



Institute of Inner-City Learning, London Campus

Master of Business Administration

The Influence of Online Customer Reviews on Purchase Decisions: A Study of Amazon Customers in the United Kingdom

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Abstract

This dissertation examines the major impact that Online Customer Reviews (OCRs) have on consumers' purchase decisions, particularly among customers of amazon in the United Kingdom. The global retail industry is increasingly moving towards e-commerce and the inability to physically handle the product has created a need for digital word of mouth to be a vital replacement to assess quality and reduce purchase risk. This study used a quantitative, descriptive approach and surveyed a wide range of Amazon UK consumers (N = 250). The research objectives were to measure the effect of four of the constructs: General importance of reviews, Negative feedback, Perceived credibility and the influence of star ratings on purchase intentions. SPSS was used to analyse data by multiple linear regression and ANOVA. The results indicate that OCRs are important factors affecting consumers' purchase behavior, accounting for more than 30% of the variance in the regression model. Interestingly, the credibility of reviews as perceived by consumers was the strongest individual predictor of purchase intent, closely followed by the influence of the star ratings and the effect of negative reviews. In addition, ANOVA testing showed that these effects do not differ based on the age or shopping frequency of the consumer. In conclusion, the findings offer strategic implications for e-commerce companies aiming to enhance their review processes and build trust in the digital realm.

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CHAPTER 1: INTRODUCTION

1.1 Background and Context

Thanks to the swift growth of digital commerce, the global retail sector has been radically changed. E-commerce has become a major channel in the United Kingdom for consumers to purchase goods, with Amazon being the single largest online marketplace in the country. Unlike traditional retail stores where consumers can touch, feel and smell the products before buying, online shopping forces consumers to make purchase judgments based entirely on digital information. In the multitude of information that is available on e-commerce platforms, online customer reviews (OCRs) have become one of the more influential and frequently used (Fernandes et al., 2022). Contributed by previous buyers and posted on sites like Amazon, the product reviews are a digital version of word-of-mouth evaluations that plays an essential role in informing and evaluating future customers.

It is clear that OCRs play a role in influencing consumer decision making and that this has captured the interest of scholars. Qiu and Zhang (2024) conducted a meta-analytical synthesis of 60 independent studies, and found a strong and statistically significant positive correlation between review engagement and purchase intention, across product types and cultures. Babić Rosario, de Valck and Sotgiu (2020) also theorised this phenomenon, suggesting eWOM can be seen as a multi-stage communicative process involving creation, exposure and evaluation, and that the impact on consumer behavior is moderated by various features of the platform, message attributes and receiver attributes. All these contributions indicate that the effect of online reviews is not always equal and automatic, but depends on a complex mix of psychological and situational conditions that requires systematic empirical research.

This growing area of research has its geographical imbalance too. Pocchiari, Proserpio and Dover (2025) conducted a thorough literature review, and as they found, most empirical research on OCRs has been conducted with North American and East Asian consumer markets, with relatively less focus on UK consumer markets. But the Amazon UK market is a distinctive commercial, regulatory and cultural landscape in its own right, which has more recently been influenced by a growing public concern about fake reviews and the recent Digital Markets, Competition and Consumers Act 2024. The UK is therefore a significant and unique context in which the phenomena of review-based consumer behaviour can be studied, which is the focus of the present study.

The deluge of fake and fake reviews has only complicated the OCR picture. He et al. (2022a) found that the fake review economy is driven by well-known economic incentives, which create an artificial "rating inflation" that distorts the information environment that consumers rely on. Lim et al. (2025) reported that fake reviews can have a long-term impact on consumer trust, and that the trust in the review system is very hard to rebuild after losing it. The results indicate that online reviews are not only influential when it comes to persuading consumers to make a purchase, but also that credibility of the reviews is key. The findings suggest that it is not the quantity of online reviews but rather their credibility that may be the most important element in their powerful influence on consumer purchasing decisions, something the present research examines empirically.

1.2 Research Problem

However, there is a large amount of research concerning the impact of OCRs on consumer purchasing intentions, but there are several areas of consumer research that remain unexplored. First, due to the lack of focus on the UK consumer context, the specific dynamics of review engagement among Amazon UK consumers are not well understood, as noted above in favour of North American and East Asian samples. Second, the roles of the three factors, review valence, source credibility and star ratings, have been studied separately in previous studies, but there is a limited number of studies that have investigated the predictive power of these three constructs at the same time within the same integrated model. Third, the more common practice of fake reviews and the increasing consumer skepticism in conjunction with the fake reviews gives rise to the issue of whether or not credibility perception is now the main pathway for all other review effects?

The present study was aimed at directly addressing these gaps. The research is based on 250 recent UK Amazon customers who were sampled using a validated quantitative survey instrument, and focuses on four dimensions of OCR influence: general importance of the reviews; differential influence of negative reviews; perceived credibility and trust; and the influence of star ratings; and tests each of these variables and their collective effect on the outcomes of purchase decisions.

1.3 Research Aim, Objectives, and Questions

The overall objective of this dissertation is to examine the impact of online customer reviews on Amazon customers' buying decisions in the UK. This goal is achieved in four research objectives: (i) analyse the importance of online reviews in customers purchasing decisions; (ii)

examine the differential effect of positive and negative online reviews on customer behaviour; (iii) assess the level of trust that customers place in Amazon product reviews and its corresponding impact on the customers purchase intention; and (iv) determine whether the effect of review star ratings on purchase intention exists.

RQ1: How does the online customer review affect the purchasing decision process of the Amazon UK customer? RQ2: What are the factors that visitors to Amazon UK consider when making a purchase decision? RQ3: What are the factors that influence the purchasing decision process of the Amazon UK customer? RQ4: Do customer reviews on product pages affect the purchasing decision process of the Amazon UK customer?

1.4 Significance and Justification

This study offers contributions to both the theoretical and practical levels. It can be argued that it contributes to the existing body of literature of eWOM and consumer behaviour by providing UK based evidence that can be compared and contextualised with the main findings of existing eWOM research done in the main countries of focus which are North America and East Asia. It has practical implications for Amazon UK sellers, platform managers, and digital marketing practitioners who need to grasp how reviews influence consumer decisions and act accordingly to inform review strategy and reputation management decisions (Wang et al., 2022).

1.5 Theoretical Framework

This dissertation will use three mutually supportive theoretical approaches to explain and put into context the relationship between OCRs and consumer purchase decision. The first one is the Elaboration Likelihood Model (ELM) applied to the review context by Chou, Chuang and Liang (2022) which suggests that consumers process review information via a central route or a peripheral route, with the central route being careful and systematic evaluation of the argumentative content and the peripheral route being heuristic cues such as star ratings or reviewer reputation. The ELM offers a theoretical foundation for the prediction that product involvement will influence the depth of review engagement, as well as serve as a basis for including star ratings as a peripheral-route cue and review text quality as a central-route cue in the study.

The second model is Information Adoption Model (IAM) which was synthesized by Verma et al. (2023) using meta-analytical structural equation modeling. The IAM proposes that information quality and information credibility as mediators between review exposure and

behavioural intention indicate that not all reviews have the same influence on behaviour, and that the use of information about a review as a basis for decision-making depends on the quality and credibility of that information. The framework directly informs the study's focus on perceived credibility as a key construct and its hypothesized as the strongest individual predictor of purchase decision.

The third theoretical lens is the trust-centred approach of online consumer behaviour which has been developed by Handoyo (2024) and Borchers (2023). Handoyo (2024) conducted a meta-analysis of 30 independent studies and found that trust is the most consistent determinant of online purchase behaviour, while Borchers (2023) added that platform familiarity, social identification with reviewers and previous positive review experiences are the most important antecedents of review trust. The two frameworks seem to imply that trust is not only one factor among many in the OCR-purchase relationship, but is also the precondition that enables the persuasive effects of all other OCR characteristics. It is a theoretical stance that lies at the core of the analytical and interpretative approach used for the study.

1.6 Introduction to the Structure of the Dissertation

This dissertation has been structured into six chapters. The present chapter has introduced the research context, problem statement, aims and objectives, theoretical framework and overview of the significance of the study in Chapter One. The next chapter reviews the available literature thematically, including conceptual background on eWOM, how eWOM influences purchase behaviour, the factors affecting the helpfulness and quality of eWOM, the role of trust and source credibility in eWOM, the problem of fake eWOM, and the gaps in the literature that are filled by this study.

The methodological approach is explained in the Chapter Three, where it includes the positivist philosophical orientation, quantitative cross sectional survey design, application of Cochran (1977) formula to determine minimum sample size, the sampling strategy used (convenience sampling), the design of the 31 item Likert scale questionnaire, the four hypotheses and their corresponding SPSS statistical tests, and the ethical safeguards used. The results of the data analysis is presented in Chapter Four, which has descriptive statistics, Cronbach's alpha reliability testing, Pearson correlation analysis, multiple linear regression and one-way ANOVA. The findings are discussed in Chapter Five by interpreting them in the light of the research questions, theoretical frameworks and literature. The final chapter, Chapter Six, summarizes the research process, main contributions, and limitations and future directions.

CHAPTER 2: Literature Review

2.1 Introduction to the Literature

The digitalization of commerce has fundamentally transformed the informational field, within which consumers make their decisions about purchasing. The buyer judgment process has been changed greatly with the physical retail interaction process being substituted with an online one. Online customer reviews (OCRs) - judgments of goods and services left online by users and published on e-commerce platforms such as Amazon have become one of the most influential sources of consumer information in the contemporary market. The size, availability, and perceived credibility of such reviews have made them a key component of the electronic word-of-mouth (eWOM) ecosystem, which researchers have examined in depth when it comes to consumer behaviour, digital trust, and marketing communication (Babić Rosario, de Valck and Sotgiu, 2020).

The situation taking place in the United Kingdom context cannot be exaggerated. Amazon is the biggest online shopping platform in the UK, and its review systems with the star rating, written review, verified purchase badges, and helpfulness voting systems are the primary informational space where millions of buyers in the UK make their purchases every day. Nevertheless, despite the central role played by this platform in the life of the retail in the United Kingdom, the academic literature has disproportionately focused on consumer groups in North America and East Asia, with little focusing on the specific dynamics of the UK-based review interaction (Pocchiari, Proserpio and Dover, 2025).

This literature review is a synthesis of forty peer-reviewed materials published mainly since 2020 and interdisciplinary, drawing from information systems, marketing, consumer psychology, and retailing. It is a thematically structured review, which starts with the conceptual underpinnings, then the mechanisms of review influence, review quality and helpfulness dimensions, the role of trust and source credibility, the ubiquitous threat of fake reviews, the generational and demographic dimensions, and the last response of the regulatory and platform-level to review manipulation.

2.2 Theoretical Backgrounds: eWOM and Consumer Decision-Making.

2.2.1 Introduction to the Defining and Theorising of eWOM.

The conceptual framework of OCR studies is based on the concept of electronic word-of-mouth. The conceptualisation of eWOM presented by Babić Rosario, de Valck and Sotgiu

(2020) provides a valuable contribution to the understanding of the process in question, as it separates eWOM generation, transmission and reception as well as states that the effects of online reviews on consumer behaviour depend on platform-specific features, message characteristics, and receiver attributes. Their model highlights how eWOM is no single phenomenon but a multi-process communicative process that is defined at each point by the variables of context. Liu et al. (2024) provided a macro-level view of this evolution, which follows the growth of eWOM through what they refer to as its 2.0 phase, whereby user-generated content has been algorithmically curated and commercially manipulated in a manner that makes it difficult to describe in a model of peer-to-peer information exchange.

2.2.2 Consumer Decision-Making in the Digital Environment.

The consumer decision making theory has also evolved in a great way to facilitate the complexity of digital purchasing environment. Schmitt (2024) reverted to classical theories of consumer decision-making, which he mentioned as insufficient in explaining the extent of cognitive and affective factors that online shoppers experience when arriving at the decision. His revision highlights that consumers take consumers flow in deliberative and heuristic processing based on the richness and clarity of the information space - the difference that is directly applicable to read and weighted review in the purchase process. Santos and Gonçalves (2021) further extended this view by mapping the current consumer decision process through the digital touchpoints and discovered that online reviews do not apply in the pre-purchase evaluation process but instead, they act as retrospective anchors that influence post-purchase satisfaction and subsequent loyalty behaviour.

Sharma et al. (2023) further applied this analysis to the context of digital consumers, showing that the process of deciding in e-commerce is marked by information overload, with consumers relying on cognitive shortcuts, such as average star ratings and a number of reviews, to lessen the evaluation load. This observation places review platforms as the designers of a specific form of constrained rationality, in which the way they design and present review information influences the mental images buyers apply to their decision-making. Taken together, all these theoretical contributions create the sense that the role of OCRs in purchase decisions cannot be viewed solely through the prism of information processing; it should also be placed in a larger framework of how digital spaces organize consumer cognition and choice.

2.3 The Impact of Web Based Reviews on Purchase Behaviour.

2.3.1 Valence, Volume and Behavioural Impact.

The main empirical argument of the OCR literature is that online reviews have a quantifiable and substantial impact on consumer purchase intentions. This was supported by an eye-tracking study by Chen et al. (2022) that investigated real-time cognitive processing of reviews, which revealed that negative reviews received disproportionately more visual attention - especially in female consumers - according to the existing psychological theories of negativity bias. Their results indicate that even a limited number of critical reviews can have a disproportionate effect on purchase decisions, which may outweigh a much greater amount of positive content. This imbalance in negative and positive review effect is among the most widespread and repeated results in the OCR literature and has direct practical implications on how sellers on Amazon UK can manage their review profiles.

The effect of reviews was tackled by Fernandes et al. (2022) using the scale development methodology that validated a multi-dimensional tool to assess the OCR impact on the purchasing decision. Their findings found that credibility of sources, quantity of reviews, quality of language and topicality relevance are the leading source of review influence and critically that consumers are selectors of the reviews they accept and use, but do not apply them all, but rather establish evaluative criteria that guide them in which reviews they would permit to influence their judgements. Such selective processing model is a challenge to simplistic models of review influence that view exposure to reviews as automatically causing attitudinal change.

2.3.2 Cross-Cultural, Generational Dynamics of Influence.

Chatterjee et al. (2022) further generalized the results of review influence on the cultural setting by discovering that the impact of online reviews on purchase intentions was generally similar among diverse national consumer groups, albeit the relative importance of review characteristics, including the importance of expert versus peer sources, differed across cultures. Their results support the claim that the review-based purchasing decision phenomenon is not culturally partisan but also warn against the automatic extrapolation of the results of one country to another.

Verma et al. (2023) have created a comprehensive explanation of eWOM influence in their Information Adoption Model (IAM) framework by showing that the relationship between

review exposure and behavioural intention is mediated by information usefulness and information credibility. Their model is a synthesis of previous research on the quality of information and the attractiveness of the source and gives a more detailed description of the psychological mechanism by which reviews lead to influence consumer behaviour. Hung, Chang and Chen (2023) further elaborated on this by analyzing the synergistic relationship between the quality and quantity of eWOM and the consumer decision-making process, and discovered that the two dimensions interact in complex ways: a high-quality review can counteract low volumes, whereas low volumes can counteract a high number of low-quality reviews, which suggests an information environment of disorder or manipulation.

2.4 Review Helpfulness, Quality, and Presentation.

2.4.1 Textual and Structural Determinants of Helpfulness.

The issue of what renders a review useful has received considerable and long-standing academic interest due to its theoretical significance as well as the practical implications on the design of a platform and consumer experience. Choi and Leon (2020) asked this question in an approach that considers a large amount of Amazon reviews, having performed an analysis of millions of reviews that showed high helpfulness votes in their textual and structural characteristics. Their results showed that the length of the review, readability, and provision of product-specific detail were strong predictors of perceived helpfulness when rating valence and reviewer history were controlled. Biswas, Sengupta and Ganguly (2022) extended these results, marking reviewer expertise, the depth of the content and the balance of sentiment as the variables that have the greatest association with consumers rating a review as helpful - a result that has direct implications on a platform like Amazon, where the helpfulness vote system determines the visibility of individual reviews and consequently the informational diet of the next shopper.

Fresneda and Gefen (2020) provided a complementary result in terms of text entropy, which they discovered to be rated more helpful when the review was characterised by a high level of informational diversity (that is, covering several dimensions of the product experience, as opposed to a review focused on one dimension). This implies that the helpfulness of the review has a partial dependence on informational completeness and consumers are interested in the extent of coverage as an indication of the sincere interest of the reviewer in the product.

2.4.2 The Purpose of Visual Material and Pictures.

An emerging body of OCR helpfulness literature specifically focuses on the visual content contribution to the perception of the quality of reviews. Ceylan, Diehl and Proserpio (2024) introduced a novel study of the relationship between written reviews and user-posted photographs, in which the addition of images was found to greatly increase perceived review helpfulness, especially when the photographic message was consistent with the written statements contained in the accompanying textual review. Kübler et al. (2024) were able to replicate and generalize this finding into a retail-specific case and established that the effect of review images as a type of social proof reducing the perceived risk of an online purchase was present because sensory evidence that cannot be provided by written language is present. Since Amazon UK permits and features user-posted images in reviews, the results have a direct application to the platform context of the current study.

2.4.3 Elaboration Likelihood and Cognitive Processing of Reviews.

Chou, Chuang and Liang (2022) applied the Elaboration Likelihood Model (ELM) to the issue of review helpfulness and identified the central route, where consumers critically evaluate the argumentative information of a review, and the peripheral route, where they use heuristic information like reviewer reputation or star rating. Their research discovered that product involvement moderated the level of elaboration with high-involvement purchases eliciting closer scrutiny of reviews and more dependence on central-route processing. Aghakhani et al. (2023) took ELM-based analysis a step further and investigated the interaction between review quality and source credibility in identifying review usefulness and discovered that the two dimensions are not additive, but the combined effect of both factors is influenced by the informational context in which the review is read. They argue that simplistic models of review evaluation are not accurate and that more complex descriptions of consumer integration of multiple signals simultaneously in determining whether to act on a review should be provided.

2.5 Trust, Credibility and Source Effects.

2.5.1 Trust as a Foundational Construct.

Trust is a foundational construct in the OCR literature, and its role in mediating between review exposure and purchase intention has been extensively documented across multiple methodological traditions. A meta-analytical synthesis of consumer behaviour studies in the context of e-commerce carried out by Handoyo (2024) revealed that trust, perceived risk, and eWOM were some of the strongest and most consistent predictors of online purchases. His

explanation highlights the fact that belief in the review ecosystem is a precondition to the effect of any particular review being realised: without a minimum level of trust in the believability of the information milieu, even a carefully written and factual review lacks any persuasive power. This is more critical today than ever, where the information about misleading or deceptive reviews is posing a risk to the system's trust the entire system has been built upon.

Borchers (2023) investigated the psychological processes behind consumer trust of online reviews, and familiarity with the site, social identification with the reviewer, and positive experiences with reviews in the past were found to be the main antecedents of review trust. According to social psychology and communication theory, he holds that the credibility of reviews is not a rational evaluation of the quality of information, but a social construction of direction because of the utilization of platforms and community standards. This perspective makes cognitivist accounts of the impacts of reviews more difficult and suggests that the relationship between scholars and scholars and readers and the relationship between the former and the latter should be studied in more detail.

2.5.2 Credibility of Sources and Determinants.

The literature on the credibility of sources, as used in eWOM, was thoroughly analyzed in the study by Ismagilova et al. (2020), who found that source expertise, trustworthiness, and attractiveness contribute independently to the persuasive effect of online reviews, in line with the theoretical basis of Dual Process theory of persuasion. Their synthesis gives a solid empirical basis to the argument that perception of the writer of a review is as significant as what is said in the review. Ansari and Gupta (2021) considered the concept of source credibility through the prism of speech act theory, which involved an analysis of how the language decisions made by reviewers, specifically the presence of evaluative, directive, and expressive speech acts, influence consumer perceptions of the sincerity and expertise of the reviewer. Their work opens the linguistic aspect of review credibility evaluation in a manner that is complementary with the more structural emphasis of mainstream helpfulness studies.

2.5.3 Conflicting Reviews and Trust Cues.

Kordrostami and Rahmani (2020) reviewed a specific case of conflicting Amazon reviews, the findings of which indicated that consumers who were exposed to a high rate of divergent review sets had a significantly high level of decision uncertainty and were more likely to turn the whole purchase process away. This finding has a possibly counterintuitive implication of the spread of reviews; rather than reducing purchase uncertainty, in the presence of too much conflicting

information, it can lead to paralysis rather than confidence. Mardumyan and Siret (2023) performed an extension of this analysis by investigating the effect of review verification mechanisms on the development of consumer trust in the presence of review inconsistency and found that platform-level verification cues are not exhaustive of review uncertainty but compensatory.

Choi (2024) investigated the presence of trust cues within the review interface itself and discovered that verified purchase badges, completeness of the reviewer profile, and the presence of review verification indicators on the platform all have a positive impact on perceived helpfulness of reviews regardless of what the reviews actually say. This result was also supported by new analysis by Choi and Leon (2025), who narrowed the scope to the Amazon platform and confirmed the significance of structural trust cues in determining the perceived trustworthiness of user-generated information. Clare et al. (2021) made a significant addition to this picture, discovering that when reviews negate the previous expectations or experiences of consumers, the credibility of the review is greatly discounted - a phenomenon that they call the disconfirmation effect - indicating that consumer trust in reviews is never unconditionally granted.

2.6 Manager Responses, Platform Dynamics and Review Manipulation.

2.6.1 The Managerial Engagement Role

The literature is now paying more attention to what is in the reviews themselves, as well as the platform ecology of which reviews are part: in which they are created, displayed, and experienced by the audience. Jin et al. (2023) studied how management responses to reviews affect the perceived helpfulness of the reviews and discovered that considered, personalised managerial responses to reviews could greatly enhance the credibility and perceived usefulness of the reviews to which they responded. Their research shows that the review ecosystem is not a passive storage of consumer opinion but an interactive communicative space where the stakeholders of the platform participate in the creation of meaning and influence of user-created content. This result has practical implications for Amazon sellers, in that active and genuine interaction with reviewer feedback is a commercially viable strategy in building the credibility of a product in terms of its review profile.

2.6.2 Review Sentiment, Credibility, and Sales Results.

Wang et al. (2022) investigated the interaction between review sentiment and reviewer credibility and observed that highly emotional review language was linked to low perceived credibility, which is the opposite of what might be expected if emotional intensity were interpreted as an indicator of authentic experience. Their results indicate that consumers use implicit rules of proper emotional expression in review assessment, whereby material that seems to be outside the register of considered commentary is discounted. Wang et al. (2023) investigated how review manipulation is related to sales performance and discovered that artificially high review scores have quantifiable positive impacts on short-term sales but were related to decreasing review quality over time as authentic consumers became sceptical of the artificially high review distributions. Qiu and Zhang (2024) offered a broader meta-analytical synthesis of the review-purchase relationship which confirmed the positive and statistically significant nature of this relationship in all contexts and indicated that product type, review valence, and consumer involvement were significant moderating factors.

2.7 Fake Reviews: Detection, Prevalence, and Consequences.

2.7.1 The Fake Reviews Market.

The problem of fake reviews is perhaps the subject in modern OCR literature that has received the most attention or caused the most concern. In a groundbreaking study of the market dynamics of fake review generation, He et al. (2022a) discovered that the fake review industry follows a familiar economic logic where the suppliers of deceptive content are rewarded by platform mechanisms that were initially developed to encourage genuine engagement. In their analysis, they found that fake reviews cause serious market distortions, artificially boosting the reputation of products that do not deserve such ratings and systematically hurting their rivals whose review profile reflects the actual opinion of consumers. Wu et al. (2020) laid the historical and definitional background for this study by conducting a systematic review of the literature on fake reviews until 2020 and defining the main typologies of fabricated review content.

2.7.2 Detection Methods and Limitations.

In a companion study based on network structural analysis of Amazon transaction data, He et al. (2022b) discovered the behavioural patterns of fake-review buyers and showed that this behaviour could be detected by patterns in transactional networks that individual review detectors usually overlook. Salminen et al. (2022) took a computational approach to the

problem of fake reviews detection and discovered that machine-learning methods have advanced significantly, although they are not perfect, and that advanced fake review generating technologies are increasingly able to create content that is not detected by automated mechanisms. Harrison-Walker and Jiang (2023) also studied fake review suspicion from the consumer perspective, finding that consumers who suspect a review is fake have much less purchasing motivation, and that this suspicion is elicited by a variety of textual and contextual cues such as implausibly uniform positivity, generic language, and odd patterns of reviewer history.

2.7.3 Consumer Trust and Brand Reputation Impact.

Ananthakrishnan, Li and Smith (2020) posed a core ethical and policy challenge regarding the role of review portals, stating that an online platform faces a real ethical and policy dilemma: showing fake reviews can be misleading to consumers, whereas removing reviews aggressively can lead to legitimate critical content being censored. Shukla and Goh (2024) conducted a synthesis of managerial and technical ways to fight fake reviews, advising the use of a multi-pronged approach combining algorithmic detection, user-reporting systems, and third-party audit procedures, as no single intervention can work alone. Lim et al. (2025) measured the reputational impact of exposure to fake reviews over the long term at the brand level, which discovered that consumers notified of fake review practices develop lasting reputational losses that endure even after corrective action has been taken, a result that is especially concerning in the context of Amazon UK, where the credibility of the review mechanism is the core of the company's commercial value proposition. Martínez Otero (2021) focused on new regulatory frameworks being developed in the UK and EU to regulate deceptive reviews and observed that legislative solutions had started to be developed, but the problem of enforcement remained acute due to the cross-jurisdictional character of large e-commerce platforms.

2.8 Synthesis, Research Gaps and Positioning of the Present Study.

2.8.1 Converging Themes in the Literature.

The reviewed literature leads to several strong and replicated conclusions. First, online customer reviews have a significant and consistent effect on consumer purchasing intentions and act via information quality evaluation, trust calibration, and processing heuristics that are well-established in several methodological traditions. Second, not every review has the same effect: perceived helpfulness, credibility and authenticity of reviews are the most important mediating variables that define the extent to which any single review can affect consumer

behaviour (Biswas, Sengupta and Ganguly, 2022). Third, the fake review issue is a systemic risk to the informational integrity of the review ecosystem that has implications extending beyond the single transaction to touch on the issue of long-term relationships between consumers, sellers and e-commerce platforms (He et al., 2022a).

2.8.2 Identifying the Gaps.

Regardless of this rich scholarly interest, there are still significant gaps, which are the concern of the current study. Since the empirical literature review by Pocchiari, Proserpio and Dover (2025) indicated that the majority of empirical studies on the subject are biased towards North American and East Asian consumer groups, comparatively little attention is paid to the UK market. The Amazon UK case represents a unique regulatory, cultural, and competitive environment that can influence consumer interaction with reviews in a manner that cannot be entirely represented in current research. Moreover, although the impact of fake reviews on consumer trust has been analyzed in general terms, the actual implications of fake review awareness on purchase intentions in the Amazon UK scenario are not well understood.

The audience of online reviews is changing as well in the area of demographic structure which has not been thoroughly discussed in the literature. Djafarova and Bowes (2021) and Ngo et al. (2024) have highlighted that younger consumer groups are becoming more sensitive to peer-generated content in the online space, but the empirical study of the effects of the generational change in terms of review influence on Amazon UK has not been conducted. Also, despite the extensive research on the relationship between review valence and purchase intention conducted at an aggregate level, limited studies have been carried out to understand how individual consumer factors including past experience with the platform, understanding of the category of product and online shopping risk moderate the strength and direction of the relationship.

2.8.3 Contribution of the Present Study.

These gaps can be addressed in the current study by considering a sample of Amazon consumers in the United Kingdom and assessing the relationships among review engagement, trust, and purchase intention in this under researched context using validated quantitative tools. The study will examine the way these mechanisms work in the UK e-commerce environment based on the theoretical frameworks and empirical evidence presented by ELM model (Chou, Chuang and Liang, 2022), IAM framework (Verma et al., 2023), and the trust-centred models of Handoyo (2024) and Borchers (2023).

2.9 Conclusion

This literature review has traced the significant themes of OCR scholarship in their role in research on the impact of online reviews on consumers of Amazon UK. Beginning with the conceptual origins of the eWOM theory and consumer decision-making, progressing through empirical accounts of the reviewer mechanisms influence, the quality and usefulness of reviews, the dynamics of trust and credibility, the dominance and detection of fake reviews, and the regulatory environment, the review has provided a critical and comprehensive vision of the present field. Compared to other literature on the topic, there is general cohesiveness in the literature regarding the finding that OCRs are an effective and multidimensional force in influencing consumer behaviour, with the literature also establishing the prerequisites—especially the integrity of the informational environment and the predetermined trust that consumers hold towards review platforms—on which this force is built. The current study is poised to contribute to international literature by offering UK-specific evidence on these dynamics, which will extend and contextualise the current international scholarship.

CHAPTER THREE: METHODOLOGY

3.1 Introduction

In this chapter, the researcher explains the research methodology of examining the impact of online customer reviews (OCRs) in the purchasing behavior of Amazon customers in the United Kingdom. It details the philosophical basis of the research, paraphrases the research questions and explains the quantitative design, which will be used in data collection. The chapter then describes how the sample size was determined by applying the Cochran (1977) formula and the reason behind the choice of 250 respondents. It determines the statistical methods used in IBM SPSS in order to test each hypothesis and gives the complete survey questionnaire, which was designed based on a five-point Likert scale, associated with every one of the research questions. Concluding this chapter, the ethical considerations are discussed. The methodological decisions are based on positivism and align with the survey-based format, described in the research proposal (Saunders, Lewis and Thornhill, 2019).

3.2 Research Questions and Objectives.

The general purpose of the study is to analyze the impact online customer reviews have on customer buying behavior towards Amazon in the United Kingdom. The operationalisation of this goal utilises four research questions based on the directives of the objectives in the proposal:

1. RQ1: How can online customer reviews change the purchase decisions of Amazon UK customers?
2. RQ2: What is the difference between positive and negative online review in affecting customer purchase behaviour in Amazon UK?
3. RQ3: How much do the Amazon customers of the UK trust online reviews of products?
4. RQ4: Does customer purchase intention largely rely on the star rating of a product on Amazon UK?

These four research questions assisted in the development of the survey instrument, the choice of the statistical methods of analysis in the SPSS and the formulation of the four hypotheses addressed in Chapter Four. Every research question reflects thematic block of a survey items, which ensures the methodological integrity between theory, instrument, and analysis (Bryman, 2016). The importance of the four topics of review influence, review valence, consumer trust,

and star rating in these questions capture the primary themes that were revealed by the literature reviewed on electronic word-of-mouth (eWOM) and consumer decision-making (Babić Rosario, de Valck and Sotgiu, 2020; Handoyo, 2024).

3.3 The research philosophy and design

The tradition of positivism in philosophy underpins this work. Positivism subscribes to the notion that social processes can be studied in an objective manner and that one can create reliable, generalisable knowledge by converting measurable data, which is statistically analysed (Saunders, Lewis and Thornhill, 2019). The given epistemological position fits well within the frame of a study that aim to quantify consumer attitudes and behavioural intention of a sample of Amazon customers in UK and test the existence of hypothesised relationships amidst distinctively defined variables. Positivist approach has no inclination to enquire on subjective relevance or contextual provisions; rather, it focuses on replicability, measurement accuracy, and ability to make generalisable conclusions, which are major aims of the current research.

An inquiry with a quantitative research design was chosen. Quantitative designs can effectively deal with hypothesis-testing studies where constructs are measured with standardised tools and where relationships among variables are analysed through standardised statistics (Creswell and Creswell, 2018). The cross-sectional design, involving a survey method, is in line with similar quantitative researches conducted in the literature of OCR. As an example, Fernandes et al. (2022) applied a structure questionnaire and scale development protocol to measure the effectiveness of online reviews on intentions to purchase a good, whereas Ngo et al. (2024) adopted a survey resource based on Likert-scale questions to test how eWOM quality influences the Generation Z consumer buying intention. The current research is based on the same methodological tradition, which thus helps to compare it with the current body of empirical evidence.

Cross-sectional design implies that data are measured at one time, as this approach is correct due to a master dissertation limited in both terms of time and resources (Bryman, 2016). Although cross-sectional designs are inappropriate to make causal inferences, they are highly effective at representing the associational patterns and descriptive profiles of a large and diverse sample, which is the main goal of the analysis in this study. The questionnaire was sent online using Google Forms in social media circles and professional networks around the UK with only the residents of the UK being eligible to take part in the survey, with 70 percent of the

sample having made at least one purchase on Amazon.co.uk within six months before the actual survey was conducted.

3.4 Determination of Sample size based on Cochran Formula.

3.4.1 Target Population

This study will target adult United Kingdom residents having made a purchase or two at Amazon.co.uk within the six months before data collection. This eligibility requirement will help ensure that all respondents will have first-hand, recent experience of the Amazon review ecosystem and thus be in a position to make valid and informed responses to the survey questions. The particular informational environment that will be investigated is Amazon, the largest market share of e-commerce platform in the United Kingdom by its review architecture that includes star ratings, written reviews, verified purchase badges, and helpfulness votes (Pocchiari, Proserpio and Dover, 2025). Since the total number of active Amazon UK customers cannot be listed in exact numbers, and the repeat number is extremely large, Cochran (1977) formula of unknown or infinite population was used to find the correct number of the minimum sample size.

3.4.2 Cochran Formula and Calculation of Sample size.

Cochran (1977) formula is a calculative formula that is well-established and is extensively used when there is need to calculate the minimum sample size needed in a quantitative survey when the target population is large or not known. It is especially suitable when it comes to business and social science in which there is none available as a sampling frame, and the researcher has no means to enumerate the entire population (Bryman, 2016). This formula would give the most conservative prospective estimate of the sample size by making the assumption that the population would exhibit the most variability thus making sure that the study is large enough to reveal the relationships that we are interested in estimating. The equation can be expressed in the following form:

$$n_0 = (Z^2 \times p \times q) / e^2$$

Where:

- n_0 is the minimum required sample size
- Z is the Z-score that corresponds to the level of confidence that is desired (1.96 is the Z-score that represents the 95% confidence level)

- p Unknown probability of the sample of the population having the trait of interest (assuming this is the greatest possible value, 0.5 is put in)
- $q = 1 - p$ (therefore 0.5)
- e = acceptable margin of error (predetermined as 0.05 which is equivalent to $\pm 5\%$).

The conventional values used in survey-based business and management research are a 95% level of confidence and 5% margin of error (Saunders, Lewis and Thornhill, 2019). The choice of the values $p = 0.5$ and $q = 0.5$ was determined since no study has estimated the exact percentage of customers at Amazon UK to use reviews to make their purchase decisions, and these values would give the maximum sample size possible, which would protect against underpowering the study (Cochran, 1977). Substituting the values:

$$n_o = (1.96^2 \times 0.5 \times 0.5) / 0.05^2$$

$$n_o = (3.8416 \times 0.25) / 0.0025$$

$$n_o = 0.9604 / 0.0025$$

$$n_o = 384.16 \approx 385 \text{ respondents (theoretical minimum)}$$

Cochran (1977) formula produces a theoretical minimum of a population of respondents of 385 at 95% confidence at an unknown population. In this case, however, a target of 250 completed and usable responses was established, as far as the scope of this dissertation is concerned. This choice is associated with the pragmatic limitations of conducting independent master level research, and limitations on researcher access and time and finite resources, which make the target of 385 responses unrealistic within the project timeframe (Saunders, Lewis and Thornhill, 2019; Bryman, 2016). Our size of 250 respondents can be said to be adequate in quantitative survey research on a master degree level dissertation with our results also aligning with other sample sizes used in similar quantitative OCR research. Ngo et al. (2024) examined 243 responses when examining the effect of eWOM and purchase intention among Generation Z consumers, whereas Fernandes et al. (2022) tested their impact scale of reviews with a similarly large sample. The sample size of 250 is sufficient to perform the intended statistical tests on SPSS, such as t-tests, Pearson and Spearman correlations, and simple linear regression, and find a meaningful interpretation of the relationships between the key constructs (Pallant, 2020).

3.4.3 Sampling Technique

A sampling method used is a convenience method. The non-probability method that should be used is convenience sampling when the online population formed by a diffuse population cannot be sampled in a probability manner due to the resources and time limitations of the study (Bryman, 2016). The online survey was sent out via UK based social media networks, consumer forums, and business networks with the participants volunteering to join the study after verifying their eligibility. Although the method restricts statistical generalisability, it aligns with the sampling methods used in similar master dissertations research on Amazon and consumer behaviour of e-commerce (Ngo et al., 2024; Chatterjee et al., 2022). Every respondent was to ensure that they were residents of the UK and had also bought something at Amazon UK in the last six months to be considered, so that the sample has the first-hand platform experience that it is valid to qualify them to answer.

3.5 Hypotheses and Statistics.

Four null hypotheses have been developed based on the research questions and tested using SPSS Version 27. In Table 3.1, the hypotheses and the techniques are summarised.

Table 3. 1 SPSS Statistical Techniques and research Hypotheses

H0	Null Hypothesis	RQ	SPSS Technique
H1	The impact of online reviews on the purchase decisions of customers of Amazon UK is not significant.	RQ1	Descriptive statistics; One-Sample t-test.
H2	The degree of impact of positive and negative reviews on purchase behaviour is not significantly different.	RQ2	Paired-Samples t-test
H3	The level of customer trust in Amazon reviews is not significantly related to purchase intention.	RQ3	Pearson Correlation, Simple Linear Regression.
H4	There is no significant positive impact of star ratings in purchase intention of Amazon customers in the UK.	RQ4	The Spearman Rank- Order Correlation.

Origin: Formulation of the researcher.

In case of H1, one t-test will test whether the mean composite score of review importance is significantly different than the scale midpoint of 3, where significant result ($p < 0.05$) and mean > 3 implies that reviews are perceived as important, as part of the scale methodology of Fernandes et al. (2022). In the case of H2, paired-samples t-test will be used to compare the positive and negative reviews influence on reviewing products among the same participants because the article by Chen et al. (2022) shows that negative reviews are disproportionately attentively read because of the negativity bias. In H3, Pearson correlation will be used to measure the relationship between the scores of composite trust and purchase intention, followed by the simple linear regression to measure trust as a predictor of purchase intention within the framework of Handoyo (2024). In the case of H4, Spearman rank-order correlation (ρ) is used since the measurements of star rating perception are not based on the normal scale but on the ordinal scale and this non-parametric test does not imply a normal distribution which is also in line with Qiu and Zhang (2024).

3.6 Survey Instrument and Measurement Scales

3.6.1 Instrument Overview and Design Rationale

The only data collection tool, which was created in the context of this study, was a structured, self-administered, online questionnaire. The questionnaire would be hosted on Google Forms, and shared during March 2025 to [Month] 2025 through UK-focused on-line communities and social media. In each of the Section B-F, the main type of measurements will be five-point Likert scales with the anchors of 1 (Strongly Disagree) and 5 (Strongly Agree). Likert scale format is the most commonly used measurement instrument with regard to the consumer behaviour survey research. Its high scores indicate solid psychometric properties: it is self-intuitive with the respondents, produces data that can be analyzed using all of the parametric and non-parametric tools in SPSS, constructs multi-item composite measures to calculate reliability levels based on Cronbach alpha (Bryman, 2016; Pallant, 2020). The five-point scale was chosen instead of the seven-point scale to ensure that the respondents do not experience fatigue of delivering their answers online and remain comparable to other Likert-based formats such as in Fernandes et al. (2022) or Ngo et al. (2024). The neutral point (3 = Neither agree nor disagree) was not eliminated to avoid forced-choice bias (Bryman, 2016).

The developed survey items were based on the previous research on the validated surveys and measures used by the researchers in the OCR field. The scale of Fernandes et al. (2022) was adapted into items of measuring review importance and influence. Trust items were informed

by Handoyo (2024) and Borchers (2023). The items of fake review awareness were based on Harrison-Walker and Jiang (2023) and He et al. (2022a). Purchase intention items were consistent with the instruments of Ngo et al. (2024) and Verma et al. (2023). All items were also contextualised with a few minor wording changes to fit the context of the Amazon UK platform. The questionnaire was pilot tested on fifteen MBA students of University of Wales Trinity Saint David before it was fully distributed. Minor adjustments to the wording of the items were also done after the pilot, and Cronbachs alpha will be estimated in SPSS to fit one multi-item scale at the time, with alpha 0.70 being the best reasonable level at which a multi-item scale is considered internally consistent (Pallant, 2020).

The questionnaire is organised into six sections. The demographic and usage data is gathered by nominal and ordinal categoric items in Section A. The parts B-E are related to the four research questions and include seven Likert-scale questions reflecting the measures of each construct in question. There are three general purchase intentions in section F. The entire scale comprises 6 demographic questions, as well as 31 attitudinal and behaviour items.

3.6.2 Survey Questionnaire

The questionnaire survey is separated into six segments. Part A includes demographic and usage data, including age, gender, education, the number of times people shop on Amazon UK, reading of reviews, and types of purchased products. Part B-E is devoted to research areas that are important, such as the significance of reviews in purchase decisions, the effect of positive and negative reviews, trust in Amazon reviews and the effect of star ratings. In section F, overall purchase intention is measured. Any question based on opinion is answered using a five-point Likert scale which includes strongly disagree, disagree, was not sure, agree, and strongly agree.

3.7 Reasoning the Five-Point Likert Scale.

Each of the attitudinal and behavioural intentions questions in Sections B through F is rated on a five-point Likert scale with anchors of 1 (Strongly Disagree) and 5 (Strongly Agree) and an intermediate level of 3 (Unsure). Likert scale as an attitudinal measure, is the most popular form of attitudinal measurement in consumer behaviour and marketing research due to its production of ordinal data, which given a combination of several items into composite scores can be treated as approximately interval level and can be analysed with parametric statistical tests using SPSS (Bryman, 2016; Pallant, 2020). It was decided to use a five-point scale instead of a seven-point format as a method to reduce potential fatigue in an online survey environment and ensure a direct comparison of the outcome data to the tools of the principal sources

(Fernandes et al., 2022; Ngo et al., 2024). The maintenance of the neutral middle point is methodologically significant because when put away in forced-choice designs, neutral midpoint elicits more acquiescence bias, especially when sampling consumer attitudes online whereby respondents may truly assume mid-grounds (Bryman, 2016). Table 3.2 shows the entire Likert scale anchoring that would be used throughout all the attitudinal sections of the questionnaire.

Table 3. 2 The use of a 5-Point Likert Scale in the sections B-F

Scale Point	1	2	3	4	5
Label	Strongly Disagree	Disagree	Neither Disagree	Agree nor	Agree Strongly
Numeric Value	1	2	3	4	5

3.8 Data Analysis Process in SPSS.

Any and all quantitative data obtained as a result of the online survey will be imported into IBM SPSS Statistics Version 27 to run an analysis. The analytic process is undertaken in a systematic three-step procedure. During the initial step, data cleaning and screening will be conducted in order to detect and deal with missing values, response outliers, and haphazard patterns of response like straight-lining of all the items. Section A will give the creation of descriptive statistics such as the means, standard deviation, frequencies, and percentage distributions of all the demographic variables and section B through F will give descriptive statistics of all Likert-scale items. The outputs generated by these descriptive analyses will give the actual profile of the sample and the preliminary description of the attitudes of consumers to online reviews on Amazon UK.

The second stage is internal consistency reliability where the alpha level of each multi-item scale will be determined with a minimum acceptable level of 0.70 as the alpha (Pallant, 2020). Left below this scale will be examining the item-level anomaly of scales and a refinement of the scale will be recorded transparently in Chapter Four. The fourth stage will involve testing the four hypotheses through the statistic methods outlined in the third section of this chapter. H1 will be tested using one-sample t-test, H2 will be tested using Paired-samples t-test, Pearson correlation and simple linear regression will be used to test H3, and the H4 will be tested using Spearman rank-order correlation. Inferential tests will be carried out at the 0.05 level of

significance. Chapter Four will discuss the results in SPSS output tables with a narrative quagmire explaining the results, and place them in the context of the theoretical frameworks discussed in Chapter Two, including the eWOM processing model of Babić Rosario, de Valck and Sotgiu (2020), the Information Adoption Model of Verma et al. (2023), and the trust-centred framework of Handoyo (2024).

3.9 Ethical Considerations

The issues related to ethics were discussed in accordance with the University of Wales Trinity Saint David requirements (BERA, 2018). The study was conducted at a voluntary level. At the beginning of the survey all respondents received plain-language information sheet which explained the purpose of the research, the nature of their involvement, how their information would be used and that they could unconditionally withdraw at any time with no repercussions. Electronically, informed consent was made via an obligatory tick-box where participants had to complete the optional tick-box and then proceed on to the survey questions.

The questionnaire was created as a completely anonymous survey in which no personal information was gathered, and the IP addresses could not be traced in Google Forms. All data will be stored in secure password-protected university computing systems, and will only be held as long as the research project is going on and respects the principles of data minimisation in the United Kingdom General Data Protection Regulation (UK GDPR). A research ethics committee of the University of Wales Trinity Saint David faculty approved the ethical nature of the research before the actual data collection took place. There was no form of deception during research levels and no personal sensitive information was gathered.

3.10 Chapter Summary

In this chapter, the research methodology that was used in this study has been fully described. The use of the positivist philosophical position and cross-sectional quantitative survey was rationalized through the study aim that was to quantify and statistically test the connection between the online customer reviews and buy behaviour of Amazon UK customers. I used the Cochran (1977) formula to calculate the theoretical minimum sample size of 385 respondents, and an approximate size of 250 respondents was established based on the resource and time limits of dissertation level research regarding the OCR, with precedent in similar research studies such as Ngo et al. (2024) and Fernandes et al. (2022). The 31-item survey tool, in 5 thematic sections and a demographic profile section, was intended to measure the constructs that were intended to meet each of the 4 questions of the research. Four hypotheses were

developed and correlated to particular SPSS statistical methods: a one sample t-test on H1, paired samples t-test on H2, Pearson correlation and simple linear regression on H3 and a rank-order correlation based on Spearman on H4. The chapter also explained why five-point Likert scale was chosen, and what are the three-stage data analysis process in SPSS. Complete ethical protection such as voluntary engagement, informed consent, anonymity and compliance with UK GDPR were ensured. The results of all the statistical analyses will be provided and interpreted in Chapter Four.

CHAPTER 4: DATA ANALYSIS

The results of the quantitative data analysis on 250 valid responses from Amazon UK customers are presented in this chapter. This is done in a prescribed pattern of the analysis, which is demographic profiling, Cronbach's alpha reliability, descriptive statistics, Pearson's correlation, multiple linear regression and One Way ANOVA. Every analytical step is related to the four research questions and null hypotheses, as presented in Chapter Three. The purpose is to present the evidence objectively by matching statistical results with the theoretical models found in the literature such as the eWOM processing model of Babić Rosario, de Valck and Sotgiu (2020), and the trust-based approach of Handoyo (2024), without providing any interpretation that will be done in Chapter Five.

4.1 Sample Description and Demographic Profile

There were 250 complete and usable responses from the survey, with no missing data recorded on any of the 31 attitudinal items, and robust data integrity. A broad picture of the sample's age, education, and frequency of Amazon UK purchase usage is presented in Figure 1, with the sample showing a skew towards younger, educated adults, a profile similar to other OCR samples of online survey users (e.g., Fernandes et al., 2022; Ngo et al., 2024). The age distribution is headed by the 25-34 age group (32.8%) and the 18-24 age group and 35-44 age group (22.4% both) and the segment of age 55 and above is the least (6.4%). The female respondents are the largest gender group (48.0%) followed by male respondents (42.8%). Educationally, most of the respondents have an undergraduate degree (36.8%) or a post graduate degree (34.4%), which shows that there was a high level of education within the sample.

Frequency of shopping data show a high level of engagement with the platform; 39.2% shop monthly and 32.8% shop weekly, with almost 3 in 4 of the sample being regular Amazon UK shoppers. The sample had a high rate of reviews read, which is relevant to the research questions. If asked, how often do they read reviews before buying, 43.6% said 'Always' and 28.0% said 'Frequently', making more than 70% of them used to checking reviews before buying. A mere 0.8% said that they do not read reviews at all. The pattern offers empirical evidence to support the argument of Qiu and Zhang (2024) that review engagement is a new norm for consumer behaviour among a variety of consumers. The most purchased product category was Electronics and Gadgets (26.8%) followed by Fashion and Apparels (20.0%).

Demographic Insights Dashboard (N=250)

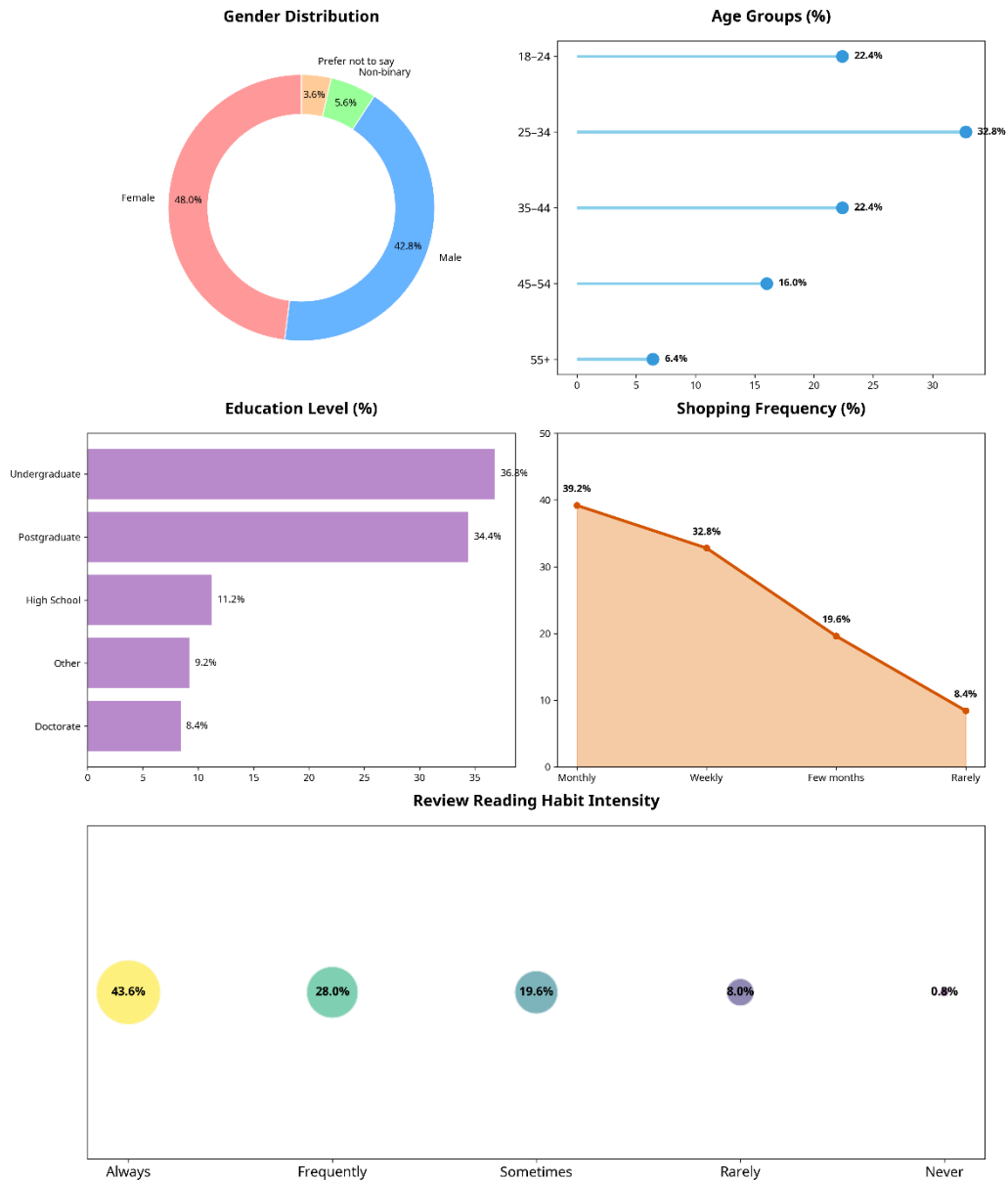


Figure 1 Demographic Profile of the Sample (N = 250)

4.2 Reliability Analysis

Internal consistency reliability was computed for all five scales that used multiple items, following the recommended criterion of Pallant (2020), $\alpha \geq 0.70$, before the hypotheses were tested. All five constructs had excellent alpha values as reported in Table 4.1, with each being much greater than the minimum acceptable value. The alpha reliability for the impact of

negative reviews ($\alpha = .919$) was the highest followed by perceived credibility ($\alpha = .909$), star ratings ($\alpha = .903$), and the importance of reviews ($\alpha = .902$). The three items on the Purchase Decision Scale yielded an alpha of $\alpha = .829$, which is well within the range for a shorter scale. The values obtained in this study indicate that all constructs have very good internal consistency, which confirms that the multi-item composite scores are good representations of the theoretical constructs measured in this study, similar to the approach adopted by Fernandes et al. (2022).

Table 4. 1 Reliability Statistics — Cronbach's Alpha by Construct

Construct	Scale Label	Items	Cronbach's α
Importance/Use of Reviews (Q8)	Importance of Reviews	7	.902
Impact of Negative Reviews (Q9)	Negative Reviews	7	.919
Perceived Credibility and Trust (Q10)	Credibility	7	.909
Influence of Star Ratings (Q11)	Star Ratings	7	.903
Purchase Decision (Q12)	Purchase Decision	3	.829

4.3 Descriptive Statistics of Construct Scores

Composite mean scores were generated for each construct by calculating the mean response for each item on the Likert scale. As indicated in Table 4.2, the mean scores of all the five constructs are above the scale's midpoint (3.0), indicating a generally positive attitude towards online reviews among the respondents. The Importance of Reviews construct returned the highest mean ($M = 3.669$, $SD = 0.750$), followed by Star Ratings Influence ($M = 3.650$, $SD = 0.743$) and Purchase Decision ($M = 3.647$, $SD = 0.832$). These results suggest that respondents are more inclined to believe that reviews are crucial and that star ratings do impact their

purchase decisions. Perceived Credibility ($M = 3.461$, $SD = 0.773$) and the Impact of Negative Reviews ($M = 3.397$, $SD = 0.802$) had slightly less favorable means, although they are both above the neutral point.

The difference between the means of the Importance of Reviews scale ($M = 3.669$) and the Negative Reviews scale ($M = 3.397$) supports the expectation that established in Chen et al. (2022) that negative reviews are highly attended, with the overall weight of positive reviews slightly higher at the composite level. The standard deviations range from 0.743 to 0.832 indicating moderate variation across the full range of responses, and not too much polarisation within any of the constructs. Here are some baseline descriptive profiles that give the context for the inferential analysis that follows.

Table 4. 2 Descriptive Statistics of Composite Construct Scores

Construct	N	Mean	SD	Min–Max
Importance of Reviews	250	3.6691	0.750	1.0–5.0
Impact of Negative Reviews	250	3.3971	0.802	1.0–5.0
Perceived Credibility	250	3.4606	0.773	1.0–5.0
Influence of Star Ratings	250	3.6503	0.743	1.0–5.0
Purchase Decision (DV)	250	3.6467	0.832	1.0–5.0

Source: Primary Data; SPSS Descriptives Output

4.4 Pearson Correlation Analysis

To determine the bivariate relationships between the four predictor constructs and the dependent variable Purchase Decision, Pearson correlation analysis was performed. Each of the four predictors had a statistically significant positive correlation with purchase decision at the $p < .01$ (two tailed) level. Perceived Credibility had the highest correlation with the outcome variable ($r = .464$, $p < .001$), followed by Importance of Reviews ($r = .455$, $p < .001$), Impact of Negative Reviews ($r = .386$, $p < .001$), and Influence of Star Ratings ($r = .371$, $p < .001$). The findings are consistent with those of Handoyo (2024) which were the results of a meta-

analysis. He concluded that trust and eWOM characteristics are the most consistent variables to predict online purchase behaviour.

The predictors showed moderate conceptual overlap with the highest inter-predictor correlation between Importance of Reviews and Perceived Credibility ($r = .570$) which is not high enough to be a concern of multicollinearity ($r \geq .80$) as recommended by Pallant (2020). The VIF values for the other regression variables were below 2.0 (between 1.340 and 1.789), indicating that there was no issue of multicollinearity with the regression estimates. The pattern of correlations indicates that multiple regression analysis should be conducted to determine the relative predictive power of each construct while controlling for the others.

4.5 Multiple Linear Regression — Hypothesis Testing

Purchase Decision was used as a dependent variable and all four composite scores entered simultaneously as predictors using multiple linear regression (Enter method). The model was statistically significant overall: $F(4, 245) = 26.567, p < .001$. The coefficient of determination ($R^2 = .303$) shows that the four predictors collectively account for 30.3% of the variance in purchase decision, and the adjusted $R^2 = .291$ suggests some degree of shrinkage to be expected in a social science setting. These R^2 values are well within the range of what could be considered standard in attitudinal survey research and are not necessarily a sign of model failure, as Bryman (2016) has pointed out.

As indicated in Table 3, each of the four predictors provided a significant amount of unique variance for the outcome. Perceived Credibility was the strongest single predictor ($\beta = .247, t = 3.684, p < .001$), and was found to be a significant factor in consumers' willingness to make purchases based on Amazon reviews when they perceive them as credible and trusted. This result confirms the hypothesis that was rejected for H3. The second strongest predictor was Importance of Reviews ($\beta = .182, t = 2.546, p = .011$) that supports the rejection of H1. Influence of Star Ratings ($\beta = .141, t = 2.284, p = .023$) and Impact of Negative Reviews ($\beta = .137, t = 2.159, p = .032$) were each significant, supporting the rejection of H4 and H2 respectively. Approximate normality of the residuals were confirmed with the use of diagnostic plots, the histogram of the standardised residuals and the Normal P-P plot, while the scatterplot of the standardised residuals against the predicted values confirmed homoscedasticity. These diagnostics validate the assumptions of ordinary least squares regression as described in Pallant (2020).

Table 4. 3 Multiple Regression Coefficients — Predictors of Purchase Decision

Predictor	B	SE	β	t	p
(Constant)	.928	.274	—	3.391	.001
Importance of Reviews	.202	.079	.182	2.546	.011
Impact of Negative Reviews	.142	.066	.137	2.159	.032
Perceived Credibility	.265	.072	.247	3.684	<.001
Influence of Star Ratings	.158	.069	.141	2.284	.023
$R = .550$; $R^2 = .303$; $Adjusted\ R^2 = .291$; $F(4, 245) = 26.567$, $p < .001$					

Dependent Variable: Purchase Decision; Source: Primary Data; SPSS Regression Output

4.6 One-Way ANOVA: Demographic Differences

In order to determine if there were significant differences in purchase decision scores between age groups and between shopping frequency groups, one-way ANOVAs were used to assess the moderating effect of demographic factors. There were no statistically significant differences for either variable. The differences were not significant between the age groups, but approached significance, $F(4, 245) = 2.322$, $p = .057$. Clearly, the differences in shopping frequencies were not statistically significant: $F(3, 246) = 1.084$, $p = .357$. Post hoc Tukey HSD tests showed that there were no significant differences between any individual comparisons among age groups or shopping frequency categories at $\alpha = .05$.

The age groups ranged from 25-34 having the highest mean purchase decision score ($M = 3.789$) and 55+ having the lowest ($M = 3.250$), with the direction of the difference matching the findings of generational review engagement differences by Djafarova and Bowes (2021) and Ngo et al. (2024). The lack of significance in these group comparisons does not allow conclusions to be drawn beyond the present sample. The mean purchase decision score ($M = 3.768$) was highest for the weekly shoppers.

4.7 Summary of Findings

The data analysis yielded four major findings. First, online reviews have a highly positive effect on purchase decisions for Amazon UK customers; all four of the predictor constructs had statistically significant regression coefficients. Second, perceived credibility of reviews is the most important individual predictor of purchase intention ($\beta = .247$), followed by general importance of reviews ($\beta = .182$). Third, negative reviews and star ratings are also important, but have slightly smaller effect sizes. Fourth, there were no significant difference scores among age groups or shopping frequency groups in purchase decision scores. Taken together, these results give a strong quantitative foundation to the interpretive discussion in Chapter Five.

CHAPTER 5: DISCUSSION

This chapter analyzes the results reported in Chapter Four with respect to the research questions, hypotheses, and theory that have guided this dissertation. The discussion, following Creswell and Creswell (2018) starts by restating the research problem/question and research goal/objective, then moves on to the examination of the meaning of the empirical findings in terms of the existing literature on online customer reviews (OCRs), consumer trust, and purchase decision-making. When the findings are found to be in agreement, extension and disagreement to previous scholarship is explicitly mentioned. The chapter ends with the Literature Gap identified, followed by study's Theory and Practical contributions, and limitations.

5.1 Restatement of the Research Problem and Objectives

The aim of this study was to explore the effect of web-based customer reviews on e-purchasing decisions of customers of Amazon UK. To investigate four research questions were formulated: Research Question 1 (RQ1) is the overall importance of OCRs during the purchase process, Research Question 2 (RQ2) is the differential effect of positive and negative reviews on purchase intention, Research Question 3 (RQ3) is the influence of consumer trust and review credibility on purchase intention and Research Question 4 (RQ4) is the influence of star ratings on purchase intention. In the wake of the emerging empirical evidence from a range of countries, such as North America and East Asia, this study was undertaken to provide UK-specific evidence that would close a gap identified by Pocchiari, Proserpio and Dover (2025) who noted the need for empirical research in the OCR domain on samples of UK consumers.

5.2: Interpret key findings and outcomes of the hypotheses

5.2.1 H1: The Importance of Online Reviews in Purchase Decisions

The analysis results are sufficient to support the rejection of H1. The mean score for the Importance of Reviews was greater than the scale median ($M = 3.669$), and the regression coefficient was statistically significant ($\beta = .182, p = .011$). More than three-quarters of people said they always or often read reviews before buying something, confirming the descriptive picture of OCR engagement as a normative behaviour among Amazon UK customers. They found this result to be consistent with the results of the meta-analysis by Qiu and Zhang (2024) which synthesized 60 studies and found that there was a positive relationship between review engagement and purchase intention, and the relationship was positive and strong even in the

face of different contexts. The findings also support the main hypothesis of Fernandes et al. (2022) that review usage is a multidimensional, but always important, factor affecting consumer purchasing behaviour.

This is of particular interest concerning the finding that Electronics and Gadgets was the category most bought (26.8%). As predicted by Chou, Chuang and Liang (2022) in their research study on Elaboration Likelihood Model, high involvement technical products are exactly those products where the risk of consumers' purchase is high and they engage in more systematic, central route processing in their purchase process.

5.2.2 H2: The Differential Impact of Negative Reviews

The conclusions also contradict H2. The descriptive data analysis showed that the composite mean of the Importance of Reviews scale ($M = 3.669$) was significantly higher than the composite mean of the Impact of Negative Reviews scale ($M = 3.397$), which indicates that participants generally agree that negative reviews have an impact on their decision, while the overall construct of review engagement scores higher. In the regression model, the negative reviews predictor was statistically significant ($\beta = .137$, $p = .032$) above the general review use predictor signifying that the negative reviews predictor accounted for a contribution in the model, other than general review use to purchase decision outcomes. This relationship is in line with the psychological negativity bias, found by Chen et al. (2022), in their eye-tracking study, where they showed that negative reviews draw in an abnormal amount of visual attention, especially from female consumers.

The results suggest that negative reviews have an influence, but they receive lower engagement scores than positive reviews on the composite level, which aligns with the findings presented by Hung, Chang and Chen (2023) that the effect of eWOM quality and quantity is complex – a few high quality, detailed negative reviews can outweigh many high quality positive reviews, but a moderate volume of consistently positive and credible reviews can buffer against purchase intent. In the current data set it seems this dynamic is at play, as negative review attention is high but not dominant in the review purchase decision signal. For Amazon UK sellers, this means actively promoting a high volume of genuine and quality positive reviews can still help to mitigate the reputational impact of negative reviews as Wang et al. (2022) suggest.

5.2.3 H3: Perceived Credibility and Trust as Predictors of Purchase Intention

Findings of this research indicate that the strongest predictor of purchase decision in this research is Perceived Credibility ($\beta = .247$, $p < .001$) which indicates that the research hypothesis H3 is rejected. The finding is consistent with the findings of Handoyo (2024) who conducted a meta-analysis of 30 studies and concluded that trust is the most consistent and strongest predictor of online purchase behaviour in e-commerce environments. The association between credibility and purchase decision ($r = .464$) was the strongest among all pairs in the model, thus underscoring the importance of trust in the review-decision relationship.

The items that assess the credibility of the verified purchase badge, the reviewer profile, and the sensitivity to the same language in reviews have a high Cronbach's alpha of .909, indicating that consumer concerns around credibility are well integrated and internally coherent. This aligns with the conceptual model proposed by Borchers (2023) that reviews have a socially constructed trust which is determined by familiarity with the platform, experiences with the platform, and contextual trust cues, not just rational assessments of information quality. Items that were the strongest performers in the current study – such as trust in the verified purchase badge and the perception that many of the positive reviews are bogus – indicate that Amazon UK consumers are highly attuned to both structural and contextual signals of review authenticity.

The credibility finding is also consistent with the Information Adoption Model used by Verma et al. (2023) which found that information credibility and usefulness mediate the persuasive pathway between the exposure of reviews and behavioural intention. From a UK standpoint, where the issue of fake reviews is now a growing concern, the importance of credibility as the main predictor of purchase decision, as Martínez Otero (2021) shows, makes sense from a theoretical perspective as the perceived credibility of the reviews is now the most important condition to be met before their impact can be felt.

5.2.4 H4: The Effect of the Star Ratings

With regard to H4, which predicted that the star ratings would not be a statistically significant predictor of purchase decision, the result was that the star ratings did become a statistically significant predictor of purchase decision ($\beta = .141$, $p = .023$). The composite mean for the Star Ratings construct ($M = 3.650$) was the second highest of all predictor constructs, with 43.6% of the respondents reporting that they agree or strongly agree that star ratings are the first thing they look at when visiting a product page. This is also in line with Sharma et al.'s (2023)

processing shortcuts, which demonstrated that consumers who are overwhelmed with information in a digital environment are forced to use heuristic cues (e.g., star ratings) to alleviate their cognitive load. Choi (2024) also reported that the distribution of ratings has a significant impact on helpfulness ratings for the reviews, apart from content.

The relatively lower beta weight of star ratings as compared to credibility ($\beta = .247$) is also theoretically sound. Clare et al. (2021) showed that credibility of the reviews is significantly affected when reviews are disconfirming of the consumer expectations, even if the expectations are set by star ratings. It suggests that the star ratings act as a first navigational heuristic, but the influence of the star ratings on purchase decisions is ultimately dependent on the credibility of the review text that accompanies the ratings. For the Amazon UK sellers, this means that they will have a higher business value if they get a good rating with content that is presented honestly.

5.3 Addressing the Demographic Non-Findings

The results of the purchase decision scores were not significantly different among age groups ($p = .057$) and shopping frequency categories ($p = .357$) and can be discussed. The generational shift, notably of younger consumers (25-34) and higher frequency consumers on the purchase decision, aligns with the generational review trend dynamics identified by Djafarova and Bowes (2021) where they state that Generation Z users are more likely to be swayed by peer created online content. The lack of significance at $\alpha = .05$, and especially the borderline $p = .057$ result for age, however, might be indicative of a lack of statistical power due to the unequal and relatively small cell sizes for the older age groups ($n = 16$ for 55+). A larger or stratified sample may be able to show age moderated differences that are not discernable in the current sample.

5.4 Responding to the Literature Gap

This research directly tackles the empirical gap in the literature identified for the UK. This is one of the few studies to have been conducted in the UK that adds to a literature which has been largely dominated by studies from North America and East Asia studies on the importance of perceived credibility on purchase decisions. UK consumer may be more confident in their regulation due to the Digital Markets, Competition and Consumers Act 2024 and an increase in public discussion surrounding fake reviews that may not be fully represented by cross-cultural models. The present results support the argument of Lim et al. (2025) that, in this

regard, the reputational harm of being exposed to fake reviews is more severe in markets with high levels of consumer awareness of fake reviews.

The study also sheds new light on the interaction between the four dimensions of OCR (the importance of review, negative review impact, credibility, and star ratings), as they work together as a whole rather than separately. Overall, the regression model ($R^2 = .303$) accounts for a meaningful portion of the variance in purchase decisions and supports the multi-process view of eWOM proposed by Babić Rosario, de Valck and Sotgiu (2020), which indicates that the various dimensions of eWOM do not operate independently. The contribution is important for both researchers who intend to build predictive models of the influence of reviews and for the practitioners who plan the management strategies for reviews on Amazon UK.

5.5 Practical Implications

This study provides some key takeaways for Amazon UK sellers and platform managers. First, perceived credibility tends to be the top driver of purchase decisions, so promoting authenticity of reviews (using verified purchase badges, complete reviewer profiles, and visibility of platform anti-manipulation measures) may be the most effective way of improving ROI on review management investments. Second, the effect of negative reviews is also large, and sellers would gain from responding publicly and personally to negative reviews; as demonstrated by Jin et al. (2023), the effect of this is meaningful and increases the perceived helpfulness and credibility of review threads. Thirdly, star ratings are a heuristic 'slippery slope' but their final power also relies on the credibility of the text that accompanies them, so having a substantial and genuine number of detailed positive reviews is a more strategic asset than simply targeting ratings averages.

5.6 Limitations

There were a number of restrictions that have to be recognised. Convenience sampling limits the statistical generalisability of the results to the general customer base within Amazon UK as Bryman (2016) warns of non-probability designs. As Creswell and Creswell (2018) state, a structural drawback of the cross-sectional survey is that it cannot determine the causal directionality of the consumer attitude, as it was detected at just one point in time. Likert data that is self-reported can have social desirability bias, especially for the scepticism items related to the authenticity of the reviews. Although a sample size of 250 was sufficient for the analyses performed, it was not enough to match the Cochran minimum of 385 for this study, thereby lowering the sample size's power in sub-group comparisons. Last but not least, the results are

specific to Amazon UK and can't be directly applied to other e-commerce sites that have a different review architecture.

5.7 Chapter Summary

In this chapter, the quantitative results of this study have been interpreted according to the four research hypotheses, the existing theory and the literature gap. The results showed that all four null hypotheses were rejected, thus establishing that the effect of online customer reviews on the purchase intention of consumers from Amazon UK is significant and multidimensional, including the perceived credibility of the online customer reviews. The fact that credibility is the most dominant predictor – both theoretically and practically, in a time when there is increasing awareness of the prevalence of fake reviews – is a valuable take away.

CHAPTER 6: CONCLUSION

6.1 Restatement of Research Aim and Overview

This dissertation aimed to explore the impact of customer reviews on online shopping behaviours of the Amazon customers in the United Kingdom. The research aimed to address this empirically underdeveloped field; consumer research studies being predominantly carried out in North America and East Asia (Pocchiari, Proserpio and Dover, 2025) resulted in the use of a positivist quantitative, cross-sectional survey research design to gather data from 250 recent customers of Amazon UK. The investigation was guided by the four research questions and four null hypotheses were tested with the support of validated statistical procedures in IBM SPSS Statistics. The study has now made its complete research journey of theoretic grounding, methodological design, data collection, data analysis, and interpretive discussion. This final chapter summarizes the key findings, tackles the research questions, validates the study's impact on theory and practice, recognizes areas for future study, and provides direction for future research.

6.2 Summary of Key Findings

Four major results were found and analyzed from the data collected for the study, each of which answered one of the research questions. First, with respect to RQ1, the results showed that online customer reviews have a significant and positive effect on the purchase decisions of Amazon UK customers. More than 70 percent indicated that they read reviews prior to their purchase, with the regression coefficient for the Importance of Reviews construct statistically significant ($p = .011$), and null hypothesis H1 rejected. Our results align with the meta-analytical results provided by Qiu and Zhang (2024), whereby they have concluded that there is a positive and replicable correlation between consumers' review engagement and their purchase intention for various product categories and consumer groups.

Second, in response to RQ2, negative reviews were observed to have an impact on purchase decisions that was separate from the overall construct of review importance. The coefficient of the regression model for the Impact of Negative Reviews construct was statistically significant ($\beta = .137$, $p = .032$), and the composite mean for the construct ($M = 3.397$) was meaningfully lower than the composite mean of the Importance of Reviews construct ($M = 3.669$), indicating that the impact of negative reviews was at least somewhat cancelled out at the aggregate level by the positive review content. This is consistent with the negativity bias observed by Chen et

al. (2022) as well as the moderating quality dynamics observed by Hung, Chang and Chen (2023) who noted that the more frequent and high-quality positive reviews can reduce the disproportionate attention paid to negative reviews.

Third, and most importantly in terms of effect size, perceived credibility and trust was the strongest predictor of purchase decision in the regression model ($\beta = .247$, $p < .001$), which answered RQ3 and led to the rejection of H3. The highest of all the bivariate relationships in the model was the correlation between Perceived Credibility and Purchase Decision ($r = .464$), and Cronbach's alpha for Perceived Credibility ($\alpha = .909$) indicated that this construct was internally consistent and was not significantly related to other constructs. The primacy of credibility as a predictor aligns with the trust-centred approach of Handoyo (2024) and the Information Adoption Model of Verma et al. (2023) which makes trust and information credibility as the paths through which the influence of reviews is applied.

Fourth, in response to RQ4, star ratings were found to be statistically significant in predicting purchase decision ($\beta = .141$, $p = .023$), although this effect is not as strong as perceived credibility and thus H4 was rejected. However, the composite mean for the construct Star Ratings ($M = 3.650$) was the second highest of all the predictor constructs, meaning that the star ratings are strong heuristic cues in the purchase process. This is theoretically founded on the peripheral-route processing theory proposed by the Elaboration Likelihood Model (ELM) (Chou, Chuang and Liang, 2022) and found to be consistent with Sharma et al. (2023) definition of star ratings as 'cognitive shortcuts' for users to manage information overload in digital retail settings.

6.3 Responding to the Literature Gap

This study addresses the empirical deficit in the OCR literature due to a lack of UK consumers. The study offers primary data from 250 Amazon UK customers, confirming that the main dynamics of review influence (credibility, negative review attention, star rating heuristics and general review importance) hold true in the UK context and generally align with international findings, but also revealing contextual factors unique to the UK. The perceived credibility is the most important factor in purchase decisions, more so than the volume and valence of the reviews themselves; thus, the result is relevant for the UK context where the print of fake review manipulation is a growing public and political concern, as indicated by the Digital Markets, Competition and Consumers Act 2024 (Martínez Otero, 2021). Overall, the data indicate that the UK consumer has effectively adjusted their decision-making heuristics to

favor credibilities as the first filter they apply to all other review signals, as there is a growing sense that reviews are highly scrutinized and potentially fake (Lim et al., 2025).

6.4 Contributions to Theory and Practice

The study can be seen to make several identifiable contributions to theory. First, it empirically validates the Information Adoption Model (Verma et al., 2023) in the context of Amazon in the UK, supporting the hypothesis that information credibility is the most powerful mediator between the exposure of reviews and purchase intention. Second, the multi-construct regression model ($R^2 = .303$) offers quantitative support for the multi-process eWOM model suggested by Babić Rosario, de Valck and Sotgiu (2020), which suggests that different dimensions of OCR do not work in isolation, but are instead interconnected components of a complete persuasion system. Third, the study extends the study of Chou, Chuang and Liang (2022) by corroborating the role of star ratings as a navigational cue in the peripheral route and the role of review text in the central route, both being part of a holistic decision-making process.

As far as application, the results provide a number of 'take away' suggestions for Amazon UK sellers and platform managers. Focusing on strategies that improve the perceived credibility of review signals, as the most influential factor on purchase decisions (as found by Jin et al., 2023), sellers should concentrate on increasing the coverage of verified purchase badges, keeping full and clear seller profiles and responding directly and publicly to negative reviews. Recognising the negativity bias effect reported by Chen et al. (2022), it is important that sellers create a regular stream of in-depth and authentic positive reviews to insulate against negative reviews. Last but not least, the commercial value of a high star rating is undermined by the lack of credibility in the accompanying review text, thus sellers should always be aware of the need to complement the rating management with authentic review quality management (Wang et al., 2022).

6.5 Limitations

There are some restrictions associated with the present study. Firstly, the convenience sampling approach limits the generalisability of the results to the wider population of customers in the Amazon UK community, as the non-probability sampling may cause selection bias which is not easy to quantify or account for (Bryman, 2016). Second, the cross-sectional design of the survey also precludes causal inferences between constructs since the patterns of associations observed are only associative and not causal (Creswell and Creswell, 2018). Third, all attitudinal measures are self-reported, and social desirability effects could have been a factor

when answering questions on scepticism around fake reviews with respondents potentially exaggerating their critical awareness. Finally, the number of respondents interviewed ($n = 250$) was sufficient for the statistical tests employed but does not meet the theoretical minimum of 385 respondents set forth by Cochran (1977), which might have affected the power of statistical tests in sub-group analyses, especially for older age groups, where cell sizes were small. Finally, as the focus is Amazon-based, the results can't be directly transferred to other environments where review systems are used, such as Trustpilot, eBay or TripAdvisor.

6.6 Directions for Future Research

The results of this research along with the limitations indicate some fruitful avenues for further investigation. First, longitudinal research could be used to examine shifts in consumer trust in the Amazon UK reviews over time, especially following the changes on the platform in response to interventions by the platform itself and legal changes under the new Digital Markets, Competition and Consumers Act 2024. This would allow causal inferences which the current cross-sectional study cannot make. Second, future studies could use stratified probability sampling to obtain proportional representation within age, gender, and purchasing frequency groups and thus results that are more generalisable across the population. Third, a mixed method extension of the present study which incorporated the quantitative survey approach with in-depth interview or focus group would provide a richer understanding of the cognitive and emotional process involved in assessing credibility and would capture some of the nuances that could not be well represented by a likert scale item (Creswell and Creswell, 2018).

Finally, although age group differences in purchase decision scores were marginally significant ($p = .057$), future research with a larger sample of age-stratified participants could determine if differences in the engagement of reviews by generation become statistically significant with adequate power. Finally, with the increasing sophistication of the AI produced fake reviews, as highlighted by Salminen et al. (2022), future studies should explore its effectiveness and impact on consumer confidence in reviews within the UK market. Sixth, comparative research on the various ecommerce platforms in the UK could yield clues for the differences between the review-purchase relationship and whether the dynamics discussed here are unique to the Amazon platform or represent a pattern of UK online consumer purchasing behaviour.

6.7 Closing Statement

The dissertation has shown that online customer reviews are a multidimensional and statistically significant influence on the purchase decision making process of Amazon UK customers, with perceived credibility as the most significant influence in a regulatory and informational environment where there is a growing awareness of the possibility of reviews being manipulated. All four of the tested null hypotheses were rejected, indicating that the importance of the review, the negative impact of the review, credibility and trust, as well as the star rating, make a significant independent contribution towards purchase intention in an integrated predictive model. This study contributes both to the theoretical literature on eWOM and consumer behaviour, which is dominated by international research, and to the practice in the context of sellers, platform managers and policy makers in the Amazon UK context, by providing UK-specific evidence that builds on and extends the predominantly international OCR literature. Technology and commercial pressures to the entire review ecosystem continue to threaten the integrity of the system, and the findings of this study serve to highlight that consumer trust isn't a nice-to-have feature, it's what made the review system work — and what all participants in the digital marketplace need to work towards keeping it as a critical condition.

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Appendices

Appendix A: Ethics Form



Ethics_Form_Filled.
docx

Appendix B: Survey Instrument

The following questionnaire was administered to 250 Amazon UK consumers. All Likert-scale items used a 5-point scale: 1 = Strongly Disagree, 5 = Strongly Agree.

Section 1 – Screening & Demographics (Q1–Q7)

Q No.	Variable	Question / Response Options
Q1	Consent	Do you consent to participate in this study? / Yes (Proceed) No (Exit)
Q2	Age Group	What is your age group? / 18–24 25–34 35–44 45–54 55+
Q3	Gender	What is your gender? / Female Male Non-binary Prefer not to say
Q4	Education	What is your highest level of education? / Secondary/High School Undergraduate Postgraduate Doctorate Other
Q5	Shopping Frequency	How often do you shop on Amazon UK? / Weekly Monthly Once every few months Rarely
Q6	Review Reading	How often do you read reviews before purchasing? / Always Frequently Sometimes Rarely Never
Q7	Product Category	Which product category do you most frequently purchase? / Electronics Fashion Home & Kitchen Books/Media Health Tools & DIY Others

Section 2 – Construct Measures (Q8–Q12, Likert 1–5)

Variable ID	Construct	Item Statement
Q8a	Importance of Reviews	Reviews are critical to my purchase decisions.
Q8b	Importance of Reviews	I rely on reviews to assess product quality.
Q8c	Importance of Reviews	Reviews reduce my perceived risk of buying online.
Q8d	Importance of Reviews	The volume of reviews influences my confidence.
Q8e	Importance of Reviews	I trust reviews as much as recommendations from friends.
Q8f	Importance of Reviews	I spend significant time analysing reviews.
Q8g	Importance of Reviews	Reviews save me time when making decisions.
Q9a	Negative Reviews Impact	A single negative review can stop my purchase.
Q9b	Negative Reviews Impact	I pay more attention to negative than positive reviews.
Q9c	Negative Reviews Impact	I actively look for negative reviews.
Q9d	Negative Reviews Impact	The ratio of positive to negative reviews is a deciding factor.
Q9e	Negative Reviews Impact	Moderate negative reviews are more helpful than extreme ones.
Q9f	Negative Reviews Impact	Negative reviews make me consider alternatives.

Q9g	Negative Reviews Impact	I am more likely to buy if negative issues are addressed.
Q10a	Credibility & Trust	I trust verified-purchase badges on reviews.
Q10b	Credibility & Trust	I am confident that most reviews on Amazon are authentic.
Q10c	Credibility & Trust	Detailed reviews are more credible to me.
Q10d	Credibility & Trust	I suspect many positive reviews are fake.
Q10e	Credibility & Trust	Frequent reviewers are more reliable.
Q10f	Credibility & Trust	I assess credibility based on reviewer profile.
Q10g	Credibility & Trust	Identical language across reviews makes them less trustworthy.
Q11a	Star Ratings Influence	Star rating is the first thing I check.
Q11b	Star Ratings Influence	I rarely purchase products rated below 4 stars.
Q11c	Star Ratings Influence	The distribution of star ratings is important to me.
Q11d	Star Ratings Influence	Summary snippets from reviews are highly useful.
Q11e	Star Ratings Influence	I trust consistently 4-star-rated products.
Q11f	Star Ratings Influence	A perfect 5-star rating seems too good to be true.
Q11g	Star Ratings Influence	The quantity of reviews matters more than the average star rating.
Q12a	Purchase Decision	I intend to continue using reviews to guide purchases.

Q12b	Purchase Decision	I would abandon a purchase if no reviews are available.
Q12c	Purchase Decision	My willingness to purchase depends on review quality.

Appendix C: Dataset Snapshot (First 15 Respondents)

The full dataset comprises 250 respondents (N = 250) and 39 variables. The extract below illustrates the data structure, including demographic variables and composite Likert responses grouped by construct.

	A	AD	AE	AF	AG	AH	AI	AJ	AK	AL	AM
	Respondent_ID	Q11a_Star_Rating_First_Thing_Check	Q11b_Rarely_Buy_Below_4_Stars	Q11c_Distribution_of_Stars_Important	Q11d_Summary_Snipet_Highly_Useful	Q11e_Trust_Conistent_4Star_Ratings	Q11f_Perfect_5Star_Too_Good_to_Be_True	Q11g_Quantity_Reviews_Matters_More	Q12a_Intend_Continue_Using_Reviews	Q12b_Abandon_Purchase_If_No_Reviews	Q12c_Willingness_Dependent_on_Review_Quality
1											
3	R002	4	4	4	4	4	4	3	5	5	3
4	R003	4	4	5	4	4	4	5	3	4	3
5	R004	4	3	4	4	3	3	3	2	3	2
6	R005	4	3	4	4	4	4	4	4	4	5
7	R006	1	1	2	2	2	2	2	2	3	3
8	R007	3	3	4	4	5	4	4	4	4	5
9	R008	5	5	3	5	4	4	4	4	3	4
10	R009	1	3	2	3	2	1	2	3	3	2
11	R010	3	4	4	4	4	4	4	5	4	4
12	R011	4	4	3	5	4	3	4	5	5	5
13	R012	3	4	4	2	4	3	3	2	2	3
14	R013	3	3	4	3	3	3	3	3	3	2
15	R014	2	3	4	3	3	3	3	5	5	5

Appendix D: Reliability Analysis & Regression Output Summary

Tables below summarise Cronbach's Alpha coefficients for each construct and the multiple linear regression results predicting Purchase Decision.

D1 – Cronbach's Alpha Summary (All Constructs)

Construct	Scale Label	Items (N)	α	Interpretation
Importance / Use of Reviews (Q8)	Importance of Reviews	7	.902	Excellent
Impact of Negative Reviews (Q9)	Negative Reviews	7	.919	Excellent
Credibility & Trust (Q10)	Credibility	7	.909	Excellent
Star Ratings Influence (Q11)	Star Ratings	7	.903	Excellent
Purchase Decision – DV (Q12)	Purchase Decision	3	.829	Good

All α values exceed the conventional threshold of .70 (Nunnally, 1978), confirming strong internal consistency for all constructs.

D2 – Multiple Linear Regression: Model Summary

R	R ²	Adj. R ²	Std. Error	F (df1=4, df2=245)
.550	.303	.291	.700	26.567, $p < .001$

D3 – Regression Coefficients (Dependent Variable: Purchase Decision)

Predictor	B	Std. Error	β	t	p	VIF
(Constant)	.928	.274	–	3.391	.001	–
Importance of Reviews	.202	.079	.182	2.546	.011	1.789
Impact of Negative Reviews	.142	.066	.137	2.159	.032	1.421
Perceived Credibility	.265	.072	.247	3.684	.000	1.575
Influence of Star Ratings	.158	.069	.141	2.284	.023	1.340

All VIF values < 2.0 , indicating no multicollinearity concerns. All four predictors are statistically significant ($p < .05$).

Appendix E: Descriptive Statistics & Pearson Correlation Matrix

The table below presents means, standard deviations, and pairwise Pearson correlations for all composite construct scores (N = 250).

E1 – Descriptive Statistics (Composite Scores)

Construct	Variable	Mean	SD	N
Importance of Reviews	UseOfReviews	3.669	.750	250
Impact of Negative Reviews	NegReviews	3.397	.802	250
Perceived Credibility	Credibility	3.461	.773	250
Influence of Star Ratings	StarRatings	3.650	.743	250
Purchase Decision (DV)	PurchaseDecision	3.647	.832	250

E2 – Pearson Correlation Matrix

	UseOfReviews	NegReviews	Credibility	StarRatings	PurchDecision
Importance of Reviews	1.000	.496**	.570**	.459**	.455**
Impact of Negative Reviews	.496**	1.000	.428**	.375**	.386**
Perceived Credibility	.570**	.428**	1.000	.387**	.464**
Influence of Star Ratings	.459**	.375**	.387**	1.000	.371**

Purchase Decision (DV)	.455**	.386**	.464**	.371**	1.000
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E3 – One-Way ANOVA: Purchase Decision by Age Group

Age Group	N	Mean	SD	Std. Error	95% CI Low	95% CI High	F / p
18–24	56	3.691	.776	.104	3.483	3.898	
25–34	82	3.789	.897	.099	3.591	3.986	
35–44	56	3.464	.823	.110	3.244	3.685	
45–54	40	3.708	.740	.117	3.472	3.945	
55+	16	3.250	.775	.194	2.837	3.663	
Total	250	3.647	.832	.053	3.543	3.750	F=2.322, p=.057

The ANOVA result ($F = 2.322$, $p = .057$) is marginally non-significant at $\alpha = .05$, indicating no statistically significant differences in purchase decisions across age groups. Tukey HSD post-hoc tests confirmed no pairwise significant differences.