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A Quantitative Study Examining the Determinants of Online Purchasing Behaviour: A Case of Generation Z in Australia

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ABSTRACT: The proliferation of digital technologies and easy internet access has fundamentally transformed online retail, giving rise to global expansion of e-commerce. Generation Z, a cohort distinguished by advanced digital literacy and extensive engagement with online platforms, is considered as a critical market segment by online retailers. Despite the prominence of Generation Z in shaping digital consumption, studies examining the determinants of their online purchasing behaviour in the Australian context remains sparse. This study adopts an exploratory quantitative approach to identify latent constructs influencing Generation Z's online shopping decisions. Data was obtained utilizing convenience sampling strategy through a self-administered online survey of 62 Generation Z consumers aged 19 to 29 years. Exploratory Factor Analysis using Principal Axis Factoring and Varimax rotation revealed six underlying dimensions influencing online buying behaviour of Generation Z in Australia. The identified factors are Inflation, Perceived Value & Convenience, Artificial Intelligence, Perceived Risk, Corporate Social Responsibility and Sustainability. Inflation emerged as the most salient determinant, indicating economic concerns as the topmost priority for Generation Z while shopping online. Artificial Intelligence and Perceived Risk also had notable influence, indicating the influence of both technology and security motivators when shopping online. In addition, the results show that for Generation Z, ethical considerations are important but less influential in shaping immediate online buying decisions. These findings suggest that Generation Z's buying behaviour is shaped by a blend of pragmatic, technological, and value-driven factors and hence this study reveals Generation Z's complex behaviour with online shopping. The findings offer practical insights for e-commerce businesses and digital marketers in Australia, enabling more targeted and ethically aligned engagement strategies. Results need cautious interpretation as small sample size and convenience sampling may affect the generalizability.

KEYWORDS: Generation Z, online shopping, exploratory factor analysis, consumer behaviour, e-commerce, Australia

1. INTRODUCTION

The proliferation and continuous innovation in digital technologies and the widespread accessibility of internet have reshaped the global retail landscape with unprecedented adoption of e-commerce. Online retailing has become a defining feature of contemporary consumption, reshaping how individuals search for information, evaluate alternatives, and make purchasing decisions. Advances in mobile technology, platform ecosystems, and data driven personalization have transformed online shopping from a functional transaction into a socially embedded, experience driven activity. The convenience, speed, and accessibility offered by e-commerce platforms have significantly altered the traditional in-store retail experience of customers who now are increasingly adopting digital channels to make purchases (Alwiyah et al., 2024).

E-commerce in Australia has seen substantial growth over the past decade, driven by increasing internet penetration, evolving consumer preferences, and improvements in digital infrastructure. According to Australia Post report (Australian Post, 2025), 9.8 million households shopped online in 2024 spending more than AUD 69 billion online. This shift reflects a change in consumer behaviour, with e-commerce now a permanent component of Australia's retail landscape. Among the most prominent drivers of this digital transformation in Australia is Generation Z (Gen Z), a cohort of consumers noted for their distinguished digital fluency, frequent interaction with social media, a clear inclination toward personalized consumption experiences and a strong sensitivity to social and environmental issues. Gen Z generally distinguishes themselves from previous generations such as generation X and generation Y especially in terms of values, attitudes, and behaviours. According to 2021 Australian census data, 18.4% of the populations are Gen Z (Australian Bureau of Statistics, 2026) and this number is expected to increase in coming years. Gen Z spent 11.9 billion AUD shopping online in 2024, making a 5.5% increase compared to the previous year (Australia Post, 2025). As Gen Z are exposed to an unprecedented amount of technology during childhood and adolescent, they are very comfortable with maneuvering varying digital environments and engaging with new online applications. They are the potential market segment for online shopping. Generation Z consumers are deeply embedded in digital ecosystems, interacting with brands through social media, mobile applications, peer networks, and algorithmic interfaces on a daily basis. Their online purchasing behaviour is therefore not merely a reflection of technological adoption but a manifestation of broader social, psychological, and cultural dynamics shaping digital consumption. Therefore, it is utmost important to understand consumer behaviour of such potential market segment and the factors affecting their online buying decisions.

While there is a consensus among researchers regarding the categorization of generational cohort into five categories, there still exists inconsistency when defining the birth year range for Gen Z. For instance, Laitkep & Repkova Stofkova (2021) defined Gen Z as those who are born between 1994 to 2004. Whereas Salguero et al., (2024) considered 1995 to 2010 as the birth year for Gen Z. In the context of present research, people who are born between the year 1996 and 2010 are considered as Gen Z. This definition of generation Z aligns with the definition provided by Australia Bureau of Statistics (2026) and is considered appropriate for the present study.

Consumer behaviour is a well-established field with roots in psychology, economics, and sociology. Behavioural theories and technology acceptance models, including the Theory of Planned Behaviour (Ajzen, 1991), the Theory of Reasoned Action (Fishbein & Ajzen, 1975), and Technology Acceptance Model (Davis, 1986; Venkatesh et al., 2022; Venkatesh & Bala, 2008; Venkatesh & Davis, 1996) have been extensively used to understand factors affecting online buying behaviour of consumers. Among the factors, attitude, convenience and accessibility are frequently cited as primary motivators for digital purchases (Lina et al., 2022; Zhang, 2024). In addtion, trust and perceived risk specifically in relation to data privacy, transaction security, and product quality have also been identified as primary motivators affecting online buying decision (Bisnis et al., 2025; Mulyani et al., 2019). More recently, sustainability and corporate social responsibility (CSR) have emerged as a pivotal factor influencing the online shopping behaviour of Gen Z, a cohort that demonstrates heightened environmental and social consciousness compared to previous generations (such as Gen X, Gen Y). Similarly, artificial intelligence (AI) is also reshaping the landscape of online retail, enabling unprecedented levels of personalization, interactivity, and automation in consumer experiences (Guerra-Tamez et al., 2024). For tech-savvy generations such as Gen Z, AI plays a significant role in influencing online shopping behaviour. Personalization enhances the shopping experience by reducing search effort, increasing perceived relevance, and improving convenience. More recently, economic conditions, particularly inflation, have also impacted consumer shopping behaviour, including online shopping practices. One of the direct impacts of inflation is on cost of living and purchasing power. This will have direct impact on volumes of purchases made, delay in non-essential purchases, or shift towards substitutes of lower quality and price. The impact of these factors on online buying behaviour of Gen Z in Australian context is not fully known. Furthermore, most studies carried out to investigate online consumer behaviour (c.f. Catană et al., 2025; Gajdzik et al., 2024; Shetu, 2025) have relied on hypothesis based confirmatory approach using existing consumer behaviour theories and technology acceptance models. These frameworks have provided robust explanations of how factors such as attitudes, subjective norms, perceived usefulness, and perceived ease of use influence behavioural intentions in online contexts. However, these models were largely developed in earlier phases of digital commerce, when online shopping was novel, transactional, and relatively detached from social identity and everyday digital life. For Gen Z consumers who have never experienced a world without the internet, online shopping is not an innovation to be adopted but socially mediated practice intertwined with self-expression, peer validation, and ethical considerations. The methodological approach adopted in such studies is mainly dominated by theory driven, confirmatory designs, primarily using structural equation modelling and regression analysis. While these approaches offer statistical robustness, they presuppose the relevance and completeness of selected constructs. As a result, they risk reinforcing existing theoretical boundaries rather than uncovering new or context specific dimensions of behaviours suitable to capture the subtle and context sensitive factors in a rapidly evolving world, more so, in the context of a dynamic group such as Gen Z. Moreover, studies focused on Australian context remain scarce.

The current state of the literature does not fully correspond to the aims of identifying, ranking, and understanding Gen Z’s perceived influencing factors in online shopping, particularly within the Australian context. Most studies focus on whether specific variables matter, rather than how they cluster, interact, or are prioritized by consumers themselves. The dominance of confirmatory methodologies further constrains theoretical development by limiting the discovery of emergent dimensions. This study responds to these gaps and adopted exploratory quantitative approach to investigate factors influencing online shopping behaviour of Gen Z in Australia. By allowing factors to emerge empirically, the research provides a more integrated and context sensitive understanding of Gen Z’s online shopping behaviour. In doing so, it not only complements existing theory driven research but also lays the groundwork for more refined conceptual models and targeted empirical testing in future studies. The subsequent section describes the methods adopted in the present study and presents the results of exploratory factor analysis (EFA).

2. METHODS

The methodology adopted in the present study to empirically examine latent factors affecting Gen Z online buying behaviour was quantitative methodology. The methodological approach employed in the current research was guided by the framework of Research

Onion (Saunders et al., 2023) . The Research Onion provides a structured framework for designing and articulating the various stages of research starting from philosophical assumptions to data collection and analysis.

2.1. Participants and Instruments for Data Collection

Data was collected using convenience sampling through a self-administered survey from a target population of Gen Z aged 19 and above and living in Australia at the time of the study. Convenience sampling is very common in behavioural and social sciences research when the primary objective is exploratory or when access to a full sampling frame is impractical. The rationale for using convenience sampling in this study was twofold. First, the research focused on Gen Z with experience in online shopping, and convenience sampling facilitated quick access to Gen Z through digital platforms. Selection of participants through convenience sampling based on accessibility has also been noted by Emma et al. (2022). Second, the study was conducted within time and resource constraints, making probability sampling methods such as random or stratified sampling less feasible. Such practicality associated with probability sampling made convenience sampling more suitable to gather data quickly at a low cost when research is subjected to constraints such as time and budget. Furthermore, convenience sampling is often used in online consumer behaviour research, where digital engagement itself can serve as a contextual filter for inclusion.

2.2. Survey Administration

The survey was administered online in Microsoft Teams platform. The research data was collected using web-based online questionnaires. The web-based online questionnaire allows respondents to answer survey questions anonymously without any social pressure and thus is considered suitable to minimize the condition for social desirable bias. There are various advantages associated with online data collection approach. The web-based survey is cost effective, time efficient, and less prone to data error than other modes of survey such as telephone or mailed questionnaire which largely requires manual data entry (Khanal & Royhan, 2025). Before data collection, ethics approval was obtained from Education Center of Australian, Human Research Ethics Committee. A pilot was conducted prior to the main data collection to assess the clarity, reliability, and overall usability of the survey instrument. The pilot study involved 15 participants selected from the target population. During the data collection, first informed consent was obtained electronically from the participants. Ethical issues such as privacy, confidentiality, right to withdraw or omission of items were addressed through the proper setting of the online survey administration tool. The survey was designed under two sections. Section A consisted of five demographic questions. Whereas second section consisted of twenty-nine questions designed to solicit information on online buying behaviour of Gen Z living in Australia The questionnaire consisted of items measured on a five-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree).

2.3. Data Analysis

Survey responses were electronically recorded in spreadsheet format in Microsoft Forms, as a result errors often encountered in manual data entry were avoided. Spreadsheet data was separately downloaded and prior to the analysis, data were screened for completeness, accuracy, and suitability for exploratory factor analysis. Cases with invalid responses (less than 1%) were excluded to ensure data integrity and missing variables within the survey items were handled through median imputation. Sixty-two (62) valid responses were used for final data analysis using an open-source statistical analysis software Jamovi (Jamovi, 2024).

3. RESULTS

The subsequent sections present results of the EFA carried out using the Jamovi (version 2.6.44).

3.1. Reliability and Sample Adequacy

Since this study employed a non-probability sampling strategy, traditional probabilistic sample size calculations were not applicable. Instead, the suitability of sample size was determined based on established methodological guidelines for exploratory factor analysis. While a sample size of 62 is modest, Costelllo and Osborne (2005) reported that EFA can yield reliable results with samples under 100 with high factor loading. In addition, sample size of 50 is reported as reasonable absolute minimum for EFA (de Winter et al., 2009). Furthermore, Hair et al., (2018) recommends factor loadings of 0.50 or greater for small to moderate sample sizes to be practically significant. Moreover, Fabrigar et al., (1999) recommend using higher loading cutoffs in small samples to reduce the risk of retaining spurious or unstable factor structures. They argue that strong loadings increase the likelihoods that the factor pattern is not a product of sampling error. Therefore, with sample size of 62 and factor loading cutoff of 0.5, this study addressed the concerns related to sample size limitation and ensured that only strong, theoretically meaningful, and statistically robust relationships between items and factors were retained. In addition, the acceptable Kaiser- Meyer-Olkin (KMO) measure, significant Bartlett's test of sphericity, and high communalities further support the adequacy of sample size for EFA. Table 1 presents the results of reliability test and test of sample adequacy for EFA performed on questionnaire items.

Table 1: Measures of Reliability and Adequacy of Data for EFA

Measure	Value
Cronbach's α	0.859
McDonald's ω	0.864
Bartlett's Test of Sphericity	χ^2 (300) = 903, p< .01
Kaiser-Meyer-Olkin Measure of Sample Adequacy (KMO)	0.667

It is evident from Table 1 that the Bartlett's Test of Sphericity produced a chi-square value of χ^2 (300) = 903 with p< .01, suggesting that the observed correlations between items were statistically significant. This result indicates that the variables are sufficiently correlated to justify the application of EFA. Also, the result of Table 1 shows the KMO value of 0.667, suggesting that the sample was adequate for conducting EFA as per Hair et al. (2018). This result supports the factorability of the correlation matrix and indicates that the patterns of correlations are compact enough to produce distinct and reliable factors. These tests confirmed that the sample size of N = 62 was adequate for EFA and was factorable and appropriate for uncovering the latent constructs. It is also evident from the result of Table 1 that the high value of reliability measure was obtained for the survey items. The Cronbach's alpha of 0.859 and McDonald's omega of 0.864, both of which exceed the recommended threshold of 0.70 (Hair et al., 2018), indicating a high level of internal consistency among the items in the scale. This suggests that the items are reliably measuring the same underlying construct. These preliminary test values validated that distinct and reliable underlying factors could be generated from the data obtained in the survey.

3.2. Factor Extraction and Factor Rotation

Principal Axis Factoring (PAF) was employed as the method of factor extraction in the EFA. PAF is a commonly used technique that aims to identify the underlying latent constructs by analyzing the shared variance (common variance) among observed variables. PAF focuses solely on the variance that is shared among variables, making it more suitable for identifying latent factors from the observed variables. The decision to use PAF was based on both theoretical and methodological considerations. The goal of the analysis was to uncover the underlying behavioural constructs measured by the survey items, where measurement error and unique variance were not of primary interest. With PAF as an extraction method and Kaiser criterion of eigenvalue > 1, 6 latent factors were extracted. The suitability of retaining the six factors was confirmed by the Cattell's scree plot (Cattell, 1966), which is shown in Figure 1. In Figure1, the point just before the inflexion (shown by the arrow), often referred to as the elbow, is considered as the optimal number of factors to retain.

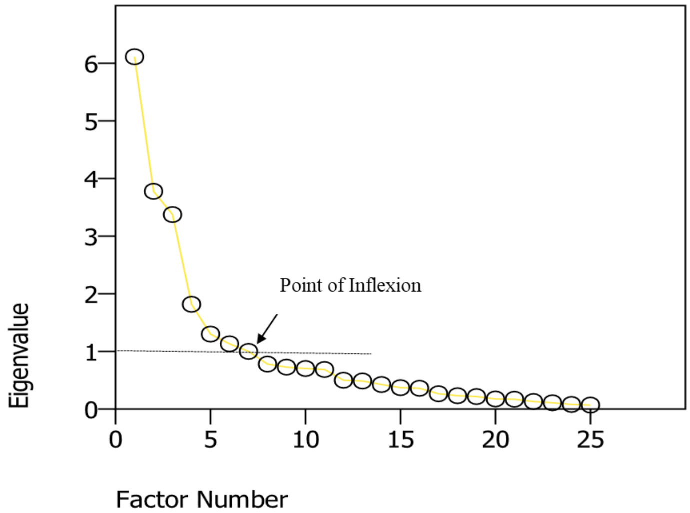

Figure 1: Cattell Scree Plot

To understand the variance accounted by extracted six factors, total variance extracted is computed. Table 2 shows the total variance explained by six extracted factors.

Table 2: Total variance explained by six extracted factors

	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance-	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	6.11	24.5%	24.5%	5.78	23.1%	23.1%	3.81	15.3%	15.3%
2	3.78	15.1%	39.6%	3.35	13.4%	36.5%	3.26	13.0%	28.3%
3	3.37	13.5%	53.1%	2.98	11.9%	48.5%	2.69	10.8%	39.1%
4	1.82	7.3%	60.3%	1.46	5.8%	54.3%	1.68	6.7%	45.8%
5	1.30	5.2%	65.5%	.91	3.7%	57.9%	2.06	8.2%	54.0%
6	1.13	4.5%	70.1%	.76	3.0%	61.0%	1.74	7.0%	61.0%
7	1.00	4.0%	74.1%						
8	.78	3.1%	77.2%						
9	.73	2.9%	80.1%						
10	.70	2.8%	82.9%						
11	.69	2.7%	85.6%						
12	.50	2.0%	87.6%						
13	.49	1.9%	89.6%						
14	.43	1.7%	91.3%						
15	.37	1.5%	92.8%						
16	.36	1.4%	94.2%						
17	.27	1.1%	95.3%						
18	.23	.9%	96.2%						
19	.22	.9%	97.1%						
20	.17	.7%	97.8%						
21	.17	.7%	98.4%						
22	.13	.5%	99.0%						
23	.11	.4%	99.4%						
24	.08	.3%	99.7%						
25	.07	.3%	100.0%						

It is seen in Table 2 that 61% of the total variance in the dataset is accounted for by six extracted factors. This indicates that the majority of the variability in the measured variables can be explained by these six underlying latent constructs, and this is considered acceptable in behavioural and social science research (Hair, L.D.S. Gabriel, et al., 2019). The remaining unexplained variance may be attributed to unique variance or measurement error, which is expected in real-world data.

Following the factor extraction, Varimax rotation method was applied to simplify the factor loadings to enhance interpretability of factor structure. Rotation simplifies the initial structure by maximizing high loadings and minimizing low loadings within each factor, thereby aligning variables more clearly with specific factors (Field, 2024). This process does not alter the total amount of variance explained but redistributes the variance among the factors to reveal a more interpretable solution. Varimax rotation is an orthogonal rotation technique that aims to maximize the variance of the squared loadings of each factor, thereby producing a clearer pattern of relationships between variables and underlying latent constructs (Field, 2024). In this study Varimax was chosen as a method of rotation based on theoretical assumptions of no correlation between factors influencing online shopping behaviour of Gen Z in Australia. In EFA, factor loadings represent the strength and direction of the relationship between observed variables (measured items) and underlying latent factors. A higher loading indicates that the variable is more strongly associated with the factor. Factor loadings of 0.50 or higher are considered practically significant and suitable for interpretation (Hair et al., 2018). These loadings help determine items that best represent each latent construct and are essential for interpreting and naming the extracted factors.

It is to note that, for final factor structure, two items (Item 9 and Item 21) were not retained as their loading values were less than the cutoff value of 0.5. In addtion, to improve the clarity and distinctiveness of the factor structure, Item 14 was carefully reviewed in light of the recommendation by Mirabelli et al. (2022) and assigned it to Factor 6 where it was loading with higher value than in Factor 1 and thus the issue of cross loading was addressed. Table 3 shows the final rotated Factor structure with items having loading cutoff values greater than 0.5. Furthermore, the strength of the loadings of all six underlying constructs supports the Construct Validity of the factor, with no evidence of weak items.

Table 3: Rotated Factor Loadings for Retained Items (Factor Loading ≥ 0.50)

Q. No	Item Statement	Factor					
		1	2	3	4	5	6
1	I feel that shopping online from my Favorites shops is good and rewarding		0.64				
2	I feel excited to buy online as I get the products easily from the websites, I used to purchase		0.68				
3	I like buying online as I trust the retailers' websites which facilitate the shopping process		0.68				
4	Online shopping provides product characteristics like 3D images, colour pictures and text in user friendly format and provides the possibility for price comparisons on the website		0.64				
5	Online shopping provides benefits like discounts, coupons and membership		0.74				
6	Online shopping is user friendly, and it is easy for me to place or amend orders and make payments		**0.79**				
7	I am concerned that my billing information might be misused on online platforms				0.68		
8	I am concerned that I might be overcharged when shopping online				**0.83**		
10	I buy products online as it helps to reduce carbon footprint	0.74					
11	I buy online from companies that promote eco-friendly packaging	0.84					
12	I buy online from companies that implement programs to minimize electronic waste	**0.86**					
13	I am willing to pay a premium price to purchase greener products	0.68					
14	I buy online from companies which donate a portion of their profits to a social organization						**0.57**
15	I buy from companies that support fair labor practices throughout their supply chain						0.56
16	I buy products online from companies which promote diversity, equity and inclusion in hiring practices						0.55
17	I buy products online from companies which support and promote employee wellbeing and people engagement in driving social change						0.55
18	I buy online from those platforms (websites and Apps) which integrates recent and advanced technology and suggests products based on my previous search and buying history					0.65	
19	I buy online from those platforms (websites and Apps) which have chatbot to answer my inquiries and help me to track my order					**0.71**	
20	I use those search engines which utilize advanced search technologies to help me find products faster by suggesting relevant keywords and filters					0.70	
22	Rising prices for household goods have impacted on my online shopping			**0.77**			
23	I buy alternate cheaper brands online and look for products that offer better value for money			0.70			
24	I shop online only after making extensive price comparisons between products across various retailers			0.71			
25	I buy online from companies who provide promotional offers to members			0.67			

Extraction method = Principal Axis Factoring; Rotation method = Varimax with Kaiser Normalization. Bold values indicate the item's primary factor loading.

3.3. Factor Naming and Conceptual Framework

Factor naming involves assigning a concise, representative label to each factor based on the content and thematic alignment of the items that load strongly on it. In the present study, the naming of factors is informed by the existing literatures and theoretical models on online shopping and customer behaviour. Furthermore, it was ensured that the factor naming encapsulates the common theme among high loading items that were retained and related to semantic topic the items measured (Fein et al., 2021). In addition, a balance was strike between descriptive clarity and theoretical precision of the factor such that both the empirical basis and the conceptual meaning of each factor become clear. Table 4 presents a summary of the retained items and factor interpretation.

Table 4: Summary of Retained Items and Factor Interpretation

Factor	High loading Retained Items	Semantic Topics that Items Measured	Factor Interpretation based on Common Themes
Factor 1	10, 11, 12, 13	Carbon footprint, eco-friendly packaging, green products, e-waste minimization	Sustainability
Factor 2	1,2,3,4,5,6	Good feelings, trust, reward, convenience, functional value, ease of use, benefits	Perceived Value & Convenience
Factor 3	22,23,24,25	Rising price impact, value for money, price comparison, promotional offer	Inflation
Factor 4	7,8	Misuse of information, wrong billing	Perceived Risk
Factor 5	18,19,20	Technology integration, chatbot, smart search	Artificial Intelligence
Factor 6	14,15,16,17	Social cause, fair labor, diversity, equity, inclusion, people engagement, social change	Corporate Social Responsibility

The conceptual framework that emerged from the present study is presented in Figure 2, which shows six factors, namely Inflation, Perceived Value & Convenience, Artificial Intelligence, Perceived Risk, Corporate Social Responsibility and Sustainability. To the best of the author's knowledge no such context specific conceptual framework to understand online buying behaviour of Gen Z is available in open literature.

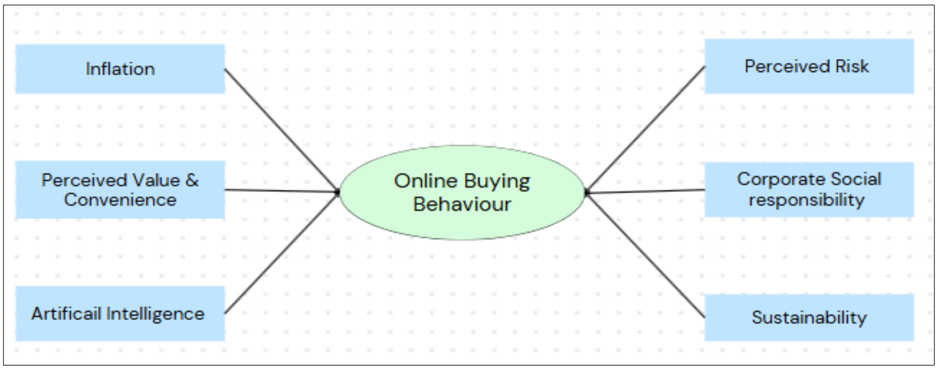

Figure 2: Conceptual Framework based on six factors solution

To evaluate the internal consistency of the six latent constructs identified through EFA, two reliability coefficients were computed. Cronbach's Alpha (α) is one of the most widely used indicators of internal reliability, while McDonald's Omega (ω) is considered a more robust estimator in cases where the assumption of tau-equivalence is not met (Hayes & Coutts, 2020; McNeish, 2018). These measures provide estimates of scale reliability, with values above 0.70 generally considered acceptable and those above 0.80 indicating good to excellent internal consistency (Hair et al., 2018). Table 5 presents the internal consistency estimates for each factor, which shows the close alignment between Cronbach's Alpha and McDonald's Omega values across all factors reinforces the internal coherence of the items within each construct.

Table 5: Internal consistency of extracted factors using Cronbach's Alpha and McDonald's Omega

Factor	Number of Items	Cronbach's Alpha	McDonald's Omega
Sustainability	4	0.881	0.890
Perceived value& Convenience	6	0.850	0.852
Inflation	4	0.816	0.818
Perceived Risk	2	0.751	0.751
Artificial Intelligence	3	0.771	0.783
Corporate Social Responsibility	4	0.850	0.852

3.4. Factor Ranking

To understand Gen Z' s overall perceptions related to each of the extracted factors influencing online buying behaviour, Mean Summated Scores were computed. These scores reflect the average agreement level on grouped items for each factor, using a 5-point Likert scale (1 = Strongly Disagree, 5 = Strongly Agree). This approach allows a direct and meaningful interpretation of how strongly participants endorsed each factor. Summated factor scores were calculated for each extracted factor averaging the item scores corresponding to that factor. Higher summated scores indicate stronger agreement or endorsement of the construct represented by the factor. These scores were used to assess Gen Zs' overall perceptions across key dimensions of online buying behaviour. Table 6 presents the key descriptive statistics for Mean summated factor scores. These scores allow to rank the influence of each factors which were extracted through EFA.

Table 6: Descriptive Summary of Mean Summated Factor Scores

Factor	Items	Score Range	Mean (M)	Median	SD
Inflation	4	2–5	3.92	4	0.68
Perceived value & Convenience	6	1–5	3.68	3.67	0.65
Perceived Risk	2	1–5	3.62	3.67	0.76
Artificial Intelligence	3	1–5	3.62	4	0.89
Corporate Social Responsibility	4	1–5	3.42	3.5	0.78
Sustainability	4	1–5	3.04	3	0.82

It is evident from Table 6 that among 6 extracted factors, Inflation is the most influential factor with highest summated mean score. The next influential factor is Perceived Value & Convenience followed by Perceived Risk and Artificial Intelligence both of these factors have same mean factor score. The least influential factor is Sustainability whereas Corporate Social Responsibility has moderate influence.

4. DISCUSSION & CONCLUSION

This study presented an analysis and critical interpretation of the empirical findings obtained through Exploratory Factor Analysis conducted to uncover the underlying dimensions shaping online buying behaviour among Gen Z consumers in Australia. The analysis revealed six factor solutions and provides an insight into an emerging interplay between economic constraints, technological adoption, and ethical awareness affecting online buying behaviour of Gen Z. The results suggest that Gen Z consumers prioritize economic concerns and convenience, while also exhibiting growing engagement with digital technologies like AI. Though, Gen Z in Australia value ethical and sustainability considerations, it appears to be secondary motivators in making online purchasing decisions. Unlike earlier research, this study highlights the emerging role of Perceived Value & Convenience as a single standalone factor.

The influence of Inflation highlights the salience of macroeconomic conditions in shaping Gen Z's digital consumption. This supports and extends Consumer Demand Theory (Deaton et al., 1980). The high agreement of participants to the items related to inflation suggests that Gen Z, often portrayed as socially conscious and brand oriented, is pragmatically responsive to real-world financial pressures and is highly attuned to economic constraints. This is consistent with recent studies indicating that younger cohorts are more price conscious amidst global economic volatility (Nwoke, 2025; Spohn, 2024). The centrality of Inflation challenges static views in consumer models, indicating that consumer preferences are highly elastic in response to external financial stressors. This aligns with recent empirical findings showing that economic uncertainty reduces discretionary spending, particularly among younger consumers (Nwoke, 2025). This result emphasizes that any theory of digital consumer behaviour must account for the contextual volatility of economic environments.

The prominence of Perceived Value & Convenience and AI features underscores the continued relevance of the Technology Acceptance Model and its extensions. While Technology Acceptance Models (TAM2, TAM3) and UTAUT2 frameworks have traditionally emphasized perceived value and convenience as two separate constructs, the current findings suggest that perceived value and convenience are no longer a separate construct but a central value proposition in itself. The findings also suggest that

Artificial Intelligence is no longer merely a facilitator but a central value proposition. Gen Z appears to value efficiency and convenience facilitated by AI-powered personalization, recommendation systems, and chatbots. These findings suggest that existing technology acceptance models should explicitly incorporate AI as a distinct construct, reflecting the shift from passive technology adoption to immersive, algorithmically tailored experiences.

The finding related to Perceived Risk as an influential factor is consistent with the prior online buying behaviour studies (Jadil et al., 2022). Equal mean factor score for PR and AI suggests a paradoxical relationship. While Gen Z embraces innovation and value technology, they remain cautious about the privacy threat, misleading product information, and identity fraud in online shopping. Similarly, corporate social responsibility (CSR) shows a moderate positive influence on the online buying behaviour of Gen Z in Australia. This finding concurs with the findings of earlier research of Arachchi et al., (2022) which showed that the companies' CSR commitment has positive influence on online buying behaviour of a consumer. The result of this study shows that Sustainability has least influence on online buying behaviour of Gen Z in Australia. This result suggests that though Gen Z are aware of sustainability issues, it is not the prime motivator regarding online buying decisions and Gen Z when confronted with a choice between sustainable and non-sustainable product option, they may choice the latter one as a result of inflationary dilemmas.

While this study provides a novel insight into the factors influencing online buying behaviour of Generation Z in Australia, a moderate sample size may affect the generalizability and interpretation of the findings for a larger population. It is therefore suggested that future study should consider a large sample size from a population of Gen Z across different geographical locations in Australia. Although EFA was appropriate for the study's aim of identifying latent constructs, EFA is limited in its capacity to confirm hypothesized models or establish causal relationships. Therefore, to find a causal relationship and establish a theoretical model based on framework developed in this study, confirmatory factor analysis supported by SEM is recommended for future study.

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