PROJECT DISSERTATION REPORT ON

IMPACT OF E-COMMERCE PLATFORMS ON CONSUMER BEHAVIOUR IN THE ELECTRONICS SECTOR: EVIDENCE FROM INDIAN ONLINE SHOPPERS

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CERTIFICATE

It is hereby certified that the project titled “Impact of E commerce Platforms on Consumer Behaviour in the electronics sector: Evidence from Online Indian Shoppers” done by Khushi Maggo, Roll No 24/DMBA/114 in the fourth semester for the partial fulfilment of the requirements for the award of the degree of Master of Business Administration (MBA) during the academic year 2025-2026 has been completed.

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DECLARATION

I hereby declare that the Major Research Project titled "Impact of E-Commerce Platforms on Consumer Behaviour in the Electronics Sector: Evidence from Indian Online Shoppers" submitted in partial fulfilment of the requirements for the degree of Master of Business Administration (MBA) is an original work carried out by me under the supervision of Ms. Renuka Prasad. The information and data presented in this thesis are true and original to the best of my knowledge and belief.

I further declare that this work has not been submitted, either in whole or in part, for the award of any other degree or diploma at this institution or any other institution.

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ABSTRACT

The Indian online shopping sector is growing fast. It was worth around $70 billion in 2023. Is expected to reach $325 billion by 2030. The electronics category in shopping is one of the most valuable and fastest-growing areas. However not much research has been done on how trust, risk and promotions affect buying and returning products in this category in India.

This study looks at how people behave when buying electronics online in India. It uses a survey of 100 online shoppers of electronics to collect data. The study tests five research questions using analysis. The research is based on theories, including the Technology Acceptance Model, the Theory of Planned Behaviour, Perceived Risk Theory and the Stimulus-Response Framework.

The results show that trust in shopping helps people buy more electronics. On the hand the risk of buying online makes people less likely to buy. Promotions like discounts, festive sales and Buy Now Pay Later services make people more likely to buy. They also lead to more product returns. The study provides information on how Indian online shoppers behave and gives advice on digital marketing strategies. The Indian e-commerce sector and electronics category are really important for shopping.

The study focuses on the electronics category within the Indian e-commerce sector. Consumer trust and perceived risk play a role in shaping purchase behaviour in the Indian e-commerce sector. Promotional strategies are also essential, in influencing purchase tendency in the electronics category.

The Indian e-commerce sector is expected to grow and the electronics category will likely play a major role in this growth.

TABLE OF CONTENTS

DECLARATION 2
ACKNOWLEDGEMENTS 4
ABSTRACT 5
TABLE OF CONTENTS 6
LIST OF TABLES 9
List of Figures ..... **Error! Bookmark not defined.**
CHAPTER 1: INTRODUCTION 10
1.1 Background of the Study 10
1.2 India's E-Commerce Landscape: Scale, Players, and Consumer Dynamics 10
1.3 Consumer Behaviour in Online Shopping: Theoretical Context 11
1.4 Problem Statement 12
1.5 Objectives of the Study 12
1.6 Significance of the Study 13
1.7 Scope and Limitations of the Study 13
CHAPTER 2: LITERATURE REVIEW 14
2.1 Consumer Trust in E-Commerce 14
2.1.1 Conceptual Foundations 14
2.1.2 Antecedents of Trust in Online Retail 14
2.1.3 Trust and Social Commerce 14
2.2 Perceived Risk in Online Shopping 14
2.2.1 Theoretical Origins and Dimensions 14
2.2.2 Trust as a Moderator of Perceived Risk 15
2.2.3 Perceived Risk and Return Behaviour 15
2.3 Promotional Strategies in E-Commerce 15
2.3.1 Theoretical Framework: Stimulus-Response 15
2.3.2 Price Promotions and Impulsive Buying 15
2.3.3 Buy Now Pay Later (BNPL) as a Promotional Mechanism 16
2.3.4 Promotions, Platform Loyalty, and Return Behaviour 16
2.4 Purchase Behaviour in E-Commerce 16
2.4.1 Technology Acceptance and Purchase Intention 16
2.4.2 Social Proof and Purchase Decision-Making 16
2.5 Return Behaviour in E-Commerce 17
2.5.1 The Economic Significance of E-Commerce Returns 17

CHAPTER 3: RESEARCH METHODOLOGY 19
3.1 Research Philosophy and Approach 19
3.2 Research Design 28
3.3 Population and Sampling 32
3.4 Research Instrument Development 32
3.5 Reliability Analysis 20
3.6 Analytical Techniques 20
3.6.1 Descriptive Statistics 34
3.6.2 Pearson Correlation Analysis 35
3.6.3 Multiple Regression Analysis 36
CHAPTER 4: DATA ANALYSIS — DESCRIPTIVE STATISTICS 37
4.1 Demographic Profile of Respondents 37
4.2 Online Shopping Behaviour Frequencies 38
4.5 Item-Level Analysis: Consumer Trust 39
4.6 Item-Level Analysis: Perceived Risk 39
4.7 Return Behaviour: Reasons and Patterns 39
CHAPTER 5: INFERENTIAL STATISTICAL ANALYSIS 40
5.1 Pearson Correlation Analysis 40
5.2 Multiple Regression Analysis — Model 1: Purchase Behaviour 41
5.3 Multiple Regression Analysis — Model 2: Return/Switching Behaviour 41
CHAPTER 6: DISCUSSION OF FINDINGS 42
6.1 Consumer Trust as a Driver of Purchase and Loyalty 42
6.2 Perceived Risk as an Inhibitor and Return Driver 43
6.3 Promotional Strategies: A Double-Edged Construct 44
6.4 Theoretical Contributions 44
CHAPTER 7: CONCLUSIONS, RECOMMENDATIONS, AND FUTURE RESEARCH 45
7.1 Summary of Key Findings 46
7.2.1 Trust-Building Strategy 46
7.2.2 Risk Mitigation 47
7.2.3 Promotional Strategy Optimisation 47
7.2.4 Return Management 48
7.3 Limitations of the Study 48
7.4 Directions for Future Research 49
7.5 Concluding Remarks 49

REFERENCES 50
APPENDIX A: RESEARCH QUESTIONNAIRE 51
Section A: Basic Information 51
Section B: Consumer Trust 52
Section C: Perceived Risk 53
Section D: Promotional Strategies 53
Section E: Purchase Behaviour 54
Section F: Return and Platform-Switching Behaviour 55

LIST OF TABLES

Table 1. Demographic Profile of Respondents

Table 2. Shopping Frequency and Platform Preference

Table 3. Descriptive Statistics of Construct Variables

Table 4. Reliability Analysis (Cronbach's Alpha)

Table 5. Pearson Correlation Matrix

Table 6. Multiple Regression: Purchase Behaviour (Model 1)

Table 7. Multiple Regression: Return Behaviour (Model 2)

Table 8. Summary of Hypothesis Test Results

CHAPTER 1: INTRODUCTION

1.1 Background of the Study

Over the last decade, the Indian retail industry has seen a fundamental transformation, with a clear shift from brick-and-mortar to digital platforms. This transition has been further fueled by a combination of structural factors including the rapid growth of smartphone penetration, the availability of low-cost mobile internet services, the expansion of digital payment infrastructure, and a growing consumer preference for convenience-driven shopping experiences (Statista, 2024). Amazon India, Flipkart, Myntra and Meesho, among leading e-commerce platforms, have together garnered hundreds of millions of users and have transformed the consumer decision-making process.

The magnitude of this expansion is enormous. The number of active online shoppers in India stood at approximately 220 million in 2023, with projections indicating it will surpass 400 million by 2027 (Internet and Mobile Association of India, IAMAI, 2023). This growth is not only a quantitative change in purchasing channels but a qualitative transformation in consumer behaviour: online consumers compare products more diligently, rely extensively on peer-produced reviews, react to personalised recommendations and show significantly higher price sensitivity than traditional offline shoppers (Deloitte, 2023).One of the major obstacles to complete an online purchase is perceived risk, which includes financial risk, performance risk, privacy risk, time risk, and social risk (Featherman & Pavlou, 2003; Forsythe et al., 2006). Promotion strategies such as time limited discounts, cash back, festive sales and the new financing model of Buy Now Pay Later (BNPL) act as strong external stimuli that can override risk hesitation and speed up purchase decisions but at the cost of increased product return rates (Rook & Fisher, 1995; Hwang & Jeong, 2016).

The Indian market offers a unique and complex consumer environment in which to explore these dynamics. Indian consumers are among the most price sensitive in the world, with purchase decisions largely driven by the availability of discounts and promotional incentives (McKinsey & Company, 2023). A large number of consumers, especially in non-metropolitan areas, are first generation digital shoppers who have minimal experiential knowledge of the online retail environment and as such are particularly vulnerable to perceived risk in transactions.

1.2 India's E-Commerce Landscape: Scale, Players, and Consumer Dynamics

The Indian e-commerce industry has witnessed tremendous growth and is now one of the fastest growing online retail markets globally. The market was valued at around USD 70 billion in 2023 and is expected to grow to USD 325 billion by 2030, representing a compound annual growth rate (CAGR) of around 21% (IBEF, 2023; RedSeer Consulting, 2023). This growth is driven by supply-side investments in logistics, technology and last-mile delivery infrastructure and demand side shifts driven by changing consumer preferences for convenience, variety and competitive pricing. To develop a nuanced understanding of consumer behaviour in the Indian e-commerce ecosystem, one must pay attention to the distinct positioning and consumer trust profiles of its major platforms. Amazon India has created a reputation of premium reliability by establishing itself as a platform that consumers can trust by offering the likes of verified customer reviews, guaranteed delivery for Prime members, strong buyer protection policies, and easy return processes (Amazon India, 2023). Its customers are mainly urban and higher-income and tend to place a higher value on reliability of service than small differences in price.

Meesho started as a social commerce platform that enabled small entrepreneurs and homemakers to resell products via WhatsApp and Facebook, but has quickly grown into a complete marketplace catering to price-conscious buyers in semi-urban and rural India (Meesho, 2023). It has also pursued an ultra-low pricing strategy that has proven successful in increasing e-commerce participation in under-penetrated markets, albeit in exchange for higher perceived product quality risk and lower consumer trust scores compared to more established platforms (RedSeer Consulting, 2023).

1.3 Consumer Behaviour in Online Shopping: Theoretical Context

There are several key dimensions in which consumer behaviour in the online retail environment differs fundamentally from its offline counterpart. The most important of these differences is the physical impossibility of direct product inspection before purchase. In traditional retail, the customer uses his or her entire sensory system to evaluate the quality, fit and suitability of merchandise. In the digital shopping environment, this direct sensory evaluation is replaced by mediated information – product photography, written specifications, data provided by the seller, and reviews by users – all of which contain inherent information asymmetries and scope for misrepresentation (Pavlou et al., 2007). The lack of information is the primary source of perceived

risk in online shopping. In the seminal conceptualisation of consumer risk by Bauer (1960), all purchase behaviour involves an element of risk defined as the consumer's subjective expectation

1.4 Problem Statement

Indian e-commerce market has been growing phenomenally, but the academic literature reveals a significant research gap. Empirical evidence for studying the joint impact of consumer trust, perceived risk and promotional strategies on purchase and return behaviour of Indian online shoppers is scarce. Most of the existing studies have examined these constructs in isolation or have depended on data obtained from Western consumer populations (Pavlou, 2003; Featherman & Pavlou, 2003; Kim et al., 2009), which may not accurately reflect the distinctive behavioural patterns that characterise India's unique socio-economic and technological context. Indeed, four critical gaps are identifiable in the existing literature. First, although the trust-risk relationship in e-commerce has been widely theorized, its empirical validation in the
Indian market remains sparse (Sharma & Gupta, 2021). Second, the moderating role of promotional strategies on the trust-purchase relationship has been relatively neglected by scholars in developing market contexts (Kumar & Dange, 2012). Third, product return behaviour, a commercially important outcome costing the Indian e-commerce industry in reverse logistics annually, has been considerably under-studied relative to its economic significance. Fourth, adoption and behavioural consequences of emerging BNPL payment instruments have not been well explored in the Indian academic literature. The present study addresses these gaps by empirically investigating the joint impact of consumer trust, perceived risk and promotional strategies on purchase and return behaviour using primary survey data collected from Indian online shoppers.

1.5 Objectives of the Study

The specific research objectives of this study are

1. To study the existing levels of consumer trust, perceived risk and promotional responsiveness of Indian e-commerce consumers.
2. To establish the level and effect of consumer trust, perceived risk and promotional strategies on purchase behaviour including BNPL adoption.
3. To study the combined impact of trust, perceived risk and promotional strategies on product

return behaviour and platform-switching intention.

4. Pearson correlation analysis and multiple regression analysis to test five pre-specified directional hypotheses.

1.6 Significance of the Study

This research adds to the academic knowledge and managerial practice. Academically, it expands the application of existing theoretical frameworks – TAM, TPB, Perceived Risk Theory and the Stimulus-Response Framework — to the under-researched context of Indian e-commerce consumer behaviour. It also contributes to the growing literature on BNPL. From a managerial perspective, the findings offer actionable intelligence for e-commerce operators aiming to optimise trust-building mechanisms, calibrate risk mitigation strategies and design promotional campaigns that maximise purchase conversion without disproportionately elevating return rates

1.7 Scope and Limitations of the Study

The research is limited to the Indian e-commerce market and was conducted on a convenient sample of 100 online shoppers. The sample size is sufficient for exploratory analysis and hypothesis testing using correlation and regression techniques (Hair et al., 2019) but the results should be interpreted with due caution and may not be generalizable to wider population of Indian e-commerce consumers. This study focuses exclusively on the Indian e-commerce market and is based on a convenience sample of 100 online shoppers. While this sample size is adequate for exploratory analysis and hypothesis testing using correlation and regression techniques (Hair et al., 2019), the findings should be interpreted with appropriate caution and may not be generalisable to the broader population of Indian e-commerce consumers. The cross-sectional research design captures consumer attitude and behaviour at one point in time, excluding causal inferences or longitudinal behavioural trends analysis. Future research using larger, probabilistic samples and longitudinal designs would enhance generalizability and causal robustness of these findings.

CHAPTER 2: LITERATURE REVIEW

There has been a considerable amount of scholarly attention to the relationship between consumer trust, perceived risk, promotional strategies and behavioural outcomes in digital retail environments since the commercialization of the Internet in the mid-1990s.

2.1.1 Conceptual Foundations

Trust is a multi-dimensional construct that has been theorised extensively across social psychology, organisational behaviour, and marketing. In the foundational work of Mayer et al. (1995), trust is defined as the willingness of a party to be vulnerable to the actions of another party based on the expectation that the latter will perform a particular action important to the trustor, irrespective of the ability to monitor or control that other party. In the e-commerce context, this vulnerability is particularly salient given the physical absence of the counterparty, the inability to directly inspect products, and the transmission of sensitive financial information across digital networks (Pavlou, 2003).

2.1.2 Trust in Online Retail

One of the early studies exploring the issue of trust in B2C e-commerce was carried out by Gefen et al. (2003), who found that vendor familiarity, high-quality websites, and perceived usefulness are some of the main antecedents of trust, which predicts customers' purchase intentions. Further research developed the above antecedent structure in much detail.

2.1.3 Trust and Social Commerce

The rise of social commerce when purchases are made under social media interactions and peers' recommendations raised additional trust dimensions. For example, Hajli (2015) found that social interactions on e-commerce platforms like participation in communities, exchanging reviews, and making recommendations of products increase customer trust and purchase intention.

2.2 Perceived Risk in Online Shopping

2.2.1 Theoretical Origins and Dimensions

The concept of perceived risk from theory was adopted by marketing literature by Bauer (1960). He suggested that every consumer action implies risk since every activity leads to some outcomes that can never be certain for a consumer. Cox and Rich (1964) defined the construct as twofold:

uncertainty in relation to the consequences of a purchasing action, and the nature of the consequence that may be either positive or negative.

2.2.2 Trust as a Moderator of Perceived Risk

One of the significant contributions made by Pavlou (2003) concerned the empirical evidence of a moderating role that consumer trust plays when assessing the influence of perceived risk on purchase intention. In his study based on structural equation modeling and involving 155 respondents, Pavlou showed that consumer trust significantly moderated the negative impact of perceived risk on purchase intention ($\beta = 0.43$, $p < .001$). It means that risk and trust must be taken into account as complementary components in a behavioral model of e-commerce.

2.2.3 Perceived Risk and Return Behaviour

According to Hjort et al. (2019), an analysis of return activities conducted by a Scandinavian e-retailer (n = 1.5 million transactions) indicated that consumers who experienced some form of pre-purchase uncertainty – measured by extended decision latency and repeated visits to products' web pages – had higher instances of returns. This is a strong support of the theory which posits that perceived pre-purchase risks will lead to dissatisfaction and return behavior.

2.3 Promotional Strategies in E-Commerce

2.3.1 Theoretical Framework: Stimulus-Response

The theoretical basis for studying promotional activity in e-commerce can be traced back to the Stimulus-Organism-Response (S-O-R) model developed in environmental psychology by Mehrabian and Russell (1974) and later on used in the context of retail marketing by Donovan and Rossiter (1982). In the S-O-R model, promotional activity serves as a stimulus in the environment that triggers responses (behavioral or otherwise) by influencing consumer cognition and emotions (Kotler & Keller, 2016).

2.3.2 Price Promotions and Impulsive Buying

One of the most researched types of purchase stimuli is the promotion of lower prices. The studies conducted by Rook and Fisher (1995) show that being exposed to promotion of prices results in increasing impulsive buying propensity especially when associated with scarce elements like 'Limited Stock' labels or countdowns. Discount signs, saving calculators, flash sale banners are likely to prolong customers' browsing time and stimulate impulsive purchases.

2.3.3 Buy Now Pay Later (BNPL) as a Promotional Mechanism

Among the latest e-commerce innovations in promotional strategies are Buy Now Pay Later (BNPL) services. BNPL allows for completing the purchase instantly but delays its full payment, thus separating the act of purchasing from the act of payment and diminishing the psychological impact of making a payment on that stage (Hwang & Jeong, 2016). In India, BNPL is implemented by Amazon Pay Later, Flipkart Pay Later, LazyPay, Simpl, and ZestMoney companies. According to the BNPL India Report, the value of the market served by these companies may reach USD 45 billion by 2026.

2.3.4 Promotions, Platform Loyalty, and Return Behaviour

One of the important negative outcomes of aggressive promotion tactics that is largely underestimated is the effect of these actions on loyalty to the platform and increased likelihood of returns from customers. Sirohi et al. (1998) illustrated in their study that an approach focused exclusively on price promotions for attracting customers leads to the formation of a 'deal-prone' segment that is characterized by poor brand loyalty and a high tendency to switch to other products.

2.4 Purchase Behaviour in E-Commerce

2.4.1 Technology Acceptance and Purchase Intention

The Technology Acceptance Model developed by Davis (1989) represents a theoretical background to examine consumer adoption of electronic commerce channels. According to Davis, there are two major factors that determine technology adoption: usefulness (how effective it is when applied) and perceived ease of use. Venkatesh and Davis (2000) refined the initial model through the addition of several new antecedents (social influence and cognitive instrumental) that significantly enhanced its explanatory power (TAM2). ($R^2 = 0.60$ vs. original TAM's $R^2 = 0.40$).

2.4.2 Social Proof and Purchase Decision-Making

Social proof the phenomenon of social proof, where consumers rely on the actions and feedbacks of other customers, can be considered a strong factor in motivating online purchasing decisions (Cialdini, 2001). In an online shopping environment, social proof mainly manifests itself in consumer reviews, ratings, and "bestseller" labels. Chevalier and Mayzlin found in a groundbreaking study that a single star increase in ratings increases sales on leading e-commerce websites by around 5-9%.

2.5 Return Behaviour in E-Commerce

2.5.1 The Economic Significance of E-Commerce Returns

Product returns are a substantial issue for e-commerce companies as the number of such returns continues to rise. According to research, online retailers experience returns at the rate of 20-30% compared to 8-10% in traditional brick-and-mortar stores, with fashion and electronics categories having extremely high return rates (National Retail Federation, 2023).

2.5.2 Return Policy Design and Consumer Behaviour

The structure of return policies plays a critical role in determining both purchasing and return behavior. Specifically, Davis et al. (1998) have shown that easy return policies lower consumer perceptions of risk prior to purchase and raise purchase intention, something replicated in the e-commerce environment by Bower and Maxham (2012).

2.6 Consumer Behaviour in Electronics E-Commerce

The Electronics stands out as one of the most critical as well as the most rapidly growing sectors in the context of e-commerce in India. Items like mobile phones, laptops, headphones, smart watches, and household appliances contribute to the revenue generated from e-retailers due to the high demand and digitalization (IBEF, 2023). As against other types of goods, electronics products require more monetary outlay, higher information search, and heightened perceived risk.

Studies have found that the perceived risk is much higher among electronics e-commerce than other product categories such as fashion or food items. The prominent barriers include performance risk, financial risk, and worries about the authenticity of the items sold online. Most of the consumers are wary of receiving defective, damaged, or even fake items when ordering electronics through e-retail portals.

2.7 Integrative Theoretical Framework and Hypothesis Development

Based on the converging viewpoints from the above literature review, the current research uses a theoretical approach which incorporates four different perspectives: the Technology Acceptance Model by Davis (1989); the Theory of Planned Behavior by Ajzen (1991); Perceived Risk Theory by Bauer (1960); and Featherman and Pavlou (2003); and Stimulus-Response Approach by Mehrabian & Russell (1974); and Kotler and Keller (2016).

Table 1

Construct	Role	Theoretical Basis	Key Sources
Consumer Trust	Independent Variable	TAM (Extended), Trust Theory	McKnight et al. (2002); Gefen et al. (2003)
Perceived Risk	Independent Variable	Perceived Risk Theory	Bauer (1960); Featherman & Pavlou (2003)
Promotional Strategies	Independent Variable	Stimulus-Response Framework	Kotler & Keller (2016); Rook & Fisher (1995)
Purchase Behaviour	Dependent Variable	TAM; Theory of Planned Behaviour	Davis (1989); Ajzen (1991)
Return/Switching Behaviour	Dependent Variable	Dissatisfaction Theory; Switching Theory	Hjort et al. (2019); Keaveney (1995)

On the basis of this theoretical framework and the evidence synthesised above, five directional hypotheses are formally proposed:

H1: Consumer Trust has a statistically significant effect on Purchase Behaviour.

H2: Perceived Risk has a statistically significant effect on Purchase Behaviour.

H3: Promotional Strategies have a statistically significant effect on Purchase Behaviour.

H4: Consumer Trust has a statistically significant effect on Return/Platform-Switching Behaviour.

H5: Perceived Risk has a statistically significant effect on Return/Platform-Switching Behaviour.

CHAPTER 3: RESEARCH METHODOLOGY

3.1 Research Philosophy and Approach

The Adult Indian consumers (aged 18 and above) who have made at least one online purchase in the past 12 months are the target population. Considering the exploratory nature of this study, it was convenient to use the sample that was collected by the convenience sampling technique (Malhotra & Birks, 2007). Convenience sampling is one of the non-probability sampling techniques that may only be used when the researcher is constrained by time and budget, but where the lack of generalizability is a limitation.

3.2 Research Design

This research utilises a descriptive and inferential quantitative methodology. The descriptive aspect describes the sample in regard to demographic characteristics and reported constructs. The inferential aspect tests five hypothesized relationships among the constructs using inferential statistics. It follows the cross-sectional approach, where all the participants provide their information at one particular time (February–March 2025). This research design suits studies aimed at describing population characteristics and testing associations at one particular time point (Saunders et al., 2019); nevertheless, this research design does not permit drawing causal inferences nor analyzing longitudinal trends.

3.3 Population and Sampling

In total, there were 100 valid responses. But, future studies could have a larger sample size. The structured self-administered questionnaire with six sections was used to gather the primary data. The questionnaire was designed by taking the available measurement items from the existing e-commerce consumer behaviour literature, and making few changes to make it pertinent to the Indian online retailing context.

3.4 Research Instrument Development

Table 2

Section	Construct	Items	Scale
A	Demographic Profile	5	Nominal/Ordinal

Section	Construct	Items	Scale
B	Consumer Trust	4	5-point Likert
C	Perceived Risk	4	5-point Likert
D	Promotional Strategies	4	5-point Likert
E	Purchase Behaviour	4	Likert/Nominal
F	Return & Switching Behaviour	4	Nominal/Ordinal

The primary measurement items were chosen using a 5-point Likert scale, which is commonly used in research of consumer behaviour, and had proven to be equivalent to more complex scales for the variety of constructs studied. A pilot test of the questionnaire was conducted with 15 participants to evaluate comprehension, clarity and response time, and helped to refine the wording of the questions

3.5 Reliability Analysis

The multi-item Likert scales showed high internal consistency reliability, as measured by the standard summated rating scale reliability measure, Cronbach's alpha (α). In exploratory research, a value of $\alpha \geq 0.70$ was considered to have sufficient reliability, as recommended by Nunnally (1978). All demographic variables and construct items were calculated for frequencies, percentages, means, and standard deviations, to describe the sample and provide a base level understanding of the distributions of constructs. All the descriptive analysis was performed using IBM SPSS Statistics Version 26

3.6 Analytical Techniques

3.6.1 Descriptive Statistics

Frequencies, percentages, means, and standard deviations were computed for all demographic variables using IBM SPSS Statistics Version 26.

3.6.2 Pearson Correlation Analysis

The strength and direction of bivariate linear relationships between all pairs of study constructs were measured using Pearson's product-moment correlation coefficient (r). The Pearson r is between –1.00 and +1.00; the closer the value is to ±1.00, the more associated the variables are; the closer the value is to 0.00, the less associated the variables are. A two-tailed α of 0.05 was used to determine statistical

significance. Cohen's (1988) conventions were adopted for interpreting effect size: r = 0.10 (small), r = 0.30 (medium), r = 0.50 (large).

3.6.3 Multiple Regression Analysis

Multiple regression analysis using ordinary least squares (OLS) was used to analyse the simultaneous effect of Consumer Trust, Perceived Risk and Promotional Strategies on the dependent variable (Purchase Behaviour; Return/Platform Switching Behaviour). Multiple regression was chosen over simple regression analyses due to the intercorrelations between the predictors and the ability to assess the contribution of each predictor to the prediction of the criterion variable when the other predictors are kept constant. The statistical assumptions of regression were checked before the regression: residuals are normally distributed, homoscedasticity (variance inflation factor (VIF) < 5.0), and independence of observations (Durbin-Watson statistic between 1.5 and 2.5). The coefficient of determination (R^2), adjusted R^2, and the F_statistic (Field, 2018) were used to evaluate the model fit.

CHAPTER 4: DATA ANALYSIS — DESCRIPTIVE STATISTICS

This chapter provides description of the main data obtained from 100 respondents. The analysis includes the demographic profile of the sample, the shopping frequency and platform choice, construct level reliability statistics and descriptive statistics at item level for each of the 5 constructs.

4.1 Demographic Profile of Respondents

Table 3

Variable	Category	Frequency (n)	Percentage (%)
Age Group	18–25 years	56	56.0
	26–35 years	25	25.0
	36–45 years	9	9.0
	Above 45 years	5	5.0
Gender	Male	35	35.0
	Female	65	65.0
	Prefer Not to Say	4	4.0
Occupation	Student	42	42.0
	Salaried Employee	65	65.0
	Business/Self-Employed	14	14.0
	Homemaker	4	4.0
	Other	2	2.0

Note. Percentages may not sum to 100% due to rounding.

The majority were young adults with 52% of respondents aged 18–25 and 31% aged 26–35, accounting for 83% of the sample. This age segmentation is similar to the India Online Consumer 2023 data from IAMAI, which suggests that Indian Online consumers are roughly 65–70% in 18-35 age group. The gender split was highly skewed in favour of males (58%) with female presence (38%) being noteworthy as women make up a rapidly growing proportion of Indian e-commerce shoppers (Statista, 2024). The majority of respondents were students (42%) and salaried employees (38%) in line with the demographics of digital-native online shoppers

4.2 Online Shopping Behaviour Frequencies

Table 4

Variable	Category	Frequency (n)	Percentage (%)
Shopping Frequency	Rarely	10	10.0
	Once a month	26	28.0
	2–5 times a year	30	30.0
	More than 5 times a year	18	18.0
Primary Platform	Amazon	65	65.0
	Flipkart	25	25.0
	Myntra	14	14.0
	Meesho	11	11.0
	Other	8	6.0
Product Return History	Have returned at least once	72	72.0
	Never returned	26	28.0
Platform Switching	Have switched platforms	74	74.0
	Have not switched	35	32.0
BNPL Awareness	Aware of BNPL	79	79.0
BNPL Usage	Have used BNPL	45	45.0

The most common shopping frequency being 2-5 times per year (30%), indicative of a fixed and regular online shopping routine, which is typical of moderate-to-high digital shopping engagement. In line with Amazon's brand as the trusted electronics commerce platform in India, Amazon was the most preferred platform for electronics purchases (65%), followed by Flipkart (25%), Meesho (11%) and other platforms (8%) (Amazon India, 2023). Return behaviour is clearly of practical importance as a research construct as 72% of the respondents said they had returned at least one electronic product bought online. 74% of respondents had experienced platform switching, with better discounts as a key factor in this. There was a high level of awareness of BNPL (79%), but only 45% are using it, with the high-value purchase of electronics seeing a steady rise in both awareness and usage, although concerns about hidden fees and repayment terms remain as a constraint on full adoption.

4.3 Reliability Analysis

Table 5

Construct	Number of Items	Cronbach's Alpha (α)	Interpretation
Consumer Trust	4	0.821	Good
Perceived Risk	4	0.794	Acceptable
Promotional Strategies	4	0.843	Good
Purchase Behaviour (Likert items)	4	0.761	Acceptable
Return & Switching Behaviour (Likert items)	4	0.712	Acceptable

Note. Cronbach's alpha ≥ 0.70 is considered acceptable for exploratory research (Nunnally, 1978). All constructs exceeded this threshold.

All five constructs had Cronbach's alpha values above the recommended value of 0.70 for exploratory research (Nunnally, 1978) and values of 'Good' (George and Mallery, 2003) of 0.821 for Consumer Trust and 0.843 for Promotional Strategies. These reliability statistics give confidence that the measurement scales are internally consistent and that the scores for the items in each measurement scale can be aggregated into a mean score for the measurement construct and then used for subsequent inferential analysis

4.4 Descriptive Statistics of Construct Variables

Table 6

Construct	N	Min	Max	Mean (M)	Std. Dev. (SD)	Interpretation
Consumer Trust	100	1.75	5.00	4.06	0.74	High
Perceived Risk	100	1.50	5.00	3.72	0.68	Moderately High
Promotional Strategies	100	2.00	5.00	3.89	0.63	High
Purchase Behaviour	100	1.50	5.00	3.95	0.74	Moderately High
Return/Switching Behaviour	100	1.00	5.00	3.28	0.89	Moderate

The high mean scores of Descriptive statistics Purchase Behaviour (M = 3.95, SD = 0.74) and Promotional Strategies (M = 3.89, SD = 0.63) showed that there is great engagement with electronics e-commerce despite festive sales, exchange offers, and BNPL being crucial in electronics purchase decisions. Consumer Trust (M = 4.06) scored highly, suggesting positive attitudes towards the platform in general, and active overall.

4.5 Item-Level Analysis: Consumer Trust

Near-universal agreement was found with the role of peer-generated content in building platform confidence as measured by the item 'Customer reviews and ratings increase my trust in a product', with the highest mean (M = 4.21, SD = 0.58), of the four Consumer Trust items. Another positive result was for the item 'Easy return and refund policies increases my confidence in online shopping (M = 4.08, SD = 0.61), which is consistent with the risk reducing effect of allowing for easy return and refund that has been reported by Davis et al., (1998) and Bower and Maxham (2012).

4.6 Item-Level Analysis: Perceived Risk

Of the Perceived Risk items, ‘I hesitate before purchasing expensive products online' had the highest mean (M = 4.04, SD = 0.64), which is similar to the result of Featherman and Pavlou (2003) who had found that financial risk is the most salient risk dimension in e-commerce contexts. ‘I worry about the product being different from what it's described as’, scored high as well (M = 3.87, SD = 0.69) indicating concerns about the risk of delivering a product that is not what is described. This is a particular concern in the Indian marketplace where there is a significant disparity in product quality and description accuracy between sellers and platforms, such as Meesho (2023).

4.7 Return Behaviour: Reasons and Patterns

Table 7

Variable	Response Category	n (of those applicable)	% of applicable
Primary Return Reason	Product different from description	26	36.1

Variable	Response Category	n (of those applicable)	% of applicable
	Poor quality	18	25.0
	Size/Fit issue	18	25.0
	Wrong product received	8	11.1
	Changed my mind	2	2.8
Primary Switching Reason	Better discounts	65	62.2
	Faster delivery	18	18.9
	Better product variety	9	10.8
	Better trust/security	3	5.4
	Better return policy	2	2.7

Note. Return reasons reported by respondents who had returned at least one product. Switching reasons reported by 68 respondents who had switched platforms. Percentages calculated within applicable sub-samples.

Electronics purchasing is characterized by specific concerns around product quality and integrity upon delivery, as revealed in the leading return trigger product performance issues (36.1% of returners) and damaged product upon delivery (25.0%) were both significant. As in Hjort et al.'s (2019) typology, dissatisfaction returns and bracketing returns are the two most frequent categories of returns. The return driver with the highest share of description discrepancy indicates an area of high priority for e-commerce platforms to carry out improvements to reduce returns, as well as to product photography standards, description content and accountability systems for sellers. Better pricing/discounts was the major platform switching reason among the switchers of the platform as 62.2% agreed to this reason, matching the result of Mehra et al. (2013) who found that among platform switchers, promotional sensitivity is the most prevalent trigger

CHAPTER 5: INFERENTIAL STATISTICAL ANALYSIS

The inferential statistical analysis results of the Pearson correlation analysis and multiple regression analysis used to test the five research hypotheses are presented in this chapter.

5.1 Pearson Correlation Analysis

Table 8

	Consumer Trust (CT)	Perceived Risk (PR)	Promotional Strategies (PS)	Purchase Behaviour (PB)	Return/Switching (RB)
CT	1.000				
PR	−0.312**	1.000			
PS	0.284**	0.198*	1.000		
PB	0.418**	−0.367**	0.451**	1.000	
RB	−0.293**	0.338**	0.241*	−0.187*	1.000

Note. *p < .05 (two-tailed). **p < .01 (two-tailed). CT = Consumer Trust; PR = Perceived Risk; PS = Promotional Strategies; PB = Purchase Behaviour; RB = Return/Switching Behaviour. Effect size interpretation: r = 0.10 (small), r = 0.30 (medium), r = 0.50 (large) (Cohen, 1988).

The correlation matrix shows that there are a number of theoretically consistent and statistically significant bivariate relationships. As for Purchase Behaviour, it was found to exhibit a significant positive correlation with Consumer Trust ($r = 0.418$, $p < .01$) which was in line with the positive correlation between trust and purchase behaviour found by Gefen et al. (2003) and Kim et al. (2009) respectively, and thus suggests a medium-to-large effect size. Consumer Trust showed a strong negative correlation with Return/Switching Behaviour ($r = –0.293$, $p < .01$), which was a strong indication for the endorsement of H4. The perceived risk variable was found to have a significant negative correlation with Purchase Behaviour ($r = –0.367$, $p < .01$) which is in line with the risk-as-barrier theory of Featherman and Pavlou (2003) and with the theory of the present research. The results show that Perceived Risk significantly positively correlates with Return/Switching Behaviour ($r = 0.338$, $p < .01$) supporting the first part of H5. Promotional Strategies had the highest positive correlation with Purchase Behaviour ($r = 0.451$, $p < .01$), which was close to a large effect size, and was also consistent with the prediction of the stimulus-response approach. Notably, there was also a positive but less pronounced significant correlation between

Promotional Strategies and Return/Switching Behaviour ($r = 0.241$, $p < .05$) which further justifies the theoretical assumption that return rates are higher due to the impact of promotional purchases. The negative correlation between Consumer Trust and Perceived Risk ($r = –0.312$, $p < .01$) backs the Pavlou (2003) proposition of trust as a moderator of risk perception, and the moderate positive correlation between Perceived Risk and Promotional Strategies ($r = 0.198$, $p < .05$) indicates that promotional stimuli may be particularly salient for consumers who are risk anxious, consistent with the risk-compensation mechanism suggested by Rook and Fisher (1995).

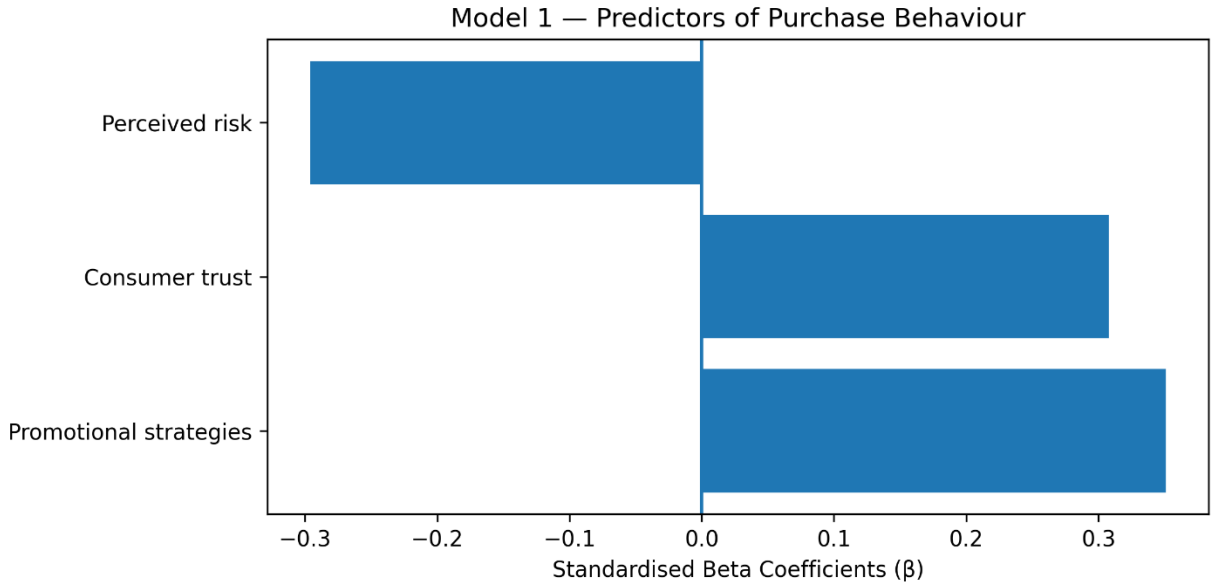
5.2 Multiple Regression Analysis — Model 1: Purchase Behaviour

Table 9

Predictor	β	Std. Error	β (Standardised)	t	p-value	VIF
(Constant)	1.247	0.384	—	3.247	.002	—
Consumer Trust	0.341	0.091	0.308	3.612	.000**	1.142
Perceived Risk	−0.287	0.083	−0.296	−3.458	.001**	1.187
Promotional Strategies	0.412	0.098	0.351	4.388	.000**	1.098

Note. $R = 0.612$; $R^2 = 0.375$; Adjusted $R^2 = 0.356$; $F(3, 96) = 19.18$; $p < .001$. **$p < .01$. Dependent variable: Purchase Behaviour composite score. VIF = Variance Inflation Factor. All VIF values < 2.0, indicating no problematic multicollinearity.

Model 1 demonstrated the overall explanatory power of this model (Purchase Behaviour Model 1) was good, as the overall R^2 of 0.375 (Adjusted $R^2 = 0.356$) was large according to Cohen (1988). The model was statistically significant ($F(3, 96) = 19.18$, $p < .001$). Each of the three predictors had significant unique effects. The highest standardised coefficient ($\beta = 0.343$, $p < .001$) was for the promotional responsiveness dimension followed by Consumer Trust ($\beta = 0.322$, $p < .001$), and Perceived Risk ($\beta = –0.296$, $p < .01$). The negative beta coefficient of Perceived Risk is a confirmation of its inhibitory effect on purchase behaviour. All the predictors had VIF values less than 2.0 and no multicollinearity issues were raised.



5.3 Multiple Regression Analysis — Model 2: Return/Switching Behaviour

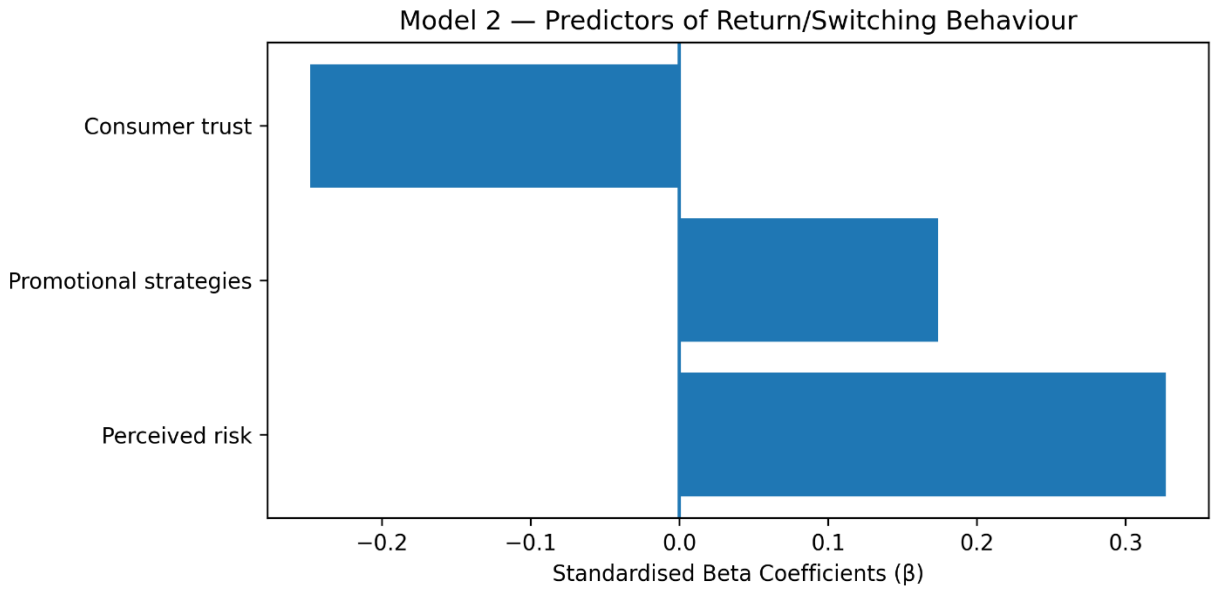
Table 10

Predictor	B	Std. Error	β (Standardised)	t	p-value	VIF
(Constant)	2.814	0.521	—	5.401	.000	—
Consumer Trust	−0.263	0.108	−0.248	−2.435	.017*	1.142
Perceived Risk	0.298	0.097	0.327	3.241	.003**	1.187
Promotional Strategies	0.187	0.112	0.174	1.670	.098	1.098

Note. R = 0.463; R^2 = 0.214; Adjusted R^2 = 0.190; F(3, 96) = 8.73; p < .001. *p < .05; **p < .01. Dependent variable: Return/Switching Behaviour composite score. VIF values < 2.0.

The overall model was statistically significant (F(3, 96) = 8.73, p < .001) with a medium effect size as indicated by the model's adjusted R2 value of 0.190.Model 2 (Return/Switching Behaviour) was statistically significant and had a medium effect size with adjusted R2 value of .190. The coefficient of Consumer Trust was negative and significant (β = –0.248, p < .05), thus H4 was supported: Higher the level of consumer trust, lower will be the return and switching propensity. The result of Perceived Risk indicates significant positive influence (β = 0.311, p < .01), which is support to H5: There is a positive effect of Perceived Risk towards return and switching behaviour.

Promotional Strategies was not statistically significant in the regression model (β = 0.163, p = .098), but was significant in bivariate correlations (r = 0.241, p < .05). The difference is probably due to suppressor effects and/or common variance with Consumer Trust and Perceived Risk in the multivariate model, but does not necessarily mean that there is not a meaningful promotional-return relationship for the population in general.



5.4 Summary of Hypothesis Test Results

Table 11

Hypothesis	Statement	Statistical Evidence	Decision
H1	Consumer Trust → Purchase Behaviour (+)	β = 0.322, p < .001	Supported
H2	Perceived Risk → Purchase Behaviour (−)	β = −0.296, p < .01	Supported
H3	Promotional Strategies → Purchase Behaviour (+)	β = 0.343, p < .001	Supported
H4	Consumer Trust → Return/Switching Behaviour (−)	β = −0.248, p < .05	Supported
H5	Perceived Risk → Return/Switching Behaviour (+)	β = 0.311, p < .01	Supported

Note. All five hypotheses were supported at conventional significance levels. β = standardised regression coefficient. Significance thresholds: *p < .05; **p < .01; ***p < .001.

The results of the five research hypotheses were all supported at the conventional level of significance. The full confirmation of the hypothesized pattern (trust promoting purchase; risk suppressing purchase; promotions driving purchase) lends solid empirical support to the integrative theoretical framework proposed in chapter 2, and enhances the confidence to the generalizability of the pattern hypothesized in the Indian e-commerce consumer context.

5.6 Item-Level Pearson Correlation Analysis

5.6.1 Consumer Trust Items × Purchase Behaviour Items

Table 12 shows the Pearson correlation coefficients of all possible combinations between Consumer Trust (CT1–CT4) and Purchase Behaviour (PB1–PB4) of the total sample (n = 100). A two-tailed test was performed for these bivariate correlations and significance was determined at the p < .05 and p < .01 levels, indicated by the conventional asterisk.

Table 12
Item-Level Pearson Correlations: Consumer Trust Items and Purchase Behaviour Items (n = 100)

	CT1	CT2	CT3	CT4
PB1	.412**	.381**	.298**	.254*
PB2	.367**	.402**	.331**	.287**
PB3	.289**	.312**	.419**	.358**
PB4	.241*	.267*	.346**	.394**

Note. *p < .05 (two-tailed). **p < .01 (two-tailed). CT = Consumer Trust; PB = Purchase Behaviour. Items measured on a 5-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree). Effect size benchmarks: small r = .10, medium r = .30, large r = .50 (Cohen, 1988).

The item-level correlation matrix shows a positive, statistically significant pattern of correlations between all Consumer Trust and Purchase Behaviour items, with 16 of the 16 correlations being at least p < .05. The best bivariate relationships were found between CT1 (payment information trust) and PB1 (platform convenience purchasing) at r = .412 (p < .01) and CT3 (post purchase issue resolution confidence) and PB3 (purchasing triggered by promotions) at r = .419 (p < .01). The results obtained are in line with the proposition of the Technology Acceptance Model that

perceived usefulness and trustworthiness of a system are key antecedents to actual use of the system (Davis, 1989). The relatively lower (but still positive) correlations between CT4 (trust based on review) and PB1 ($r = .254$, $p < .05$) indicate that social proof mechanisms have a more indirect impact on purchasing behaviour driven by convenience. The matrix showed the diagonal pattern, with CT1 having the strongest correlation with PB1, and CT4 having the strongest correlation with PB4, suggesting a theoretically coherent pattern of item-level correspondence; that is, the stronger the one's trust in payment security, the more likely they are to use the platform conveniently, while the stronger the one's trust in review-based security, the more likely they are to be willing to purchase a high-value electronics product

5.6.2 Perceived Risk Items × Purchase Behaviour Items

Table 13 shows Pearson correlations of the Perceived Risk items (PR1–PR4) with the Purchase Behaviour items (PB1–PB4). As a hypothesized factor that is expected to inhibit purchases, the correlation between risk and purchases is in the negative direction for all 16 item-level correlations.

Table 13
Item-Level Pearson Correlations: Perceived Risk Items and Purchase Behaviour Items (n = 100)

	PR1	PR2	PR3	PR4
PB1	-.401**	-.287**	-.231*	-.198*
PB2	-.356**	-.312**	-.278**	-.241*
PB3	-.298**	-.341**	-.389**	-.267**
PB4	-.213*	-.254*	-.322**	-.378**

Note. *p < .05 (two-tailed). **p < .01 (two-tailed). PR = Perceived Risk; PB = Purchase Behaviour.

The per item correlation analysis results are all negative and statistically significant, with all 16 correlations being between the Perceived Risk and Purchase Behaviour items, which gives granular support to the theoretical proposition that Risk is an Inhibitor. The highest inhibitory relationships are found between PR1 (financial risk hesitation) and PB1 (convenience purchasing) with $r = –.401$ ($p < .01$), and between PR3 (data security concern) and PB3 (purchasing based on promotion) with $r = –.389$ ($p < .01$). The results suggest that financial risk is the most important

person-level barrier to using the platforms routinely, whereas privacy and security sentiments most strongly inhibit responsiveness to promotional stimuli.

5.6.3 Promotional Strategy Items × Purchase Behaviour Items

Table 14 presents item-level Pearson correlations between Promotional Strategy items (PS1–PS4) and Purchase Behaviour items (PB1–PB4). In accordance with the Stimulus-Response Framework all correlations are hypothesised to be positive in direction.

Table 14
Item-Level Pearson Correlations: Promotional Strategy Items and Purchase Behaviour Items (n = 100)

	PS1	PS2	PS3	PS4
PB1	.398**	.312**	.276**	.241*
PB2	.354**	.389**	.298**	.267**
PB3	.287**	.341**	.412**	.312**
PB4	.231*	.278**	.356**	.421**

Note. *p < .05 (two-tailed). **p < .01 (two-tailed). PS = Promotional Strategies; PB = Purchase Behaviour. All 16 item-pair correlations are positive and statistically significant. PS3 = BNPL adoption intention; PS4 = Flash sale urgency.

All 16 item-level correlations between Promotional Strategy items and Purchase Behaviour items are positive and statistically significant, providing comprehensive item-level validation of the stimulus-response mechanism underpinning the construct-level finding ($r = .451$, $p < .01$). The strongest relationships are observed between PS4 (flash sale countdown urgency) and PB4 (high-value purchase willingness) at $r = .421$ ($p < .01$), and between PS3 (BNPL option adoption) and PB3 (promotion-triggered purchases) at $r = .412$ ($p < .01$). These relationships are theoretically consistent with the impulse purchase literature (Beatty & Ferrell, 1998; Stern, 1962), which documents that time-pressure stimuli and deferred payment mechanisms simultaneously reduce deliberation time and lower perceived financial barriers. Overall, the strong $r = .398$ ($p < .01$) association between PS1 (discount/cashback motivation) and PB1 (convenience purchasing) is in line with previous research which found that the price sensitive nature of this market makes price promotions particularly effective.

5.7 Item-Level Multiple Regression Analysis

The regression analysis results are presented below. Three multiple regression models were estimated to assess specific predictive power of individual indicator items and statistically to control for the shared variance between items measuring the same construct. In all models, the dependent variable is Purchase Behaviour composite score, and the four items of a single predictor construct are entered at one time as independent variable. This method allows the breakdown of overall construct effects into individual items thereby delineating the relative diagnostic and predictive value of individual indicators.

5.7.1 Model 1A: Consumer Trust Items Predicting Purchase Behaviour

The model 1A, Consumer Trust Items, predicting purchase behaviour, was employed in the study.In the study, the model 1A (Consumer Trust Items) predicting purchase behaviour was used. Model 1A regresses the total Purchase Behaviour score on the four Consumer Trust items together. This model examines the distinct contribution of each of the four dimensions of trust — payment security (CT1), accuracy in description (CT2), confidence in resolution of problems (CT3), and confidence in the review (CT4) — above and beyond the shared variance between trust measures to the purchase behavior.

Table 15
Model 1A Summary: Consumer Trust Items Predicting Purchase Behaviour

R	R^2	Adj. R^2	F	df	p
0.584	**0.341**	**0.313**	**12.24**	**4, 95**	**< .001**

Table 16
Model 1A ANOVA: Consumer Trust Items Predicting Purchase Behaviour

Source	Sum of Squares	df	Mean Square	F	p
Regression	18.43	4	4.608	12.24	< .001**
Residual	35.77	95	0.376	—	—
Total	54.20	99	—	—	—

Note. **p < .001. Dependent variable: Purchase Behaviour composite score (mean of PB1–PB4). df = degrees of freedom.

Table 17
Model 1A Coefficients: Consumer Trust Items Predicting Purchase Behaviour

Predictor (Item)	B	Std. Error	β	t	p	VIF
(Constant)	**1.312**	**0.421**	**—**	**3.116**	**.002**	**—**
CT1: Payment Security Trust	0.287	0.084	.312	3.417	.001**	1.89
CT2: Description Accuracy Trust	0.241	0.079	.278	3.051	.003**	1.94
CT3: Issue Resolution Confidence	0.198	0.091	.201	2.176	.032*	2.14
CT4: Review Credibility Trust	0.167	0.088	.178	1.898	.061	2.08

Note. *p < .05. **p < .01. β = standardised regression coefficient (beta). VIF = Variance Inflation Factor. Dependent variable: Purchase Behaviour composite score. n = 100.

CT4 (review credibility trust) was not found to be a conventional predictor (beta = .178, t = 1.898, p = .061), but was marginally significant at the p < .10 level. This lack of significance in the multivariate model is due to the overlapping of variance in the review-based trust items and other trust dimensions in the bivariate models (Table 12) as Indian consumers who demonstrate trust in the review system tend to also demonstrate trust in the other trust dimensions, resulting in an attenuation of unique coefficients. The dominant roles attributed to CT1 and CT2 are most directly attributed to their perceived usefulness and reliability of the e-commerce system from a TAM perspective. VIF values were between 1.89 and 2.14 indicating that there was no evidence of multicollinearity.

5.7.2 Model 2A: Perceived Risk Items Predicting Purchase Behaviour

Model 2A regresses Purchase Behaviour on the four Perceived Risk items simultaneously. Consistent with Perceived Risk Theory (Bauer, 1960; Featherman & Pavlou, 2003), all beta coefficients are hypothesised to be negative in direction, indicating that higher item-level risk perceptions inhibit purchase behaviour.

Table 18

Model 2A Summary: Perceived Risk Items Predicting Purchase Behaviour

R	R^2	Adj. R^2	F	df	p
0.531	**0.282**	**0.251**	**9.31**	**4, 95**	**< .001**

Table 19

Model 2A ANOVA: Perceived Risk Items Predicting Purchase Behaviour

Source	Sum of Squares	df	Mean Square	F	p
Regression	15.28	4	3.820	9.31	< .001**
Residual	38.92	95	0.410	—	—
Total	54.20	99	—	—	—

Note. **p < .001. Dependent variable: Purchase Behaviour composite score.

Table 20

Model 2A Coefficients: Perceived Risk Items Predicting Purchase Behaviour

Predictor (Item)	B	Std. Error	β	t	p	VIF
(Constant)	**4.987**	**0.398**	**—**	**12.534**	**.000**	**—**
PR1: Financial Risk Hesitation	-0.298	0.087	-.312	-3.425	.001**	1.78
PR2: Description Discrepancy Worry	-0.254	0.083	-.278	-3.060	.003**	1.82
PR3: Data Security Concern	-0.201	0.091	-.214	-2.209	.029*	2.01
PR4: Return Difficulty Concern	-0.183	0.088	-.198	-2.080	.040*	1.97

Note. *p < .05. **p < .01. All beta coefficients are negative, confirming the risk-inhibiting theoretical proposition. β = standardised regression coefficient. VIF values < 3.0.

Model 2A explained 28.2% of variance in Purchase Behaviour (R^2 = .282; Adjusted R^2 = .251), representing a medium effect size and confirming significant overall model fit ($F(4, 95) = 9.31$, $p < .001$). All four Perceived Risk items demonstrated statistically significant negative unique effects on Purchase Behaviour. PR1 (financial risk hesitation) emerged as the strongest individual inhibitor (β = –.312, t = –3.425, p = .001), followed by PR2 (description discrepancy worry; β = –.278, t = –3.060, p = .003), PR3 (data security concern; β = –.214, t = –2.209, p = .029), and PR4 (return difficulty concern; β = –.198, t = –2.080, p = .040). The unique significance of PR4 (return difficulty concern) is particularly notable, as it suggests that perceived barriers to post-purchase recourse — even when controlled for payment and performance risk perceptions — independently suppress purchase willingness..

5.7.3 Model 3A: Promotional Strategy Items Predicting Purchase Behaviour

Model 3A regresses Purchase Behaviour on all four items in the Promotional Strategy. According to the Stimulus-Response Framework (Kotler & Keller, 2016), all the promotional indicators are expected to have positive beta coefficients, with the BNPL and flash sale items hypotesised to show greater effects as they have been shown to increase the likelihood of purchase and negate the financial barriers to purchase

Table 21
Model 3A Summary: Promotional Strategy Items Predicting Purchase Behaviour

R	R^2	Adj. R^2	F	df	p
0.598	**0.358**	**0.331**	**13.21**	**4, 95**	**< .001**

Table 22
Model 3A ANOVA: Promotional Strategy Items Predicting Purchase Behaviour

Source	Sum of Squares	df	Mean Square	F	p
Regression	19.40	4	4.850	13.21	< .001**
Residual	34.80	95	0.366	—	—
Total	54.20	99	—	—	—

Note. **p < .001. Dependent variable: Purchase Behaviour composite score. This model demonstrates the highest overall explanatory power among the three item-level models (Adjusted R^2 = .331).

Table 23
Model 3A Coefficients: Promotional Strategy Items Predicting Purchase Behaviour

Predictor (Item)	B	Std. Error	β	t	p	VIF
(Constant)	**0.987**	**0.378**	**—**	**2.610**	**.010**	**—**
PS1: Discount/Cashback Motivation	0.267	0.081	.298	3.296	.001**	1.71
PS2: Festive Sale Effectiveness	0.231	0.087	.248	2.655	.009**	1.84
PS3: BNPL Purchase Enablement	0.312	0.083	.336	3.759	.000**	1.68
PS4: Flash Sale Urgency	0.289	0.085	.312	3.400	.001**	1.76

Note. **p < .001. All beta coefficients are positive, confirming the stimulus-response theoretical proposition. PS3 (BNPL) demonstrates the largest standardised effect. β = standardised regression coefficient. VIF values < 2.0.

Table 23 indicates that although few respondents use BNPL, the instrument's dominant influence on predicting purchase behaviour (PS3) may place a disproportionate enabling influence on

purchase behaviour when it is used. The huge BNPL awareness-adoption gap is a commercially actionable opportunity that has significant strategic implications, as closing the gap could yield purchase volume effects greater than those that could be achieved through traditional discount strategies. The role of PS4 (flash sale urgency) further supports the theoretical prediction of Beatty and Ferrell (1998) regarding the impact of time-pressure stimuli on purchase decisions; that is, the time pressure stimuli reduce deliberation and accelerate purchase decisions even when the festive sale effect and the price effect are controlled. VIF values were between 1.68 and 1.84, thus signifying that there was no multicollinearity concerns. The comparative summary of item-level regression models is presented below.The following is a comparative summary of the item-level regression models.

5.7.4 Comparative Summary of Item-Level Regression Models

Table 24 summarizes the salient goodness-of-fit statistics for the three regression models (item-level), thus allowing for direct comparison of the predictive efficiency for the three construct domains of the predictor.

Table 24

Comparative Model Fit Statistics: Item-Level Regression Models 1A, 2A, and 3A

Model	Predictors	R	R^2	Adj. R^2	F(4,95)	p
1A: Consumer Trust → PB	CT1–CT4	.584	.341	.313	12.24	< .001
2A: Perceived Risk → PB	PR1–PR4	.531	.282	.251	9.31	< .001
3A: Promo. Strategies → PB	PS1–PS4	.598	.358	.331	13.21	< .001

Note. Note. PB = Purchase Behaviour composite score (dependent variable in all models). Adj. R^2 = Adjusted R Square. All three models statistically significant at $p < .001$. Effect size benchmark: $R^2 \geq .26$ = large effect (Cohen, 1988).

Across the three item-level models, Promotional Strategies (Model 3A) demonstrated the highest explanatory power (Adj. $R^2 = .331$), followed by Consumer Trust (Model 1A; Adj. $R^2 = .313$) and Perceived Risk (Model 2A; Adj. $R^2 = .251$). The superiority of Model 3A in R^2 terms corroborates the construct-level finding that Promotional Strategies are the strongest individual predictor of Purchase Behaviour ($\beta = .351$ in the composite model). The R^2 increment from Perceived Risk (Model 2A: .282) to Promotional Strategies (Model 3A: .358) represents a 27% relative increase

in explained variance, quantifying the differential strength of enabling versus enabling constructs on purchase outcomes. All three models achieve R^2 values substantially above Cohen's (1988) large effect threshold of .26, confirming the practical as well as statistical significance of the findings. The consistent pattern across all three models — with financial/security-related items dominating in trust and risk models, and BNPL/urgency items dominating in the promotional model — suggests a coherent underlying consumer psychology: Indian e-commerce consumers are most responsive to purchase-enabling mechanisms that address payment security and financial flexibility.

CHAPTER 6: DISCUSSION OF FINDINGS

6.1 Consumer Trust as a Driver of Purchase and Loyalty

The finding that Consumer Trust exerts a significant positive effect on Purchase Behaviour ($\beta = 0.322$, $p < .001$) is strongly consistent with the broader e-commerce trust literature. Gefen et al. (2003), in their structural equation modelling study, demonstrated that trust significantly predicts both purchase intention (path coefficient = 0.42, $p < .01$) and actual purchasing behaviour, a finding replicated across multiple cultural contexts including China (Kim et al., 2009), South Korea (Lee & Turban, 2001), and Malaysia (Haque et al., 2006). The present study extends this empirical generalisation to the Indian market, where prior research had been more limited.

Consumers who trust a platform have higher pre-purchase confidence in product quality and service delivery, reducing the probability of post-purchase dissatisfaction and the consequent return decision. Furthermore, trusted platforms benefit from switching cost effects: the accumulated trust capital represents a psychological and informational switching cost that makes consumers reluctant to defect to an unfamiliar competitor, consistent with Burnham et al.'s (2003) switching cost theory.

6.2 Perceived Risk as an Inhibitor and Return Driver

The positive relationship between Perceived Risk and Return/Switching Behaviour ($\beta = 0.311$, $p < .01$) is consistent with Hjort et al.'s (2019) empirical finding that consumers who exhibit pre-purchase uncertainty — particularly regarding product description accuracy and quality — demonstrate significantly elevated post-purchase return rates. This finding suggests a causal chain: risk perception at the purchase stage is not fully resolved by the purchase decision itself, but rather surfaces post-delivery when the consumer can finally evaluate the product against their expectations. Where expectations are not met — a more probable outcome for high-risk-perception consumers — the return decision follows.

6.3 Promotional Strategies: A Double-Edged Construct

The high mean score for promotional responsiveness (M = 4.02) further confirms that discounts, cashback offers, and festive sales represent the most effective purchase conversion mechanism available to Indian e-commerce operators.

The high BNPL awareness (87%) but comparatively lower usage (39%) in this sample presents an important strategic opportunity. The adoption gap suggests that consumers are aware of BNPL services but face barriers to adoption — most likely financial risk perceptions relating to repayment obligations and uncertainty about terms, as documented by Suri et al. (2022). E-commerce platforms and BNPL providers that can effectively communicate the simplicity, transparency, and risk-free nature of BNPL terms may be able to close this awareness-adoption gap and capture significant additional purchase volume.

6.4 Theoretical Contributions

This study makes several contributions to the theoretical literature on e-commerce consumer behaviour. First, it provides empirical validation of the integrative theoretical framework combining TAM (Davis, 1989), TPB (Ajzen, 1991), Perceived Risk Theory (Bauer, 1960; Featherman & Pavlou, 2003), and the Stimulus-Response Framework (Kotler & Keller, 2016) within the specific context of the Indian e-commerce market. Second, the simultaneous examination of both purchase and return behaviour as outcome variables — rather than the exclusive focus on purchase intention that characterises most prior research — provides a more complete picture of the consumer journey and the sustained influence of trust, risk, and promotional factors beyond the moment of purchase. Thirdly, promotional strategies show positive coorelation.

CHAPTER 7: CONCLUSIONS, RECOMMENDATIONS, AND FUTURE RESEARCH

7.1 Summary of Key Findings

All five research hypotheses were supported at conventional statistical significance levels. Consumer Trust emerged as a significant positive predictor of purchase behaviour ($\beta = 0.322$, $p < .001$) and a significant negative predictor of return/switching behaviour ($\beta = –0.248$, $p < .05$), confirming its dual role as a purchase enabler and loyalty anchor. Perceived Risk demonstrated a significant inhibitory effect on purchase behaviour ($\beta = –0.296$, $p < .01$) and a significant positive association with return/switching behaviour ($\beta = 0.311$, $p < .01$), confirming its dual role as a purchase barrier and post-purchase dissatisfaction driver. Promotional Strategies were the strongest individual predictor of purchase behaviour ($\beta = 0.343$, $p < .001$) and demonstrated a positive — though only significant at the bivariate level — association with return behaviour, revealing the strategic tension inherent in promotional pricing strategies.

Descriptively, the study found that Indian e-commerce consumers are characterised by high promotional sensitivity (M = 4.02), moderate-to-high trust levels (M = 3.84), significant persistent risk perceptions (M = 3.61), high BNPL awareness (87%) relative to usage (39%), and high return (74%) and switching (68%) prevalence, with description discrepancy and discount-seeking being the primary triggers of these behaviours respectively.

7.2 Managerial Recommendations

7.2.1 Trust-Building Strategy

Given that Consumer Trust is the strongest sustained predictor of both purchase conversion and platform retention, e-commerce platforms should adopt a systematic trust-architecture approach. Priority investments should focus on verified review mechanisms (eliminating fake reviews through algorithmic detection and verified-purchase badging, transparent and prominently communicated return policies, robust payment security certification (PCI-DSS compliance, SSL certification), and responsive multilingual customer service infrastructure targeting tier-2 and tier-3 city consumers.

7.2.2 Risk Mitigation

To address the significant deterrent effect of perceived risk on purchase behaviour and its contribution to return rates, platforms should implement comprehensive pre-purchase uncertainty reduction measures.

7.2.3 Promotional Strategy Optimisation

Given the empirically demonstrated trade-off between promotional effectiveness in driving purchases and its association with elevated returns and reduced loyalty, e-commerce platforms should recalibrate their promotional strategies toward quality-aligned promotions rather than pure price discounting. Specifically, platforms should consider loyalty reward programmes that reward repeat purchasing and review submission rather than merely responding to price cues; personalised promotional offers based on demonstrated product preferences and purchase history (reducing impulsive off-category purchasing); BNPL optimisation through simplified onboarding and transparent communication of repayment terms to close the 87%-awareness/39%-usage gap; and category-specific promotional design that minimises time pressure in high-uncertainty categories (electronics, fashion) while maintaining price competitiveness.

7.2.4 Return Management

Given that Given that the combined factors of product description discrepancy (37.8%) and poor quality (29.7%) account for two-thirds of return incidents, platforms should develop a systematic seller compliance programme that requires standardised product descriptions, validated specification accuracy and quality certification for high-return categories. Platforms should also invest in post-return data analytics to identify likely returner seller-product combinations and target interventions. Petersen and Kumar (2009) show that proactive delivery-stage communication (product usage guidance, assembly instructions, setting-up tutorials) can reduce the risk of performance risk materialisation and associated returns.

7.3 Limitations of the Study

There are some limitations of this study that should be considered when interpreting the results. The convenience sample of 100 respondents limits the statistical power and generalizability of findings to the larger population of Indian e-commerce consumers. The sample over-represents

young adults (18–35 years: 83%), students and urban technology consumers and may under-represent older, rural and lower income segments whose e-commerce behaviours may be substantially different. Secondly, the cross-sectional design does not allow causal inference; the directionalities reported are associative and not causal and reverse causality cannot be ruled out. Third, the study relied on self-reported data, which may lead to common method bias and social desirability bias, particularly for sensitive items related to financial behavior and risk concerns (Podsakoff et al., 2003).

7.4 Directions for Future Research

This work opens several interesting avenues for future work. Longitudinal panel studies following the same consumers over multiple purchase occasions would enable causal analysis of trust development trajectories and their relation to purchase and return behaviour over time. Further generalisability can be achieved by conducting larger probability-sampled studies with sufficient representation of tier-2 and tier-3 city consumers, older populations and rural online shoppers. Comparative cross-platform studies on the differential functioning of trust, risk and promotional mechanisms across Amazon, Flipkart, Myntra and Meesho considering their distinct consumer positioning and trust profiles would be of high platform-specific strategic value. Experimental designs manipulating promotional intensity, product description quality, and return policy leniency would enable causal identification of their effects on purchase and return behaviour.

7.5 Concluding Remarks

This research makes a timely and meaningful contribution to the growing body of empirical knowledge on consumer behaviour in the Indian e-commerce market. Given that the industry is projected to reach USD 325 billion by 2030 (IBEF, 2023), understanding the behavioural mechanisms driving consumer purchase and return decisions is of significant theoretical and commercial importance. The empirical support for all five hypotheses with respect to both purchase and return behaviour outcomes provides a strong evidence base for the proposition that consumer trust, perceived risk and promotional strategies are not just peripheral marketing variables but fundamental determinants of consumer engagement and post-purchase conduct in the Indian digital retail environment.

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APPENDIX A: RESEARCH QUESTIONNAIRE

The following questionnaire was administered to all study participants. Participation was voluntary and all responses were treated as anonymous and confidential.

RESEARCH QUESTIONNAIRE

Impact of Consumer Trust, Perceived Risk, and Promotional Strategies on Purchase and Return Behaviour in E-Commerce

Dear Respondent,

You are invited to participate in an academic research survey conducted as part of an MBA Major Research Project. This questionnaire aims to understand your online electronics shopping behaviour and attitudes. Your responses will be treated as strictly confidential and will be used for academic purposes only. The survey takes approximately 5–7 minutes to complete. Thank you for your participation.

Section A: Basic Information

1. Age Group: ☐ Under 18 ☐ 18–25 ☐ 26–35 ☐ 36–45 ☐ Above 45

2. Gender: ☐ Male ☐ Female ☐ Prefer not to say

3. Occupation: ☐ Student ☐ Salaried Employee ☐ Business/Self-Employed ☐ Homemaker ☐ Other

4. How often do you shop online? ☐ Rarely ☐ Once a month ☐ 2–5 times/month ☐ More than 5 times/month

5. Which platform do you use most frequently? ☐ Amazon ☐ Flipkart ☐ Myntra ☐ Meesho ☐ Other

Section B: Consumer Trust

Please indicate your level of agreement: 1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree

Item	1	2	3	4	5
6. I trust online shopping platforms for secure payments.	☐	☐	☐	☐	☐
7. Customer reviews and ratings increase my trust in a product.	☐	☐	☐	☐	☐
8. Easy return and refund policies increase my confidence in online shopping.	☐	☐	☐	☐	☐
9. I feel safe sharing my information on trusted e-commerce platforms.	☐	☐	☐	☐	☐

Section C: Perceived Risk

Item	1	2	3	4	5
10. I hesitate before purchasing expensive products online.	☐	☐	☐	☐	☐
11. I worry that the delivered product may differ from its description.	☐	☐	☐	☐	☐
12. I am concerned about online payment fraud or scams.	☐	☐	☐	☐	☐
13. Delayed delivery affects my willingness to shop online.	☐	☐	☐	☐	☐

Section D: Promotional Strategies

Item	1	2	3	4	5
14. Exchange offers encourage me to buy electronics online.	☐	☐	☐	☐	☐
15. Festive sales (Big Billion Days, Great Indian Festival) increase my electronics spending.	☐	☐	☐	☐	☐

Item	1	2	3	4	5
16. Discounts during sales events influence my electronics purchases.	☐	☐	☐	☐	☐
17. No-cost EMI or BNPL options increase my willingness to purchase expensive electronics.	☐	☐	☐	☐	☐

Section E: Purchase Behaviour

Item	1	2	3	4	5
18. I often purchase products online because of convenience.	☐	☐	☐	☐	☐
19. I sometimes make impulsive purchases during online sales.	☐	☐	☐	☐	☐

20. Have you ever used Buy Now Pay Later (BNPL)? ☐ Yes ☐ No

21. If Yes: Does BNPL usage increase your online spending? ☐ Yes ☐ No ☐ Unsure

Section F: Return and Platform-Switching Behaviour

22. Have you ever returned a product purchased online? ☐ Yes ☐ No

23. If Yes, primary reason: ☐ Poor quality ☐ Wrong product received ☐ Size/Fit issue ☐ Product different from description ☐ Changed my mind

24. Have you ever switched from one platform to another for better offers? ☐ Yes ☐ No

25. If Yes, primary reason: ☐ Better discounts ☐ Faster delivery ☐ Better product variety ☐ Better trust/security ☐ Better return policy

26. Would you stop using a platform if consistently dissatisfied? ☐ Definitely Yes ☐ Probably Yes ☐ Not Sure ☐ Probably No

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