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The Role of Consumers in C2C Marketplace Engagement Views from the Academic Community on Web-Based User-Generated Content

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ABSTRACT
The importance of customer engagement in online customer-to-Consumer (C2C) markets, particularly within the education sector, is substantial in the digital age. User engagement, characterised by user-generated content, trust-building, and community development, is facilitated by the implementation of customised algorithms. User-generated evaluations and endorsements serve as crucial social proof for learners in their decision-making processes. This transformation revolutionises education by including a broader array of learning aids and more effective feedback systems, leading to continuous improvement. To thrive in the dynamic digital landscape, educational institutions must adapt by managing their online reputation, fostering flexibility, and employing data analysis to establish strategic partnerships and targeted marketing initiatives. Previous studies have utilised several models to analyse customer behaviour and identify factors influencing online purchase decisions. The Theory of Reasoned Action and the Theory of Planned Behaviour are commonly employed in developing research models to understand consumer behaviour. The perceived utility of a product significantly influences an individual's attitude towards it, thereby affecting their buying intention.

Keywords: online C2C markets, education sector, community engagement, learning tools, feedback mechanisms, data analysis, strategic alliances, marketing campaigns.

INTRODUCTION:

With the emergence of the digital era, a profound revolution has occurred, radically changing customer interactions with goods and services, especially concerning online consumer-generated advertising (CGA). In the context of ongoing digital transformation, Consumer-to-Consumer (C2C) marketplaces are flourishing as vibrant platforms for user transactions involving diverse products. The education industry has not been immune to this fast-expanding tendency. This essay will thoroughly analyse the intricate dynamics governing consumer engagement in online CGA within C2C marketplaces, with a particular emphasis on the education sector. This study will examine the essential factors influencing consumer engagement, assess the significant effects of user-generated content, and disclose the consequent implications for academic institutions.

Consumer engagement in online CGA is characterized by consumers' active participation and interaction within a digital landscape where their peers generate content, products, or services. This participation is seen in several forms within the educational sectors of C2C marketplaces, such as genuine suggestions and honest assessments, active discussions in forums, and the expansion of peer-to-peer tutoring. Several critical factors converge to promote this involvement. Trust is a cornerstone of engagement, emphasized by multiple studies as central to consumer behaviour in C2C platforms. Online C2C platforms inherently foster the creation of communities comprised of individuals with a shared interest in education and similar perspectives. By cultivating a feeling of community, these online platforms encourage individuals to participate actively in discussions, solicit guidance, and provide valuable insights. The abundance of user-generated material enables the rise of personalized recommendations. Advanced algorithms meticulously analyze user behaviour and preferences, enabling the delivery of tailored recommendations for courses or educational resources; thus, this improves user engagement.

User-generated ratings and endorsements serve as a manifestation of social proof in this situation. It validates the quality of educational services or products and significantly influences the decisions of prospective students. The influence of user-generated content in education is substantial, affecting all facets of the sector via C2C marketplaces. Students and parents acquire the confidence to make educated decisions about their academic pursuits by using the knowledge and experiences of their peers, therefore facilitating a more effective and fulfilling choosing process. The plethora of user-generated ratings and assessments serves as a potent quality assurance mechanism, encouraging educational institutions to maintain stringent standards, cognizant of the potential impact on their reputations. User-generated content often reveals many diverse educational resources, encompassing free courses, tutorials, and study aids. The existence of such diversity enhances both the accessibility and affordability of education. Academic institutions can derive useful insights from user-generated content by establishing a feedback loop that promotes innovation, responsiveness, and a culture of continuous improvement. Due to the significant influence of these disruptive dynamics on consumer-generated advertising in online C2C marketplaces, academic institutions must handle considerable consequences. In reputation management and marketing, academic institutions need to oversee their online presence in consumer-to-consumer marketplaces actively. Fostering a repository of favourable user-generated material and addressing negative criticism is essential for sustaining a positive reputation. Educational institutions must exhibit the capacity to adapt and respond to the evolving preferences of students in the dynamic landscape of instructional resources and teaching methodologies. User-generated material offers essential insights by revealing upcoming trends.

Forming strategic partnerships with significant figures and notable users on these platforms provides educational institutions with a viable means to augment their influence and improve their reputation. By adeptly leveraging the data generated from user participation, one can obtain significant insights into the behaviours and preferences of learners. Thus, this enables institutions to acquire the essential resources to enhance their services and formulate targeted marketing strategies. Trust is a cornerstone of engagement, emphasized by multiple studies as central to consumer behaviour in C2C platforms.

Perceived usefulness (PU) fundamentally refers to how individuals believe that a particular technology, product, or service will enhance their productivity and performance. Davis (1989) defines perceived usefulness (PU) as "the extent to which an individual believes that utilizing a specific system would improve his or her job performance." PU denotes the personal assessment conducted by an individual of the anticipated advantages and benefits that a specific technology or product may offer. PU transcends technology to integrate a diverse array of products and services in the field of consumer behaviour. Before concluding purchase selections, consumers assess the perceived utility of many products and services, such as smartphones, streaming service subscriptions, and innovative cooking gadgets. This evaluation profoundly influences purchase Intention (PI), denoting a consumer's inclination or preparedness to obtain a specific product or service (Ajzen, 1991). The Technology Acceptance Model (TAM) is summarized to focus on its relevance to consumer behaviour in C2C marketplaces, particularly the education sector. The Technology Acceptance Model (TAM) is summarized to focus on its relevance to consumer behaviour in C2C marketplaces, particularly the education sector.

The model's fundamental components consist of Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Behavioral Intention to Use (BI), and Actual System Use. Perceived usefulness (PU) denotes a user's conviction that employing a certain technology will improve their performance or efficiency, rendering it a pivotal factor in acceptance. PEOU, conversely, denotes the extent of effort a user believes is necessary to engage with the technology. A user-centric system is more likely to achieve adoption. Behavioural intention (BI) reflects the user's inclination or readiness to utilize the technology, directly predicting their actual usage. Ultimately, Actual System Use denotes the practical engagement and application of the technology.

The assessment of perceived usefulness (PU) frequently employs instruments such as the 7-point Likert scale, wherein users evaluate their concurrence with assertions on a technology's perceived advantages. Expressions such as "This technology would augment my productivity" are frequently employed to evaluate perceived usefulness (PU). Qualitative methods, like focus groups and interviews, yield profound insights into the benefits consumers attribute to technologies. These methods enhance quantitative evaluations and foster a sophisticated comprehension of user perspectives.

REVIEW OF LITERATURE

Personalisation is a vital element influencing engagement on online platforms. Liu et al. (2017) show that personalised recommendations, driven by algorithms that analyse user behaviour and preferences, markedly improve user engagement. In the education industry, tailored course recommendations aligned with learners' interests and objectives enhance user happiness and decision-making efficacy.

As articulated by Cialdini (1984), social proof serves as a potent psychological influence on consumer behaviour. User-generated evaluations, endorsements, and ratings in C2C marketplaces serve as persuasive social proof, impacting the decisions of potential pupils. Zhu and Zhang (2010) discovered that such content is crucial for helping customers make informed judgements and allowing students and parents to assess courses and institutions more efficiently.

The influence of UGC encompasses quality assurance and the variety of educational materials. Chevalier and Mayzlin (2006) contended that favourable user-generated evaluations function both as a marketing instrument and as a means to uphold quality standards. This guarantees prospective students the legitimacy of courses and institutions in education. Pappas (2016) emphasised that user-generated content (UGC) provides learners with various educational resources, enhancing the learning experience and facilitating accessibility.

The feedback mechanism established by user-generated content provides educational institutions with essential insights for ongoing enhancement. Huang et al. (2017) observed that institutions might utilise this input to promote innovation and adjust to changing student requirements. Institutions can improve their products and strengthen their competitive advantage by examining trends and sentiments in user-generated content.

The UGC has considerable ramifications for educational institutions, including marketing, reputation management, and curriculum modification. Muntinga et al. (2011) emphasised the necessity of proactively maintaining online reputations by engaging with user-generated content. Christensen et al. (2015) emphasised the imperative for institutions to adopt "disruptive innovation," modifying their curricula to align with evolving student preferences informed by insights in UGC. Collaborative alliances with influencers on C2C platforms, as articulated by Kaplan and Haenlein (2010), can enhance institutional outreach and legitimacy. The utilisation of data is another essential area of emphasis. Provost and Fawcett (2013) emphasised the significance of analytics in comprehending user behaviour. By examining engagement patterns and preferences from user-generated content, educational institutions can refine their offerings and improve learner satisfaction.

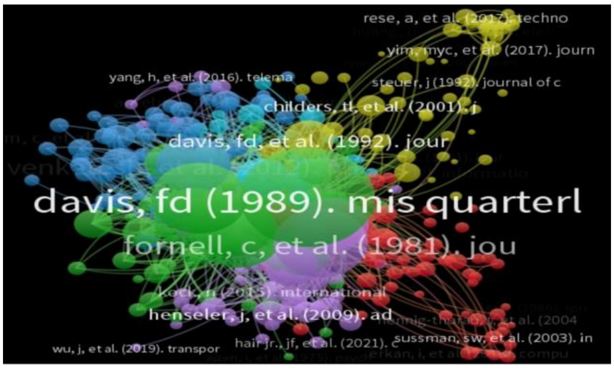

Fig 1: Bibliometric Coupling of the authors in Review of Literature with the help of Dimensions for Downloading the Bibliometric File and Vosviewer for Network Visualization of Authors

Research Gap

Identifying research gaps is essential for developing academic inquiry, as it reveals undiscovered or inadequately researched regions within the current literature. Diverse research gaps arise from the literature evaluation, indicating prospects for additional investigation and contribution. An evidence vacuum exists on the inadequate examination of the competitive advantages of online merchants compared to brick-and-mortar stores concerning cost structures and operational efficiencies. Although Lim (2012) highlighted these advantages, comprehensive research about cost-saving techniques and operational solutions is limited.

A deficiency of knowledge persists about the efficacy of social media marketing tactics in shaping customer behaviour and brand perception within online retail contexts. While Laroche, Rohm, and Bakos (2013) emphasized the influence of social media marketing on customer involvement, there is a paucity of practical assistance for optimizing these methods to achieve optimum efficacy. A technique gap exists regarding assessing the varying effects of perceived usefulness (PU) across different customer categories in online buying. Davis and Jayawardhena (2007) indicated that experience moderates the impact of perceived usefulness, but the methodologies for accurately evaluating these changes among segments necessitate additional enhancement.

A discernible empirical gap exists in the domain of sensory experiences, particularly with the use of images in online shopping settings. Elder, Schlosser, and Weathers (2017) highlighted the significance of sensory inputs in influencing consumer perceptions and purchase intentions; nevertheless, empirical evidence supporting these effects in practical contexts is insufficient. Moreover, a theoretical gap exists regarding the application of frameworks to elucidate the impact of social media marketing techniques on customer behaviour and brand perception. Although empirical evidence exists for these effects, the theoretical foundations and mechanisms influencing these behaviours remain little examined.

A neglected aspect is the population gap, indicating a lack of research on how particular demographic aspects, such as age or ethnicity, affect online retail behaviour. This gap highlights the need for focused research examining various consumer demographics, which may result in more inclusive and effective marketing strategies.

The impetus to rectify these research deficiencies arises from scholarly and pragmatic factors. Researchers seek to enhance the academic discipline by developing theoretical frameworks, improving procedures, and producing novel insights. This initiative has considerable practical ramifications, as addressing these deficiencies can assist corporations, politicians, and communities in making informed decisions and formulating effective strategies. Addressing the evidence gap in the cost structures of online retailers can yield actionable insights for operational optimization. Investigating the knowledge gap in social media marketing can give businesses practical tools to improve consumer interaction.

Detecting and addressing research gaps enhances academic knowledge and connects theory with practice. By addressing these gaps through innovative and rigorous research, researchers can provide significant contributions that impact both academic and practical realms.

Research Objectives

- Explore PU and its relationship with PI comprehensively.
- Understand the theoretical foundations of PU.
- Examine measurement methods for PU.
- Investigate the significance of PU in online shopping behaviour.

RESEARCH METHODOLOGY

The research frame adopts a qualitative approach to explore the relationship between Perceived Usefulness (PU) and Purchase Intention (PI) in the context of online shopping behaviour. Thematic analysis was employed to identify patterns and insights from qualitative data. The sampling design involves purposive sampling, aiming to select participants with diverse demographic backgrounds, internet usage patterns, and shopping preferences. Participants are selected based on age, gender, education level, occupation, and experience with online shopping to ensure a comprehensive understanding of PU and PI across different segments. The sample comprises 50 respondents, chosen through purposive sampling to achieve diversity and richness in perspectives. While the sample size may appear small, qualitative research prioritizes depth over breadth, focusing on detailed exploration rather than statistical generalization. In-depth interviews are the primary tool for data collection, allowing researchers to probe participants' perceptions, experiences, and attitudes towards PU and PI. Semi-structured interview guides are developed to ensure consistency while allowing flexibility to explore emerging themes. Audio recording and transcription facilitate accurate capturing of interview data, preserving participants' responses for analysis. The software used to conduct bibliometric coupling of authors is VOSviewer. Quantitative data analysis Python is used with the help of Jupyter Notebook. Smart PLS Version 4.1.0.2 has been utilized for performing Structural Equation Modelling. Thematic analysis was employed to identify patterns and insights from qualitative data. Thematic analysis was employed to identify patterns and insights from qualitative data. Coding involves systematically labelling data segments with descriptive or interpretive tags and identifying patterns and connections. Themes emerge through iterative coding and constant data comparison, developing coherent narratives and insights. Interpretation involves literature and themes within the research context, drawing connections to existing literature and generating meaningful conclusions.

Research Questions

- How does perceived usefulness (PU) influence purchase intention (PI) in various online shopping contexts?
- What underlying theoretical frameworks support the concept of perceived usefulness (PU) in consumer behaviour?
- What are the different measurement methods available for assessing perceived usefulness (PU) in online shopping?
- How does perceived usefulness (PU) contribute to shaping online shopping behaviour, and what factors influence its significance in this context?

Data Analysis

Thematic analysis was employed to identify patterns and insights from qualitative data, which involved various steps like importing necessary libraries, loading data, text preprocessing, feature extraction, hierarchical clustering, dimensionality reduction, cluster visualization, cluster analysis, word cloud visualization, centroid visualization and sentiment analysis.

The analysis of textual data entails multiple processes, commencing with the importation of requisite libraries. This investigation employs tools such as Pandas for rapid data manipulation and NLTK for natural language processing tasks, including tokenisation and stemming. Scikit-learn offers comprehensive machine-learning techniques, while SciPy is crucial for functions such as hierarchical clustering. Furthermore, Matplotlib and Seaborn are deployed for data visualisation, UMAP for dimensionality reduction, WordCloud for generating word clouds, and VADER for sentiment analysis.

The initial phase of the operation entails data loading. Data is extracted from an Excel file named Responses-C2C-Education-50.xlsx into a Pandas DataFrame called data. The designated sheet being loaded is titled "Sheet 1." This phase guarantees that the data is organised and prepared for preparation.

Text preprocessing is an essential stage in which unrefined text data is readied for examination. The stopwords and punkt packages from NLTK are downloaded to assist in this process. A Porter stemmer is employed to reduce words to their root forms, enhancing text analysis's efficiency. A function called preprocess_text is established to execute pre processing activities, encompass tokenisation, conversion to lowercase, elimination of stop words, and application of stemming. The modified text is retained in a new column, processed_text, within the Data Frame.

The subsequent phase is feature extraction. TF-IDF (Term Frequency-Inverse Document Frequency) vectorisation is employed to transform the text into numerical feature vectors. This transformation generates a TF-IDF matrix that measures the significance of words in each text in relation to the total corpus. This numerical form is essential for machine learning and clustering activities.

Hierarchical clustering is executed on the TF-IDF matrix utilising K-means clustering, with the cluster count established at five. The cluster labels are recorded in a new column, labelled 'cluster', within the DataFrame. This phase categorises analogous materials, facilitating a more organised examination of textual trends.

Dimensionality reduction is then employed to represent high-dimensional data in a two-dimensional space. Principal Component Analysis (PCA) condenses the TF-IDF matrix into two dimensions, yielding a diminished matrix, tfidf_matrix_reduced. This simplification facilitates the visualisation of document distribution and their cluster associations.

A scatter plot is generated to depict the clustering findings, with each point symbolising a document. The plot illustrates the clusters generated using K-means in the two-dimensional PCA space, each denoted by a unique colour.

Cluster analysis enhances comprehension of the document distribution inside each cluster. This entails quantifying the documents within each cluster and summarising descriptive statistics on cluster sizes, so providing insights into the data's structure and composition.

Word cloud visualisation enhances comprehension by illustrating the frequency of words in the analysed text. This graphic depiction emphasises the most significant terms in the text corpus, facilitating the identification of major themes and patterns.

UMAP (Uniform Manifold Approximation and Projection) is employed for a more advanced dimensionality reduction method, projecting the TF-IDF matrix into a two-dimensional space. This approach provides an alternative viewpoint on cluster distribution relative to PCA.

The UMAP visualisation of clusters is depicted via a scatter plot, offering a different perspective on the data's structure in two-dimensional space. This visualisation supports the conclusions drawn from the PCA-based scatter plot.

Centroid visualisation constitutes a vital component of the investigation. The centroids of the clusters are depicted alongside the data points in a two-dimensional space, providing a clear picture of cluster centres in relation to the data dispersion.

Ultimately, sentiment analysis is performed with VADER (Valence Aware Dictionary and Sentiment Reasoner). VADER computes sentiment scores for each document, offering insights into the emotional tone of the content. The sentiment scores are shown as a histogram illustrating the distribution of positive, neutral, and negative attitudes within the dataset.

This detailed workflow illustrates the collaboration of multiple tools and methodologies in deriving significant insights from textual data, so facilitating informed decision-making and enhanced analysis.

Table 1: Table consisting of Demographic Profile of Respondents

Professional Background	Gender	Age	Education
Modern Housewife	Female	43	MA
AI Professional	Male	35	MSc
Media Analytics Professional	Male	40	MCom
Journalist	Female	30	MPhill
Doctor	Male	27	MS
Boutique Owner	Female	42	MCom
Polytechnic Student	Female	24	BSc
Content Writer – Media	Male	34	MA
Singer	Female	39	MA
Digital Marketing Professional	Female	33	MBA
Modern Housewife	Female	38	BA
Professional Dancer	Female	33	BA
HS Teacher	Male	41	MSc
Professional - HR Electricity Department	Male	34	MBA
Marketing Professional	Female	33	MBA
Professional - Media Sales	Male	38	MBA
Professional – Brand	Male	40	MBA
CSR, Oil Industry	Male	45	BE
Banking Industry	Male	45	MBA
Consultant & Entrepreneur - Digital Marketing	Male	53	MBA
Consultant & Entrepreneur - Analytics	Male	46	MBA
Head-Purchase, Electricity Department	Male	50	MBA
Coordinator - Self Help Group	Female	45	BA
Small Business Owner	Female	45	MSc
Small Business Owner	Female	45	BA
IT Professional	Male	36	BTech
Graphic Designer	Female	29	BFA
Business Analyst	Male	31	MBA
Finance Manager	Male	39	CA
Educator	Female	32	BEd
Software Engineer	Male	28	BTech
Project Manager	Male	41	MBA
Entrepreneur	Female	36	BBA
Research Scientist	Male	37	PhD
Lawyer	Female	34	LLB
Financial Analyst	Male	30	MBA
Software Developer	Male	29	BE
Event Planner	Female	31	BBA
Architect	Male	35	BArch
Retail Manager	Male	37	MBA
HR Professional	Female	33	MBA
Chef	Female	28	Diploma
Business Owner	Male	42	BCom
Economist	Male	39	MA
Librarian	Female	36	MLIS
Journalist	Male	29	BJMC
Physiotherapist	Female	31	BPT
Civil Engineer	Male	34	BE
Psychologist	Female	35	MA
Marketing Manager	Male	38	MBA

Researcher shall dissect the table's summary by analyzing counts and percentages across all categories. Gender Distribution: The professional population comprises 23 females, accounting for 55.0% of the total, and 19 males, representing 45.0%. Age-wise, the professionals comprise a heterogeneous sample, as evidenced by the broad spectrum of experience levels represented by those between the ages of 24 and 53, with an average of 36.9 years. With 12 members comprising 28.6% of the cohort, MBAs are held by a plurality of professionals regarding educational background. The Master of Arts (MA) program also shall consist of six individuals, accounting for the same percentage (14.3%) as the Bachelor of Arts (BA), which comprises a mere 6 individuals. Four professionals, or 9.5%, possess a Bachelor of

Technology (BTech) degree. An additional ten percentile consists of individuals holding Master of Science (MSc), Bachelor of Commerce (BCom), and Bachelor of Science (BSc) degrees, all of which contribute to the group's varied educational profile albeit in lesser quantities. The gender, age, and educational diversity of the professional cohort are discussed in detail in this exhaustive dissection. The present synopsis comprehensively examines how the professionals enumerated in the table are categorized by gender, age, and extent of education.

Table 2: Cross Tabulation of Gender and Age

Gender	Age(years): 24-30	Age(years): 31-40	Age(years): 41-50	Age(years): 51-60
Female	2	9	6	6
Male	5	6	5	3

A Chi-Square test was performed to examine the relationship between gender and age group. The Chi-Square statistic was computed to be roughly 2.88. By comparing the computed Chi-Square statistic to the critical value of the Chi-Square distribution with 3 degrees of freedom at a significance level of 0.05 (7.81), we determined that the calculated statistic is smaller than the critical value. Consequently, we did not find sufficient evidence to reject the null hypothesis that Gender and age group are independent. Consequently, the dataset lacks sufficient information to indicate a substantial correlation between gender and age group. Based on this data, it can be concluded that gender and age group are independent features.

Table 3: Cross Tabulation of Gender and Education

Education	Gender: Female	Gender: Male
BA	2	4
BArch	0	1
BBA	1	2
BCom	1	1
Bed	1	0
BFA	1	0
BJMC	0	1
BPT	1	0
BSc	0	1
BTech	2	2
CA	0	1
Diploma	1	0
LLB	1	0
MA	3	3
MBA	7	5
MCom	0	1
MPhill	0	1
MS	1	2
MSc	1	0
PhD	0	0

Upon performing a Chi-Square test to investigate the correlation between gender and education level, we obtained a computed Chi-Square statistic of roughly 13.43. By comparing this number to the critical value derived from the Chi-Square distribution with 180 degrees of freedom at a significance level of 0.05, we found that the critical value is around 31.41. The p-value corresponding to our computed Chi-Square statistic is below 0.001. Given that our computed Chi-Square value (13.43) is smaller than the critical value (31.41), and the p-value is less than 0.001, we can conclude that we reject the null hypothesis, which states no correlation between education levels and gender groups. Substantial evidence in the dataset suggests a clear correlation between gender and education level.

Table 4: Cross Tabulation of Age and Education

Education	Age(years): 24-30	Age(years): 31-40	Age(years): 41-50	Age(years): 51-60
BA	3	3	0	0
BArch	0	0	0	1
BBA	0	1	1	1
BCom	0	1	1	0
BEd	0	0	1	0
BFA	0	1	0	0
BJMC	1	0	0	0
BPT	0	1	0	0
BSc	1	0	0	0
BTech	1	2	1	2
CA	0	0	1	0
Diploma	0	1	0	0
LLB	0	0	0	1
MA	0	2	1	1
MBA	3	6	4	3
MCom	0	1	0	0
MPhill	0	0	1	0
MS	0	0	0	1
MSc	0	0	0	1
PhD	0	0	1	0

The data was analyzed using a Chi-Square test to investigate the relationship between education level and age groups. The Chi-Square statistic was computed to be roughly 12.22. By comparing this number to the critical value derived from the Chi-Square distribution with 57 degrees of freedom at a significance level of 0.05, we found that the critical value is around 67.50. The p-value corresponding to our computed Chi-Square statistic is below 0.001. Given that our computed Chi-Square value (12.22) is smaller than the critical value (67.50), and the p-value is less than 0.001, we can conclude that we reject the null hypothesis. This suggests a strong correlation between education level and age groups in the dataset. Based on this data, it can be concluded that education level and age groups are not independent features.

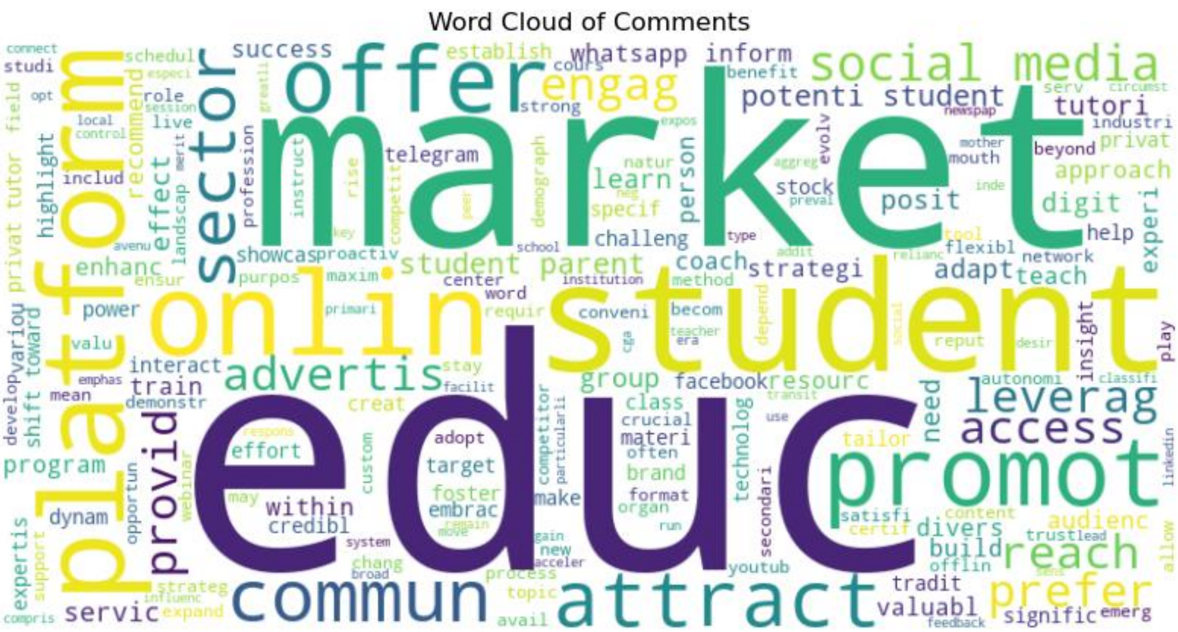

Fig 2: Word Cloud of Comments

Word cloud analysis visually summarizes textual data, making it useful in many fields. It organizes enormous amounts of text into attractive visuals using frequency-based word sizes. These visualizations help content analysis and interpretation by quickly revealing essential topics and keywords. Word clouds illustrate main ideas by emphasizing frequently recurring words, making textual material easier to interpret.

Word clouds give academics a visual picture of textual material for further investigation. They discover patterns, trends, and outliers for further study. Word clouds also effectively communicate important topics or concepts in presentations, reports, and educational materials. Their visual appeal aids comprehension.

Natural language processing and text mining depend on word clouds. Stop words and irrelevant terms can be identified to preprocess text data. Word clouds also help analyze data by visualizing text mining and sentiment analysis results. Word clouds also easily uncover reoccurring attitudes or opinions in open-ended surveys or feedback analysis. Quality feedback helps organizations prioritize improvement areas and gain actionable insights.

Word cloud analysis is a diverse and powerful way to summarize, visualize, and analyze textual data. It is essential for data analysis and interpretation in academia, research, corporate intelligence, marketing, and more.

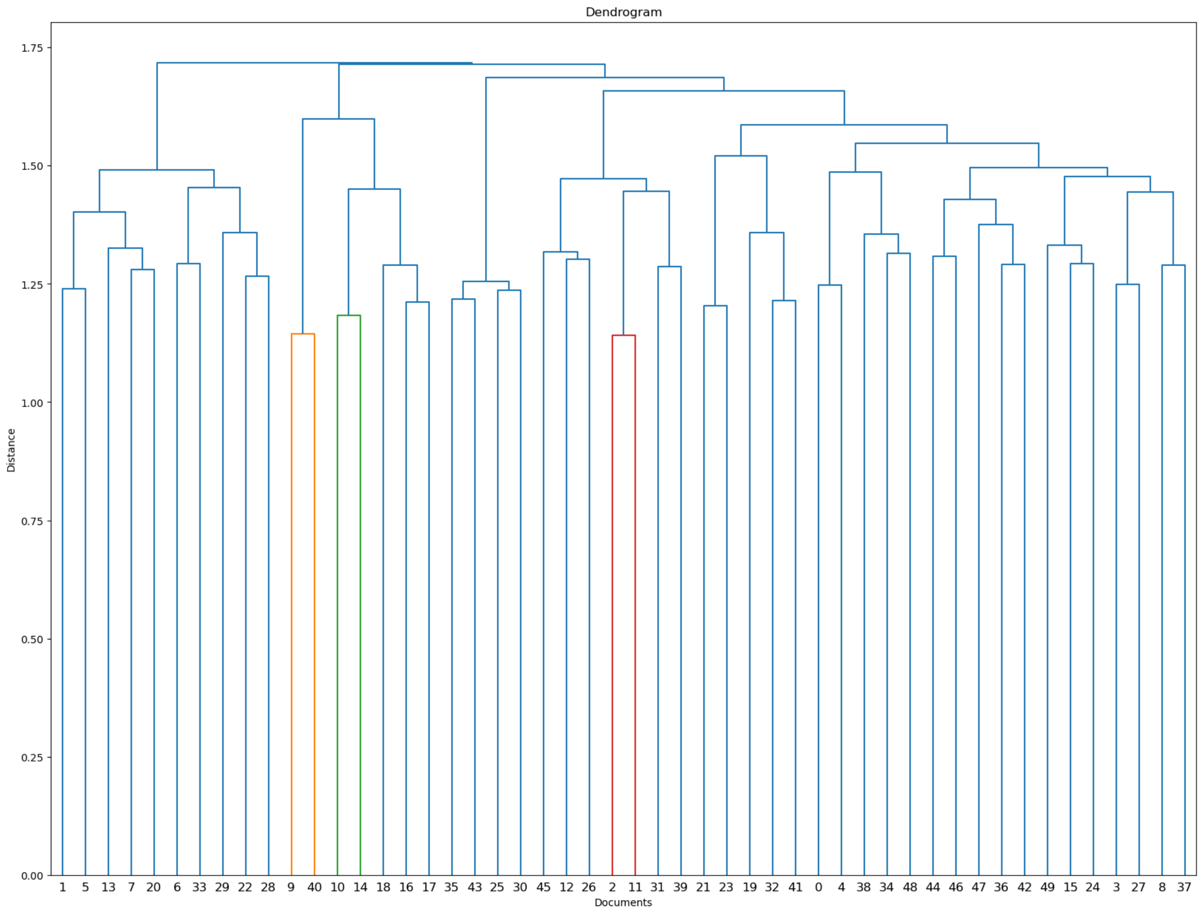

Fig 3: Dendogram of Comments

Figures, including dendrograms and cluster maps, demonstrate clear thematic clustering, reinforcing the study's findings.

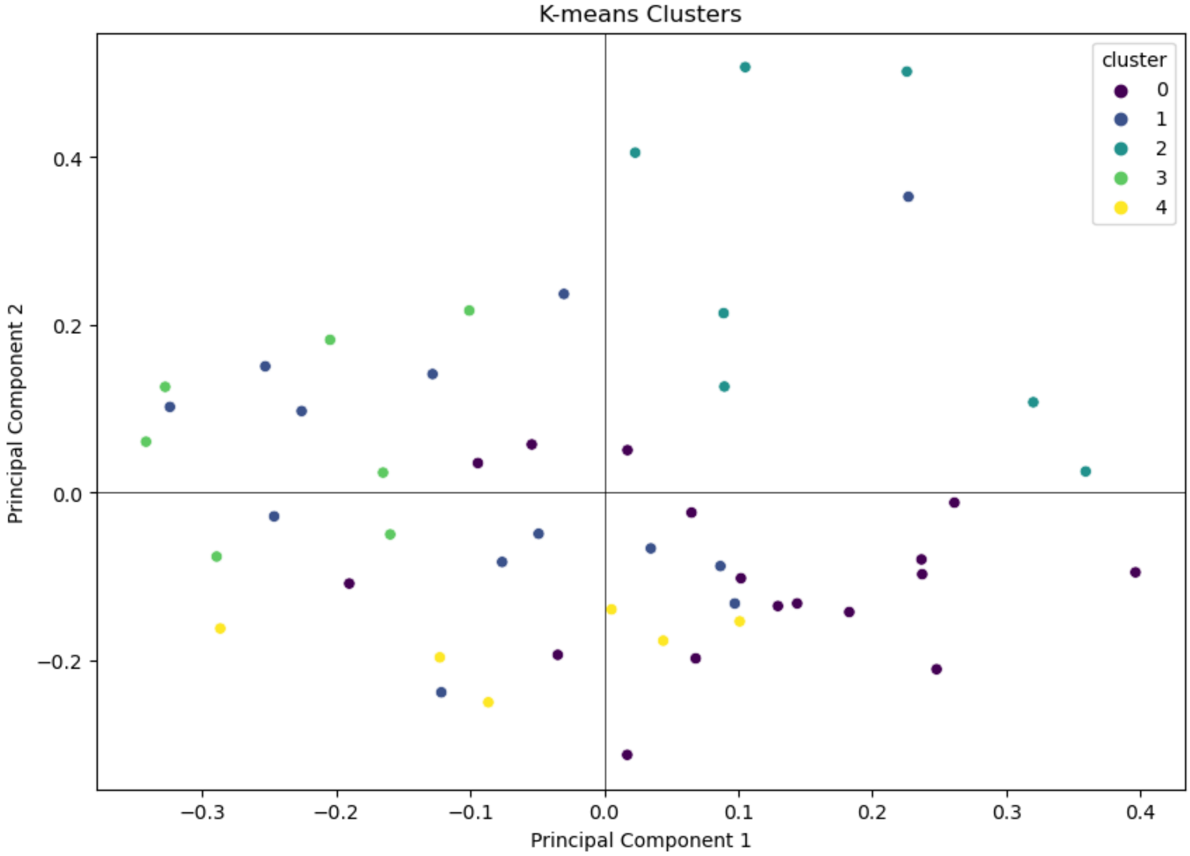

Fig 4: K-means Clusters

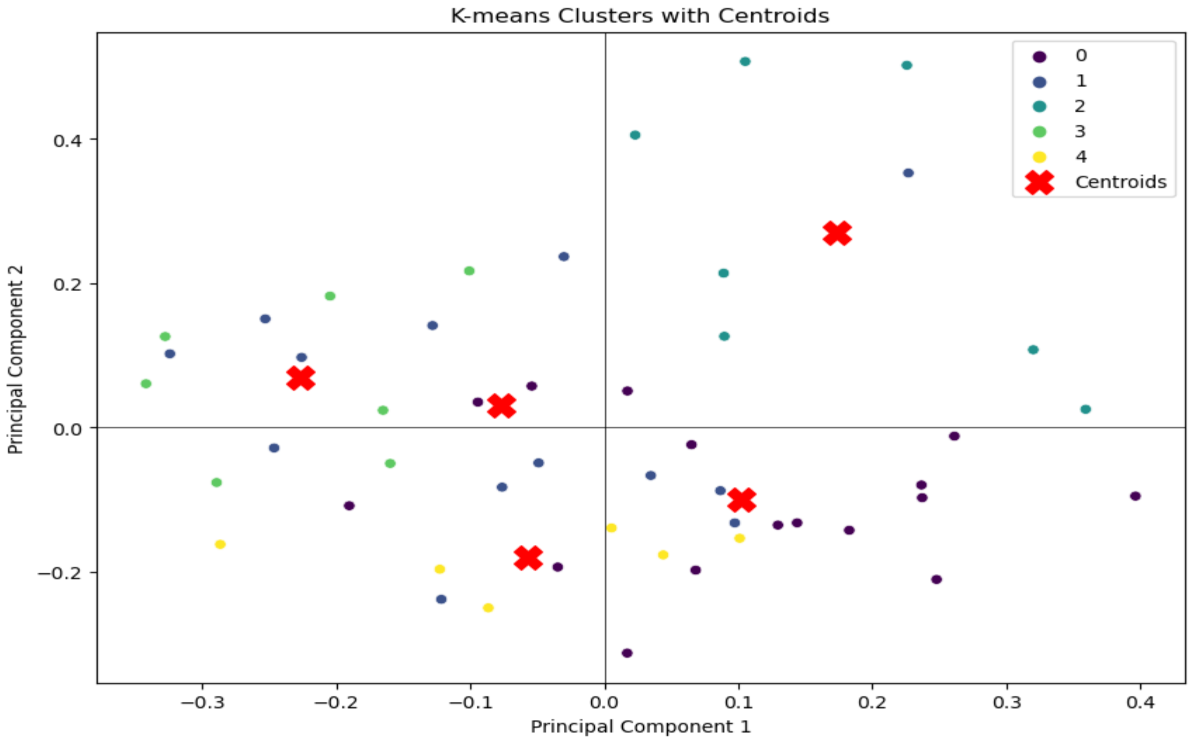

Fig 5: K-means Clusters with Centroid

To visualise data clustering and cluster central tendencies, a k-means clusters map containing centroids is essential. This method groups data points into k clusters based on their resemblance to each other and a centroid. Mapping clusters and centroids can reveal data structure and cluster characteristics.

Ultimately, a k-means clusters map with centroids helps visualise data clustering and core tendencies, explore and analyse data, evaluate clustering efficacy, and inform analysis and decision-making. Using the cluster map, researchers can find patterns and linkages in the data, improving their comprehension of the phenomena and decision-making.

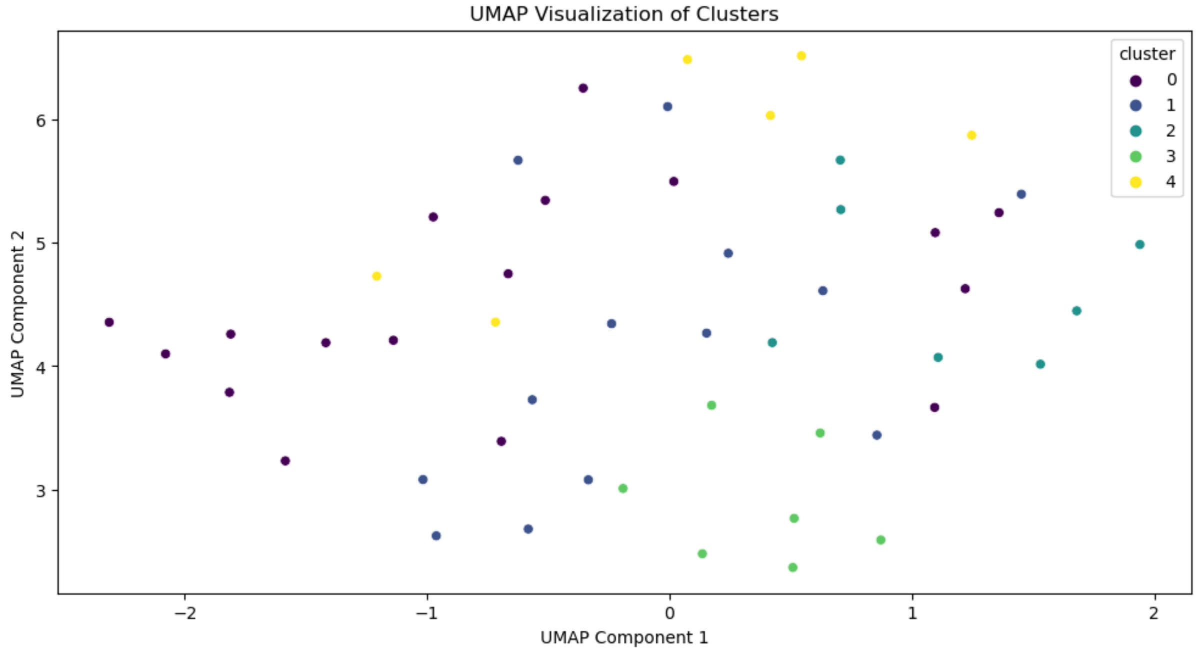

Fig 6: UMAP Visualization of Clusters

UMAP, which stands for Uniform Manifold Approximation and Projection, provides a robust method for visualizing clusters in high-dimensional data, allowing for practical exploration and comprehension. UMAP allows for the visualization of intricate data clusters more understandably by reducing the dimensionality of the data while maintaining the local and global structure. This visualization assists in discerning patterns, correlations, and groupings within the data, facilitating the exploration, analysis, and decision-making processes related to the data. In summary, the UMAP visualization technique offers researchers and practitioners a powerful tool to obtain a deep understanding of the fundamental organization of their data, enabling them to make well-informed decisions.

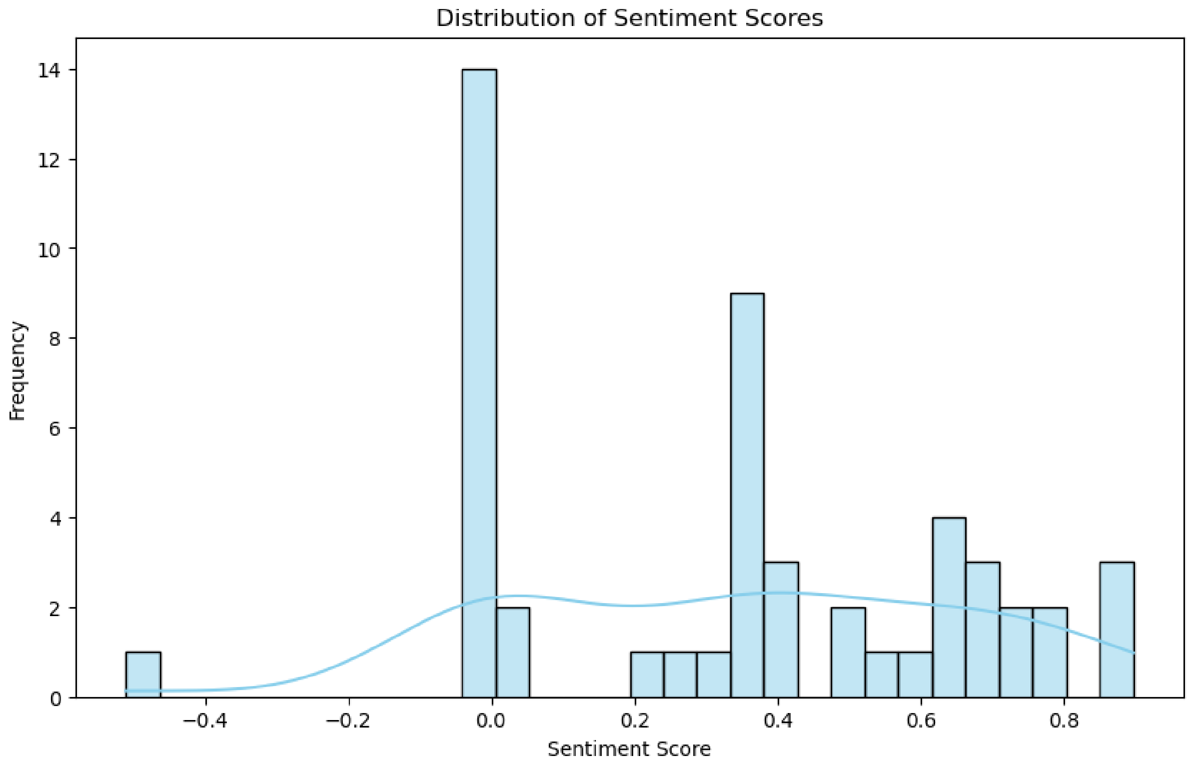

Fig 7: Distribution of Sentiment Scores

Representing sentiment analysis scores of comments provides a succinct and easy method to comprehend the overall sentiment conveyed in a dataset. By graphing sentiment scores chronologically or utilizing visualizations like bar charts or word clouds, stakeholders may readily comprehend trends, patterns, and anomalies in sentiment. This visualization facilitates the identification of essential themes, feelings, and areas of worry or satisfaction in the comments. It allows informed decision-making and focused actions to solve sentiment-related concerns or benefit from good feedback. In general, visualizing sentiment analysis scores improves comprehension and enables the extraction of practical insights from comment data.

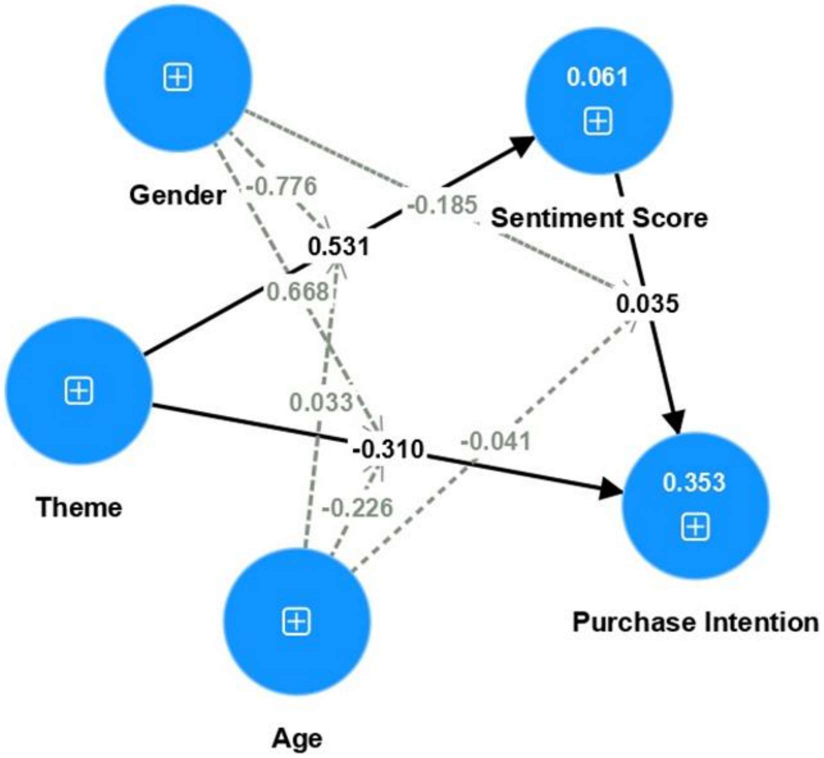

Fig 8: Structural Equation Modelling with Theme as Independent Factor, Purchase Intention as Dependent Factor, Sentiment Score as a Mediator along with two Moderators as Gender and Age

Table 5: Co linearity Statistics (VIF) -Inner Model List

Predictor	Dependent Variable	VIF
Age -> Purchase Intention	Purchase Intention	1.541
Age -> Sentiment Score	Sentiment Score	1.455
Gender -> Purchase Intention	Purchase Intention	1.817
Gender -> Sentiment Score	Sentiment Score	1.786
Sentiment Score -> Purchase Intention	Purchase Intention	2.146
Theme -> Purchase Intention	Purchase Intention	2.235
Theme -> Sentiment Score	Sentiment Score	2.081
Gender × Theme -> Purchase Intention	Purchase Intention	3.296
Gender × Theme -> Sentiment Score	Sentiment Score	3.149
Gender × Sentiment Score -> Purchase Intention	Purchase Intention	2.299
Age × Theme -> Purchase Intention	Purchase Intention	1.599
Age × Theme -> Sentiment Score	Sentiment Score	1.464
Age × Sentiment Score -> Purchase Intention	Purchase Intention	1.293

Table 6: F-Square List

Predictor	Dependent Variable	F-square
Age -> Purchase Intention	Purchase Intention	0.030
Age -> Sentiment Score	Sentiment Score	0.014
Gender -> Purchase Intention	Purchase Intention	0.240
Gender -> Sentiment Score	Sentiment Score	0.016
Sentiment Score -> Purchase Intention	Purchase Intention	0.005
Theme -> Purchase Intention	Purchase Intention	0.091
Theme -> Sentiment Score	Sentiment Score	0.034
Gender × Theme -> Purchase Intention	Purchase Intention	0.209
Gender × Theme -> Sentiment Score	Sentiment Score	0.035
Gender × Sentiment Score -> Purchase Intention	Purchase Intention	0.061
Age × Theme -> Purchase Intention	Purchase Intention	0.081
Age × Theme -> Sentiment Score	Sentiment Score	0.000
Age × Sentiment Score -> Purchase Intention	Purchase Intention	0.012

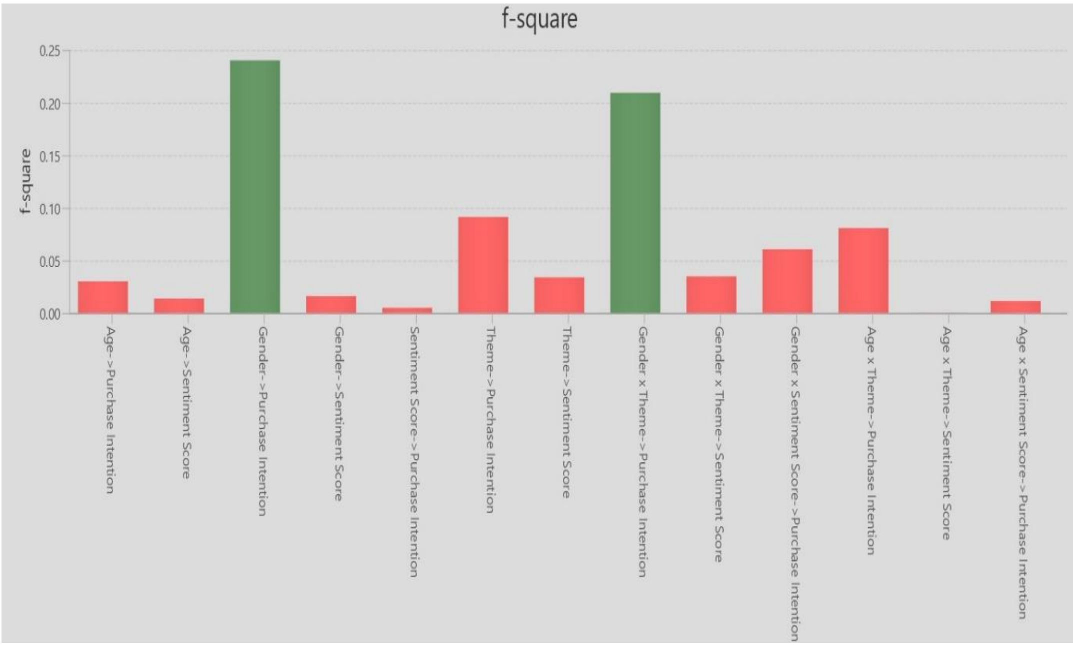

Fig 9: F-Square Bar Chart

Table 7: Indicator Data Correlation-Empirical Correlation Matrix

	Age	Gender	Purchase Intention	Sentiment Score	Theme	Age × Sentiment Score	Age × Theme	Gender × Theme	Gender × Sentiment Score
Age	1.000	-0.190	0.094	-0.145	-0.137	-0.070	0.539	-0.156	-0.119
Gender	-0.190	1.000	-0.210	0.053	0.219	-0.033	-0.135	0.599	0.044
Purchase Intention	0.094	-0.210	1.000	0.214	0.018	0.129	0.195	0.166	-0.233
Sentiment Score	-0.145	0.053	0.214	1.000	0.092	0.025	0.047	0.030	0.673
Theme	-0.137	0.219	0.018	0.092	1.000	0.063	-0.160	0.578	-0.285
Age × Sentiment Score	-0.070	-0.033	0.129	0.025	0.063	1.000	0.210	-0.228	-0.285
Age × Theme	0.539	-0.135	0.195	0.047	-0.160	0.210	1.000	-0.222	-0.158
Gender × Theme	-0.156	0.599	0.166	0.030	0.578	-0.228	-0.222	1.000	-0.065
Gender × Sentiment Score	-0.119	0.044	-0.233	0.673	-0.285	-0.285	-0.158	-0.065	1.000

Table 8: Model Fit

Model Fit Metric	Saturated Model	Estimated Model
SRMR	0.000	0.047
d_ULS	0.000	0.034
d_G	0.000	0.005
Chi-square	0.000	1.218
NFI	1.000	0.887

Examining the relationships between observable and latent variables in complex systems is fundamental to structural equation modelling (SEM), a powerful statistical method. Unlike traditional regression analysis, SEM enables researchers to simultaneously estimate numerous interrelated correlations among both observable and latent variables. Numerous disciplines employ it to evaluate hypotheses, investigate causal relationships, and assess theoretical models. These fields encompass marketing, sociology, economics, and psychology.

Simple element modelling (SEM) is predicated on two fundamental components: measurement models and structural models. The structural model delineates interactions among latent variables, whilst the measurement model articulates interactions between observable variables and their latent constructs. To acquire a more sophisticated understanding of complex events, researchers can employ this comprehensive method to examine variables' direct and indirect effects on one another through latent constructs.

Essential to structural equation modelling (SEM) is assessing model fit and determining if the specified model accurately represents the data. Model fit metrics such as chi-square (χ^2), Comparative Fit Index (CFI), Tucker-Lewis Index (TLI), Root Mean Square Error of Approximation (RMSEA), and Standardized Root Mean Square Residual (SRMR) are commonly utilized to evaluate the concordance between the proposed model and the actual data. A model is considered to fit the data well when the proposed correlations between variables accurately represent the actual patterns.

Accurate findings from SEM analysis can only be attained by attaining an adequate model fit. A poorly fitting model may indicate relationship misspecification, omitted variables, or measurement errors due to biased parameter estimations and erroneous conclusions. Researchers often make iterative revisions to their models to get an optimal fit, including altering routes, adding or eliminating variables, or refining measurement models.

In conclusion, Structural Equation Modelling is a versatile analytical instrument for exploring complex variable interactions. By verifying that the selected SEM adequately aligns with the data, researchers can be confident in the accuracy of their conclusions and get insight into the underlying structure of the phenomena.

Findings

Qualitative findings offer a comprehensive insight into how individuals evaluate Perceived Usefulness and its correlation with Purchase Intention, highlighting the necessity of addressing perceived advantages and alleviating perceived risks in marketing tactics.

Qualitative analysis is essential for examining concepts such as Perceived Usefulness (PU) and its correlation with Perceived Intention (PI). It enables researchers to reveal fundamental motivations, beliefs, and attitudes that can guide marketing tactics and product development initiatives.

This is a tabular depiction of the themes and their importance derived from the given text:

Table 9: Analysis of Themes

Theme	Significance
Theme 1: Internet Experience	- All respondents are internet users, and their internet experience is crucial for the study. Internet usage varies for different purposes, including information, entertainment, and work. Understanding levels of expertise, time spent online, and the importance of using the internet are essential for studying behavioural intentions, such as Purchase Intention.
Theme 2: Perceived Usefulness	- User's perception regarding the usefulness of purchasing via C2C (Customer-to-Customer) sites is a critical study factor. Sub-themes highlight different aspects of perceived usefulness: Theme 2.1: Shopping via C2C sites makes it easier to compare products, providing more choices and convenience in product selection. Theme 2.2: Shopping via C2C sites offers access to helpful shopping information, although conveying quality online can be challenging for sellers. Theme 2.3: Shopping via C2C sites is seen as a time-saving option, with the ability to browse and purchase products quickly. Perceived usefulness plays a significant role in shaping Purchase Intention, as it influences factors such as product comparison, access to information, and time-saving aspects in online shopping.

Table 10: Comparative Analysis of Existing Research and Present Research

Year	Existing Research	Present Research	Comparative Analysis
2007	Investigated the moderating effects of experience on the influence of perceived usefulness (PU) in online shopping contexts, indicating that PU may have varying impacts on different customer segments based on their familiarity with the technology.	Explored the role of demographic factors, such as age and education, in influencing purchase intention in online retail.	Future studies could examine how experience influences the perception of PU over time and its implications for designing personalized online shopping experiences.
2011	Highlighted the prevalence of online product research among consumers, leading to high shopping cart abandonment rates in offline purchases, suggesting the importance of seamless integration between online and offline retail channels.	Pointed out the cost advantages of online retailers compared to traditional brick-and-mortar stores.	Research could explore specific cost structures that contribute to online retailers' advantages.
2012	Pointed out the cost advantages of online retailers compared to traditional brick-and-mortar stores.	Explored social media marketing's impact on brand perception and consumer engagement.	Further studies could delve into effective social media strategies in online retail.
2013	Explored the role of social media marketing in enhancing consumer engagement and reducing information search efforts, highlighting its impact on brand-related content consumption and purchase behaviour.	Investigated the influence of user-generated content (UGC) on online shopping behaviour.	Future research could explore optimal strategies for delivering personalized content on social media platforms to maximize consumer engagement and satisfaction.
2017	Highlighted the significance of sensory experiences, particularly through images, in online consumer perceptions and purchase intentions, indicating the role of visual stimuli in shaping online shopping behaviour.	Stressed the value of reward schemes for online shoppers.	Further research could explore innovative sensory strategies in online retail.
2018	Investigated the influence of personalized product recommendations on online purchase behaviour.	Explored the influence of user-generated content (UGC) on online shopping behaviour.	Examine different personalized recommendation algorithms in various online retail environments.
2019	Explored the role of augmented reality (AR) in enhancing online shopping experiences and purchase decisions.	Investigated the differential impact of perceived usefulness (PU) on first-time and repeat online customers.	Research could examine AR adoption in online retail and its impact on purchase intentions.
2020	Examined the effects of influencer marketing on consumer behaviour in online retail environments.	Explored the influence of user-generated content (UGC) on online shopping behaviour.	Investigate influencer marketing's effectiveness and impact on consumer attitudes and brand perception.
2021	Investigated the impact of sustainability initiatives on consumer purchasing behaviour in online retail.	Explored the influence of user-generated content (UGC) on online shopping behaviour.	Examine consumer attitudes towards sustainability in online retail and its influence on purchase decisions and brand loyalty.

In 2007, researchers conducted a study to examine how experience affects the perceived usefulness (PU) of online purchasing. PU may vary among different client segments based on their degree of technological familiarity. The present study, conducted in the same year, investigated the influence of demographic factors, including age and education, on purchase intention within the online retail sector. Future research should examine how experience evolves over time, influencing the notion of perceived usefulness and facilitating the development of customized online purchasing experiences.

In 2011, there was an emphasis on the prevalent practice of online product research, leading to many individuals abandoning their shopping carts during in-store transactions. This highlighted the necessity for seamless connectivity between online and offline retail systems. The research emphasized the cost advantages of Internet retailers relative to conventional brick-and-mortar stores. A proposal was put out to undertake additional research to examine the distinctive cost structures confer advantages to internet retailers.

In 2012, the significance of cost advantages for online retailers relative to conventional shopfronts was reiterated. The study also investigated the impact of social media marketing on customer brand perception and engagement. Further research on effective social media strategies in online retail is recommended to promote customer engagement and elevate brand perception.

In 2013, a study examined the effects of social media marketing on enhancing consumer engagement and reducing the necessity for information retrieval. Concurrently, it studied the influence of user-generated content (UGC) on online purchasing behaviour. Future research initiatives are recommended to explore the most successful strategies for distributing tailored content on social media platforms to enhance consumer engagement and satisfaction.

The significance of sensory experiences, mainly through visual representations, in shaping online consumer perceptions and buying intentions was highlighted in 2017. Nevertheless, a recent study underlined the need for incentive packages for consumers who make purchases online. It was proposed that further research be undertaken to develop innovative sensory stimulation techniques in online shopping to enhance consumer engagement and impact their purchasing decisions.

A 2018 study investigated the influence of customized product recommendations on online purchasing behaviours. Additionally, it studied the impact of user-generated content (UGC) on consumer behaviour during online buying. Further research is advised to explore various personalized recommendation algorithms across online retail environments to improve customer pleasure and optimize purchasing decisions.

In 2019, a study examined the influence of augmented reality (AR) on enhancing online shopping experiences. The research investigated the differential impact of perceived usefulness (PU) on first-time versus returning internet consumers. Future research should examine the application of augmented reality (AR) in online shopping and its influence on consumers' purchasing intentions. The objective is to augment user experience and refine decision-making around product purchases.

The study undertaken in 2020 and 2021 investigated the effects of influencer marketing and sustainability efforts on consumer behaviour in online retail environments. Concurrent enquiries were made to assess the influence of user-generated content (UGC) on online purchasing behaviour. Further inquiry was advised to examine the effectiveness of influencer marketing and its impact on customer attitudes, purchasing decisions, and brand perception. Moreover, it is essential to analyze consumer perceptions of sustainability in online shopping and its impact on purchase choices and brand allegiance.

In the realm of online purchasing via Customer-to-Customer (C2C) platforms, qualitative research serves as a gateway to a comprehensive exploration of consumer perceptions and behaviours, specifically concerning the relationship between Perceived Usefulness (PU) and Purchase Intention (PI). This analytical exploration uncovers various themes and subthemes, each offering a refined lens to examine the intricacies of consumer decision-making processes.

The initial step is navigating the Internet Experience, where we will dissect the intricate network of digital interactions the respondents encounter. Throughout our stay, we encounter diverse activities, encompassing professional obligations, recreational pursuits, and information-seeking endeavours. The internet influences individuals' purchasing habits and attitudes in various ways, seen in actions that showcase its diverse utility and multifaceted roles in people's lives. Several compelling subthemes warrant further exploration, including the flexible nature of internet usage during particular life events, such as illness, and the varied influence of demographic characteristics on platform selection.

Researchers are commencing an exploration of consumer psychology as it traverses the digital economy. This marks the transition to the examination of perceived usefulness. The ease of product comparison, the accessibility of valuable purchasing information, and the time-saving attributes of online transactions are prominent aspects of this issue. Besides offering insights into consumer decision-making processes, these themes encapsulate the global factors that shape consumer perceptions and behaviours. Factors significantly affecting client intentions include the simplicity of online product comparisons and the abundance of information accessible via digital platforms. These aspects influence customers' decisions on consumer-to-consumer interactions, contingent upon their views of utility and convenience.

Researchers explore the intricacies of subthemes related to perceived usefulness. Each subtheme offers a unique perspective on customer perception and behaviour. The intricate relationship between perceived usefulness and consumer decision-making processes is underscored by aspects such as the comparative advantage of online platforms in facilitating product comparisons and the limitations of online information transmission regarding product quality. This analysis elucidates the evolving dynamics of consumer contacts in the digital era, highlighting the significance of instant communication platforms such as WhatsApp in streamlining transactions and enhancing perceived utility.

The qualitative investigation reveals a comprehensive understanding of the intricacies inherent in consumer decision-making processes within the digital economy.

A thorough understanding of the factors that shape consumers' perceptions of utility and subsequent behaviours can be achieved by examining the emerging themes and subthemes. In an increasingly competitive economy, businesses can maintain their relevance and profitability by adapting their marketing tactics and product offerings to align with customers' evolving needs and preferences. Equipped with this knowledge, enterprises can adjust their marketing strategy and product offerings.

DISCUSSION

The research results reveal important information about how consumer behaviour patterns in online C2C marketplaces continue to change especially in the educational field. The research identified that perceived usefulness (PU) played a vital role in determining purchase intention (PI) among consumers. The respondents strongly suggested that their willingness to make online learning transactions was significantly related to how they perceived the usefulness of the C2C platform regarding comparison, furnishing appropriate information, and saving time. This provides support to the applicability of the Technology Acceptance Model (TAM), in which PU and Perceived Ease of Use (PEOU) are significant drivers for technology adoption. Notably, these findings provide a rationale for the applicability of educational sites in giving prominence to aspects that provide functional utility and time-saving in order to ensure maximum user retention and conversions.

The study highlighted how important user-generated content (UGC) is for influencing consumer choices. Reviews, peer endorsements, and ratings work as strong social proof tools that build trust and confirm the quality of courses and institutions. This supports Cialdini's (1984) theory of social influence and shows that trust, developed through real user experiences, is key to engagement in C2C settings. Therefore, educational institutions need to invest in strategies for managing their reputation. They should promote positive user stories and quickly deal with negative feedback. UGC not only sways new learners but also provides ongoing feedback for institutions to spot gaps, innovate, and improve their offerings.

The demographic analysis showed that age and education level heavily influences how people view usefulness and their intent to buy. These points to a need for personalized marketing and content strategies. Although gender and age were statistically independent, their combined effects in the structural model suggest that personalized experiences should consider these differences. Additionally, qualitative responses revealed different internet usage habits. Younger users tend to focus on discovery and social comparison, while older users prioritize convenience and credibility. This highlights the need for C2C educational platforms to embrace user-centred design that addresses varying digital literacy levels and motivations.

The use of sentiment analysis, thematic clustering, and SEM modeling helped us understand how emotional responses and content themes affect purchase decisions. Positive sentiment was closely linked to higher purchase intention, especially when trust and perceived platform usefulness were involved. Therefore, institutions need to keep an eye on emotional signals in user-generated content to change their content strategies and communication style. Clustering methods like K-means and UMAP revealed patterns in learner discussions. These patterns can be used to develop predictive marketing campaigns and models for community engagement.

CONCLUSION

This study explored the relationship between perceived usefulness (PU), user-generated content (UGC), and purchase intention (PI) in online C2C marketplaces, particularly in the education sector. The findings show that PU is an important factor in consumer behavior. It is influenced by aspects like product comparison, access to information, and time efficiency. The study confirms that trust, which comes from UGC like reviews and endorsements, is key in guiding consumer choices as it serves as social proof. Demographic factors, especially education and age, also shape consumer views and indicate the need for tailored digital experiences. Using qualitative thematic analysis, sentiment analysis, and structural equation modeling (SEM), the research gives a detailed understanding of how emotional tone and content relevance influence consumer intentions. These insights validate theoretical frameworks like the Technology Acceptance Model (TAM) and Theory of Planned Behavior (TPB), and provide practical recommendations for educational institutions in C2C marketplaces. Institutions that focus on transparency, building trust, personalized engagement, and ongoing feedback can greatly improve learner satisfaction, create brand loyalty, and maintain a competitive edge in the changing digital education landscape.

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