ANALYSIS OF USER EXPERIENCE DESIGN OF TOP E-COMMERCE PLATFORMS

Abstract

The study investigates the impact of various user experience (UX) elements on the effectiveness and success of e-commerce platforms, with a focus on navigation structure, visual design, personalised content, and mobile optimisation. Primary data was collected through a survey of regular users from Leeds, UK, and Uttarakhand, India. Responses were analysed using statistical methods including descriptive statistics, reliability analysis, correlation analysis, and ordinal regression. The findings demonstrate the importance of these UX elements, emphasising the role of mobile optimisation and navigation in increasing overall user happiness. The study's limitations include a particular focus on a small number of e-commerce platforms and the fundamental subjective nature of UX evaluation. Future study recommendations include adopting new technologies such as AI and machine learning into UX design, and undertaking cross-cultural studies to better understand varied user preferences.

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Chapter 1 - Introduction

Background of the Study

The introduction of e-commerce has changed the retail industry, changing the way customers shop and engage with businesses. The transition from traditional brick-and-mortar stores to digital platforms has not only changed buying patterns, but it has also increased retailers' global reach, allowing them to engage with customers all over the world. As e-commerce expands, user experience (UX) design has emerged as an important aspect in determining the success of these platforms. User experience design includes all aspects of a customer's interaction with a firm, its services, and its goods (Garrett, 2011). For the e-commerce, UX design also includes an approach for designing interfaces that are aesthetic, intuitive as well as focused on efficient routes customised to customer needs (Nielsen et al., 2012).

A good UX design helps in providing primary comparable advantage in the digital world. This not only leads to more satisfied and loyal customers, but also helps in generating higher income while driving higher conversion rates and gaining edge in the existing market. (Tractinsky, 2013).

Top e-commerce platforms acknowledge the usefulness of UX design and hence invest in resources to improve the usability of their platforms. They use a variety of strategies to ensure seamless, engaging, and efficient shopping experiences. These strategies include user-centred design, which prioritises the needs and preferences of users in every design decision to create intuitive and accessible interfaces (Norman, 2013); responsive design, which ensures that websites are optimised for various devices, including desktops, tablets, and smartphones, to provide a consistent user experience across all platforms (Marcotte, 2010); personalisation, which leverages data analytics and artificial intelligence to deliver personalised recommendations and content, thereby enhancing user engagement and satisfaction (Chen et al., 2014); simplified navigation, which implements clear and straightforward navigation paths to help users find products and information quickly and easily (Kalbach, 2007); fast loading times, which are optimised to reduce loading times, crucial for maintaining user interest and reducing bounce rates (Krug, 2006); secure transactions, which ensure robust security measures to protect user data and build trust in the platform’s reliability and integrity (Pfleeger and

Pfleeger, 2012); and visual appeal, which uses attractive and cohesive visual elements to create a pleasant and inviting shopping environment (Lidwell et al., 2010).

Despite these initiatives, the techniques and design ideologies used by different e-commerce platforms vary significantly. According to (Mullet and Sano, 1995), some may focus on personalisation and data-driven insights while others may target aesthetic appeal and brand consistency. As a result, it becomes essential to explore UX design for these platforms. Such analysis helps in identifying best practices, targeting opportunities, and providing valuable understanding of how various design practices impact user experience and business results (Tullis and Albert, 2008). For instance, analysing the checkout processes across platforms can expose which features alters cart abandonment rates and boosts completed purchases (Appleseed and Holst, 2013). Similarly, the evaluations of visual design upon users could provide insights regarding aesthetic decisions influence effectiveness in how well a medium achieves user engagement (Kim et al., 2003)

Research Focus

Despite the widely acknowledged relevance of UX design in e-commerce, there is an affecting absence of thorough studies focusing on the UX design features of top e-commerce platforms. This research gap challenges e-commerce businesses in benchmarking their UX practices against industry leaders and identifying universal principles that contribute to superior user experiences (Nielsen, 2012). Without such knowledge, businesses struggle to implement effective design strategies that enhance customer satisfaction and drive business success.

A thorough analysis of UX design in leading e-commerce platforms offers several key benefits. It would provide a detailed evaluation of the most effective design elements, such as user-centred design practices, responsive design, personalisation strategies, navigation simplicity, loading speed optimisation, transaction security, and visual appeal (Norman, 2013; Marcotte, 2010; Chen et al., 2014; Kalbach, 2007; Krug, 2006; Pfleeger and Pfleeger, 2012; Lidwell et al., 2010). This helps e-commerce businesses prioritise their UX efforts more effectively.

Additionally, the analysis would reveal common issues and challenges in UX design, allowing businesses to avoid repeating mistakes and further improve their processes to better meet user needs. It would also facilitate the identification of industry trends and emerging UX design

practices, helping businesses stay competitive in a rapidly evolving digital landscape (Tullis and Albert, 2008).

This study aims to fill that gap by analysing the UX design strategies of top e-commerce platforms, providing valuable insights to help businesses benchmark their practices, identify best practices, and avoid common pitfalls. Ultimately, this research will contribute to more effective and engaging e-commerce environments, benefiting both businesses and their customers.

Research Objectives

The primary objective of this research is to conduct analysis of the UX design elements of top e-commerce platforms.

Davis (1989) developed the Technology Acceptance Model (TAM), which serves as the foundation for the above conceptual framework. According to TAM, perceived ease of use and perceived usefulness are critical factors influencing users' acceptance and participation with technology. The figure below, illustrates the Tam model, developed by Davis.

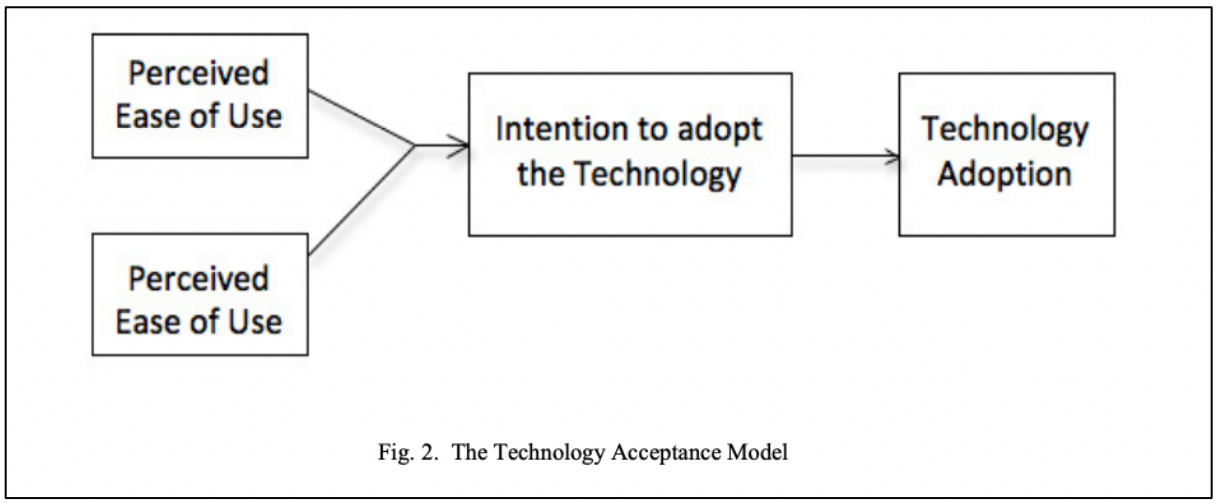

Fig. 2. The Technology Acceptance Model

Figure 1: Source- Technology Acceptance Model (Koch, S., Toker, A., Brulez, P. (2011))

In the context of e-commerce platforms, factors like navigation structure, visual design, mobile optimisation and responsive design and Personalised content can be illustrated using the TAM framework:

- Navigation and Mobile Optimisation & Responsive Design influence perceived ease of use, which influences on how easily users navigate and interact with the platform.
- Visual Design and Personalised Content impacts the perceived usefulness, accord to the relevance and satisfaction of the user experience, which in turn contributes to users' likelihood of returning or purchasing.

Figure 2 is adapted from Koch, S., Toker, A., Brulez, P. (2011) and illustrates the application of Technology Acceptance Model within the context of E-commerce. The framework has been modified to address and highlight the key components such as Navigation and Mobile Optimisation & Responsive Design, Visual Design and Personalised Content.

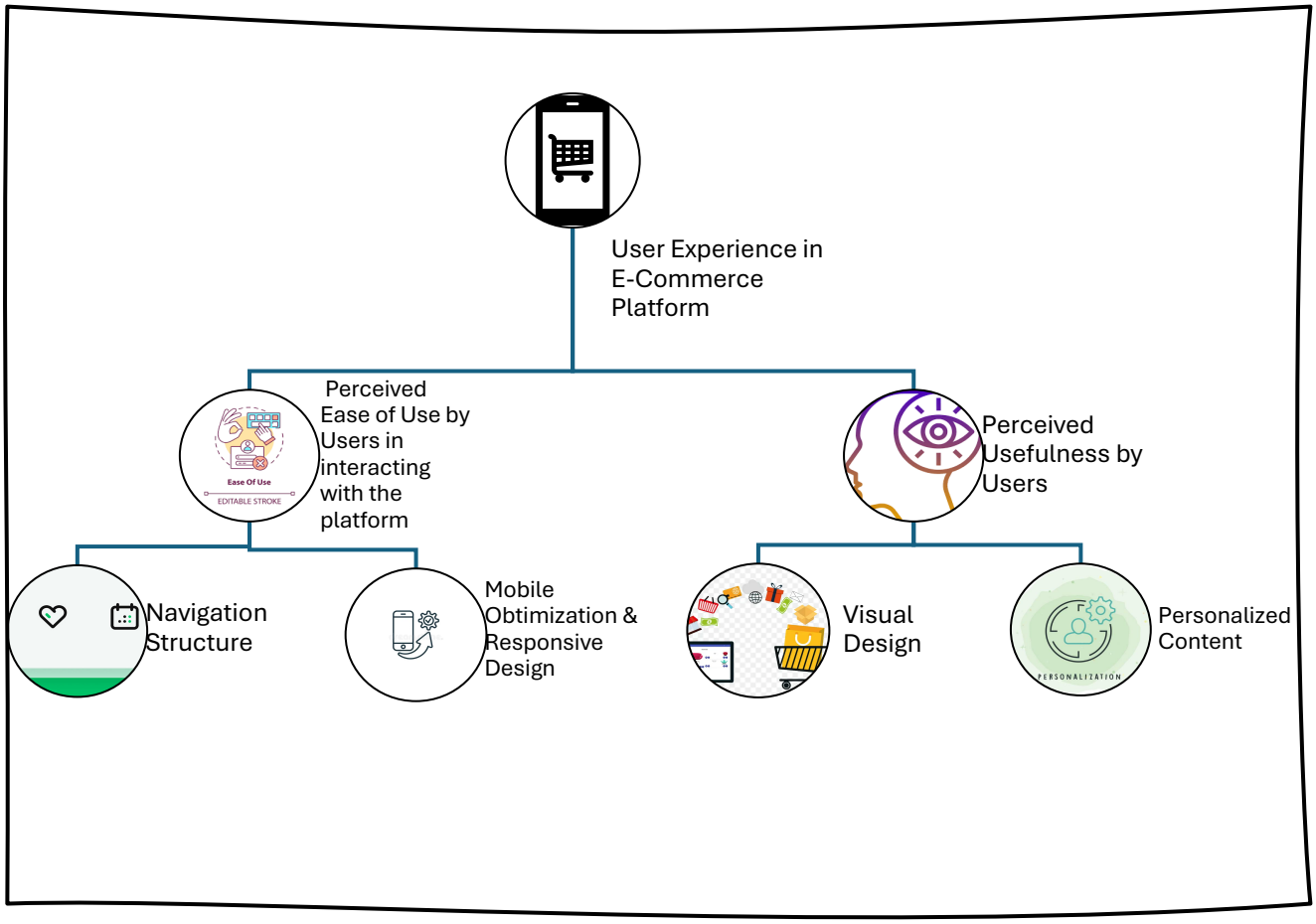

Figure 2: Extension of TAM Framework w.r.t E-Commerce

This theoretical concept and diagram should provide a strong base for analysing the factors that impact user experience in e-commerce platforms.

Research Questions

- **How is user experience affected by navigation structure of the top e-commerce platform?** This question aims to explore the differences and similarities in the way leading e-commerce platforms organise their navigation systems, and how these structures affect the ease with which users can find information and complete tasks (Nielsen, 2012; Kalbach, 2007).

  H_0 – The navigation structure of top e-commerce platforms does not significantly affect the user experience in terms of ease of finding information and completing tasks.

  H_1 – The navigation structure of top e-commerce platforms significantly affects the user experience in terms of ease of finding information and completing tasks.

- **How do visual design components affect the overall user experience of the platform?** This question explores how visual design components including layout, colour schemes, typography, and images affect user views of the platform's credibility, attractiveness, and usability (Kim et al., 2003; Lidwell et al., 2010).

  H_0 – Visual design elements, including layout, color schemes, typography, and imagery, do not have a significant impact on user perceptions of a platform's credibility, attractiveness, and ease of use.

  H_1 – Visual design elements, including layout, color schemes, typography, and imagery, have a significant impact on user perceptions of a platform's credibility, attractiveness, and ease of use.

- **How effective are personalised content and recommendation algorithms in improving user experience?** This question investigates the process and success of personalised recommendations and content in boosting the user experience, keeping users engaged, and encouraging repeat visits and purchases (Chen et al., 2014).

  H_0 – Personalised content and recommendation systems do not significantly enhance the user experience or drive user engagement and repeat purchases.

  H_1 – Personalised content and recommendation systems significantly enhance the user experience and drive user engagement and repeat purchases.

- **In what ways do mobile optimisation and responsive design alter the user experience across various devices?** This question highlights the importance of mobile

optimisation and responsive design in providing a consistent and pleasant user experience across different platforms, including desktops, tablets, and smartphones (Marcotte, 2010).

H_0 – Mobile optimisation and responsive design do not significantly influence the user experience across various devices.

H_1 – Mobile optimisation and responsive design significantly influence the user experience across various devices.

Significance of the Study

This study's findings are highly helpful to e-commerce platforms, UX designers, and researchers. This research will also help in identifying some of the principles and elements of an effective e-commerce UX design for better user experience. These results can be used by e-commerce businesses to improve their UX strategies and customer satisfaction thereby leading them towards more competitive path (Garrett, 2011; Tractinsky, 2013). This knowledge can further guide decision-making and resource management within the organisation to ensure that resources are appropriately prioritised towards UX improvements that yield the highest returns (Norman, 2013). This research also highlights innovative approaches and methods that can be adopted to enhance user satisfaction and drive engagement (Chen et al., 2014).

This chapter has established the critical role of UX design in the success of e-commerce platforms and highlighted the research gap in studies of UX design among top platforms. The research questions guide the investigation into these aspects, providing a roadmap for the study.

Chapter 2 - Literature Review

Introduction

The rapid rise of e-commerce has transformed the way consumers engage with retailers, establishing user experience (UX) design a crucial component for online platforms to succeed. Given the rising competition in e-commerce, understanding and improving UX design becomes critical for customer retention and revenue growth. This chapter delves into many aspects of UX design, reviewing the current literature to identify best practices, key elements of user experience, and opportunities for development.

Despite the great deal of research in the field, some knowledge gaps exist which should be further explored. This chapter highlights these gaps and proposes potential remedies to solve ongoing issues, with a spotlight on the exponential impact of new technologies (i.e. AI, machine learning or AR) that could help in transforming e-commerce User Experience. Additionally, the chapter discusses the importance of holistic UX metrics, longitudinal studies, and cross-cultural research to develop more inclusive and adaptive UX strategies.

This chapter aims to provide a complete overview of the current state of UX design in e-commerce by synthesising existing literature and proposing future research paths, as well as to establish a path for future advancement. This fundamental knowledge is essential for academics, designers, and practitioners who want to construct stronger and more engaging e-commerce systems.

Background of Study

The e-commerce segment has been one of the fastest-growing sectors in the last decade with technological advancements, rising internet penetration and evolving consumer behaviours (Nielsen, 2012). With the growth of online shopping, user experience (UX) on e-commerce platforms has become an important element in consumer satisfaction, engagement and loyalty. UX design involves every part of a user's interaction with a platform, such as usability, accessibility, performance, visual design, and overall satisfaction. (Garrett, 2011).

In the current competitive e-commerce market, an ideal and rewarding UX can help in differentiating the platform from its competitors, increasing customer retention and driving higher conversion rates. (Tractinsky, 2013). Intuitive navigation, personalised content relevant to the user, fast load times and appealing visual designs play a crucial role in developing an

excellent UX. Additionally, as more people prefer shopping online using a mobile device could mean that e-commerce platforms simply need to deliver consistently, optimised experiences across all devices (Marcotte, 2010).

The various factors that impact user satisfaction and behaviour have been highlighted in the UX design research for e-commerce platforms. Studies have shown that users usually stay longer on sites if they are able to locate what they are looking for, if the site loads quickly and contains content of interest for them (Kalbach 2007). Furthermore, integrating web analytics enables firms to watch user behaviour, discover pain points, and make data-driven decisions to improve UX (Chen et al., 2014).

While all that has been achieved in understanding e-commerce UX, there are still some areas that demand further investigation. Modern technologies such as artificial intelligence (AI), machine learning, augmented reality (AR), and virtual reality (VR) provide new ways to improve UX by providing personalised and immersive experiences (Tullis and Albert, 2008). Additionally, the need for holistic UX metrics that combine quantitative and qualitative data, as well as the importance of tracking long-term impact of UX changes, are critical areas for future research (Nielsen, 2012).

By solving these gaps and utilising advanced technologies, e-commerce platforms can continue to improve and provide superior user experiences that meet the ever-changing expectations of consumers (Garrett, 2011).

Review of Existing Literature.

Intuitive Navigation and Personalised Content

Agrawal and Dhar (2020) provides an extensive Indian market case study concerning B2C e-commerce applications highlighting the critical role of user experience (UX) in driving user satisfaction and market performance. Their research observed several UX elements which particularly related to generating positive user experience. One of the prominent features is intuitive navigation. A well-designed, easy-to-use navigation system allows users to find products quickly and efficiently, which is important in customer retention and providing smooth shopping experiences.

Additionally, the study focuses on the importance of personalised content. E-commerce systems may greatly increase customer engagement by personalising the purchasing experience based on their browsing history and interests. By modifying the shopping experience for individual users based on their browsing history and preferences, e-commerce platforms can significantly enhance user engagement. Personalised content helps in providing more relevant and enjoyable shopping experience boosting the chances for return visits and purchases. The research highlights the criticality of incorporating user feedback into the design process for creating an effortless and engaging shopping experience. User feedback is invaluable in identifying opportunities and areas for improvement, ensuring that the platform improves to meet user expectations (Agrawal and Dhar, 2020).

UX Analytics and Consumer Behaviour

Chauhan and Nayyar (2020) explore factors influencing online purchasing behaviour of consumers through structural modelling. Their research highlights several key factors that influences consumer decision needs on e-commerce. For instance, Website aesthetics plays a significant role in encouraging and retaining users. The visual appeal including the layout and design elements, can also greatly influence a user's first impression and overall experience on the site.

Another vital factor identified is load time. Websites that load fast enhances the user experience by cutting down wait times, that provides better conversion rates and reduced bounce rate. Ease of use is also vital as it assures simple and intuitive design that users can navigate the site without confusion or frustration. The study proposes the use of web analytics to monitor user behaviour, locate crucial points in the user journey, and proactively address them. By using analytics tools, e-commerce platforms can gain information about areas where website optimisation is needed to enhance overall satisfaction and loyalty (Chauhan and Nayyar, 2020).

The Impact of UI Design on UX

IEEE Xplore (2022) provides studies examining the connections between user interface (UI) design and user experience (UX) on popular e-commerce platforms such as Tokopedia and Shopee. The study reveals that several UI elements are essential for maintaining user engagement and satisfaction. Colour schemes are one of the significant considerations. The

palette chosen for the site can have a major effect on its tone and utility, influencing how users feel and engage with the platform.

Typography is another critical element. Clear and readable fonts also enhance the overall user experience by making content easily consumable. Interactive elements such as buttons, sliders, and graphics can also make the site more engaging and user-friendly. These elements encourage users to interact more with the platform. This increases the time spent on the website and raises the possibility of conversion. The study emphasises on the details in UI design which significantly impact user perception and interaction with the platform (Gunawan et al., 2021).

Relationship Between UX Design and Customer Experience

International Journal of Creative Research Thoughts (Kumar et al., 2023) published research examining the relationship between UX design and consumer satisfaction on websites. The study's key findings focus on importance of effective navigation structures and informs how these structures allow quick and effortless overall experience.

The study also highlights the importance of information architecture. Organising information in a logical and accessible manner improves the user experience by making it easier for users to find relevant information. Additionally, responsiveness is critical; ensuring that the website performs well across different devices and screen sizes is essential in today's mobile-first world. Continuous UX evaluation and iteration based on user feedback are necessary for maintaining a positive customer experience. This iterative process helps keep the platform up to date with evolving user expectations and technological advancements (Kumar et al., 2023).

Web Analytics for UX Improvement

SpringerLink (2020) provides a thorough literature analysis on the importance of web analytics in analysing and improving user experience on e-commerce websites. The review reveals numerous key parameters that are critical for evaluating and improving the user experience. Bounce rate, which measures the percentage of visitors who leave the site after viewing only one page, is a crucial metric. A high bounce rate causes concern as it means that the visitors are not able to find the information they require and hence may be leaving due to an intolerable user experience.

Another key measure is session duration, which represents the average amount of time users spend on the site. Longer session times usually reflect more user engagement. The conversion rate, or the percentage of visitors who accomplish a desired action, such as making a purchase, is also an important indicator of success. The evaluation focusses on best practices for leveraging these indicators to improve site usability and user engagement. By regularly monitoring and evaluating these indicators, e-commerce platforms can make data-driven decisions that improve the user experience (SpringerLink, 2020).

Key Findings from Literature.

The table below summarises the research from the literature, highlighting the UX elements addressed. This will help in conducting further research on these elements.

Table name

Study	*Key Findings*	*UX Element Addressed*	*Implications*
Agarwal & Dhar (2020)	*Intuitive navigation and personalised content enhance user engagement*	*Navigation, Personalisation*	*Improved customer satisfaction*
Chauhan & Nayyar (2020)	*Website aesthetics and load time affect user behaviour*	*Visual Design, Performance*	*User Experience*
Gunawan, R., Anthony, G., Vendly and Anggreainy, M.S. (2021) (2022)	*Colour schemes and typography impact user perceptions*	*UI Design*	*Enhanced user interactions*
(Kumar et al., 2023)	*Effective navigation and information architecture crucial for satisfaction*	*Navigation, Information Architecture*	*Better user retention*

E-commerce Platform Analysis

E-commerce platform analysis is crucial for optimising user experience across different devices. Effective navigation and product categorisation significantly enhance the desktop experience by enabling users to find information quickly (Kalbach, 2007; Nielsen, 2012). On mobile, implementing mobile-first principles and touch-friendly interactions improves usability and prevents errors (Wroblewski, 2011; Tullis & Albert, 2008). Consistent branding across platforms builds user trust and familiarity (Wheeler, 2017).

1. Desktop Experience

Navigation and Layout

- ***Clarity and Efficiency***

  The clarity and efficiency of navigation menus, search functionalities, and product categorisation are critical for desktop experiences. An intuitive navigation system enables users to locate desired products and information effortlessly, with minimal clicks and no confusion. Product categories should be logical and hierarchical, with breadcrumb trails enhancing navigation by displaying users' current locations within the site. (Kalbach, 2007)

- ***Product Categorisation***

  Proper categorisation helps users find products quickly. Proper categorisation of products can improve user experience by providing less search time. (Nielsen, 2012).

- ***Search Functionality***

  A prominently placed search bar offering autocomplete suggestions and filtering options refines search results and guides users to relevant products swiftly, significantly improving user experience. (Morville & Rosenfeld, 2007).

Visual Hierarchy

- ***Content Elements***

  Assessing the visual hierarchy of content elements such as headlines, product images, and calls-to-action (CTAs) is essential. Prioritising important information effectively guides user attention. CTAs should be visually distinctive and strategically placed to

encourage user interaction. (Lidwell, Holden & Butler, 2010). Using contrasting colours and clear, actionable text enhances CTA visibility and effectiveness. (Tullis & Albert, 2008).

Performance Optimisation

- ***Loading Times & Responsiveness***

Monitoring and minimising loading times through techniques like image compression, browser caching, and reducing HTTP requests significantly improves page load speeds and user satisfaction. (Nielsen, 2012). Ensuring the website responds quickly to user interactions and providing immediate feedback is crucial. A responsive design that adapts to various screen sizes and resolutions improves accessibility and usability. (Marcotte, 2010).

2. Mobile Web Experience

Mobile-Friendly Design

- ***Mobile-First Principles***

Employing mobile-first design principles, such as simplifying navigation paths and minimising text input requirements, accommodates mobile users' preferences for quick and efficient browsing. (Wroblewski, 2011).

- ***Touch-Friendly Interactions***

Prioritising touch-friendly interactions, such as larger buttons and adequately spaced touch targets, prevents accidental clicks and enhances the mobile browsing experience. (Tullis & Albert, 2008)

Gesture Support

- ***Intuitive Gestures***

Incorporating intuitive gestures (e.g., swipe, pinch-to-zoom) facilitates navigation and interaction on touch-enabled devices. Providing clear visual cues and feedback enhances the user experience. (Norman & Nielsen, 2010).

➢ ***Gesture Implementation***

Ensuring gesture-based interactions are consistent and intuitive prevents user confusion and enhances overall usability (Lidwell, Holden & Butler, 2010).

3. Mobile App Experience

Native App Features

➢ ***Personalised and Context-Aware Experiences***

Leveraging native app functionalities (e.g. push notifications, geolocation services) delivers personalised and context-aware user experiences, enhancing engagement by providing relevant and timely information (Klein, 2003).

➢ ***Platform-Specific Guidelines***

Integrating platform-specific design guidelines and interaction patterns aligns with users' familiarity and expectations of mobile apps, improving usability and user satisfaction (Shneiderman, Plaisant, Cohen & Jacobs, 2009).

Performance and Responsiveness

➢ ***Optimisation***

Optimising app performance by minimising load times, reducing app size, and ensuring smooth transitions between screens enhances user experience. Efficient resource use and streamlined code contribute to improved app performance. (Nielsen, 2012)

➢ ***Responsive Design***

Ensuring the app interface adapts to different screen sizes and orientations provides a consistent and seamless experience across devices, enhancing user satisfaction. (Marcotte, 2010)

4. Consistency Across Platforms

➢ ***Consistent Branding Elements***

Maintaining consistent branding elements (e.g., colour schemes, typography, logo placement) across all platforms reinforces brand identity and recognition. (Wheeler, 2017). Consistency fosters trust and familiarity among users, regardless of the platform they use.

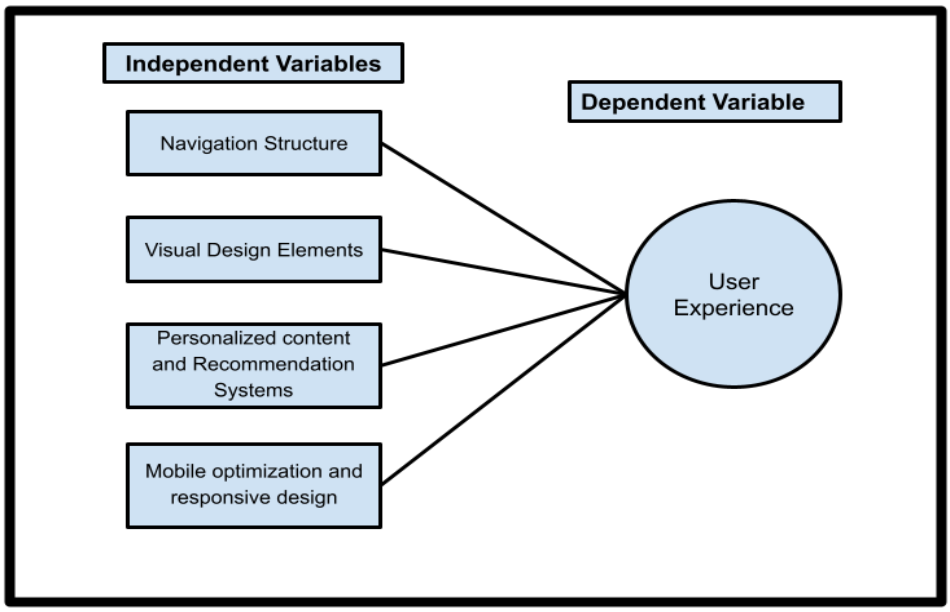

Figure 3: Variables of Research

Conclusion

This chapter has provided a comprehensive review of the existing literature on user experience (UX) design for e-commerce platforms. The review examined key research and their findings in the areas of easy navigation, personalised content, UX analytics, and the effect of UX design on usability satisfaction. It covered numerous elements that influence how consumers behave on e-commerce websites like aesthetics and access times. Furthermore, the relevance of web analytics in tracking and enhancing UX was highlighted, as well as the need for constant UX evaluation and iteration based on user feedback. It also identified several gaps in the current literature, such as the need for more research on the integration of AI and machine learning in UX design, the development of holistic UX metrics, the impact of emerging technologies such as AR, VR, and blockchain, the scarcity of longitudinal studies on UX changes, and the influence of cultural differences on UX preferences. Addressing these gaps through targeted research and inventive solutions is critical to enhancing UX design and ensuring that e-commerce platforms provide seamless, engaging, and gratifying user experiences.

Chapter 3- Research Methodology

Research purpose

The purpose of this study is to assess the influence of important UX features like navigation, visual appeal, personalisation content, mobile optimisation, and responsiveness while using e-commerce platforms. The research aims to understand how these platforms meet needs and expectations of users by using a quantitative approach. The use of random sampling in survey distribution is used to improve the generalisability figures from among various population groups (Albert, W., & Tullis, T. 2013).

Research Design

The research design chosen for this study is quantitative methodology. This is chosen because it includes both subjective user experiences and objective performance metrics within e-commerce environments thereby giving a comprehensive understanding of UX design effectiveness.

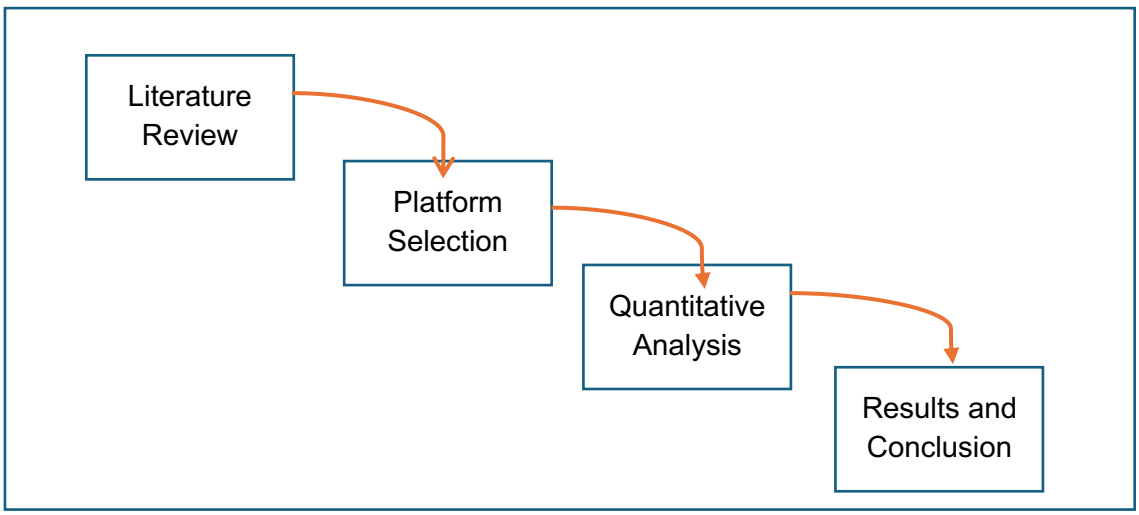

Figure 4: Flow Of Research

Quantitative data will be gathered through questionnaires distributed to different groups of platform users. These surveys use defined scales and indicators to systematically evaluate user satisfaction, usability perceptions, engagement levels, and transactional behaviours. Both

exploratory and inferential tests such as descriptive statistics, correlation analysis, regression analysis, and ANOVA, will be used to analyse quantitative data and explore relationships between UX design factors and user experience.

Data Collection Methods

Data collecting techniques are vital for gathering general insights into user experience (UX) design across leading e-commerce platforms. This research utilises structured surveys to gather the primary data. Structured surveys are fundamental quantitative approach used to gather data on various aspects to measure user experience, ease of use, perceived usefulness, and overall satisfaction with the platform's UX elements (Sauro et al., 2016; Fink, 2017). Surveys offer statistical validation and generalisability to provide a more robust understanding of the effectiveness survey is intended for (DeVellis, 2017; Fowler, 2013). To encourage participation, instructions have been provided to assure data anonymity and confidentiality (Couper, 2017). This assurance of keeping their responses will remain anonymous will help in minimising response bias, as individuals are more likely to provide genuine responses when they know their identity will be kept hidden (Couper, 2017). Surveys are distributed online using various platforms with email invites etc to reach specific user populations. Clear and transparent questions will help to reduce response bias and maintain data quality and integrity (Dillman et al., 2014; Couper, 2017).

Sampling Techniques

Sampling techniques play a vital role in ensuring the validity, reliability, and representativeness of data collected in research studies. This research uses a simple random sampling approach to gather participants for survey. Random sampling is a probability-based sampling technique that involves selecting survey participants at random from a wider group of users. It is used to obtain a representative sample based on age, geographic locations, and usage frequency. This approach improves the reliability and validity of survey data, allowing for relevant comparisons and statistical analyses across various user demographics (Babbie, 2013; Creswell et al., 2017). The focus for this research will be on users from Uttarakhand, India, and Leeds, UK. Random sampling approach minimises selection bias by ensuring that every member of the population has an equal chance of being included in the survey sample. This increases the generalisability and statistical validity of survey findings (Fowler, 2013).

Questionnaire Design

Data quality is ensured by validation checks, randomised question ordering, and attention checks to reduce answer bias and improve survey reliability (Dillman et al. 2014). The questionnaire is designed to explore the key factors influencing User Experience (UX) design on leading e-commerce platforms. It begins by collecting demographic information such as age and gender, followed by identifying the e-commerce platform most frequently used by respondents. The survey then delves into specific areas of UX, including the usability of the platform's navigation, the impact of visual design elements, and the effectiveness of personalised content and recommendations. Additionally, it assesses the user-friendliness of the platform on mobile devices, focusing on aspects like mobile navigation and responsive design. The questionnaire includes both Likert scale and nominal questions to gather detailed insights into how these UX elements contribute to overall user satisfaction.

Data Analysis Procedures

In research study, data analysis is important for gathering meaningful information from collected quantitative data. This study uses quantitative analysis, including descriptive and inferential statistics to analyse the primary data. Quantitative analysis methods use statistical techniques to summarise, interpret and draw conclusions from data collected through surveys.

Descriptive Statistics:

Descriptive Statistics is used to summarise survey data on user perceptions, satisfaction levels, and behavioural patterns related to UX design. It provides a clear summary of primary data, by calculating mean, median, standard deviation and other frequency distributions. These statistics provide information about the content and distribution of survey responses. This will help with the comparison among different UX design elements and platforms (Fowler, 2013).

Approach:

1. **Data Preparation:** Survey results are gathered and carefully cleaned to ensure data is accurate and uniform. Any missing data is addressed using imputation or removal based on study's specific guidelines (Tabachnick and Fidell, 2019).
2. **Statistical Summarisation:** Key variables from the survey, such as user experience usability ratings, and recommendations likelihood, are analysed using descriptive statistics. Visual tools like histograms, bar charts, and pie charts are often used to show data patterns and trends (Pallant, 2020).

3. **Interpretation:** The results of the descriptive statistics are crucial for understanding the survey data, as they reveal the average responses and the range of opinions among users. These insights help identify strengths, weaknesses, and potential improvements in the user experience of e-commerce platforms (Field, 2018).

Inferential Statistics:

Inferential statistics involves testing hypotheses and making inferences about population parameters based on sample data collected through surveys and analytics. Inferential statistics enable researchers to conclude the significance of differences, relationships, or effects observed in survey data related to UX design across e-commerce platforms. By applying statistical tests, researchers can assess the reliability and generalisability of findings, identifying factors that contribute to variations in user experiences and perceptions (Creswell & Creswell, 2018).

Approach:

1. **Hypothesis Testing:** Inferential statistical methods, such as analysis of variance (ANOVA), regression analysis, are used to test hypotheses about the impact of various UX design factors (e.g., navigation usability, visual appeal) on user satisfaction (Tabachnick & Fidell, 2019).
2. **Statistical Modelling:** Regression models has been used to explore the nature of relationships between independent variables (e.g., UX design attributes) and dependent variables (e.g., user satisfaction scores).
3. **Significance Testing:** Statistical significance levels (e.g., p-values) are interpreted to determine whether observed differences or relationships in survey data are likely to occur by chance. Confidence intervals provide estimates of the precision and reliability of inferential findings, guiding conclusions about the practical implications of UX design interventions (Kline, 2015).

- **Spearman Correlation Analysis**

  Spearman correlation (ρ) is a non-parametric statistical measure that evaluates the strength and direction of the association between two ranked variables. Unlike Pearson correlation, which measures linear relationships between two variables assuming normally distributed data, Spearman correlation does not require the data to be normally distributed or linearly related. Instead, it assesses how well the relationship between

two variables can be described using a monotonic function (Spearman, 1904). The formula for calculating Spearman's correlation coefficient is:

$$\rho = 1 - \frac{6\Sigma\, d_i^2}{n(n^2 - 1)}$$

where d_i is the difference between the ranks of corresponding values of the two variables, and n is the number of observations. The Spearman correlation coefficient ranges from -1 to 1, where ρ= 1 indicates a perfect positive correlation (as one variable increases, the other also increases). ρ= −1 indicates a perfect negative correlation (as one variable increases, the other decreases). ρ= 0 indicates no correlation between the variables (Spearman, 1904). This coefficient is a preferred measure of relationships between independent and dependent variables evaluated through the Likert scale.

- **Ordinal Regression Analysis**

  Ordinal regression is a statistical technique used to model the relationship between a set of independent variables and an ordinal dependent variable. An ordinal dependent variable is one which has a natural order but no consistent interval between its levels, such as ratings on a Likert scale. In the current study, the dependent variable is decision-making, which is of ordinal type with a Likert scale response of 1-5. Ordinal regression is suitable for cases where the dependent variable is ordinal. The most common type of ordinal regression is the proportional odds model, also known as the ordered logit model (Agresti, 2010). In ordinal regression, the model estimates the odds of being at or below a certain level of the ordinal dependent variable for different values of the independent variables. The coefficients obtained from ordinal regression represent the change in the log odds of being at or below a particular category of the dependent variable with a one-unit increase in the independent variable, holding all other independent variables constant.

  The main assumption in ordinal regression, particularly in the proportional odds model, is that the relationship between each pair of outcome groups is the same. This suggests that the difference between poor and fair is same as the difference between good and very good in terms of log odds (Long & Freese, 2006).

- **Kruskal-Wallis Test**

The Kruskal-Wallis test is a non-parametric statistical test used to ascertain whether the medians of three or more independent groups are so different that they could not be random. This test is particularly useful when the assumptions of the one-way ANOVA (Analysis of Variance) test, such as the assumption of normality and homogeneity of variances, are violated (Kruskal et al., 1952). The test statistic is calculated as follows:

$$H = \left[\frac{12}{n(n+1)} \sum_{j=1}^{k} \frac{R_j^2}{n_j} \right] - 3(n+1)$$

Where:

H= Kruskal-Wallis test statistic.

N= total number of observations across all groups.

k= the number of groups.

R_i = sum of ranks for the i^{th} group.

n_i = number of observations in the i^{th} group.

After calculation, if the p-value associated with the H statistic is less than 5%, the null hypothesis is rejected. This means that there is statistically significant evidence to suggest that at least one of the group medians differs from the others. If it is more than 5%, the null hypothesis is not rejected, indicating that there is no statistically significant difference between the groups.

Chapter 4 - Data Analysis

Introduction

This chapter focuses on in-depth analysis of the data collected from a study on user experience (UX) elements in e-commerce platforms. This study aims to provide a comprehensive understanding of the key factors influencing user experience, satisfaction and engagement from the quantitative approach. The quantitative data, gathered through surveys, offers a numerical overview of user ratings across various UX dimensions.

Quantitative Data Analysis

Descriptive Statistics

The quantitative data was obtained from a survey distributed to 184 regular users from Leeds, UK and Uttarakhand, India of various e-commerce platforms.

Statistics

		• I consent to take part in this research.	What is your age?	What is your Gender?	Which e-commerce platform do you use most frequently? - Selected Choice	Which e-commerce platform do you use most frequently? - Other (Please Specify) - Text
N	Valid	173	173	173	173	173
	Missing	0	0	0	0	0

Figure 5: **Summary of Valid Responses for Demographics and Platform Usage**

Figure 5 summarises the number of valid and missing responses for Demographic and E-commerce Platform Usage questions emphasising the importance of consent in considering the data. Out of the 184 survey responses received, 173 individuals (94.0%) provided valid and complete responses across all key survey questions, including consent to participate, age, gender, most frequently used e-commerce platform, and specifying another platform if applicable. These 173 respondents had no missing data and all provided consent to participate in the research. This means that 11 responses (6.0%) either had missing data or lacked consent. As a result, 94.0% of the dataset (173) consists of fully complete and valid responses, which will be used for further analysis. Therefore, only the data from those who provided consent are included in the analysis, ensuring ethical standards are upheld.

What is your age?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	18-25	38	22.0	22.0	22.0
	26-32	39	22.5	22.5	44.5
	33-40	37	21.4	21.4	65.9
	40-50	39	22.5	22.5	88.4
	51+	20	11.6	11.6	100.0
	Total	173	100.0	100.0	

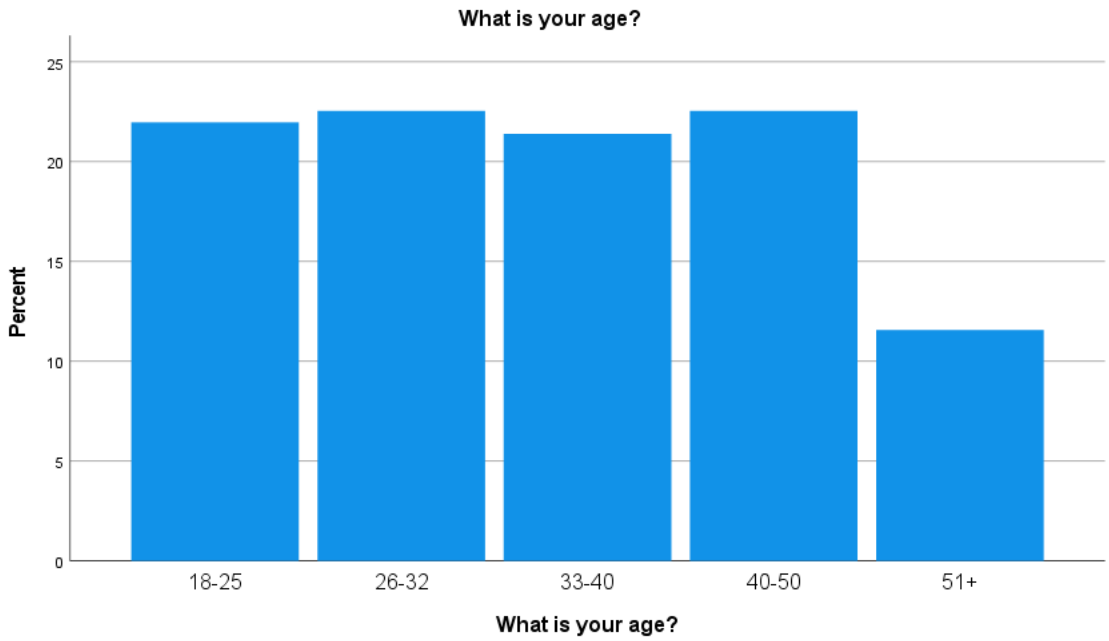

Figure 6: **Age Distribution of Survey Respondents**

The above figure illustrates the age distribution of survey respondents. The largest groups are aged 26-32 and 40-50, each representing 22.5% of valid responses. The age range 18-25 follows closely at 22.0%, and the 33-40 age range accounts for 21.4% of the respondents. The smallest group is 51+ at 11.6%. A total of 173 valid responses were collected, with no missing responses, ensuring a comprehensive representation of the age distribution among the participants.

What is your Gender?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Male	77	44.5	44.5	44.5
	Female	82	47.4	47.4	91.9
	Non Binary / Third Gender	6	3.5	3.5	95.4
	Prefer Not To Say	8	4.6	4.6	100.0
	Total	173	100.0	100.0	

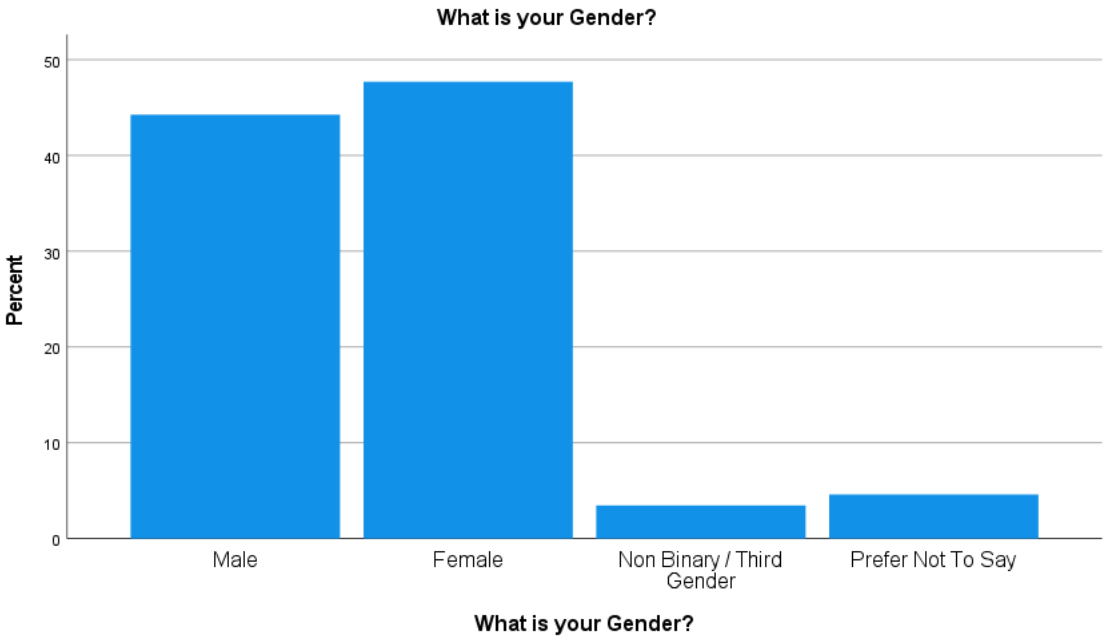

Figure 7: Gender Distribution of Survey Respondents

The above figure focuses on the gender distribution of survey respondents. The majority identify as female, with 82 respondents (47.4%), followed by male, with 77 respondents (44.5%). A smaller portion identifies as Non-Binary/Third Gender, with 6 respondents (3.5%), and 8 respondents (4.6%) prefer not to disclose their gender. Out of 173 total respondents, all provided valid responses, resulting in no missing data. This ensures a complete and

accurate representation of the gender distribution among the participants.

Which e-commerce platform do you use most frequently? - Selected Choice

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Amazon	105	60.7	60.7	60.7
	eBay	8	4.6	4.6	65.3
	Alibaba	6	3.5	3.5	68.8
	Walmart	13	7.5	7.5	76.3
	Shopify	10	5.8	5.8	82.1
	Other (Please Specify)	31	17.9	17.9	100.0
	Total	173	100.0	100.0	

Which e-commerce platform do you use most frequently? - Other (Please Specify) - Text

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid		146	84.4	84.4	84.4
	Flipkart	7	4.0	4.0	88.4
	Meesho	3	1.7	1.7	90.2
	Myntra	10	5.8	5.8	96.0
	Myntra ajio and website	1	.6	.6	96.5
	Nykka	1	.6	.6	97.1
	Shein	2	1.2	1.2	98.3
	Snapdeal	1	.6	.6	98.8
	Tata cliq	1	.6	.6	99.4
	Urbanic	1	.6	.6	100.0
	Total	173	100.0	100.0	

Figure 8: Distribution of E-commerce Platform Usage: Selected Choice and Specified Alternatives

The figure shows that Amazon is the most frequently used platform, with 105 respondents (60.7%) selecting it, followed by Walmart (7.5%) and "Other" platforms (17.9%). The second table provides details on the specific platforms mentioned under "Other." Most of these respondents specified Myntra (5.8%) and Flipkart (4.0%). In both cases, most respondents have a clear preference for specific platforms, with Amazon and custom entries like Myntra and Flipkart leading in their respective categories.

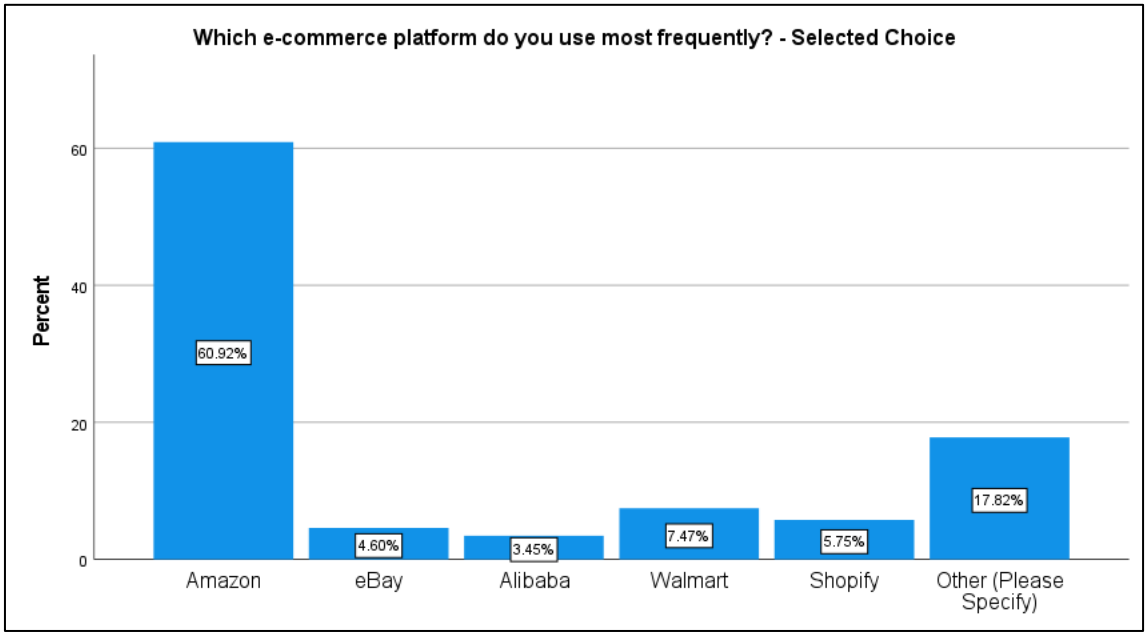

Figure 9: Preferred E-commerce Platforms Among Respondents

The above bar chart shows how survey participants answered the question "Which e-commerce platform do you use the most frequently?" Amazon is the most popular platform, with 60.92% of respondents selecting it as their favourite option. The chart clearly indicates Amazon's dominance in the e-commerce business, while simultaneously demonstrating that a sizable minority of customers prefer alternative platforms, indicating a wide range of market preferences.

Reliability Analysis

Reliability analysis is a significant to determine the consistency and stability of an analytical instrument, such as a survey. It is important in ensuring that the instrument gives accurate, reproducible data under consistent conditions. Cronbach's Alpha, which assesses internal consistency (Field, 2017), test-retest reliability, which evaluates the stability of results over time (Nunnally & Bernstein, 1994), and inter-rater reliability, which measures the accordance between different raters (Tavakol & Dennick, 2011), are all important reliability analysis methods. Cronbach's Alpha is extensively employed and regarded as useful when more than 0.7, suggesting strong internal consistency (Cortina, 1993).

Reliability Statistics (Navigation Structure)

Cronbach's Alpha	N of Items
.756	5

Reliability Statistics (Visual Design)

Cronbach's Alpha	N of Items
.821	5

Reliability Statistics (Personalised Content)

Cronbach's Alpha	N of Items
.832	5

Reliability Statistics (Mobile Obtimization & Responsiveness)

Cronbach's Alpha	N of Items
.854	7

Reliability Statistics (User Experience)

Cronbach's Alpha	N of Items
.770	4

Figure 10: Summary of Reliability Analysis

All categories show Cronbach's Alpha values above 0.7. This suggests that the items within each category consistently measure the intended construct, with Mobile Optimisation & Responsiveness showing the highest internal consistency (0.854) and Navigation Structure the lowest (0.756), though still within an acceptable range. These results indicate that the questionnaire is reliable for measuring these different aspects of user experience.

- **GS_MEAN** (General Experience Mean) - it is the average score of the overall user experience and satisfaction with the e-commerce platform.

- **NAV_MEAN** (Navigation Mean) It is the average score of survey responses related to the navigation structure variable.

- **VD_MEAN** (Visual Design Mean) - it is the average score of survey responses related to the visual design variable.

- **PC_MEAN** (Personalised Content Mean) - it is the average score of survey responses related to the personalised content variable.

- **MO_MEAN** (Mobile Optimisation Mean) – it is the average score of survey responses related to the mobile optimisation variable.

Normality Testing

Normality testing is a crucial aspect of data analysis, where you try to analyse whether your dataset follows normal distribution (it looks like bell shape curve with same distance across the centre line) or not. This normality assumption is central for many parametric statistical techniques, this includes t-tests and ANOVA (Analysis Of Variance) as well as regression analysis which rely on the properties of a normally distribution for their inferential statistics use (Field, 2017). This assumption guarantees the quality of these tests, as non-normal data can lead to misinterpreting results and even false conclusions (Ghasemi et al., 2012). If normality is confirmed Researchers can now use parametric tests, which are more powerful with this assumption premised (Pallant, 2020) Secondly, knowing the distribution of data helps in choosing suitable statistical tests —if the data are not normally distributed, non-parametric test can be more apt (Field, 2017). Normality testing will also help to identify data anomalies like outliers that may affect our result and the entire analysis (Razali et al., 2011). Hence, normality testing is a crucial step to make the statistical inferences trustworthy and more accurate.

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
GS_MEAN	.147	181	<.001	.967	181	<.001
NAV_MEAN	.097	181	<.001	.979	181	.008
VD_MEAN	.136	181	<.001	.971	181	<.001
PC_MEAN	.101	181	<.001	.979	181	.009
MO_MEAN	.080	181	.007	.952	181	<.001

a. Lilliefors Significance Correction

Figure 11: Normality test results

The table presents the results of normality tests for five variables: GS_MEAN, NAV_MEAN, VD_MEAN, PC_MEAN, and MO_MEAN, using both the Kolmogorov-Smirnov (K-S) test and the Shapiro-Wilk test. The null hypothesis for these tests is that the data is normally distributed.

- Reject the null hypothesis when **p < 0.05** indicating that the data does not follow a normal distribution.
- Fail to reject the null hypothesis when **p > 0.05**, indicating that the data is consistent with a normal distribution.

For each variable, the p-values from both tests are less than 0.05, with most being less than 0.001. These results indicate that all five variables significantly deviate from a normal distribution. This suggests that the data for these variables do not follow the normal distribution assumption, which is important to consider when choosing statistical methods.

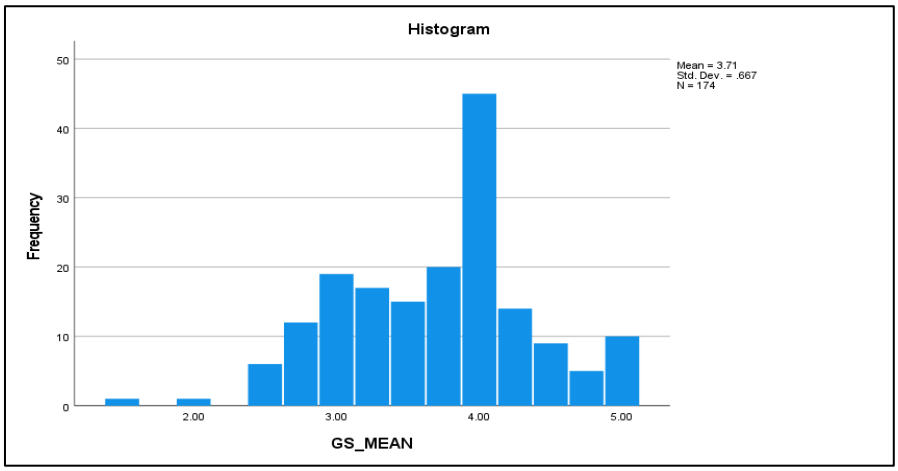

Figure 12: Histogram for gs_mean

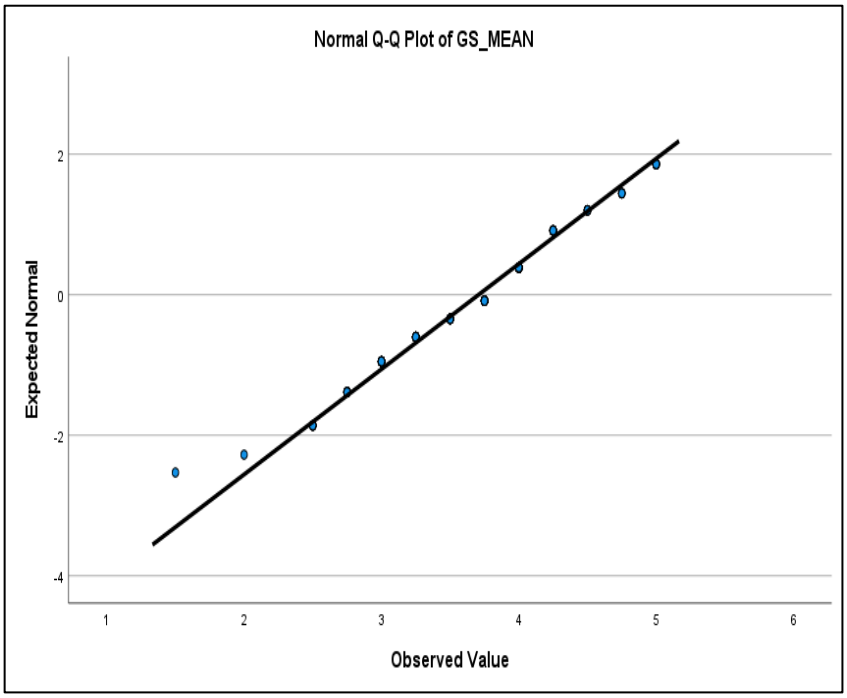

Figure 13: Q-Q PLOT OF GS_MEAN

The above histogram indicates that the **GS_MEAN** distribution is slightly negatively skewed, with most scores clustered around 4.0. The mean is 3.71 with a standard deviation of 0.667, showing moderate spread around the mean. The data is not perfectly normal due to the left skewness. The histogram for all the other variables are similar hence the data is not normally distributed. Given the non-normality, it may be suitable to use non-parametric statistical tests for further analysis.

Correlation Analysis

Correlation analysis is a statistical method used to measure the strength and direction of the relationship between two variables.(Pearce, 2024) The correlation coefficient ranges from -1 to +1, where +1 indicates a perfect positive relationship, -1 indicates a perfect negative relationship, and 0 indicates no relationship**.** The two main correlation coefficients are:

- Pearson product-moment correlation: for continuous variables, or one continuous variable and one dichotomous variable.
- Spearman rho: for ordinal level or ranked data.

The data do not follow a normal distribution, which means that parametric tests that assume normality may not be appropriate for these variables. Therefore, non-parametric statistical method (Spearman's Rank Order) is used for further analysis.

Correlations

			NAV_MEAN	VD_MEAN	PC_MEAN	MO_MEAN	GS_MEAN
Spearman's rho	NAV_MEAN	Correlation Coefficient	1.000	.733**	.571**	.701**	.724**
		Sig. (2-tailed)	.	<.001	<.001	<.001	<.001
		N	173	173	173	173	173
	VD_MEAN	Correlation Coefficient	.733**	1.000	.618**	.647**	.698**
		Sig. (2-tailed)	<.001	.	<.001	<.001	<.001
		N	173	173	173	173	173
	PC_MEAN	Correlation Coefficient	.571**	.618**	1.000	.451**	.551**
		Sig. (2-tailed)	<.001	<.001	.	<.001	<.001
		N	173	173	173	173	173
	MO_MEAN	Correlation Coefficient	.701**	.647**	.451**	1.000	.708**
		Sig. (2-tailed)	<.001	<.001	<.001	.	<.001
		N	173	173	173	173	173
	GS_MEAN	Correlation Coefficient	.724**	.698**	.551**	.708**	1.000
		Sig. (2-tailed)	<.001	<.001	<.001	<.001	.
		N	173	173	173	173	173

**. Correlation is significant at the 0.01 level (2-tailed).

Figure 14: Spearman's Rank-Order Correlation Result

The above table shows the correlation coefficients (Spearman's rho) between pairs of variables (NAV_MEAN, VD_MEAN, PC_MEAN, MO_MEAN, GS_MEAN). The values range from -1 to 1:

- **+1** indicates a perfect positive correlation.
- **-1** indicates a perfect negative correlation.
- **0** indicates no correlation.

The significance values (p-values) tell us whether the correlations are statistically significant. In the industry, **a p-value less than 0.05** generally indicates that the correlation is statistically significant. In this table, all correlations are significant at the 0.01 level (indicated by **), meaning $p < 0.01$, showing 99% confidence interval.

1. **NAV_MEAN and VD_MEAN**: The correlation coefficient is **0.733**, indicating a strong positive correlation, and it is statistically significant ($p < 0.001$).
2. **NAV_MEAN and PC_MEAN**: The correlation coefficient is **0.571**, showing a moderate positive correlation, and it is statistically significant ($p < 0.001$).
3. **NAV_MEAN and MO_MEAN**: The correlation coefficient is **0.701**, indicating a strong positive correlation, and it is statistically significant ($p < 0.001$).
4. **NAV_MEAN and GS_MEAN**: The correlation coefficient is **0.724**, indicating a strong positive correlation, and it is statistically significant ($p < 0.001$).

Other Notable Correlations:

- **VD_MEAN and PC_MEAN**: The correlation coefficient is **0.618**, showing a moderate positive correlation, and it is statistically significant ($p < 0.001$).

- **VD_MEAN and MO_MEAN**: The correlation coefficient is **0.647**, indicating a strong positive correlation, and it is statistically significant ($p < 0.001$).
- **MO_MEAN and GS_MEAN**: The correlation coefficient is **0.708**, indicating a strong positive correlation, and it is statistically significant ($p < 0.001$).

Overall Interpretation:

- All variables are positively correlated with each other, with correlation coefficients ranging from moderate to strong.
- All these correlations are statistically significant at the 0.01 level, meaning there is a less than 1% chance that these correlations occurred by random chance.
- The strongest correlations are seen between NAV_MEAN and VD_MEAN (0.733), and NAV_MEAN and GS_MEAN (0.724), suggesting a strong association between these variables.

This analysis indicates that as one variable increases, the other tends to increase as well, with all relationships being statistically significant.

The output indicates that there are meaningful, positive, and statistically significant relationships between the variables. These findings suggest that these variables do not operate in isolation but are interconnected, influencing each other in a consistent and measurable way.

Ordinal Regression Analysis

The data does not follow a normal distribution; hence we are choosing to use ordinal regression rather than linear regression.

Model Fitting Information

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	781.189			
Final	586.273	194.916	4	<.001

Link function: Logit.

Figure 15: Model Fitting Information Table for Ordinal Regression Analysis

The above table from the ordinal regression analysis shows that the final model, which includes the specified predictors, significantly improves the fit to the data compared to the intercept-only model. The -2 Log Likelihood value for the final model is substantially lower, and the Chi-Square test result (194.916, df = 4) is highly

significant ($p < 0.001$). This indicates that the predictors in the model provide valuable information in explaining the outcome variable, making the model statistically robust.

Pseudo R-Square

Cox and Snell	.674
Nagelkerke	.681
McFadden	.248

Link function: Logit.

Figure 16: Pseudo R-Square Values for Ordinal Regression Analysis

Pseudo R-square values are used in regression models, such as logistic regression and ordinal regression, where traditional R-square (used in linear regression) is not applicable. These models do not involve predicting a continuous dependent variable, so they lack a direct equivalent of the R-square measure. Pseudo R-square measures are a way to evaluate the overall fit of a model by estimating how much variance in the dependent variable is explained specifically by all independent variables (Menard, 2000). Nagelkerke R-square (Pseudo r-squared) is one of the most common approaches for calculating the proportion in variation explained by binary logistic regression models, it often modifies Cox and Snell to satisfy with an indexing condition: a minimal value is 0 while maximal value may be closer but not reaches to 1. The range of R-square lies between 0 to 1, which can be comparable (but not less than) the traditional one in linear fashion. Figure 17 shows a Nagelkerke R-square value of **0.681.** This indicates that 68.1% of the variance in the dependent variable is explained by the independent variables included in the model.

While it does not have the same interpretation as R-square in linear regression, it provides a useful metric for evaluating the explanatory power of the model in non-linear regression contexts. This makes Nagelkerke R-square particularly valuable when comparing models or understanding how well the predictors capture the underlying patterns in the data.

Parameter Estimates

		Estimate	Std. Error	Wald	df	Sig.	95% Confidence Interval	
							Lower Bound	Upper Bound
Threshold	[GS_MEAN = 1.50]	7.538	1.297	33.789	1	<.001	4.997	10.080
	[GS_MEAN = 2.00]	8.627	1.210	50.829	1	<.001	6.256	10.999
	[GS_MEAN = 2.50]	11.125	1.231	81.640	1	<.001	8.712	13.538
	[GS_MEAN = 2.75]	12.744	1.267	101.152	1	<.001	10.260	15.227
	[GS_MEAN = 3.00]	14.253	1.330	114.872	1	<.001	11.646	16.859
	[GS_MEAN = 3.25]	15.270	1.377	122.917	1	<.001	12.571	17.970
	[GS_MEAN = 3.50]	16.024	1.413	128.616	1	<.001	13.254	18.793
	[GS_MEAN = 3.75]	16.937	1.457	135.106	1	<.001	14.081	19.793
	[GS_MEAN = 4.00]	19.054	1.576	146.238	1	<.001	15.966	22.142
	[GS_MEAN = 4.25]	19.979	1.625	151.185	1	<.001	16.794	23.164
	[GS_MEAN = 4.50]	20.875	1.676	155.128	1	<.001	17.590	24.160
	[GS_MEAN = 4.75]	21.631	1.724	157.501	1	<.001	18.253	25.009
Location	NAV_MEAN	1.261	.370	11.637	1	<.001	.537	1.986
	VD_MEAN	1.051	.337	9.751	1	.002	.391	1.711
	PC_MEAN	.625	.252	6.138	1	.013	.131	1.119
	MO_MEAN	1.541	.327	22.199	1	<.001	.900	2.181

Link function: Logit.

Figure 17: Results of Ordinal Regression

The above figure shows the ordinal regression analysis that all the predictors - NAV_MEAN, VD_MEAN, PC_MEAN, and MO_MEAN have positive and statistically significant effects on the outcome variable, GS_MEAN. All independent variables—NAV_MEAN (Estimate = 1.261, p <.001), VD_MEAN (Estimate = 1.051, p <.001), PC_MEAN (Estimate = 0.625, p =.013), and MO_MEAN (Estimate = 1.541, p <.001)—significantly influence the dependent variable, GS_MEAN.
MO_MEAN has the greatest impact, showing that greater mobile optimisation most effectively improves user experience.

The p-values associated with each estimate are all below .05 (most are < .001), confirming that these relationships are statistically significant. This means the likelihood that these results are due to random chance is very low, and we can be confident in the influence of these factors on GS_MEAN. Overall, the findings indicate that navigation structure, visual design, personalised content, and mobile optimisation of e-commerce platforms significantly affect the user experience.

Conclusion

The analysis conducted in this study provides a comprehensive examination of user experience (UX) elements in e-commerce platforms, focusing on various aspects such as demographic characteristics, platform usage, reliability, correlations among UX factors, and the influence of these factors on user experience (GS_MEAN).

From the data, it was observed that the majority of the respondents provided valid and complete data, ensuring a robust foundation for the analysis. The demographic analysis revealed a diverse age distribution with a balanced gender representation, offering insights into the preferences of different user groups. **Amazon** emerged as the most frequently used e-

commerce platform, with a significant preference compared to others, highlighting its dominance in the market.
The significance of the independent variables (NAV_MEAN, VD_MEAN, PC_MEAN, and MO_MEAN) in relation to the dependent variable (GS_MEAN, representing user experience) reflects how different aspects of an e-commerce platform contribute to overall user experience. In this context:

- **NAV_MEAN -** significant p-value (< 0.001) associated with NAV_MEAN indicates that effective navigation is a critical factor in enhancing user experience.

- **VD_MEAN -** VD_MEAN also shows a highly significant relationship with GS_MEAN ($p < 0.001$), implying that the visual design of the platform plays a crucial role in shaping user experience.

- **PC_MEAN -** Although PC_MEAN has a slightly higher p-value (0.013), it still shows a statistically significant effect on GS_MEAN. This indicates that personalised content is important, but perhaps not as critical as navigation or visual design.

- **MO_MEAN**- The p-value for MO_MEAN (< 0.001) shows that mobile optimisation is the most significant predictor of user experience among the variables considered. This shows that the responsiveness of the platform is the most important factor out of all in impacting the user satisfaction.

In conclusion, this study highlights how important UX factors are, in influencing user satisfaction on e-commerce platforms. These results underscore the significant contribution of streamlined navigability, visual appeal, and mobile responsiveness to user satisfaction as platforms that prioritise these elements are more likely to result in increased traffic explained above. The integrity of these insights is guaranteed by the strong statistical methods, making them a salient stepping-stone for future research and practical solutions in the field of e-commerce.

Chapter 5 – Conclusion

The introduction ascertains that the User Experience (UX) design is significant in e-commerce platforms and creates a lot of difference on user experience and engagement. The study establishes four key research questions and evaluates the effect of navigation structure, visual design elements, personalised content, mobile optimisation on user experience. This

study reviews previous studies in the area of UX design for e-commerce to identify the independent variables. The data was collected by surveying 184 regular users from Leeds, UK and Uttarakhand, India to gather information about their experience with different e-commerce platforms. Statistical methods, including descriptive statistics, reliability analysis, normality testing, correlation analysis, and ordinal regression, were used to analyse the data and address the research questions.

The null hypotheses (H0) in this study represent the initial statements tested against the collected data, positing that factors like navigation structure, visual design, personalised content, and mobile optimisation do not significantly affect user experience. If the p-value obtained from the analysis is less than the standard significance level (typically 0.05), we reject the null hypothesis, thereby indicating a statistically significant effect (Nielsen, 2012; Field, 2017). The alternative hypotheses (H1) suggest that these factors do have a significant impact on user experience. The results of the study confirm the acceptance of all alternative hypotheses, as the p-values indicate significant relationships. Specifically, p-values less than 0.001 indicate highly significant results, providing strong evidence that these variables affect user experience. For personalised content, a p-value of 0.013 indicates a significant result, showing moderate evidence of its impact on user experience. Overall, the hypothesis testing results demonstrate which null hypotheses were rejected and highlight the significance of the findings related to enhancing user experience on e-commerce platforms.

The significance of these independent variables in relation to the dependent user experience variable (GS_MEAN) indicates that multiple factors contribute to user satisfaction, with navigation, visual design, and mobile optimisation being particularly influential. The results suggest that by focusing on improving these areas, especially mobile optimisation and navigation, an e-commerce platform can substantially enhance the overall user experience. Personalisation also plays a role, though it may have a slightly lesser impact compared to the other factors. Thus, these findings provide actionable insights for prioritising design and development efforts to improve user experience on the platform.

Navigation Structure

The results indicate that navigation structure of an e-commerce platform is a significant factor which influences user experience. This aligns with the study by Nielsen (2012) which states that efficient navigation is essential to user satisfaction in a digital environment because it reduces the time and efforts required to find required products.

Visual Design

The study findings confirmed the significant influence of visual design elements on user perception of e-commerce platforms. This supports Lidwell et al. (2010) and Kim et al. (2003), who highlight the importance of visual aesthetics in user engagement. The findings show that while conventional visual design rules are important, the designers must first focus on the mobile-compatible designs.

Personalised Content

The results support the idea by Chen et al. (2014), that personalised content is a valuable factor which enhance user experience and retain user engagement on e-commerce platform. It also suggests that the e-commerce platforms must constantly keep their personalised suggestion system updated to meet evolving customer expectations.

Mobile Optimisation

Mobile optimised and web responsive design of e-commerce platform were found to be significant determinants of the user experience. This supports the idea by Marcotte's (2010) that user-friendly and consistent designs across devices are vital for avoiding user confusion, increasing application usability and enhancing user satisfaction. This reveals that with the increasing mobile usage, the integration of desktop and mobile experiences becomes essential.

Table 2 : Hypothesis testing results

Null Hypothesis (H_0)	Alternate Hypothesis (H_1)	Outcome	Significance (p-value)
The navigation structure of top e-commerce platforms does not significantly affect the user experience in terms of ease of finding information and completing tasks.	The navigation structure of top e-commerce platforms significantly affects the user experience in terms of ease of finding information and completing tasks.	**H_1 Accepted**	**$p < 0.001$ Highly significant**
Visual design elements, including layout, color schemes, typography, and imagery, do not have a significant impact on user perceptions of a platform's credibility, attractiveness, and ease of use.	Visual design elements, including layout, color schemes, typography, and imagery, significantly impact user perceptions of a platform's credibility, attractiveness, and ease of use.	**H_1 Accepted**	**$p < 0.001$ Highly significant**
Personalised content and recommendation systems do not significantly enhance the user experience or drive user engagement and repeat purchases.	Personalised content and recommendation systems significantly enhance the user experience and drive user engagement and repeat purchases.	**H_1 Accepted**	**$p = 0.013$ Significant**

Mobile optimisation and responsive design do not significantly influence the user experience across various devices.	Mobile optimisation and responsive design significantly influence the user experience across various devices.	**H_1 Accepted**	**$p < 0.001$** **Highly significant**

Limiting Factors[1]

The below factors focus on the constraints within which the study operates and underscore the importance of considering these limitations when interpreting the findings and generalising.

Scope of Platforms: The study focuses on a selected number of top e-commerce platforms, which may not represent the entire spectrum of UX practices across the industry. This selection bias could limit the generalisability of the findings.

Subjectivity in UX Evaluation: Assessing UX design elements involves a degree of subjectivity, which can lead to variations in interpretation and analysis. Different evaluators might have different perceptions of what constitutes good UX design (Nielsen, 2012).

Dynamic Nature of E-commerce: E-commerce platforms continuously evolve, with frequent updates and changes in UX design. The findings of this study represent a snapshot in time and may not capture future developments. Ongoing changes in technology and user behaviour can quickly render the study's conclusions outdated (Garrett, 2011).

Data Accessibility: Access to proprietary data and detailed user interaction metrics from e-commerce platforms may be limited, affecting the depth of analysis. This limitation can constrain the ability to perform a thorough evaluation of certain UX elements and metrics (Chen et al., 2014).

Recommendations and Future research

Despite substantial study on improving user experience in e-commerce, several gaps remain. While this research gives vital insights into the user experience (UX) design tactics used by top e-commerce platforms, it is crucial to highlight that the study acknowledges but does not explicitly address some gaps in the current literature. These gaps are emphasised for their theoretical significance, as well as areas where future study could help us understand more.

⇒ **Integration of AI and Machine Learning in UX Design:** While the current studies emphasise the importance of personalised content and web analytics, there is limited research on the integration of advanced AI and machine learning algorithms to further enhance UX. These technologies can provide more accurate personalisation, predictive analytics, and real-time adaptation to user behaviour (Tullis and Albert, 2008).

[1] Methodological limitations encountered during the analysis.

⇒ **Holistic UX Metrics:** Most studies focus on isolated UX metrics such as bounce rate, session duration, and conversion rate. However, there is a lack of research on developing a comprehensive, holistic UX metric that can combine multiple indicators to give a more accurate picture of user satisfaction and engagement (Nielsen, 2012).

⇒ **Cultural Differences in UX Preferences:** While some studies have looked at specific markets (like Agrawal and Dhar's focus on the Indian market), there is a need for more research on how cultural differences impact UX preferences and behaviours. This can help in designing more globally inclusive e-commerce platforms (Tractinsky, 2013).

Real world Implications

Based on the findings, UX/UI designers should keep the following points in mind to enhance the user experience.

1. **Navigation Structure's Impact on User Experience**

A well-structured and intuitive navigation system allows users to easily find what they are looking for, thereby increasing their overall satisfaction. This suggests that improvements in navigation could lead to a more positive user experience.

2. **Visual Appeal's Impact on User Experience**

Visual appeal, including the layout, aesthetics, and the ease of interacting with the visual elements, directly influences how users perceive and engage with the platform. A better visual design can significantly improve the overall user experience.

3. **Personalisation**

Personalisation enhances user experience by making the content more relevant and engaging, which can lead to increased satisfaction when users feel that the platform caters to their individual needs.

4. **Mobile Optimisation**

As mobile usage continues to grow, optimising for mobile becomes increasingly critical for maintaining and enhancing user experience.

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