# Predicting Online Purchase Intention from Consumer Behaviour: A Comparative Analysis of Regression and Machine Learning

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***Abstract—Online purchase intention reflects multiple, overlapping behavioural factors, yet studies rarely compare how strongly such factors explain intention statistically against how strongly they predict it. This study examines seven behavioural constructs—Price Sensitivity, Review/Ratings Influence, Quality and Brand Trust, Website Convenience, Fulfilment and Security, Social Influence, and Previous Experience—as predictors of Online Purchase Intention among Indian online shoppers, comparing multiple regression with five machine-learning algorithms on the same survey data (N = 228; 227 usable). Six constructs showed significant positive bivariate relationships with purchase intention; Social Influence did not. The regression model was significant ($R^2 = 0.1914$, adjusted $R^2 = 0.1656$, $F(7,219) = 7.4065$, $p < 0.001$), with Quality and Brand Trust the only significant unique predictor ($B = 0.211$, $p = 0.025$). Among Linear Regression, Decision Tree, Random Forest, Support Vector Regression, and K-Nearest Neighbours, Support Vector Regression achieved the highest holdout $R^2$ (0.185), while Linear Regression achieved the highest mean cross-validated $R^2$ (0.123). Permutation importance ranked Previous Experience and Fulfilment and Security highest. Predictive performance was modest overall, and all multi-item constructs had Cronbach's alpha below 0.70. Statistical significance, unique linear contribution, and predictive importance therefore capture different aspects of behavioural relevance and should be treated as complementary rather than interchangeable evidence in online consumer research.***

***Keywords— online purchase intention; consumer behaviour; electronic commerce; machine learning; multiple regression; predictive analytics; Cronbach's alpha; India***

## I. INTRODUCTION

E-commerce has transformed how consumers search, compare and purchase products, while simultaneously creating a more complex decision environment in which price cues, reviews, trust, website design, delivery reliability, payment security, social influence and prior experience can all shape buying intentions. Purchase intention is therefore not a single-factor outcome but a behavioural response formed from multiple cognitive, experiential and risk-related evaluations. Foundational e-commerce research has consistently identified trust and perceived risk as central to online transaction intention [1], [2], while later work has demonstrated the roles of price/value perceptions [3], online reviews [4], [5], website quality [6], fulfilment and security risks [7], and previous experience [8]. More recent syntheses likewise show that online purchase intention is associated with a broad set of technology, trust, security, electronic word-of-mouth and contextual factors [9].

At the same time, predictive analytics has become increasingly important in electronic commerce. Machine-learning studies have shown that purchase-related outcomes can be modelled from behavioural or session-level information, although predictive accuracy and interpretability are distinct objectives [10], [11]. This creates an important methodological question for consumer research: whether the variables that appear important under conventional statistical inference are also the variables that contribute most strongly to out-of-sample prediction.

Existing research often examines behavioural antecedents through regression or structural-equation approaches, while machine-learning research frequently focuses on predictive performance using clickstream or platform data. The present study links these traditions by applying correlation analysis, multiple regression and five machine-learning algorithms to the same set of survey-derived behavioural constructs. It also reports both a single independent holdout test and five-fold cross-validation rather than presenting one favourable model ranking.

The study addresses three objectives. First, it evaluates the bivariate and multivariate relationships between seven behavioural constructs and Online Purchase Intention. Second, it compares predictive performance across Linear Regression, Decision Tree, Random Forest, Support Vector Regression (SVR) and K-Nearest Neighbours (KNN). Third, it examines whether model-based permutation importance produces the same substantive ranking as conventional statistical significance. The Indian online-shopping context provides an applied setting in which these questions are particularly relevant to retailers operating across marketplaces, brand-owned channels and mobile-first shopping environments.

## II. LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

### *A. Conceptual Framework*

The seven predictors are organised into four broader behavioural mechanisms. Price Sensitivity represents value-related evaluation; Review/Ratings Influence represents information and electronic word-of-mouth; Quality and Brand Trust together with Fulfilment and Security represent trust/risk reduction; Website Convenience represents interface and shopping-process utility; and Social Influence together with Previous Experience represent social and experiential inputs. This framework does not claim that the constructs are interchangeable. Rather, it provides a common behavioural architecture for examining whether distinct mechanisms contribute differently to association, unique linear explanation and predictive performance.

### *B. Price Sensitivity and Perceived Value*

Price information provides consumers with a reference point for perceived value. Grewal et al. [3] showed that store, brand and price-discount cues shape internal reference price, perceived quality and perceived value, which in turn affect purchase intentions. In digital commerce, comparison tools, dynamic discounts and promotional displays make price information particularly salient. Accordingly, consumers who are more sensitive to price or responsive to discounts may report stronger purchase intention when online offers are perceived as attractive.

H1. Price Sensitivity has a significant relationship with Online Purchase Intention.

### *C. Online Reviews and Ratings*

Online reviews reduce information asymmetry by allowing prospective buyers to observe prior customers' evaluations. Chevalier and Mayzlin [4] demonstrated that online reviews can influence sales, while Park et al. [5] showed that review quality and quantity affect purchase intention. Recent evidence also reports relationships between online reviews, social influence and purchase intention [12], while meta-analytic evidence indicates an overall relationship between review characteristics and purchase intention [13].

H2. Review/Ratings Influence has a significant positive relationship with Online Purchase Intention.

### *D. Quality and Brand Trust*

Trust is one of the persistent explanatory constructs in e-commerce. Pavlou [1] integrated trust and perceived risk with the Technology Acceptance Model, while Kim et al. [2] demonstrated that reputation, information quality, privacy and security antecedents shape trust and transaction intention. Konuk [14] linked perceived quality and trust to perceived value and purchase intention. Recent cross-market evidence likewise finds that reputation, security and website quality contribute to e-commerce trust, which is positively associated with purchase intention [15].

H3. Quality and Brand Trust have a significant positive relationship with Online Purchase Intention.

### *E. Website Convenience*

Website quality and convenience reduce the effort required to search, evaluate and transact online. Kim and Lennon [6] showed that website quality influences emotional response, perceived risk and purchase intention. Contemporary evidence continues to identify website quality as an antecedent of trust and online purchase intention [16]. In the present study, Website Convenience captures usability, shopping-from-home convenience and the informational support offered by the website or application.

H4. Website Convenience has a significant positive relationship with Online Purchase Intention.

*F. Fulfilment, Payment Security and Risk Reduction*

Online transactions expose consumers to uncertainty surrounding delivery, product performance, returns, financial loss and information security. Forsythe and Shi [7] identified multiple forms of perceived Internet-shopping risk, while a systematic review by Phamthi [17] highlights delivery, financial and information-security risks as persistent determinants of e-commerce purchase intention. Reliable fulfilment, flexible return arrangements and secure payment options should therefore reduce perceived transaction risk.

H5. Fulfilment and Security have a significant positive relationship with Online Purchase Intention.

*G. Social Influence*

Social cues may affect purchase intention through recommendations, social support and perceived norms. Lăzăroiu et al. [18] reported significant social-media and social-interactivity effects in social-commerce contexts. However, such effects may depend on platform type and the extent to which purchasing occurs in explicitly social environments. The mixed-platform sample used here provides an opportunity to test whether social influence remains significant outside a purely social-commerce setting.
H6. Social Influence has a significant relationship with Online Purchase Intention.

*H. Previous Online-Shopping Experience*

Repeated successful transactions can increase familiarity, confidence and perceived control. Chiu et al. [8] showed that trust, perceived usefulness, ease of use and enjoyment contribute to online repurchase intention. Previous experience may therefore operate both as a direct behavioural cue and as a predictive summary of prior interactions with online retail.

H7. Previous Experience has a significant positive relationship with Online Purchase Intention.

*I. Statistical Explanation versus Machine-Learning Prediction*

Regression and machine learning answer related but non-identical questions. A regression coefficient estimates a predictor's unique linear association with the dependent variable after controlling for other included predictors. In contrast, permutation importance measures how much a fitted model's predictive performance deteriorates when the information in a predictor is disrupted. Variables can therefore be statistically non-significant in a multivariate regression while still contributing to prediction through nonlinearities, interactions or shared information. The present study treats these approaches as complementary rather than assuming that one necessarily supersedes the other.

## III. MATERIALS AND METHODS

*A. Research Design and Sample*

The study employed a quantitative, cross-sectional online survey and combined confirmatory statistical hypothesis testing with exploratory predictive modelling. A total of 228 responses were recorded. One observation was excluded because the dependent-variable item was missing, resulting in an analytical sample of N = 227. No additional imputation or exclusion was applied. The sample was concentrated in the 18–24 and 25–34 age groups. Smartphones were the most common primary shopping device, and Amazon was the most frequently reported platform. The sample included students, employed respondents, self-employed respondents and other employment categories, providing a mixed online-shopping population rather than a platform-specific customer panel.

*B. Measures and Construct Formation*

Online Purchase Intention was measured on a 1–5 scale in response to the item, "How likely were you to purchase the product/service you were considering?" The seven predictors were created from one to three Likert-scale items (1 = Strongly Disagree to 5 = Strongly Agree). Composite scores were calculated by averaging the constituent items. Previous Experience was represented by a single item.

| Construct | Items | Conceptual content |
|---|---|---|
| Price Sensitivity | 2 | Price sensitivity; response to discounts/offers |
| Review/Ratings Influence | 2 | Review checking; effect of product ratings |
| Quality and Brand Trust | 2 | Perceived product quality; trust in brand |
| Website Convenience | 3 | Website/app usability; convenience; product information |

| | | |
|---|---|---|
| Fulfilment and Security | 3 | Delivery reliability; return/refund policy; payment security |
| Social Influence | 2 | Friends/family recommendations; social-media/influencer effect |
| Previous Experience | 1 | Prior positive online-shopping experience (single item) |

*C. Reliability Assessment*

Cronbach's alpha was computed for each multi-item construct. The reliability results are a material limitation of the study: all six multi-item constructs produced alpha values below the conventional 0.70 threshold. These values are reported without adjustment, and construct-level findings are interpreted cautiously as a result. Because Previous Experience is a single-item measure, internal consistency could not be assessed using Cronbach's alpha.

| Construct | Cronbach's alpha | Interpretation |
|---|---|---|
| Price Sensitivity | 0.3070 | Low internal consistency |
| Review/Ratings Influence | 0.4515 | Low internal consistency |
| Quality and Brand Trust | 0.4194 | Low internal consistency |
| Website Convenience | 0.3849 | Low internal consistency |
| Fulfilment and Security | 0.5412 | Low internal consistency |
| Social Influence | 0.2825 | Low internal consistency |
| Previous Experience | N/A | Single-item construct |

*D. Statistical Analysis*

Descriptive statistics were computed for the dependent variable and seven constructs. Pearson correlations were used to test H1–H7 at $\alpha = 0.05$. A multiple linear regression model then entered all seven constructs simultaneously to estimate joint explanatory power and unique predictor contributions. Variance Inflation Factors (VIFs) were calculated to evaluate multicollinearity; all VIF values fell between 1.03 and 2.03, well below conventional concern thresholds.

*E. Machine-Learning Analysis*

Five regression algorithms were evaluated: Linear Regression, Decision Tree Regressor, Random Forest Regressor, Support Vector Regression (SVR), and K-Nearest Neighbours (KNN) Regressor. The data were divided into an 80% training set and a 20% independent holdout test set. Separately, five-fold cross-validation was performed. Performance was evaluated using Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and $R^2$. The holdout-best model was defined as the model with the highest holdout $R^2$, while the cross-validation-best model was defined as the model with the highest mean cross-validated $R^2$; these rankings were intentionally reported separately rather than combined into a single ranking.

Permutation feature importance based on $R^2$ was calculated for the SVR model (the holdout-best model). Importance represents the mean decrease in $R^2$ when a predictor is randomly shuffled while other predictors are retained, and should therefore be interpreted as predictive contribution within the fitted model rather than as a causal effect.

*F. Software*

All statistical and machine-learning analyses were conducted in a Python-based analysis environment using standard open-source libraries for data management (pandas, NumPy), statistical modelling (statsmodels, for the multiple regression and VIF diagnostics), and machine learning (scikit-learn, for train–test splitting, the five regression algorithms, five-fold cross-validation, and permutation importance). Exact package version numbers were not recorded in the underlying analysis file and should be verified before submission.

## IV. RESULTS

A. Descriptive Statistics

| Variable | N | Mean | SD |
|---|---|---|---|
| Online Purchase Intention (DV) | 227 | 3.313 | 1.368 |
| Price Sensitivity | 227 | 3.286 | 1.067 |

| | | | |
|---|---|---|---|
| Review/Ratings Influence | 227 | 3.355 | 1.1318 |
| Quality and Brand Trust | 227 | 3.392 | 1.105 |
| Website Convenience | 227 | 3.320 | 0.922 |
| Fulfilment and Security | 227 | 3.357 | 1.010 |
| Social Influence | 227 | 3.057 | 1.012 |
| Previous Experience | 227 | 3.326 | 1.401 |

*B. Correlations and Hypothesis Tests*

Six of the seven behavioural constructs were significantly and positively correlated with Online Purchase Intention. Fulfilment and Security showed the strongest bivariate relationship (r = 0.3650), followed by Quality and Brand Trust (r = 0.3312) and Website Convenience (r = 0.3178). Social Influence was the only non-significant predictor (r = 0.0653, p = 0.3270). All Variance Inflation Factors remained below 2.1, indicating no serious multicollinearity concern among the seven predictors.

| Hyp. | Construct | r | p | Decision |
|---|---|---|---|---|
| H1 | Price Sensitivity | 0.2567 | <0.001 | Supported |
| H2 | Review/Ratings Influence | 0.2597 | <0.001 | Supported |
| H3 | Quality and Brand Trust | 0.3312 | <0.001 | Supported |
| H4 | Website Convenience | 0.3178 | <0.001 | Supported |
| H5 | Fulfilment and Security | 0.3650 | <0.001 | Supported |
| H6 | Social Influence | 0.0653 | 0.3270 | Not supported |
| H7 | Previous Experience | 0.2674 | <0.001 | Supported |

*C. Multiple Regression*

The full regression model was statistically significant, $R^2 = 0.1914$, adjusted $R^2 = 0.1656$, $F(7,219) = 7.4065$, $p < 0.001$. Thus, the seven constructs jointly explained approximately 19.1% of the observed variance in Online Purchase Intention (16.6% after adjustment for the number of predictors).

| Predictor | B | SE | t | p | Sig. |
|---|---|---|---|---|---|
| Price Sensitivity | 0.1076 | 0.0903 | 1.1917 | 0.2347 | n.s. |
| Review/Ratings Influence | 0.0322 | 0.0919 | 0.3507 | 0.7261 | n.s. |
| Quality and Brand Trust | 0.2114 | 0.0938 | 2.2523 | 0.0253 | * |
| Website Convenience | 0.1008 | 0.1234 | 0.8166 | 0.4150 | n.s. |
| Fulfilment and Security | 0.2094 | 0.1173 | 1.7851 | 0.0756 | n.s. |
| Social Influence | 0.0248 | 0.0835 | 0.2971 | 0.7667 | n.s. |
| Previous Experience | 0.0990 | 0.0669 | 1.4810 | 0.1400 | n.s. |

Quality and Brand Trust was the only predictor that retained a statistically significant unique coefficient (B = 0.2114, p = 0.0253). The contrast with the bivariate results indicates that significant zero-order associations for several constructs overlap with variance shared across correlated predictors—most notably Website Convenience and Fulfilment and Security (r = 0.630).

*D. Machine-Learning Model Comparison*

| Model | Holdout MAE | Holdout RMSE | Holdout $R^2$ | Mean CV $R^2$ | SD CV $R^2$ |
|---|---|---|---|---|---|
| Linear Regression | 1.1911 | 1.4113 | 0.0164 | 0.1230 | 0.0922 |
| Decision Tree | 1.3775 | 1.6793 | -0.3925 | -0.1673 | 0.1187 |
| Random Forest | 1.1671 | 1.3732 | 0.0688 | 0.1009 | 0.0445 |
| Support Vector Regression | 1.0910 | 1.2846 | 0.1851 | 0.1146 | 0.1132 |
| K-Nearest Neighbours | 1.1025 | 1.3213 | 0.1379 | 0.1092 | 0.0743 |

Support Vector Regression achieved the strongest independent holdout performance ($R^2$ = 0.1851, RMSE = 1.2846, MAE = 1.0910), followed by K-Nearest Neighbours ($R^2$ = 0.1379). In contrast, Linear Regression achieved the highest mean five-fold cross-validated $R^2$ (0.1230), narrowly exceeding SVR (0.1146) and KNN (0.1092). The Decision Tree performed worst under both evaluation strategies, including a negative holdout $R^2$ (−0.3925), indicating performance below a simple mean-prediction benchmark.

The divergence between the holdout-best model (SVR) and the CV-best model (Linear Regression) is substantively important rather than an error. With a total sample of 227, the 20% holdout contains approximately 46 cases and is correspondingly sensitive to sampling variation, whereas the cross-validation estimate averages performance across five partitions and provides a broader view of model stability. Across all models and both evaluation methods, $R^2$ values ranged from approximately −0.39 to 0.19, indicating modest rather than high predictive capability.

*E. Permutation Feature Importance*

| Rank | Predictor | Mean importance | SD | Interpretation |
|---|---|---|---|---|
| 1 | Previous Experience | 0.1741 | 0.0547 | Positive contribution |
| 2 | Fulfilment and Security | 0.1106 | 0.0520 | Positive contribution |
| 3 | Price Sensitivity | 0.0833 | 0.0348 | Positive contribution |
| 4 | Social Influence | 0.0611 | 0.0364 | Positive contribution |
| 5 | Review/Ratings Influence | 0.0549 | 0.0296 | Positive contribution |
| 6 | Quality and Brand Trust | 0.0453 | 0.0493 | Positive contribution |
| 7 | Website Convenience | -0.0463 | 0.0323 | Negative/unstable |

Previous Experience and Fulfilment and Security were the two strongest predictive contributors to the SVR model, followed by Price Sensitivity. Social Influence ranked fourth in predictive importance despite being the only construct that was not a statistically significant bivariate predictor, illustrating that permutation importance and bivariate statistical significance can diverge and should not both be treated as causal rankings. Website Convenience produced a negative mean permutation importance; this should not be interpreted as evidence that convenience reduces purchase intention, but rather as unstable or redundant predictive contribution once the strongly correlated Fulfilment and Security construct is already in the model.

## V. DISCUSSION

The findings illustrate why explanatory and predictive evidence should not be treated as interchangeable. At the bivariate level, six constructs were significantly associated with purchase intention. Once all seven constructs were entered simultaneously, however, only Quality and Brand Trust remained statistically significant. This result is consistent with longstanding e-commerce trust literature [1], [2] and with more recent evidence that trust remains central to purchase intention across digital markets [15], [16].

Fulfilment and Security showed the strongest bivariate correlation and the second-highest SVR permutation importance, reinforcing the practical role of reliable delivery, returns and payment security. This aligns with risk-based accounts of online purchasing [7], [17]. Price Sensitivity was also significant bivariately and ranked third in permutation importance, suggesting that value-related cues retain practical predictive relevance even when their unique linear regression coefficient is not significant.

The Social Influence result deserves caution. It was non-significant in the correlation analysis, yet ranked fourth in SVR permutation importance. Rather than treating this as contradictory, the two statistics should be understood as measuring different properties. The very low Cronbach's alpha of the Social Influence scale (0.2825) also limits substantive interpretation. In addition, the sample included mixed shopping platforms rather than exclusively social-commerce environments, which may partly explain the contrast with social-commerce research [18].

The most distinctive cross-method finding concerns Previous Experience. Although it did not remain significant in the multivariate regression, it achieved the highest permutation importance. Previous experience may summarise nonlinear, cumulative or interaction-based information about consumers' confidence and prior outcomes that is not fully captured by a single controlled linear coefficient. This interpretation is consistent with repurchase-intention research emphasising the importance of accumulated experience [8], but it remains exploratory because the measure is a single item and the sample is relatively small.

Across methods, explanatory and predictive power remained modest. The regression $R^2$ was 0.1914, while most cross-validated $R^2$ values were close to 0.10–0.12. These values indicate that short self-report behavioural scales capture only part of the variance in individual purchase intention. Contemporary predictive e-commerce systems often combine attitudinal variables with transaction, session and clickstream signals [10], [11]. The present results therefore support a hybrid view in which survey-based behavioural constructs provide interpretable consumer insight but should not be treated as a stand-alone high-accuracy prediction system.

## VI. THEORETICAL AND METHODOLOGICAL CONTRIBUTIONS

### *A. Theoretical Contribution*

The study contributes to online consumer-behaviour research in three ways. First, it integrates seven commonly studied behavioural dimensions within one empirical framework rather than examining trust, value, reviews, convenience, fulfilment, social influence or experience in isolation. Second, it explicitly distinguishes association, unique linear contribution and predictive contribution. Third, it demonstrates that predictor rankings can change materially across these analytical perspectives, cautioning against describing a variable as simply "important" without specifying the evidential criterion used.

### *B. Methodological Contribution*

The parallel use of holdout testing and five-fold cross-validation provides a methodological contribution for small-sample predictive consumer research. The study shows that a model identified as best on one independent split may not be the model with the strongest average cross-validated performance. Reporting both results reduces the risk of selectively presenting a favourable split. Permutation importance is similarly reported as a predictive diagnostic rather than being interpreted as causal evidence.

## VII. MANAGERIAL IMPLICATIONS

For e-commerce managers, trust-related interventions have the strongest support from the multivariate analysis. Verified seller information, credible quality signals, authentic review systems and transparent policies can therefore be treated as core rather than peripheral elements of conversion strategy. Fulfilment reliability and payment security also deserve attention because they remain prominent across bivariate and predictive analyses.

Pricing and promotion remain relevant but should be interpreted in conjunction with trust and fulfilment rather than as isolated levers. Similarly, review visibility can assist information processing and confidence formation, but simple review metrics should not substitute for broader trust-building. Previous positive experience emerged as the strongest model-based predictive feature, implying that retention and repeat-experience quality may be as strategically important as acquisition.

For analytics teams, the study cautions against selecting a production model from one favourable train–test split. Cross-validated performance, stability, calibration and business relevance should be considered together. Given the modest $R^2$ values observed here, behavioural survey variables are best combined with transactional, browsing and session-level signals when the objective is operational prediction.

## VIII. LIMITATIONS AND FUTURE RESEARCH

The study has several important limitations. First, the analytical sample of 227 respondents is modest for machine-learning analysis and leaves only approximately 46 observations in the independent holdout test. Second, the study is cross-sectional and based on self-reported purchase intention rather than observed purchase behaviour, preventing causal inference and limiting behavioural validation. Third, the sampling frame may not represent the wider Indian online-shopping population.

The most important measurement limitation is internal consistency. All six multi-item constructs produced Cronbach's alpha values below 0.70, with particularly low values for Social Influence and Price Sensitivity. These results limit construct-level inference and suggest that future research should redesign and validate the measurement instrument before testing the same framework at larger scale. Several constructs combine conceptually related but non-identical ideas—for example, website usability, shopping-from-home convenience and information detail—so future scale development should use validated multi-item measures and factor-analytic assessment.

Previous Experience was measured using a single item, so its high permutation importance should be replicated using a richer scale. Future research should also collect larger probability-based or well-defined panel samples, incorporate actual transaction outcomes, and combine survey constructs with clickstream, browsing and platform-level behavioural data. Moderation and interaction effects, including interactions between prior experience and fulfilment/security, are additional priorities suggested by the divergence between regression and permutation-importance rankings.

## IX. CONCLUSION

This study compared traditional statistical analysis and machine-learning prediction of Online Purchase Intention using seven behavioural constructs among 227 online shoppers. Six constructs were significantly associated with purchase intention at the bivariate level, but only Quality and Brand Trust remained a significant unique predictor in the multiple regression model. Support Vector Regression achieved the best holdout performance, whereas Linear Regression achieved the strongest mean five-fold cross-validated $R^2$. Previous Experience and Fulfilment and Security were the strongest SVR permutation-importance features.

The central conclusion is not that machine learning outperforms regression. Rather, the study shows that different analytical frameworks reveal different dimensions of variable importance and that model rankings are sensitive to validation strategy. Trust, fulfilment reliability and previous experience emerge as important managerial themes, while the modest predictive performance and low scale reliability require cautious interpretation. A larger, better-validated and behaviourally richer replication would provide the strongest next test of the framework.

## X. STATEMENTS

*A. Funding*
This research received no external funding.

*B. Institutional Review / Ethics*
PES University did not issue a formal ethics/IRB approval number for this academic survey. No institutional approval number is therefore reported. This statement does not assert an institutional exemption or waiver. Respondents were provided with an information statement describing the academic purpose of the study, its voluntary nature, the approximate completion time, and the confidential, aggregate use of responses before participation.

*C. Informed Consent*
Participation was voluntary. Before completing the questionnaire, respondents were presented with an information statement explaining the academic purpose of the study, the approximate completion time (5–7 minutes), the confidential and aggregate use of responses, and the voluntary nature of participation.

*D. Data Availability*
The survey dataset and analysis workbook are not publicly available. The materials are retained by the authors for research documentation and verification.

*E. Use of Generative AI*
During preparation of the manuscript, a generative AI tool was used to assist with restructuring the underlying research report into journal format, language editing, and reference-formatting support. The authors reviewed and edited the output and take full responsibility for the accuracy and integrity of the content.

*F. Conflicts of Interest*
The authors declare no conflicts of interest.

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