfaction and intention to purchase. In considering

Table 11: P value

Hypothesis	Path	BETA COEFF	Standard deviation	T statistics (|O/STDEV|)	P-values	Decision
H_1	CHS -> CE	0.41	0.034	12.138	0.000	Supported
H_2	PM -> CE	0.371	0.035	10.468	0.000	Supported
H_3	TI -> CE	0.36	0.034	10.49	0.000	Supported
H_4	Overall Omnichannel Adoption -> CE	R^2=0.438				Supported

Source: PLS-SEM

Figure 2: Updated conceptual model (PLS-SEM)



Source: PLS-SEM

the moderate effect ($f^2 = 0.230$), it suggests that the strategic role of technology had a role in the successful implementation of omnichannel excellence.

Hypothesis 4 (H_4), Finally the overall omnichannel technology adoption construct has a positive and statistically significantly effect on FMCG customer experience ($R^2 = 0.438$, Adjusted $R^2 = 0.434$, $Q^2 = 0.428$). This is to say that the combined influence of CHS, PM and TI explains approximately 43.8% of the variance in customer experience which supports the robustness and predictive power of the model. Therefore, the results support H_4 and these results are contemporaneous with previous research (Verhoef, 2021; Cai and Lo, 2020) which emphasizes the role of omnichannel technology as a key enabler of convenience, consistency and value in modern retail today.

Figure 2 illustrates the final conceptual model of this study, developed using partial least squares structural equation modeling (PLS-SEM). The model illustrates that three validated constructs, namely channel synchronization (CHS), personalized marketing (PM) and technology integration (TI) all contribute to an increase in FMCG customer experience (CE). The diagram illustrates the relationships among these constructs and how each element of the omnichannel strategy contributes positively to the customer experience. In addition, the model indicates that these three constructs combined account for 43.8% of the variance in CE ($R^2 = 0.438$) and shows strong predictive relevance ($Q^2 = 0.428$), thus supporting the proposed omnichannel model robustness.

7. CONCLUSION

This study examined how bundled strategic omnichannel technology adoption affects customer experience (CE) in the fast-moving consumer goods (FMCG) sector. The findings support that all three constructs of bundled strategic omnichannel technology adoption positively and significantly influence CE, with channel synchronization being the strongest, followed by a personal touch of marketing (targeted advertisements or promotions) and technology integration. The medium-sized explanatory power ($R^2 = 0.438$) and predictive relevance ($Q^2 = 0.428$) of the model suggest that these three omnichannel technology strategic dimensions of presented sufficient evidence to draw meaningful conclusions about the unwanted assumptions of customer experience. The study also accentuates that these results confirm that improving customer experience is not achieved by improved isolated initiatives, rather by a bundled approach that results in operational efficiency, digital personalization and technological integration. This study contributes to the nascent area of omnichannel strategy research by providing new evidence of the interdependent multilateral relationships of how digital marketing, technology integration and consumer expectations co-exist in the context of rapid technological retail disruption.

7.1. Management Implications

The study findings have several practical implications for managers in the FMCG industry. Companies should prioritize fostering an integrated omnichannel environment whereby online and offline channels are harmonized to ensure a seamless customer experience. Managers should utilize customer data analytics to tailor personalized marketing strategies based on consumer preferences and purchasing behavior. The integration of technology such as customer relationship management technology, recommendations engines, artificial intelligence (AI) based recommendations engines and real time inventory tracking may improve responsiveness and quality of service. Additionally, the results indicate that organizations need to move beyond traditional marketing methods and consider a more integrated, data driven and technology-enabled approach toward customer experience. The organization should consider establishing strategic partnerships with validated influencers and technology partners to strengthen brand interaction and boost customer trust. Effectively aligning technology and marketing strategies across channels gives firms a competitive advantage and is likely to lead to long-term relationships with customer through brand loyalty.

7.2. Limitations

Despite the valuable contributions of this study, it should be noted that there are limitations. The study was conducted in the FMCG industry in a specific area, potentially limiting the transfer-ability of the findings to other industries or cultural settings. The cross-sectional study limits casual inference because data collection happened at one single point in time. Additionally, the study was conducted using self-reported measures making the data subject to social responsibility and common method variance bias. The current study examined only three independent variables - channel synchronization, personalized marketing and technology integration. However, other relevant variables such as brand image, perceived convenience, service quality and customer trust were not incorporated. Further research examining these study limitations can provide a broader understanding of the factors influencing on customer experience within an omnichannel context.

7.3. Suggestions for Future Research

Future research could build upon this study by testing the proposed model in a variety of settings such as industries, cultural contexts and demographic segments to increase its generalizability. It is recommended longitudinal research designs capture the dynamic nature of constructs and account for the establishment of casual relationships. Future scholars, may also expand on the values found in this study and include variables such as brand image, customer trust, emotional engagement or perceived convenience to the original proposed conceptual model. Also, mediating or moderating factors such as customer satisfaction, loyalty or direct literacy would provide more valuable insight into the relationships of the omnichannel strategy components and customer experience. Taking the above factors into account, future studies could help develop more refined theoretical framework that examines how digital transformation, personalization and technological come together to positively affect customer experience in the modern-day marketplace.

REFERENCES

Ailawadi, K.L., Farris, P.W. (2017), Managing multi- and Omni-channel distribution: Metrics and research directions. Journal of Retailing, 93(1), 120-135.

Beck, N., Rygl, D. (2015), Categorization of multiple channel retailing in multi-, cross-, and omni-channel retailing for retailers and retailing. Journal of Retailing and Consumer Services, 27, 170-178.

Bollen, K.A. (1989), A new incremental fit index for general structural equation models. Sociological Methods and Research, 17(3), 303-316.

Brereton, R.G. (2019), ANOVA tables and statistical significance of models. Journal of Chemometrics, 33(3), e3019.

Cai, Y.J., Lo, C.K.Y. (2020), Omni-channel management in the new retailing era: A systematic review and future research Agenda. International Journal of Production Economics, 229, 107729.

Chin, W.W. (1998), The partial least squares approach for structural equation modeling. In: Marcoulides, G.A., editor. Modern Methods for Business Research. United States: Lawrence Erlbaum Associates. p295-336.

Elmas, T. (2023), The Impact of Data Persistence Bias on Social Media Studies. In: Proceedings of the 15th ACM Web Science Conference. p196-207.

Fornell, C., Larcker, D.F. (1981), Evaluating structural equation models with unobservable variables and measurement error. Journal of Marketing Research, 18(1), 39-50.

Fortin, M. (2009), Fondements et Étapes du Processus de Recherche. Canada: Gaetan Morin Cheneliere Education.

Gentile, C., Spiller, N., Noci, G. (2007), How to sustain the customer experience: An overview of experience components that co-create value with the customer. European Management Journal, 25(5), 395-410.

Goel, S., Madan, P. (2025), The future of FMCG sales: Leveraging omnichannel strategies for sustainable growth. International Journal of Research and Analytical Reviews (IJRAR), 12(3), 344-350.

Hair, J.F., Black, W.C., Babin, B.J., Anderson, R.E. (2014), Multivariate Data Analysis. 7th ed. India: Pearson Education.

Henseler, J., Ringle, C.M., Sarstedt, M. (2015), A new criterion for assessing discriminant validity. Journal of the Academy of Marketing Science, 43(1), 115-135.

Herhausen, D., Binder, J., Schoegel, M., Herrmann, A. (2015), Integrating bricks with clicks: Retailer-level and channel-level outcomes of online-offline channel integration. Journal of Retailing, 91(2), 309-325.

Huré, E., Picot-Coupey, K., Ackermann, C.L. (2017), Understanding Omni-channel shopping value: A mixed-method study. Journal of Retailing and Consumer Services, 39, 314-330.

Lemon, K.N., Verhoef, P.C. (2016), Understanding customer experience throughout the customer journey. Journal of Marketing, 80(6), 69-96.

Mohajan, H.K. (2017), Two criteria for good measurements in research: Validity and reliability. Annals of Spiru Haret University. Economic Series, 17(4), 59-82.

Nunnally, J.C., Bernstein, I.H. (1994), Psychometric Theory. 3rd ed. United States: McGraw-Hill.

Robinson, O.C. (2014), Sampling in interview-based qualitative research. Qualitative Research in Psychology, 11(1), 25-41.

Robson, C. (2002), Real World Research. 2nd ed. United States: Blackwell Publishers.

Saunders, M., Lewis, P., Thornhill, A. (2007), Research Methods for Business Students. 4th ed. London: Pearson Education.

Shankar, V., Kushwaha, T. (2020), Omnichannel marketing: Are cross-channel effects symmetric? International Journal of Research in Marketing, 38, 290-310.

Stevens, J.P. (1996), Applied Multivariate Statistics for the Social Sciences. 3rd ed. New Jersey: Lawrence Erlbaum Associates.

Tavşan, N., Erdem, Y.C. (2021), The customer experience measurement scale. İstanbul Ticaret Üniversitesi Sosyal Bilimler Dergisi, 20(42), 1247-1268.

Tyrväinen, O., Karjaluoto, H., Saarijärvi, H. (2020), Personalization and hedonic motivation in creating customer experiences and loyalty in omnichannel retail. Journal of Retailing and Consumer Services, 57, 102233.

Verhoef, P.C. (2021), Omni-channel retailing: Some reflections. Journal of Strategic Marketing, 29(7), 608-616.

Verhoef, P.C., Kannan, P.K., Inman, J.J. (2015), From multi-channel retailing to omni-channel retailing. Journal of Retailing, 91(2), 174-181.

Warrell, J.G., Jacobsen, M. (2014), Internet research ethics and the policy gap for ethical practice in online research settings. Canadian Journal of Higher Education, 44(1), 22-37.

Zhao, K. (2020), Sample representation in the social sciences. Synthese, 198(2), 1-19.

APPENDIX

Appendix 1: Constructs versus items

???	Items	Authors
CHS1	Product information (price, features) is identical across store, app and website	Verhoef (2021)
CHS2	Promotions and discounts are consistently applied and visible across channels	
CHS3	I can check real-time product availability across online and nearby physical stores	
CHS4	My loyalty points and offers work the same across all channels	
CHS5	Order history is accessible and consistent whether I use the app, website, or store	
PM1	Offers and recommendations I receive are relevant to my past purchases	Tyrväinen et al. (2020)
PM2	Marketing messages are tailored to my preferences	
PM3	The brand remembers my choices and suggests suitable products	
PM4	I receive personalized promotions across channels (email/app/in-store)	
PM5	Personalization improves my shopping convenience	
TI1	Store staff can access my online order information when needed	Cai and Lo (2020)
TI2	Information systems (inventory/CRM) are integrated and up to date	
TI3	I can do buy-online-pickup-in-store (BOPIS) or return online purchases in store without problems	
TI4	The brand uses technologies (apps/QR codes/self-checkout) that make shopping easier	
TI5	Technology helps resolve issues faster than before	
CE1	My overall shopping experience with this brand/store is excellent	Tavşan and Erdem (2021)
CE2	The shopping process is convenient and saves me time	
CE3	I feel satisfied with how the brand handles transactions and issues	
CE4	The brand provides a consistent and pleasant experience across channels	
CE5	I am likely to repurchase because of the overall experience	

Source: Own elaboration