Research Article

Human-Centric Consumption Intelligence and Explainable AI (HCCI-XAI): Framework for Aspirational Consumption and Responsible Consumer Behaviour in Industry 5.0

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Abstract

The connection between purchase behaviour, social identity, financial decision making and psychosocial well-being in the lives of young adults has changed due to the digitally mediated consumption. Young buyers consider several factors in the product evaluation process which include: words of the influencers, Brand image, Social media trends, product impressions, Social bandwagon effect and peer feedback as well. These are the advancements driven by automation and have been supported by Artificial Intelligence and advanced ML techniques to motivate consumers to make informed purchase decisions. From the consumers' perspectives these are all opportunities leading to "Self-expression" however raising questions related to financial pressure, consumer autonomy and the over interference of digital technologies in consumer's purchase decision. In the new paradigm of Industry 5.0 consumers and machines interacted and coordinated with each other to facilitate the purchase process. However in the upcoming evolution of industry 6.0 three core elements: Human centric, Sustainability and Resilience shape up the entire digital ecosystem. Thus this study aims to create a Human-Centric Consumption Intelligence framework with Explainable Artificial Intelligence (HCCI-XAI) to explore the behavioural determinants of aspirational purchasing among the post-graduates students of Bengaluru city, India. The research was based on structured primary data collected in the period of March-July 2026 with the participation of 386 survey respondents and 35 recorded variables. The six behavioural constructs studied in this article include: Masstige Perception, Symbolic Consumption Orientation, Value Consciousness, Consumer Orientation, Digital Influence and Ethical Orientation. Statistical tools such as descriptive statistics, Spearman's rank correlation, Ridge regression, Random Forest regression, repeated cross-validation and K-means clustering have been used. Findings show that the most strongly endorsed construct is Value Consciousness (M = 4.210), and the construct with the highest positive correlation with Purchase Intention is Ethical Orientation ($\rho = 0.475$, $p < 0.001$). Ridge regression has a mean cross-validated coefficient of determination value of 0.3151 and a Random Forest of 0.2805 under the reported model configurations. K means clustering finds two clusters with a silhouette coefficient of 0.2485, indicating that there is moderate behavioural differentiation. The results show that the intention to purchase is linked to ethical concerns, digital influence and symbolic motives and affordability assessments. The study further contributes to Industry 5.0 research by showing the applicability of Machine Learning with Human-Centric Consumer Intelligence. It does not include validated mental health outcomes and its contribution to psychological wellbeing as it remains conceptual rather than diagnostic. The research creates an empirical basis to further explore the prime constructs such as: consumption behavior, financial well-being, psychosocial development, and preventive digital health promotion.

Keywords: Young Adult Health, Aspirational Consumption, Digital Influence, Explainable Artificial Intelligence, Machine Learning, Financial Well-Being, Psychological Well-Being, Industry 5.0, Masstige Consumption, Responsible Consumer Behaviour.

1. Introduction

Nowadays, the digital economy has revolutionized how youth are forming their buying habits, their sense of self and personal achievement (Brandesis, n.d.; Ebongo, 2026; World Economic Forum, 2026). The purchase habits are now shaped by digital engagement and highly expected value driven consumption. The mentality of the youth, especially the earning population, is multifold: Self of Sense (SoS), Meaningful Lifestyle (ML), My Life My Rule (MLMR) motto and My Money My Decision (MMMD) attitude. Consumption is becoming more and more connected to digital environments in which commercial communication, social interactions, and algorithmically curated recommendations coexist. Fortunately, social media channels give consumers a glimpse of carefully crafted messages such as products to boost social status, personality boosting, and the real feel of being confident to enhance the sales. Thus, these factors affecting the purchase behaviour are no longer just economic and value based but with "a motive to impress the society". The complexities of personal aspirations, symbolic motivations, financial resources and digital social spaces are becoming critical to explore. Youth also find it very critical to examine the influence of these variables impacting their purchase decision and do not take efforts to predict the post purchase outcomes (Sense of happiness or guilt). The change from adolescence to adulthood is often accompanied by important transitions in terms of education, social factors, financial independence and identity. Buyers' choices could be expressions of personal achievement, social belonging or desired identities,

during this time. Digital platforms can potentially further influence these processes by providing commercially produced images and representations of success and attractiveness. Arnett (2000) presented a concept of emerging adulthood as a unique developmental period of life that is defined by identity exploration, instability and changing possibilities. Consumption-related experiences during this developmental phase can be explored within the context of the boundaries set by this developmental period, which differ across cultures and socioeconomic settings. Social comparison theory provides a valuable insight into the ways in which digital environments can impact consumer desires. Adding to Social Comparison Theory recent research by James et al., 2026; Martins et al., 2026; Sekar et al., 2026), highlights the importance of self-esteem, self-perception, psychological wellbeing and self-enhancement being interconnected especially when Generation Z involve in purchase process. Long back in pioneer research studies related to consumer behaviour Festinger (1954) suggested that people compare themselves to others, when there are no objective measures to evaluate themselves. Even in 2026 the Social Comparison Theory remains relevant with contemporary research focussing on variables such as: appearance based comparison, body image, self - dignity etc demonstrating the theoretical significance (Festinger, 1954; Tylka & Wood-Barcalow, 2026). In a digitally mediated consumption context, these comparisons can include branded objects, experiences of lifestyle, and experience of wealth and social success that can be seen. But the relevance of social media comparison processes to psychological research was established by Vogel et al. (2014), who found relationships between social media comparison and self-esteem. The relationships, however, are complex and should not be understood as demonstrating that the use of digital media always leads to negative psychological consequences. In addition, few researchers have also written about the connection between material aspirations and personal well-being. Richins and Dawson (1992) defined materialism as a value orientation in which the importance of possessions was seen to be a part of success, happiness and personal identity. In their meta-analysis Dittmar et al. (2014) found an inverse relationship between materialism and personal well-being. The results indicate that there is a possibility that the consumption-related motivations may have ramifications beyond the commercial aspect. However, preferences for high-quality products are not necessarily synonymous with materialisms and psychological discomfort or lower levels of well-being. Consumers can still fall and fit into the premium category remaining financially responsible and holding the sense of ethical buy. Such considerations suggest an empirical context of “Masstige consumption” as a suitable construct to investigate purchase complexities. Consumer values and situational motives were shown to affect consumers' purchase intentions by Uluturk and Asan (2024); and the interplay of status-seeking motives (extrinsic) and self-fulfillment motives (intrinsic) was demonstrated by Roy et al. (2025) in the case of masstige consumption. Shah et al. (2026) further validated the relevance of masstige consumption in recent years by describing the importance of cultural orientations, interpersonal influences, and acculturation's effects on consumers' behaviour. Overall, these results highlight the theoretical and empirical significance of masstige consumption in the context of understanding the multidimensional determinants of purchase intention (Uluturk & Asan, 2024; Roy et al., 2025; Shah et al., 2026). It is a notion of combining mass-market accessibility with the prestige-related product positioning, whereby consumers can enjoy some aspects of a premium brand, but not engage in the traditional luxury market. The growth of available luxury was identified as an important shift in consumer markets by Silverstein and Fiske (2003) and Paul (2015) further developed the conceptualisation and measurement of masstige marketing. To the young consumer, masstige products could be a compromise between price, value, social status, and a person's self-fulfillment. But, the psychological and developmental significance of masstige consumption is not yet fully understood and is not part of standard predictive marketing research. Current studies often focus on purchase motivation, brand preference and segmentation of consumers, with less consideration given to the consequences of aspirational consumption on the autonomy of consumers, their financial situation and their responsible digital interaction. When it comes to using Artificial Intelligence & Machine Learning models to forecast and drive purchases, this factor assumes significance; however remains unexplored.

AI has helped greatly to broaden the analytical options for consumer researchers. Conventional regression models do not necessarily show nonlinear relationships or interactions or behavioural patterns that may be shown by machine learning algorithms. Ensemble learning methods like random forest and gradient boosting offer flexible ways of prediction, and explainable AI could enhance the interpretability of algorithmic results (Breiman, 2001; Chen & Guestrin, 2016; Lundberg & Lee, 2017). However, the level of predictive accuracy is not enough when the analytical system is used in situations that require autonomy and potentially sensitive behavioral traits in humans. Industry 5.0 offers a suitable paradigm to rethink the role of consumer intelligence. In 2021, the European Commission (EC) said that technological development should go hand in hand with the efficiency of industries and human-centricity, sustainability and resilience. Consumer analytics should be used to support and inform, not to maximise conversions or play with consumers' sensitivities, but to facilitate clear decision making and to guide consumer buying, while maintaining ethical and responsible commercial operations, with the help of AI. This interdisciplinary intersection is tackled in the present research by creating a Human-Centric Consumption Intelligence framework based on Explainable Artificial Intelligence (HCCI-XAI). This study uses primary survey data of postgraduate students in Bengaluru to explore the relationship between aspirational consumption, symbolic orientation and affordability-oriented preferences and purchase

intention, as well as the impact of digital influence and ethical orientation. The study combines the approaches of statistical analysis, supervised machine learning and unsupervised clustering, which are used to study predictive relationships and behavioural heterogeneity. The study falls under the umbrella of young adult health promotion, since experiences in digital consumer environments may be a part of the broader psychosocial experiences, and the ability to make financial decisions and develop a social identity may be relevant to these experiences. It does not, however, presume buying attitudes to be direct measures of psychological health. Rather, it provides a behavioural foundation that is grounded in empirical factors for future research that can include validated mental health instruments.

2. Research Problem and Significance

The growing use of commercial content in digital social contexts has made the consumer aspiration and decision-making more complex. A recent research by Nageswari et al. (2025) highlights a few interesting facts that social media influences more than purchase intention due to which consumers have become active participants in the market. Even though they do not buy them anything they are involved in window shopping very actively. This provides a spark to frame a major research problem for this study which focuses on the complex interplay between digital exposure considering masstige consumption among the youth community. Moreover, young consumers are constantly exposed to opportunities to compare products, assess brands and see lifestyle representations being sold and marketed via digital channels. They can affect not only people's buying habits but their ideas of being able to afford something as well as their sense of being successful and satisfying the expectations of others. A number of these processes have been studied under the traditional paradigm of consumer behaviour using theories of perceived value, symbolic consumption, brand equity, and purchase intention. The former methods provide some clues to the phenomenon of purchase but fail to consider the larger developmental and humanistic issues. Concurrently, research on well-being of young adults has started to examine the relationship between digital environments and psychosocial experiences. Keles et al. (2020) did a review of the evidence on social media and depression, anxiety, and psychological distress in adolescents, and found some potentially important associations. This type of finding calls into question the idea that all digital interaction is evil; digital experiences should be examined. The outcomes of this research will be highly valuable because the sellers should understand that consumers do not involve themselves in purchase just because they have knowledge about a product/service but a personal connection to buy, use, enjoy, feel. The empirical findings could also help different stakeholders because at the end of the day everyone is a consumer. Hence more digital awareness, financial responsibility, purchase guidelines will be a great nudge. Moreover, the research analyzes the human-centricity of Industry 5.0, highlighting the need to take into account the importance of transparency, ethics and responsible decision-making as a part of the AI driven purchase evaluation process.The study does not assume fact that the more complex algorithms produce better results; however it is a test for the predictive performance to analyze situations with high complexity.

3. Review of Literature and Theoretical underpinning

3.1 Aspirational Consumption and Identity Formation

Consumers buy products for social status and this has always been a way of expressing themselves with a lot of pride and dignity. Consumers have always been buying products not just for functional purposes but to showcase their identity, social status, pride and achievement (Maheshwari et al., 2025). Kristina et al (2026) suggest conspicuous/ aspirational consumption on digital media serves as a reinforcement of self-image and a means of creating social distinction. Likewise, Potluri et al. (2026) found that status symbolism, brand image and perceived prestige are important factors influencing luxury consumption choices. Even many years before the prior research work by Belk (1988) suggested that possessions can be an extension of the self, symbolizing the nature of possessions and personal identity. This view is especially relevant when purchasing for aspiration, as consumers might be assigning meanings to products which go beyond what their function is. For young adults, product knowledge, peer influence and personal growth may shape identity-oriented consumption. Perceived achievement, sophistication and sense of belonging are possible messages conveyed by the premium brands. But these variables are not necessarily synonymous with materialism. A masstige product is a combination of the prestige and the accessibility that it offers to consumers who are looking for a perceived added value but don't necessarily go for traditional luxury products. This positioning and the perceptions of masstige was conceptualized by Paul (2015). This is the reason why the present study investigates the relationship between the masstige perception and the symbolic consumption orientation with purchase intention in a wider behavioural context: affordability, digital influence and ethical orientation.

3.1.1 Masstige Perception

Alongside Aspirational Consumption it is important to bring to light a newly evolved concept known as “Masstige Perception”. Masstige products combine mass market access and a prestige product positioning. Moreover young adults who are aspirational consumers often evaluate and make a buying decision based on social status, dignity, prestige and the financial practicality. In this context the concept of masstige perception captures the dual desire. Hence Masstige Perception (MP) has been used as a prime variable.

3.2 Digital Influence and Social Comparison

Digital media has emerged as a significant socialisation space for consumers which has changed the way people make decisions. They are able to compare their lifestyles, aspirations, and buying habits with others. Tian et al. (2023) highlights that the social comparison with influencers leads to feelings of admiration, aspiration, and envy, all of which affect brand attitudes and purchase intentions. Likewise, Elshaer et al. (2026) found that social media exposure enhances the consumption experiences and increases purchase intentions. Online reviews, influencers' endorsements and social media material help in new product discovery, brand awareness, and clear purchase decisions. These can be mediated by informational influence, perceived credibility, and social identification and repetition. Social comparison theory proposes that people can compare themselves by their perceived situation and success of others (Festinger, 1954). This can be exaggerated in digital contexts through the selective presentation of content and through lifestyle representations mediated by the business markets. Vogel et al. (2014) found that consumers also compare themselves with others on social media platforms and this can sometimes enhance self-esteem and psychological wellbeing.

3.3 Value Consciousness and Financial Well-Being

Value conscious consumers tend to think more about the usefulness and goodness of the products/services bought, values received for the cost paid and the responsible use of products before making impulse purchases. Yuvita and Permatasari (2025) concluded that financial well-being completely mediates the association between frugal living and buying decisions for the Generation Z population. Dahiya et al. (2025) observed financial well-being as one of the dimensions of overall consumer well-being. Likewise, Sharma et al. (2026) found that budget awareness and reporting, gamification, and digitised, transparent financial systems are effective in sustaining financial goals and financial health. Hence from these practical illustrations it has to be understood that value consciousness is what consumers place on getting the right quality for the price given. It is linked to comparing prices, evaluating discounts and considering ways to buy. Lichtenstein et al (1990), investigated the perceptions of price and consumer shopping behaviour, which further extended the knowledge on the importance of price-related evaluations on consumers' purchase decisions. Further to income and expenditure, financial well-being encompasses perceptions of financial security for the present and for the future as well. Brüggen et al., (2017) created a conceptual model that focuses on the multidimensionality of financial well-being, where he says financial wellbeing is not about how much money a person has but how confident he feels. For post-graduate students, the issue of affordability is a special concern as the income of post-graduate students may be dependent upon family support, scholarships, part time employment and other financial arrangements. However it does not mean that those with high value consciousness are necessarily poor. It can also be indicative of rational decision-making and responsible consumption.

3.4 Ethical Consumption and Human-Centric Decision-Making

Ethical consumption involves taking into account the environment, social and organisational responsibility when purchasing a product/service. Consumers can consider products based on sustainability, fair business practices, and perceived environmental impact. Recent research work also explored the concept of “Ethical Consumption” where it is defined as a form of consumption that involves taking into account personal values, social responsibility and environmental conservation in purchase decisions, which demonstrates a shift towards human-centric decision making. However ethical purchase remains very artificial with no real time moral values being followed. For example, an Indian consumer calls himself/herself an organic buyer and ends up purchasing an imported avocado and placing it into a degradable carry bag rather than purchasing the farm grown Indian avocado. Huang et al. (2025) found that ethical beliefs and individual-level factors were significant influences on ethical purchase intentions, and Kutaula et al. (2024) emphasized cultural contexts and social responsibility as factors influencing ethical consumer behaviour. Likewise, Suttharattanagul et al. (2025) concluded that responsible consumption is important to increase sustainability values and green purchasing intentions, which further illustrates the value of mindful consumption. In the context of Industry 5.0, ethical consumption is relevant to the overall goal of Industry 5.0, which is integrating technological and commercial systems with human and societal welfare. The European Commission (2021) emphasized the need for a hand-in-hand approach of sustainable development and a people-centred approach with technological innovation. Ethical orientation is included as a part of the present research, so that the purchasing intention can be investigated beyond prestige and affordability. Recognizes that young consumers may have multiple motivations for purchasing products that include quality, social implications, value for money, and the environment.

3.5 Artificial Intelligence and Explainable Consumer Analytics

Machine learning offers analytical techniques that can detect correlation between various behavioural variables, even if there are not all linear relationships. Breiman (2001) introduced a new ensemble method called random forest that uses several decision trees to increase the robustness of predictions. Gradient boosting is an optimized version of gradient boosting, the XGBoost algorithm (Chen and Guestrin, 2016), which is able to model complex relationships efficiently. Machine learning's versatility, though, can create issues of overdifferentiation, interpretability, and fairness of algorithms. Such issues are particularly pertinent to modelling in the domain of human behaviour. Explainable AI tackles a part of this issue by offering techniques to analyse the role of each predictor in the model's computations. To provide a unified framework for understanding the predictions of models, Lundberg and Lee (2017) introduced a unified framework for interpreting model predictions, called SHapley Additive exPlanations (SHAP). In the present research, an explicit design principle is the technique of explainability and the distinction of completed empirical analysis and proposed advanced modelling components. This separation is required since a mathematical description of an algorithm is not proof of implementation or valid proof of the algorithm.

4. Research Objectives

The main motivation of this research is to examine the relationships between Masstige Perception (MP), Symbolic Consumption Orientation (SCO), Value Consciousness (VC), Consumer Orientation (CO), Digital Influence (DI), Ethical Orientation (EO) and Purchase Intention (PI) among young adults using interpretable statistical and Machine Learning methods. The study also aims to compare the predictive ability of the regularised linear regression with the nonlinear ensemble learning, to cluster the consumer behaviours and to provide a baseline for responsible Consumer Intelligence under Industry 5.0. The proposed HCCI-XAI framework is based on the combined six measured behavioural domains in a single predictive structure. The focussed dependent variable in this study is “Purchase Intention”. Consumer purchase autonomy, Financial responsibility, Digital mentality are all connected to the broad conceptual framework. Though these variables are not empirically measured it has been theoretically interpreted.

For respondent i, the behavioural feature vector is represented as:

$$X_i = [MP_i, SCO_i, VC_i, CO_i, DI_i, EO_i]^T$$

The predictive objective is expressed as:

$$\hat{PI}_i = f\vartheta(X_i)$$

where $\widehat{PI}_i$ denotes predicted purchase intention and f_θ represents the learned prediction function.

The framework also incorporates behavioural segmentation:

$$C_i = g\varphi(X_i)$$

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$$C_i = g\varphi(X_i)$$

where C_i represents the cluster membership of respondent i.

Together, these components allow the investigation of predictive relationships and behavioural heterogeneity without assuming that consumption patterns constitute psychological diagnoses.

5. Research methodology and design

5.1 Research Design

The study incorporates multiple analytical dimensions which include: quantitative, cross-sectional research design with psychometric measurement, descriptive analysis, statistical associations, Supervised Machine Learning and Unsupervised Behavioural Segmentation test being done. The analytical approach aims to explore the relationships between the consumers' attitudes to predict the purchase intention. This research follows an explanatory approach and is predictive in implementation. However, there is no emphasis on experimental intervention or longitudinal observation. Thus, the findings are presented as associations and predictive relationships and not as causal effects. The data was collected using a standard survey with a set of well structured questions distributed to the post-graduate students of Bengaluru, India. Bangalore is a metropolitan city in the state of Karnataka with a student population having high exposure to digital tools and technologies. Considering this to be a very important criteria the research opted for purposeful sampling as a standard sampling technique. The original survey responses for this study are 386 responses and 35 variables, including demographic data, income characteristics and survey questions on consumption behavior. Data was gathered from March to July 2026. The CPIFusion-XAI workbook has been expanded from the

original CPIFusion-XAI manuscript of 178 observations to 386 observations. The study has collected data only from urban students and has not considered rural consumers.

5.2 Respondent Characteristics (Youth adult - Postgraduate students)

The population of the respondents is mainly the young adult (postgraduate) students from Bangalore. The ages of the respondents are distributed within this category where (N = 203) persons are in the age range 18-20 years, (N = 95) in the age range 24-26 years and (N =27) persons in the age range of 27 years and above. However, 2.0% of respondents did not report their age. This age grouping of respondents is representative of the focus to understand adulthood in this study. The age composition is relevant to the exploration of consumption aspirations, financial decision making and digital involvement as part of the process of making the transition towards economic independence. Other data included in the dataset are gender, monthly personal disposable income and source of income. These variables are descriptive of a respondent's economic situation. Income categories are important for understanding value consciousness and purchasing preferences related to affordability, while income does not capture the subjective financial stress.

5.3 Questionnaire Structure (Refer to Annexure 2)

This questionnaire consists of 29 items grouped under Masstige Perception, Symbolic Consumption Orientation, Value Consciousness, Consumer Orientation, Digital Influence, Ethical Orientation and Purchase Intention. The Masstige Perception is assessed by 4 items that are related to premium quality, prestige, affordability and accessible luxury and lifestyle associations. A symbolic Consumption Orientation scale is operationalized using four items related to brand identity, social recognition, image enhancement and success projection. Value Consciousness is assessed by four items that focus on comparing prices, assessing quality, being price sensitive and being responsive to discounts. Consumer Orientation is captured by eight items related to Product Exclusivity, Personalised Service, Affordability Preferences, Prestige, Aspirational Ownership, Instalment Purchase, Brand Switching and Prestige vs Practical Value. Digital Influence is assessed by three items focusing on social media, online reviews and influencer endorsements. Ethical Orientation is assessed based on three questions related to sustainability, ethical business practices and environmentally responsible purchasing. Purchase Intention is shown by three Purchase items related to future purchase, brand recommendation and emotional connection. Emotional connection is included within Purchase Intention for psychometric evaluation as emotional attachment is a construct which is theoretically different from behavioural intention. There are also some dimensions that appear to be potentially heterogeneous in Consumer Orientation. Therefore, it is considered as a provisional interpretation until dimensionality and internal consistency are determined, as it is a composite construct.

5.3.1 Data Preparation

A total of 386 surveys from young adult consumers were initially gathered. In the data screening process, 10 respondents were found who had incomplete responses in the three variables that measured the dependent variable in the predictive models, which were Purchase Intention. Thus, an accurate composite Purchase Intention score was not possible for these observations. Since the 10 cases were not observed, they were not included in the predictive analysis and the final analytical sample consisted of 376 respondents (97.41% of the original sample). Another 2.59 percent of observations were omitted only because of dependent-variable data missing; the other 1 percent were omitted because of respondent characteristics or subjective screening criteria. Median imputation was applied within the cross validation process, in order to address the missing values of the predictor variables among the retained observations, whilst minimising data leakage. To ensure consistency in the reported predictive and segmentation analyses, the same analytical sample of 376 respondents was used for the K-means cluster analysis. The original sample (386 respondents) was retained and the exclusion was limited to analyses that required the specified analytical sample.

5.4 Behavioural Feature Engineering

The questionnaire had 29 question statements related to behavioural aspects excluding the demographic constructs. The questionnaire was administered using Likert's five point scale. All the 29 constructs were grouped into 9 broad dimensions *(Refer to Annexure 2)*

For respondent i, the composite score for behavioural construct k is represented as:

$$C_{ik} = \frac{1}{m_{ik}} \sum_{j \in O_{ik}} Q_{ij}$$

where Q_{ij} denotes the response to questionnaire item j, O_{ik} represents the observed items associated with construct k, and m_{ik} denotes the number of valid responses.

This transformation produces six explanatory features and one outcome variable.

The behavioural features of respondent i is expressed as:

$X_i = [MP_i, SCO_i, VC_i, CO_i, DI_i, EO_i]^T$

The dependent variable is calculated as:

$$PI_i = \frac{1}{m_{i,PI}} \sum_{j \in O_{i,PI}} Q_{ij}$$

Using the original five point Likert scale interpretation the composite scores are retained and also this reduces the dimensionality of the questionnaire. However for factor analysis or reliability testing these composite scores are not useful. This process also clears the missing values and makes the data ready for further process. The supervised learning sample consequently comprised 376 respondents. Missing predictor values were treated through median imputation within the training folds. This approach is also supported with the work of Barakat et al. (2017), who also demonstrated the process to clear missing values to maintain the predictive power of the model. As a part of the data clearing process the email addresses were excluded from modelling because they constitute personal identifiers rather than theoretically relevant behavioural predictors.

5.5 Descriptive Statistical Analysis

To understand the respondents overall perception and the behavioural tendencies descriptive statistics were generated taking into account the central tendency scores. The arithmetic mean for construct k is defined as:

$$\underline{C_k} = \frac{1}{n_k} \sum_{i=1}^{n_k} C_{ik}$$

where n_k denotes the number of respondents with a valid composite score. The descriptive analysis provides an initial understanding of the relative strength of respondents' reported consumption preferences. It also establishes a foundation for interpreting the subsequent correlation and machine learning findings.

5.6 Correlation Analysis

To investigate the monotonic associations between the Behavioural constructs and Purchase Intention, Spearman's rank correlation has been used. This method is more suitable for examining the ordinally derived composite scores without requiring the same distributional assumptions as Pearson's product-moment correlation. In the absence of tied ranks, Spearman's correlation can be expressed as:

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

where d_i denotes the difference between paired ranks. Because questionnaire scores contain ties, practical computation uses the Pearson correlation of ranked observations with appropriate treatment of tied values. The analysis examines the direction, strength and statistical significance of associations between Purchase Intention and each behavioural construct. The significance threshold is set at 0.05, while the interpretation also considers effect magnitude rather than relying exclusively on p-values.

5.7 Supervised Machine Learning

Supervised Machine Learning (SML) was employed to evaluate the predictive relationships between the six behavioural constructs and Purchase Intention. The prediction problem is represented as:

$$\mathcal{D} = \{(X_i, PI_i)\}_{i=1}^{N}$$

$\mathcal{D}$ = Supervised machine learning dataset

X_i = Behavioural predictors of respondent i

PI_i = Actual purchase intention of respondent i

$\hat{PI}_i$ = Predicted purchase intention

$f\theta$ = Machine learning prediction function with learned parameters θ

N = Total number of respondents in the modelling dataset (376)

θ = Parameters learned by the predictive model

The objective is to estimate a function f_θ such that:

$$\hat{PI}_i = f\theta(X_i)$$

The analysis compares Ridge regression and Random Forest regression. These models provide contrasting approaches to predictive learning, allowing the study to evaluate whether nonlinear ensemble methods offer measurable advantages over regularised linear estimation.

5.8 Ridge Regression

Ridge regression extends ordinary least squares regression through an L2 regularisation penalty. The penalty discourages excessively large coefficient estimates and can improve generalisation when predictors are correlated.

The model is expressed as:

$$\widehat{PI}_i = \beta_0 + \beta_1 MP_i + \beta_2 SCO_i + \beta_3 VC_i + \beta_4 CO_i + \beta_5 DI_i + \beta_6 EO_i$$

The optimisation objective is:

$$L_Ridge = \Sigma_{i=1}^{N} (PI_i - \hat{PI}_i)^2 + \lambda \Sigma_{j=1}^{6} \beta_j^2$$

where λ denotes the regularisation parameter.

The model provides an interpretable benchmark for estimating the combined predictive contribution of the behavioural constructs. Other researchers who have used Ridge Regression also claim that this method improves predictive stability Akhtar and Alharthi (2025), ability to balance model complexities Huang et al. (2024) and more benefits of adaptive regularisation Peng et al. (2026). Hence being used for this research as well.

5.9 Random Forest Regression

Random Forest regression is an ensemble learning method that combines predictions from multiple decision trees. Breiman (2001) demonstrated that ensemble tree methods can improve predictive performance by reducing instability associated with individual decision trees.

The Random Forest prediction is represented as:

$$\hat{PI}_i = (1/T) \times \Sigma_{t=1}^{T} f_t(X_i)$$

where T represents the number of trees and f_t denotes the prediction generated by tree t. The previously reported implementation used 200 trees and a minimum terminal leaf size of four observations. Unlike Ridge regression, Random Forest does not require a predefined linear relationship between predictors and the outcome. It can represent nonlinear associations and interactions, although this flexibility may increase overfitting risk in relatively small datasets.

5.10 Cross-Validation and Model Evaluation

Predictive performance was evaluated through repeated five-fold cross-validation with three repetitions, producing 15 evaluation folds. Cross-validation partitions the modelling dataset into training and validation subsets. Each observation contributes to validation in a controlled manner, allowing the model's predictive capability to be assessed beyond the observations used for fitting. The coefficient of determination is expressed as:

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (PI_i - \widehat{PI}_i)^2}{\sum_{i=1}^{n} (PI_i - \underline{PI})^2}$$

Mean absolute error is calculated as:

$$MAE = \frac{1}{n} \sum_{i=1}^{n} |PI_i - \widehat{PI}_i|$$

The cross-validation results are interpreted using mean performance across evaluation folds. Because mean fold-level R^2 is not mathematically identical to a single pooled out-of-fold R^2, the article reports the results specifically as mean cross-validated estimates.

5.11 Unsupervised Behavioural Segmentation

To group the respondents with similar features based on their behaviour K - Means clustering has been used.

The clustering objective is expressed as:

$$J = \Sigma_{k=1}^{K} \Sigma_{i \in C_k} ||X_i - \mu_k||^2$$

Where K denotes the number of clusters, C_k represents the set of respondents assigned to cluster k, and μ_k denotes the centroid of cluster k. The behavioural variables were standardised before clustering to reduce differences in feature dispersion. Candidate solutions containing two, three, four and five clusters were evaluated using the silhouette coefficient.

For respondent i, the silhouette coefficient is defined as:

$$s(i) = \frac{b(i) - a(i)}{max\{a(i), b(i)\}}$$

where $a(i)$ denotes the average distance to other observations within the same cluster and $b(i)$ represents the smallest average distance to observations in another cluster. Higher silhouette values indicate stronger separation between clusters.

6. Empirical Results

The following section reports the descriptive, correlation, regression and clustering estimates from the preceding analytical work. These are the available empirical results; the proposed attention-learning, graph-learning and SHAP extensions are not represented as completed experiments. Detailed empirical results are given in tables *(Refer to annexure 1)*.

6.1 Descriptive Results

The descriptive analysis revealed that among all the constructs the highly endorsed construct was Value Consciousness (VC) with a mean score of 4.210. This was followed by Masstige Perception (MP) at 3.854, Ethical Orientation (EO) at 3.742, Purchase Intention (PI) at 3.676, Consumer Orientation (CO) at 3.614, Digital Influence (DI) at 3.511 and Symbolic Consumption Orientation (SCO) at 3.335. The results indicate that price and quality are generally important factors when it comes to purchasing decisions. Value Consciousness is relatively high, suggesting that people are mindful of buying while tending to be positive towards premium and aspirational products. There was also relatively high endorsement for Masstige Perception, indicating that consumers are aware of the attraction of their prestige-priced products. This finding also supports the conceptualisation of masstige as being a premium consumption (Paul, 2015). Also, respondents show favourable attitudes towards sustainability and responsible business practices with a mean score of 3.742 for Ethical Orientation. Ethical preferences and aspirational purchases suggest that consumer decision-making may be driven by more than one value system, rather than the prestige motivation. The mean of Symbolic Consumption Orientation was the lowest of the constructs investigated. This indicates that the motivations involving social images were weaker than the value motives. The mean, however, is still slightly superior to the midpoint of the response scale, which suggests that symbolic consumption does not entirely form part of the respondents' stated preferences. There is always a misconception that young consumers always prefer premium and are status seekers from a generic human centric perspective in consumer behaviour studies. However the descriptive study reveals the importance of quality, ethics and affordability in consumers purchase decisions.

6.2 Correlation Results

Statistically significant positive correlations were found between the six behavioural constructs and Purchase Intention, as revealed by Spearman's rank correlation analysis. The highest correlation coefficient was found for the variable Ethical Orientation with 0.475 and reported p-value < 0.001 with the variable Purchase Intention. The other factors that showed a positive correlation were Consumer Orientation at 0.465, Masstige Perception at 0.416, Digital Influence at 0.407, Symbolic Consumption Orientation at 0.350 and Value Consciousness at 0.246. The correlations reported were significant at $p < 0.001$. The findings indicate that Ethical Orientation is positively associated with Purchase Intention, indicating that those who are more inclined towards sustainability and responsible business practices also seemed to be more inclined towards purchasing. This result is relevant to Industry 5.0 because of the possibility of ethical concerns alongside aspirational purchases. Consumer Orientation was also found to be positively associated with Purchase Intention relatively, with positive association. The finding indicates that there is a relationship between the broader purchasing preferences of product exclusivity, personalised service, affordability and aspirational ownership, and the purchases intention of the respondents regarding masstige products. The results revealed a positive correlation of 0.416 between masstige perception and the purchase intention of accessible premium products, which suggests that positive evaluation of accessible premium products is related with positive purchase intentions. This finding aligns with the premise of masstige marketing that prestige and affordability work together to drive consumer appeal. For Digital influence the correlation was positive (0.407). This suggests that users who say that social media, online reviews and digital endorsements have a greater influence on their purchases also say that they have a greater purchasing intention. The discovery confirms the importance of digital environments in the buying choices of young adults. But the findings shouldn't be read as proof of the psychological distress or compulsive use of digital platforms. These outcomes are not directly measured in the questionnaire. Positive correlation of 0.350 was obtained for Symbolic Consumption Orientation which indicates that the identity-related and socially expressive purchasing motivations had a positive relationship with purchasing intention. With the highest descriptive mean, but a weakest positive correlation of 0.246, was Value Consciousness. This distinction has significance, albeit in theory. While the participants strongly agree that they take the time to consider price and quality, some constructs and not all are more likely to predict purchase intention. The overall results of correlation show that the purchasing intention is related to

several behavioral dimensions. There are meaningful relationships between the outcomes and ethical considerations, as well as consumer preferences, perceived product prestige, digital influence and symbolic motivations.

6.3 Ridge Regression Results

The reported mean cross-validated R^2 for the Ridge regression model was 0.3151 while the mean absolute error was 0.6060. The model on average across the evaluation folds accounted for about 31.5% of the variance in purchase intention, compared to the respective fold specific baseline. The Mean Absolute Error (MAE) shows the average absolute difference between the actual and predicted purchase intention was about 0.606 points on the original composite scale of five points. These outcomes show good predictive skills. A meaningful relationship between the measured constructs of behaviour is captured in the model but a significant amount of variance is not explained. These unexplained variations may be due to other factors that were not included in the questionnaire, such as personal experiences, financial situations at home, preferences for the brands and so on and social influences. The factors are not proven but only potential explanations. The Ridge results also indicate that a linear model with regularisation can achieve a good predictive performance for the current data set without the need of a very complex architecture. This is significant to Human-Centric Artificial Intelligence (HCAI) because the interpretability of the model needs to be considered along with the ability of the model to predict. If there is a relatively simple model that is competitive, more complexity requires more empirical justification.

6.4 Random Forest Results

Random forest analysis reported a mean cross-validated R^2 and mean absolute error for the Random Forest regression model as 0.2805 and 0.6050, respectively. The coefficient of determination shows the percentage of the variation in purchase intention that can be accounted for by the nonlinear ensemble, on average, across the evaluation folds, which is about 28.1%. The mean absolute error was slightly better than the mean absolute error of Ridge regression, but was very small. The results show that Random Forest was not always predictive better than Ridge regression. While Random Forest achieved a slightly lower absolute error, Ridge regression achieved a higher mean R^2. The discovery is significant since it has been a common assumption that nonlinear algorithms are likely to perform better than traditional statistical models. The present analysis indicates that these assumptions need to be tested empirically, especially when sample sizes are rather small and predictors are composed of constructs from questionnaires. The close agreement between the performance of the two models also indicates that the relationships measured by them can be reasonably well described by a regularised linear system, but it does not imply that the underlying behavioural processes are linear.

6.5 Comparative Interpretation of Predictive Models

The comparative evaluation shows that Purchase intention has moderate predictive power for both Ridge regression and Random forest. Ridge regression had the highest mean cross validated R^2 and Random Forest had the slightly lowest Mean Absolute Error (MAE) MAE. There are no formal paired uncertainty estimates to support a statistical significance of the differences. The conclusions are therefore conservative: The predictive performance could not be improved significantly by increasing the complexity of the algorithms under the tested setups. The outcome has implications for the proposed HCCI-XAI framework, in the sense that the application of the proposed framework will be the same as the previously mentioned application of the XAI framework. Technical sophistication isn't the only reason for implementing an advanced machine learning architecture. They should be measured in terms of measurable improvements in prediction, interpretability, robustness or fairness. In the current study, Ridge regression is used as a baseline model for comparison with the more advanced models.

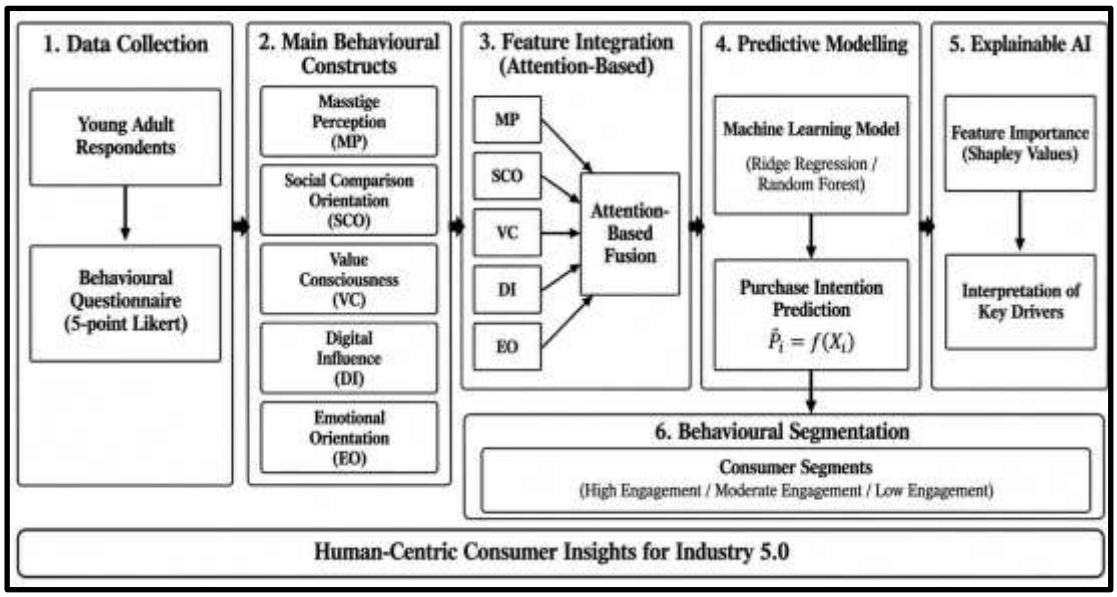
6.6 K-means Clustering Results

The six standardised predictor constructs were used in k-means clustering to identify behavioural similarities between respondents. Silhouette coefficients were 0.3578, 0.2485, 0.1941 and 0.1994 for the two-cluster, 3-cluster, 4-cluster and 5-cluster solutions, respectively, and 0.1648 for the 5-cluster solution. The two-cluster solution gained the highest silhouette coefficient of the alternatives evaluated. The clustering distribution consisted of 199 and 177 respondents in the first and second clusters, respectively, which accounted for about 52.9% and 47.1% of the 376 respondents in the modelling sample, respectively. The cluster distribution is not too skewed, implying that the algorithm did not find a very small number of strange observations. However, the silhouette coefficient is 0.2485, suggesting minor intra-cluster separation. The finding indicates that there is some behavioural heterogeneity among respondents, although there are some similarities regarding consumption characteristics. The cluster solution is thus not intended to create consumer segments, but rather to provide a basis for recognizing the presence of potentially meaningful behavioural differences. To assign substantive descriptions to the groups, cluster centroids need to be calculated first. For instance, it would be improper to classify one cluster as being financially vulnerable or psychologically distressed, without supporting measurements. The clustering results indicate the need for responsible interpretation from an Industry 5.0 point of view. Algorithmic segmentation should not be translated into potentially stigmatising classifications, especially with regard to human behavior.

6.7 Integrated Empirical Interpretation

Overall, the descriptive, correlation and machine learning results suggest that there is an interplay between affordability-related preferences, ethics, perceived prestige, digital influence and symbolic consumption when it comes to young adults purchasing intention. The descriptive results show that value consciousness is high in the sample. However, the bivariate relationships with purchase intention are stronger for the ethical orientation and for the general consumer orientation, as revealed in the correlation analysis. Results of supervised machine learning show that these behavioral constructs are of moderate predictive value. It is observed that Ridge and Random Forest are similar in performance, which implies that the complexity of the model is not necessarily associated with better prediction. In addition, the clustering analysis results show that there is behavioural heterogeneity among respondents but the groups are overlapping to a large degree. These results are combined to contribute to a multilevel view of aspirational consumption. Young adults can also appreciate quality, price, and ethical considerations, as well as digital information. The combination of their purchasing behaviour cannot be clearly explained by a status oriented explanation. The findings also provide a basis for further research on the interaction between these patterns of consumption and financial well-being and consumer autonomy and psychosocial experiences. The present data, however, do not allow for direct conclusions to be drawn on mental health.

7. Proposed Advanced HCCI-XAI Architecture



Note: The HCCI - XAI Architecture has been developed by the authors of this research and is an original work.

7.1 Development of Human-Centric Consumption Intelligence

The empirical results provide a basis for creating a more comprehensive explainable machine learning system. The HCCI-XAI framework is an extension of statistical and machine learning analyses adding to adaptive feature representation, attention-guided learning, consumer similarity modelling and explainability. The advanced architecture is not just designed to be more accurate in predicting the result. Instead, it is to create an analytical system that represents consumers' diverse preferences in a transparent and responsible manner. The proposed architecture is a complementary division of the computational components of behavioural representation, predictive optimisation and explanation.The respondent-level input vector is defined as:

$$X_i = [MP_i, SCO_i, VC_i, CO_i, DI_i, EO_i]^T$$

A behavioural embedding:

$$Z_i = \sigma(W_e X_i + b_e)$$

Where W_e represents the learnable embedding matrix, b_e denotes the bias vector, and σ represents a nonlinear activation function. The resulting representation is intended to capture interactions among behavioural constructs that may not be fully represented by their original composite scores. Because the present dataset contains only six composite predictors and a modest sample size, embedding dimensions must be restricted to avoid unnecessary model complexity.

7.2 Attention-Guided Feature Fusion

The proposed attention mechanism allows the model to assign different predictive weights to behavioural dimensions. The attention coefficient for construct k and respondent i is expressed as:

$$\alpha_{ik} = \frac{exp\ (g_{ik})}{\sum_{j=1}^{K} \quad exp\ (g_{ij})}$$

where g_{ik} denotes the learnable attention score.

The fused behavioural representation is:

$$H_i = \Sigma_{k=1}^{K} \alpha_{ik}\ Z_{ik}$$

The attention weights satisfy:

$$\sum_{k=1}^{K} \quad \alpha_{ik} = 1$$

This architecture would allow the predictive system to assign different weights to behavioural dimensions across respondents. For example, affordability-related characteristics may be more informative for some respondents, whereas ethical orientation or digital influence may contribute more strongly to predictions for others. However, attention weights should not automatically be interpreted as causal importance or as explanations of psychological motivation. Their reliability must be assessed through appropriate validation and comparison with independent explanation methods. The attention architecture remains a proposed extension. Its predictive performance and learned parameters have not yet been established by the reported empirical analysis.

7.3 Graph-Based Consumer Similarity Learning

The original CPIFusion-XAI manuscript proposes graph-based learning to represent behavioural similarities among consumers. This principle can be adapted to HCCI-XAI.

A consumer similarity graph is defined as:

$$G = (V, E)$$

where V represents respondents and E represents similarity-based connections.

Cosine similarity between respondents is calculated as:

$$S(i,j) = (X_i^T X_j) / (||X_i|| \times ||X_j||)$$

Connections may be established through a predefined similarity threshold or a nearest-neighbour procedure. A graph attention mechanism can then aggregate information from behaviourally similar respondents and is represented by:

$$h_i^{(l+1)} = \sigma(\Sigma_{j \in \mathcal{N}(i)}\ \alpha_{ij}\ W^{(l)}\ h_j^{(l)})$$

G = Consumer similarity graph

V = Set of respondents represented as graph nodes

E = Set of similarity-based connections between respondents

S(i,j) = Cosine similarity between respondents i and j

X_i = Behavioural feature vector of respondent i

X_j = Behavioural feature vector of respondent j

X_i^T = Transpose of respondent i's feature vector

$||X_i||$ = Euclidean norm of respondent i's feature vector

$\mathcal{N}(i)$ = Set of neighbouring respondents connected to respondent i

α_{ij} = Attention coefficient assigned to neighbour j

$W^{(l)}$ = Learnable weight matrix at graph layer l

$h_j^{(l)}$ = Hidden representation of respondent j at layer l

$h_i^{(l+1)}$ = Updated hidden representation of respondent i at the next layer

σ = Nonlinear activation function

The graph is intended to represent statistical similarity rather than actual social relationships. An important methodological requirement is that graph construction must respect cross-validation boundaries. Validation observations must not influence the construction of training representations in ways that leak information into model fitting. Given the sample size and relatively small feature space, graph learning should be treated as an experimental extension rather than an assumed improvement.

7.4 Explainable Artificial Intelligence

Explainability is central to the proposed framework because the research seeks to understand behavioural relationships rather than generate opaque predictions. SHapley Additive exPlanations provide a method for decomposing model outputs into feature contributions (Lundberg & Lee, 2017).

The explanation function is expressed as:

$$\widehat{PI}_i = \phi_0 + \sum_{k=1}^{K} \phi_{ik}$$

$\hat{PI}_i$ = Predicted purchase intention of respondent i

φ_o = Baseline model prediction

φ_{ik} = SHAP contribution of behavioural feature k to respondent i's prediction

K = Total number of behavioural features (6)

Σ = Summation of individual feature contributions

i = Individual respondent

k = Behavioural feature index

Global explainability would examine the relative contribution of behavioural features across the sample. Local explainability would investigate how individual combinations of features influence particular predictions. For example, the analysis could determine whether a respondent's predicted purchasing intention is associated more strongly with ethical orientation, masstige perception, value consciousness or digital influence. However, SHAP values would describe predictive contributions rather than establish causal effects. The present study has not yet reported computed SHAP values. Consequently, the correlation coefficients presented in the empirical findings must not be interpreted as feature attribution estimates.

7.5 Proposed Hybrid Optimisation Function

The advanced HCCI-XAI architecture may integrate predictive error, model regularisation and explanation stability within a unified objective. A possible formulation is:

$$L_HCCI\text{-}XAI = L_prediction + \lambda_1 \Omega(\vartheta) + \lambda_2 L_stability$$

The prediction component (Prediction loss function) can be expressed as:

$$L_prediction = (1/N) \times \Sigma_{i=1}^{N} (PI_i - \hat{PI}_i)^2$$

An explanation stability (Explanation stability loss function) objective could be formulated as:

$$L_stability = (1/N) \times \Sigma_{i=1}^{N} ||\varphi(X_i) - \varphi(\tilde{X}_i)||_2^2$$

L_HCCI-XAI = Total optimisation loss of the proposed HCCI-XAI framework

L_prediction = Prediction error measured using mean squared error

L_stability = Explanation stability penalty

λ_1 = Regularisation coefficient controlling model complexity

λ_2 = Weight assigned to explanation stability

$\Omega(\vartheta)$ = Regularisation function applied to model parameters

ϑ = Learnable model parameters

N = Total number of respondents in the modelling dataset (376)

PI_i = Actual purchase intention of respondent i

$\hat{PI}_i$ = *Predicted purchase intention of respondent i*

X_i = *Original behavioural feature vector of respondent i*

$\tilde{X}_i$ = *Valid, slightly perturbed behavioural feature vector*

$\varphi(X_i)$ = *SHAP feature attribution vector for the original input*

$\varphi(\tilde{X}_i)$ = *SHAP feature attribution vector for the perturbed input*

$\| \|_2^2$ = *Squared Euclidean norm measuring differences between attribution vectors*

Σ = *Summation operator*

8. Discussion

The empirical findings give an interdisciplinary understanding on young adult consumer's consumption pattern due to the relevance of value consciousness, ethical orientation, digital influence and symbolic motivations and aspirational purchase preferences. Value Consciousness had the highest descriptive mean and thus suggests that participants generally consider price and quality as a part of their evaluation when purchasing. This is a test of a simplistic assumption of young adult aspirational consumption, that it is largely concerned with prestige or social recognition. It is also noted that the Ethical Orientation and Purchase Intention variables are positively correlated, which suggests that there is no conflict between consumers' ethical preferences and their desire for affordable premium products. This relationship is valid in the dimension of sustainability of Industry 5.0, which is focused on the convergence of economic growth, environmental and sociological aspects. The correlation between Digital Influence and Purchase Intention highlights the importance of the online world in the consumer decision making process of these days. Digital platforms provide information and comparative evaluations of products, social recommendations and even expectations of commerce and idealized images of consumption. From a psychosocial viewpoint, these results justify the investigation and comprehension of the interactions between digital consumption surroundings and identity formation and perceived monetary independence. However, it is unable to conclude if the anxiety and social comparison distress and reduction in well-being resulting from digitally-influenced purchase is caused by the product. The results of predictive machine learning are a methodological addition. Increased computational complexity did not lead to better predictive performance as seen when Ridge regression had a slightly higher mean cross-validated R^2 than Random Forest. This is especially true in the case of artificial intelligence (AI) focussing on "Human Centric Ecosystem". When the predictive performance of a simple model is comparable to that of a more complex model, it may be better. These models can help to interpret the data more clearly and simplify unwanted implementation. The results of clustering also offer insights into behavioural heterogeneity. The two cluster solution suggests that it may be possible to classify respondents with regard to their attitude towards the purchase to some degree. The small silhouette coefficient, however, indicates that there are high overlaps between groups. The results suggest that a continuum of consumer behavior instead of a classification perspective might be better. This is a well-resonated interpretation since it refrains from attaching potentially inappropriate labels to people. Considering the whole picture, the findings are favourable to a person-centric consumption intelligence strategy, using predictive analytics to analyse human behavior but respecting individual autonomy and without psychological classifications without support.

9. The implication for the health and well-being of young adults.

Young adults experience numerous transitions –social pressure, work pressure, and financial expectations and obligations. These changes can come at a time when the consumption decision can be associated with personal objectives and fantasies about others. The present study demonstrates the measurability of digital influence and furthermore symbolic consumption and preferences related to affordability in purchasing behaviour of young adults. The dimensions could be relevant to health related research as financial well-being and experiences with digital technologies are part of a wider social environment within which young people grow up. Results can be utilized in educational programmes on digital consumer literacy. These programmes might assist students to assess influencer promotion, understand the difference between commercial persuasion and independent information, and make the buying decisions in line with their own financial situation. The high rating for Value Consciousness indicates that the factor of affordability and quality is already a very important factor for the respondents. Financial education programmes can then adapt their messages to take account of consumers' existing preferences and behaviours rather than assuming youth don't know that consumers know the difference between price and value. The results also offer a foundation for interdisciplinary collaborative efforts between educators, public health researchers and psychologists and consumer behaviour specialists. The present study, however, cannot be definitive in determining that the respondents are experiencing psychological

distress related to aspirational consumption. Nor can it state whether or not specific buying patterns will have a positive or negative impact on mental health. These are relevant questions that could be answered in future studies using validated instruments to assess perceived stress, symptoms of anxiety, subjective financial well-being, social comparison, and consumer autonomy.

10. Industry 5.0 Implications

The significance of Artificial Intelligence for the wellbeing of consumers can be viewed as a part of the new industrial revolution. Industry 5.o and 6.o have been more values oriented and human centered. The theme is very plain and simple “make things appear to be better and non complicated”. The European Commission (2021) highlighted the importance of Industry 5.0 not only being technologically efficient, but also human-centric, sustainable and resilient. Consumer analytics algorithmic systems should not only boost business engagement, but also decisions based on knowledge. The HCCI-XAI framework adds to this view by combining the behavioural prediction with explicit interpretability and responsible application. The findings of this study indicate that the ethics, preference based on price and digital influence are relevant to the purchasing behavior of young adults. These are insights that can be used for developing consumer information systems, which can offer better comparisons of products, more clear recommendations and information about sustainability. The misconception on adults that they tend to spend more and are not financially responsible is not true and this is the game changer which has to be understood by brands. Consumer segmentation models, based on financial constraints and/or psychological sensitivity, could be modified to target consumers for exploitation, resulting in new discoveries. The present research is thus to be interpreted as a confirmation of the aggregate behavioural analysis and not for any commercial use of the target group. The framework should also cover privacy protection, fairness assessment, human oversight, and clear guidelines for the use of predictive outputs. In this sense, HCCI-XAI is not only the prediction of the intention to purchase but the power of the behaviour analytics to be integrated into a larger context of human welfare and intelligent technologies. The results offer a basis for creating evidence-based consumer education programs for young adults, Financial and digital media literacy, and motivation to involve in a responsible consumption process. In addition these principles can be incorporated into student development programmes in educational institutions. These could include the impact of social media advertising, premium brand positioning, installment purchasing and ethical product evaluation. This will also enhance students' critical thinking, sense of deep observational skills and ability to engage in competitive buying rather than just being carried away by desires nudged by brands.

Value Consciousness is also well supported and indicates that financial education can create more awareness to be more responsible and seek products/services which render more value and benefits. The research has significant public policy implications in the areas which include: transparent digital marketing, consumer protection, cyber issues in algorithmically mediated platforms etc. In addition, recommendation systems and financial conditions, consumer autonomy and commercial persuasions should be taken into account when developing responsible artificial intelligence policies. However, policy recommendations should be considered in the light of evidence but to be proportionate. This current study offers associations and predictive results for purchasing behaviour, but does not directly address mental health outcomes or harmful business practices. The first problem encountered in this study is the limitation of the study population restricted to a particular group. The respondents were mostly young adults – mostly post-graduate students – at educational institutions in Bengaluru. Therefore, the results may not be applicable to other adolescents or to young adults who are from rural settings who have varying socioeconomic backgrounds. The second constraint relates to the cross-sectional research design. Since the questionnaire measures behavioural attitudes in the past, the ordering or causal inference of behaviour is not made. The third restriction concerns data that is self-reported. Recalls may affect responses or social desirability and personal interpretation of items in questionnaires can affect responses. The fourth constraint is for the construct measurement. Behavioural variables were created by aggregating the items from questionnaires. This is conveniently done mathematically, but the reliability and factor validation of the measure must be formalized to ensure that the measure is of good quality. The fifth constraint is related to predictive performance. The Ridge and Random Forest models were quite moderate in predictive capacity, suggesting a significant amount of unexplainable variation in Purchase Intention. The sixth limitation is that of the relatively small sample size. While the dataset can be used for exploratory machine learning, more intricate models like graph neural networks and attention-based ones might be prone to overfitting. The seventh restriction is cluster related. Modest separation is illustrated by the best reported silhouette coefficient and cluster stability has yet to be verified with repeated resampling. The eighth restriction is in relation to the Consumer and Psychological Health distinction. There are no validated measures of anxiety, depression, perceived stress or psychological well-being in the questionnaire. As a result, there is no current data to support a mental health diagnosis, vulnerability classification or psychological risk prediction. Last, the proposed HCCI-XAI architecture is a methodological extension. Further it needs to be

implemented and independently validated in order to make empirical claims on its performance for its attention mechanisms, graph learning, and explanations based on SHAP values.

13. Future Research

Further studies could build upon the current research by combining the current study with longitudinal study involving a deep investigation to find the changes in consumer behaviour, digital influence, financial situations, and psychological well-being over time. Longitudinal data can be used to examine whether the changes in aspirational consumption lead to changes in financial pressure or psychological experiences. Follow-up studies should use validated mental health instruments in addition to the current consumer questionnaire. Instruments like the Perceived Stress Scale, Generalized Anxiety Disorder scale and Patient Health Questionnaire may be used (Cohen et al., 1983; Spitzer et al., 2006; Kroenke et al., 2001). The proposed Consumption-Related Psychosocial Vulnerability construct also needs to be conceptually developed and validated independently. It should be developed so that measures of social comparison, external purchasing pressure, perceived financial anxiety and related psychological outcomes are directly included. Future computational studies could be done to compare Ridge regression and Random Forest with other approaches such as XGBoost, CatBoost, attention-based neural networks and graph-learning architectures. Comparisons should be done using the same cross-validation partition, a good hyperparameter search, and clear performance reporting. Through the use of SHAP analysis, this study could offer some other explanations of the behaviour of the model, such as finding out in what proportion individual predictors influence the purchasing intention. More external validation by city, institution and socioeconomic groups would increase the generalisability of the findings. Studies with younger adolescent groups would also help to ensure the framework is more consistent with research on adolescent health. These investigations would involve age-appropriate questionnaires, appropriate consent protocol and safeguards regarding psychological information of a sensitive nature.

14. Conclusion

The present study aimed to examine the aspiration consumption and buying intention of young adults (mostly post-graduates) from the city of Bangalore in Karnataka using statistical analysis and machine learning methodologies. The results indicate that there are various dimensions such as value consciousness, ethical orientation, masstige perception, consumer orientation, digital influence and symbolic consumption that are linked to the purchase behavior of the young adult population. The highest mean score in purchase behaviour influence is Value Consciousness with a mean score of 4.210. In addition to this the results of correlation showed that there was a positive and significant relationship between Ethical Orientation and Purchase Intention, followed by Consumer Orientation and Masstige Perception and Digital Influence. Moderate predictive ability was shown with supervised machine learning and this is because consumer purchase intention is complex in nature and is highly influenced by market trends, changing emotions and situational factors. The later reported model configuration, with Ridge regression giving a reported mean cross-validated R^2 of 0.3151, and Random Forest 0.2805. This is not because the dataset was small (N = 376). The sample size used in this research is decent however; the observations in this study did not guarantee higher predictive power. The study advances the study of consumer behaviour with its multidimensional approach to aspirational purchase and the benefit of interpretable predictive modelling. In the context of Industry 5.0, its relevance is that it can make consumer knowledge "human-centric" and make transparency, sustainability, autonomy and responsible use of technology important factors that influence and nudge purchase intentions. The overall results provide an empirical basis for examining the potential linkages between young adult psychosocial development, digital consumer environments, abilities in financial decision making and social identity, from a mental health promotion standpoint. The present study, however, does not report direct measures of mental health in relation to the study because it does not address psychological constructs like anxiety, purchase phobia or emotional wellbeing. The proposed “HCCI-XAI” structure can be a starting point for future research that will integrate validated psychological instruments and responsible machine learning in the development of digital consumer ecosystems for informed decisions and human well-being.

References

1. Arnett, J. J. (2000). Emerging adulthood: A theory of development from the late teens through the twenties. American Psychologist, 55(5), 469–480. https://doi.org/10.1037/0003-066X.55.5.469
2. Akhtar, N., & Alharthi, M. F. (2025). Enhancing accuracy in modelling highly multicollinear data using alternative shrinkage parameters for ridge regression methods. Scientific Reports, 15, Article 10774. https://doi.org/10.1038/s41598-025-94857-7

3. Barakat, M. S., Field, M., Ghose, A., Stirling, D., Holloway, L., Vinod, S., Dekker, A., & Thwaites, D. (2017). The effect of imputing missing clinical attribute values on training lung cancer survival prediction model performance. Health Information Science and Systems, 5, Article 16. https://doi.org/10.1007/s13755-017-0039-4
4. Belk, R. W. (1988). Possessions and the extended self. Journal of Consumer Research, 15(2), 139–168. https://doi.org/10.1086/209154
5. Brandesis. (n.d.). Youth consumer behavior. Brandesis Brand Library. https://brandesis.com/terms/youth-consumer-behavior/
6. Breiman, L. (2001). Random forests. Machine Learning, 45, 5–32. https://doi.org/10.1023/A:1010933404324
7. Brüggen, E. C., Hogreve, J., Holmlund, M., Kabadayi, S., & Löfgren, M. (2017). Financial well-being: A conceptualization and research agenda. Journal of Business Research, 79, 228–237. https://doi.org/10.1016/j.jbusres.2017.03.013
8. Chen, T., & Guestrin, C. (2016). XGBoost: A scalable tree boosting system. In Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (pp. 785–794). Association for Computing Machinery. https://doi.org/10.1145/2939672.2939785
9. Cohen, S., Kamarck, T., & Mermelstein, R. (1983). A global measure of perceived stress. Journal of Health and Social Behavior, 24(4), 385–396. https://doi.org/10.2307/2136404
10. Dahiya, A., Banerji, D., & Filieri, R. (2025). Consumer well-being: A systematic literature review and future research directions. Spanish Journal of Marketing – ESIC, 29(4), 465–490. https://doi.org/10.1108/SJME-12-2023-0355
11. Deci, E. L., & Ryan, R. M. (2000). The "what" and "why" of goal pursuits: Human needs and the self-determination of behavior. Psychological Inquiry, 11(4), 227–268. https://doi.org/10.1207/S15327965PLI1104_01
12. Dittmar, H., Bond, R., Hurst, M., & Kasser, T. (2014). The relationship between materialism and personal well-being: A meta-analysis. Journal of Personality and Social Psychology, 107(5), 879–924. https://doi.org/10.1037/a0037409
13. Ebongo, L. (2026, March 5). Gen Z consumer behaviour in 2026: Value, trust and community are reshaping spend. dentsu. https://www.dentsu.com/uk/en/blog/gen-z-consumer-behaviour-in-2026
14. Elshaer, I. A., Azazz, A. M. S., Fayyad, S., & Elziny, M. N. (2026). Digital social comparison and consumer behavior: The roles of status motivation and benign envy in green hotel booking decisions. Societies, 16(10), Article 330. https://doi.org/10.3390/soc16100330
15. European Commission, Directorate-General for Research and Innovation. (2021). Industry 5.0: Towards a sustainable, human-centric and resilient European industry. Publications Office of the European Union. https://doi.org/10.2777/308407
16. Festinger, L. (1954). A theory of social comparison processes. Human Relations, 7(2), 117–140. https://doi.org/10.1177/001872675400700202
17. Huang, L., Nor, K. M., Ma, X., & Khatib, S. F. A. (2025). Trends and future directions of consumers' intention to buy ethical products: A systematic literature review. Cogent Business & Management, 12(1), Article 2534528. https://doi.org/10.1080/23311975.2025.2534528
18. Huang, W., Cai, Y., & Zhang, G. (2024). Battery degradation analysis through sparse ridge regression. Energy & System, 4(4). https://hal.science/hal-05038531
19. James, T. L., Whelan, E., & Conboy, K. (2026). Is fitness technology-facilitated social comparison the thief of well-being? The mediating role of social comparison on the relationships between passion and performance self-esteem. Information Systems Research, 37(1). https://doi.org/10.1287/isre.2021.0083
20. Keles, B., McCrae, N., & Grealish, A. (2020). A systematic review: The influence of social media on depression, anxiety and psychological distress in adolescents. International Journal of Adolescence and Youth, 25(1), 79–93. https://doi.org/10.1080/02673843.2019.1590851
21. Kristina, A., Tsaniyah, A. E., & Kamsin, K. (2026). Veblenian consumption in the digital age: Self-image, social status, and the performance of distinction. The Journal of Society and Media, 10(1), 58–77. https://doi.org/10.26740/jsm.v10n1.p58-77
22. Kroenke, K., Spitzer, R. L., & Williams, J. B. W. (2001). The PHQ-9: Validity of a brief depression severity measure. Journal of General Internal Medicine, 16(9), 606–613. https://doi.org/10.1046/j.1525-1497.2001.016009606.x
23. Kutaula, S., Gillani, A., Gregory-Smith, D., & Bartikowski, B. (2024). Ethical consumerism in emerging markets: Opportunities and challenges. Journal of Business Ethics, 191, 651–673. https://doi.org/10.1007/s10551-024-05657-4
24. Lichtenstein, D. R., Netemeyer, R. G., & Burton, S. (1990). Distinguishing coupon proneness from value consciousness: An acquisition-transaction utility theory perspective. Journal of Marketing, 54(3), 54–67. https://doi.org/10.1177/002224299005400305
25. Lundberg, S. M., & Lee, S.-I. (2017). A unified approach to interpreting model predictions. Advances in Neural Information Processing Systems, 30.

26. Maheshwari, T., Singh, K., Kumari, K., Sharma, K., & Keshri, K. (2025). Emotions, identity, and consumption: A study of symbolic consumer behaviour. NIET Journal of Management, 15(2).
27. Martins, R. M., Barros, L. S. G., Zambaldi, F., Ponchio, M. C., & Lourenço, C. E. (2026). The role of social comparison and self-enhancement on consumer-to-consumer helping behavior in online communities. Journal of Business Research. https://doi.org/10.1016/j.jbusres.2025.115912
28. Nageswari, Ch., Doodipala, M. R., Rao, N. J., Krishna, M. V., & Srinivas, K. (2025). Power of social media marketing: Driving customer engagement in the digital era. Journal of Marketing & Social Research, 2(2), 71–86. https://doi.org/10.61336/jmsr/25-02-13
29. Paul, J. (2015). Masstige marketing redefined and mapped: Introducing a pyramid model and MMS measure. Marketing Intelligence & Planning, 33(5), 691–706. https://doi.org/10.1108/MIP-02-2014-0028
30. Potluri, R. M., et al. (2026). Conspicuous consumption in an emerging luxury market: A Veblenian, signalling, and social identity perspective from Kazakhstan. Social Sciences & Humanities Open. https://www.sciencedirect.com/science/article/pii/S2590291126012398
31. Peng, L., Chattopadhyay, A., Zancato, L., Nunez, E., Xia, W., & Soatto, S. (2026). Gated KalmaNet: A fading memory layer through test-time ridge regression. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR 2026).
32. Richins, M. L., & Dawson, S. (1992). A consumer values orientation for materialism and its measurement: Scale development and validation. Journal of Consumer Research, 19(3), 303–316. https://doi.org/10.1086/209304
33. Roy, A., Das, M., Lim, W. M., & Kalai, A. (2025). Masstige consumption: A motivation-desire-outcome framework with implications for luxury brand management. Journal of Global Marketing, 38(1), 27–58. https://doi.org/10.1080/08911762.2025.2449697
34. Sekar, D., Ramesh, A., Mahesh, G., & Bhuvaneswari, M. (2026). Beauty ideals, consumer choices, and their impact on adolescent self-esteem and psychological well-being. International Journal of Spa and Wellness, 9(1), 94–105. https://doi.org/10.1080/24721735.2026.2615568
35. Shah, M. A. R., Shah, A. Z., & Kamran, M. (2026). Beyond borders: Unraveling the cultural dynamics in masstige consumption. Quality & Quantity. https://doi.org/10.1007/s11135-026-02746-6
36. Sharma, P., Gaba, P., & Sharma, B. (2026). Can cognitive nudges in gamified digital payments foster digital financial well-being? In Proceedings of the 13th International Youth Conference in the series of "Youth for India @2047, AI Disruption and Opportunities: Preparing Youth for Global Challenges" (Advances in Intelligent Systems Research, Vol. 208). https://doi.org/10.2991/978-94-6239-676-0_17
37. Silverstein, M. J., & Fiske, N. (2003). Luxury for the masses. Harvard Business Review, 81(4), 48–57.
38. Spitzer, R. L., Kroenke, K., Williams, J. B. W., & Löwe, B. (2006). A brief measure for assessing generalized anxiety disorder: The GAD-7. Archives of Internal Medicine, 166(10), 1092–1097. https://doi.org/10.1001/archinte.166.10.1092
39. Suttharattanagul, S. L., Santipiriyapon, S., & Daengrasmisopon, T. (2025). Mindful consumption and sustainability values: Shaping purchase intentions and well-being among Generation Z. Sustainability, 17(21), Article 9725. https://doi.org/10.3390/su17219725
40. Tian, S., Cho, S. Y., Jia, X., Sun, R., & Tsai, W. S. (2023). Antecedents and outcomes of Generation Z consumers' contrastive and assimilative upward comparisons with social media influencers. Journal of Product & Brand Management. https://doi.org/10.1108/JPBM-02-2022-3879
41. Tylka, T. L., & Wood-Barcalow, N. L. (2026). Self-oriented comparison scale for appearance (SOCS-A): Development and psychometric evaluation. Body Image. https://www.sciencedirect.com/science/article/pii/S1740144526001336
42. Uluturk, A. S., & Asan, U. (2024). Examining the moderating role of reasons in masstige luxury buying behavior. Behavioral Sciences, 14(1), Article 67. https://doi.org/10.3390/bs14010067
43. Vogel, E. A., Rose, J. P., Roberts, L. R., & Eckles, K. (2014). Social comparison, social media, and self-esteem. Psychology of Popular Media Culture, 3(4), 206–222. https://doi.org/10.1037/ppm0000047
44. World Economic Forum. (2026). Youth pulse 2026: Insights from the next generation for a changing world. https://reports.weforum.org/docs/WEF_Youth_Pulse_2026.pdf
45. World Health Organization. (2024). Mental health of adolescents. https://www.who.int/news-room/fact-sheets/detail/adolescent-mental-health
46. Yuvita, H., & Permatasari, I. (2025). The effect of frugal living on purchase decisions among Generation Z: The mediating role of financial well-being. Jurnal Sains Sosio Humaniora, 9(1), 145–156. https://doi.org/10.22437/jssh.v9i1.56701

Annexure 1: Statistical and Machine Learning Analysis Tables

Table 1. Dataset characteristics and analytical sample

Parameter	Value
Total respondents	386
Total recorded variables	35
Behavioural questionnaire items	29
Independent behavioural constructs	6
Dependent construct	Purchase Intention
Missing behavioural item responses	204
Valid observations for supervised ML	376
Measurement scale	Five-point Likert
Data collection period	March–July 2026

Table 2. Age distribution of respondents

Age category	Frequency	Percentage
18–20 years	20	5.18%
21–23 years	253	65.54%
24–26 years	95	24.61%
27 years and above	16	4.15%
Missing	2	0.52%
Total	**386**	**100.00%**

The sample predominantly represents young adults aged 21–23 years.

Table 3. Descriptive statistics of behavioural constructs

Behavioural construct	Abbreviation	Valid N	Mean
Masstige Perception (Independent)	MP	385	3.8543
Symbolic Consumption Orientation (Independent)	SCO	383	3.3351
Value Consciousness (Independent)	VC	384	4.2096
Consumer Orientation (Independent)	CO	382	3.6143

Digital Influence (Independent)	DI	381	3.5109
Ethical Orientation (Independent)	EO	375	3.7422
Purchase Intention (Dependent)	PI	376	3.6755

Interpretation: Value Consciousness recorded the highest mean, followed by Masstige Perception and Ethical Orientation. Symbolic Consumption Orientation recorded the lowest mean.

Table 4. Spearman's rank correlation with Purchase Intention

Independent variable	Valid pairs	Spearman's ρ	Significance
Masstige Perception	376	0.4157	$p < 0.001$
Symbolic Consumption Orientation	376	0.3500	$p < 0.001$
Value Consciousness	376	0.2459	$p < 0.001$
Consumer Orientation	375	0.4655	$p < 0.001$
Digital Influence	375	0.4073	$p < 0.001$
Ethical Orientation	374	0.4749	$p < 0.001$

Interpretation: All six predictors demonstrated statistically significant positive associations with Purchase Intention. Ethical Orientation showed the strongest bivariate association, followed by Consumer Orientation.

Table 5. Supervised machine learning model configuration

Model parameter	Ridge Regression	Random Forest
Outcome variable	Purchase Intention	Purchase Intention
Predictor variables	MP, SCO, VC, CO, DI, EO	MP, SCO, VC, CO, DI, EO
Modelling sample	376	376
Missing predictor treatment	Median imputation	Median imputation
Cross-validation	Repeated 5-fold × 3	Repeated 5-fold × 3
Evaluation folds	15	15
Regularisation α	1	N/A
Number of trees	N/A	200
Minimum leaf size	N/A	4
Random seed	42	42

Table 6. Comparative machine learning performance

Evaluation metric	Ridge Regression	Random Forest
Mean cross-validated R^2	0.3133	0.2798
Standard deviation of R^2	0.0972	0.0913
Mean absolute error (MAE)	0.6059	0.6051
Number of validation folds	15	15

Interpretation: Ridge regression achieved higher mean cross-validated R^2, whereas Random Forest achieved a marginally lower MAE. The results do not establish statistically significant superiority for either model.

Table 7. K-means clustering validation

Number of clusters (K)	Silhouette coefficient
K = 2	0.2485
K = 3	0.1932
K = 4	0.1994
K = 5	0.1655

Interpretation: The two-cluster solution achieved the highest silhouette coefficient among the evaluated alternatives, although the relatively low value indicates modest cluster separation.

Table 8. Distribution of the selected two-cluster solution

Cluster	Respondents	Percentage
Cluster 1	199	52.93%
Cluster 2	177	47.07%
Total	**376**	**100.00%**

Interpretation: The clustering results identified two relatively balanced groups. Their substantive behavioural characteristics cannot be determined without examining cluster centroids.

Table 9. Summary of empirical findings

Analytical technique	Key result	Research implication
Descriptive statistics	VC mean = 4.2096	Value-related considerations are strongly endorsed
Spearman correlation	EO–PI, ρ = 0.4749	Ethical orientation has the strongest observed bivariate association with purchase intention
Spearman correlation	DI–PI, ρ = 0.4073	Digital influence is positively associated with purchase intention
Ridge Regression	R^2 = 0.3133	Regularised linear modelling provides moderate predictive performance

Random Forest	$R^2 = 0.2798$	Nonlinear ensemble modelling did not improve mean R^2
K-means clustering	Optimal tested K = 2	Some behavioural heterogeneity is present
Silhouette validation	0.2485	Cluster separation is modest

Table 10. Alignment between proposed HCCI-XAI techniques and empirical evidence

Analytical component	Formula or technique	Empirical status
Behavioural feature engineering	Construct mean aggregation	Completed
Correlation analysis	Spearman's ρ	Completed
Regularised prediction	Ridge regression	Completed
Ensemble prediction	Random Forest	Completed
Behavioural segmentation	K-means clustering	Completed
Cluster validation	Silhouette coefficient	Completed
Gradient boosting	XGBoost	Not yet evaluated
Explainable AI	SHAP	Not yet evaluated
Attention-guided feature fusion	Softmax attention	Proposed only
Graph-based similarity learning	Graph neural network	Proposed only
Mental health prediction	Validated psychological outcomes	Not supported by dataset

Annexure 2 - Questionnaire constructs (Excluding demographic variables)

1. Masstige Perception (MP)	
Q7: I prefer brands that offer premium quality at reasonable prices.	**Q8:** I feel masstige brands provide a balance between prestige and affordability.
Q9: Masstige brands help me experience a sense of luxury within my budget.	**Q10:** I associate masstige brands with modern lifestyle and social acceptance.

2. Social Comparison Orientation (SCO)	
Q11: The brands I use reflect who I am.	**Q12:** I feel proud when others notice the brands I use.
Q13: I prefer brands that enhance my social image.	**Q14:** I buy certain brands to project success or sophistication.

3. Value Consciousness (VC)	
Q15: I carefully compare prices before buying premium products.	**Q16:** I seek the best quality for the money I spend.

Q17: Even for prestigious brands, price matters to me.	**Q18:** Discounts strongly influence my purchase decisions.

5. Digital Influence (DI)	
Q27: Social media affects how I perceive premium brands.	**Q28:** Online reviews influence my purchase decisions.
Q29: Influencers increase my confidence in certain brands.	

6. Ethical Orientation (EO)	
Q30: I prefer brands that care about sustainability.	**Q31:** Ethical business practices influence my brand choice.
Q32: I am willing to pay slightly more for environmentally responsible products.	

7. Purchase Intention (PI) & Additional Item	
Q33: I plan to continue buying masstige brands in the future.	**Q34:** I would recommend these brands to others.
Q35: I feel emotionally connected to certain masstige brands.	

4. Consumer Orientation (CO)	
Q19: I prefer exclusive products even if they cost slightly more.	**Q20:** Personalized service makes me loyal to a brand.
Q21: I can afford luxury brands but prefer value-for-money alternatives.	**Q22:** I look for both status and practical benefits in a brand.
Q23: I aspire to own prestigious brands even if they are expensive for me.	**Q24:** EMI or installment options influence my buying decisions.
Q25: I change brands based on price and offers.	**Q26:** I balance prestige and affordability when choosing brands.