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# Survey-Based Statistical Analysis of AI Shopping Assistants Employing IBM SPSS and the Anderson–Darling Test in Python

**Praveen Kumar Kanumarlapudi***

*Data AI/ML Architect, Amazon web services, TX, United States*

## Abstract

Artificial intelligence-powered shopping assistants represent transformative technologies reshaping consumer behavior and retail operations through machine learning, natural language processing, and recommendation algorithms. This study empirically evaluates user perceptions across multiple dimensions of AI shopping assistant effectiveness, addressing a significant research gap in comprehensive assessment of trust, accuracy, usefulness, enjoyment, and overall experience metrics. The primary objective investigates the relationship between AI accuracy and user trust in AI-powered shopping systems to determine whether higher accuracy translates to increased trust levels. Using IBM SPSS Statistics version 27, survey data from 503 respondents were analyzed, yielding a Cronbach's alpha of 0.850, confirming high measurement reliability. The sample consisted predominantly of young to middle-aged professionals (81.1% aged 18-40), with 57.1% male respondents and high educational attainment. This python using Anderson-Darling normality tests revealed non-normal distributions across all variables, necessitating robust analytical approaches. Regression analysis produced unexpected findings: AI accuracy demonstrated a statistically significant negative relationship with user trust ($\beta = -0.090$, $p = 0.008$), contradicting conventional assumptions that higher accuracy increases trust. Additionally, AI trust showed no significant predictive power for recommendation intention ($\beta = 0.034$, $p = 0.627$, $R^2 = 0.000$). These counterintuitive results suggest complex psychological mechanisms underlying user-AI interactions that warrant further investigation. Future research should explore mediating factors such as transparency, explain ability, and user expectations that may influence the accuracy-trust relationship in AI shopping contexts.

**Keywords:** AI Shopping Assistants, User Trust, Accuracy Perception.

## Introduction

Artificial intelligence-powered shopping assistants have emerged as transformative technologies reshaping consumer behavior and retail operations. These intelligent systems leverage machine learning, natural language processing, and recommendation algorithms to personalize shopping experiences, streamline product discovery, and enhance customer engagement. As e-commerce continues to dominate global markets, AI shopping assistants provide retailers with competitive advantages through improved user satisfaction and conversion rates. However, understanding user perceptions regarding trust, accuracy, enjoyment, and overall experience remains critical for optimizing these systems and fostering widespread adoption in diverse market segments. Generative AI-powered shopping assistants enhance the overall customer experience while increasing conversion rates and fostering long-term customer loyalty. Ongoing research focuses on helping these systems effectively learn from various data sources such as user interactions, feedback, and product details, continuously improving their accuracy and performance. Generative AI shopping assistants are reshaping the way consumers engage with online retail platforms. Unlike conventional chatbots that depend on predefined responses, these assistants leverage advanced generative AI techniques to interpret context, user preferences, and subtle nuances in real time. By utilizing vast amounts of data, generative AI shopping assistants can analyze customer behavior, preferences, and feedback, thereby continuously refining and improving their responses. [1-5].

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***Corresponding Author:** *PK Kanumarlapudi, Data AI/ML Architect, Amazon web services, TX, United States., E- mail: praveen.connects37@gmail.com*



These observations underscore the potential of agent-based AI shopping assistants in reducing user effort, and the importance of addressing gaps in personalization and user control. A small portion of the responses mentioned future intentions; participants indicated that they would 'frequently use AI shopping assistants [6]. To improve the design and management of generative AI shopping assistants, it provides practical recommendations to designers and managers. Consumer research on artificial intelligence-based shopping assistants being developed in developing countries reveals several methodological and contextual shortcomings that have not received sufficient attention. Although full-scale commercialization has not yet been achieved, developing countries are actively spearheading the use of generative artificial intelligence shopping assistants [7]. In generative artificial intelligence shopping assistants, systems typically utilize natural language processing, contextual awareness, and multimodal feedback mechanisms to enhance users' sense of control and mastery. Generative AI shopping assistants establish a dynamic feedback loop based on language understanding and contextual learning, ensuring that each interaction delivers a certain level of personalization and novelty. The integrated mediation chain can provide profound theoretical insights into the relationship between users and generative artificial intelligence shopping assistants. [8].

The British retail company ASOS has introduced virtual assistants to help customers choose the correct size and select suitable holiday gifts. AI-powered voice assistants offer unique experiences, and consumers may be

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motivated to use them for shopping or purchasing activities for functional, hedonic, social, or cognitive purposes. Amazement which can arise from feelings of admiration encourages customers to share their experiences and discuss the product with others, making them more likely to use it more often. The motivational aspects of consumers' innovative mindset in using artificial intelligence-powered voice assistants play a significant role in shaping the purchase intentions and immersive experiences of online fashion customers [9]. The absence of hedonic mediation further clarifies the theoretical understanding that the satisfaction pathways triggered in AI-mediated shopping differ from those observed in traditional media-based applications and satisfaction research, highlighting the dominant role of instrumental benefits in constrained decision-making contexts. This underscores the market potential of voice commerce. Using AI algorithms and advanced search engines, voice assistants can provide comprehensive market insights and adapt to users' needs. [10]A notable application of smartphone-based technology is the Augmented Reality Shopping Assistant application (hereinafter referred to as ARSAA). This type of application incorporates augmented reality to enhance the shopping experience by overlaying digital information onto the physical environment, thereby helping users make more informed purchasing decisions. [11-12]

These shopping assistant apps can recommend suitable products, provide summaries of customer reviews and product information, compare alternative products, and answer users' questions regarding product features, order status, and delivery details. In complex decision-making scenarios, such as choosing the optimal recommendation system for a generative AI-based shopping assistant, it provides a systematic and unbiased framework for determining the most suitable alternative. [13]To overcome these limitations, this study introduces an artificial intelligence-based shopping assistant system integrated into a smart shopping cart. Unlike current approaches that rely on separate devices and disconnected functionalities, the proposed system offers an integrated and cohesive solution. This study presents an artificial intelligence-based shopping assistant aimed at assisting visually impaired and blind individuals by enhancing their independence and autonomy when purchasing groceries. [14] Therefore, it is essential to have a clear understanding of virtual shopping assistants and the challenges associated with them. Since artificial intelligence technology forms the basis of virtual shopping assistants, it is discussed first before addressing other related aspects. Amazon Alexa voice AI, Walmart's text-to-shop service, and the Ali Express Messenger shopping assistant are examples of platforms that use virtual assistants to provide product information, recover abandoned shopping carts, and deliver notifications and alerts to users. [15] We propose the design of a comprehensive shopping assistance system that enables people of all demographics, including the elderly and those with disabilities, to receive support from a live assistant throughout the entire shopping process. This system further enhances the shopping experience by providing seamless integration with the supermarket's resources and an intuitive, user-friendly interface. This handheld device identifies products in their relevant context and recommends suitable complementary items. Through this, it enhances the shopping experience by displaying products directly on the screen with useful information. [16-17]

**Research Gap**: Current research lacks comprehensive empirical evaluation of user perceptions across multiple dimensions of AI shopping assistant effectiveness. Specifically, limited studies simultaneously examine trust, accuracy, usefulness, enjoyment, and overall experience metrics to understand how these factors collectively influence user satisfaction and behavioral intentions in shopping contexts.

**Objective:** To investigate the relationship between AI accuracy and user trust in AI-powered shopping systems and determine whether higher accuracy translates to increased trust levels.


**FLOW CHART 1:** Survey on AI Shopping Assistant

The flow chart illustrates the structured process followed in designing and administering the survey on AI shopping assistants. It begins with the collection of basic demographic information, including age, gender, marital status, and education or occupation, ensuring a clear understanding of respondent profiles. The process then transitions to evaluative questions measured on a five-point Likert scale, capturing users' perceptions of AI accuracy, cost-effectiveness, ease of use, engagement, logical recommendations, and information matching. Further stages assess enjoyment, future usefulness, trust, recommendation intention, and manipulation concerns.

Anderson-Darling (A-D) Test: The Anderson–Darling (A-D) Test is a statistical test used to examine whether a given sample of data follows a specific probability distribution, most commonly the normal distribution. It is a goodness-of-fit test that compares the empirical cumulative distribution function (ECDF) of the sample data with the cumulative distribution function (CDF) of the theoretical distribution being tested. Unlike some other normality tests, the Anderson–Darling test places greater emphasis on the tails of the distribution, making it especially sensitive to deviations at extreme values. This feature is important in many real-world applications where outliers or tail behavior can significantly affect results. The test produces a test statistic, known as the A-D statistic, which measures the squared distance between the observed and expected distributions, weighted more heavily at the tails. This statistic is then compared to critical values or converted into a p-value to determine statistical significance. If the p-value is less than the chosen significance level (such as 0.05), the null hypothesis that the data follow the specified distribution is rejected. Because of its sensitivity and robustness, the Anderson–Darling test is widely used in quality control, reliability engineering, finance, and social science research to assess distributional assumptions before applying further statistical analyses. [20-21]

## Methodology

Data were collected through a structured survey administered to 503 respondents, capturing demographic information (age, gender, marital status, education, and occupation) and AI shopping assistant perceptions. The survey employed a five-point Likert scale to measure key constructs including AI accuracy, cost-effectiveness, ease of use, engagement, logical recommendations, information matching, enjoyment, future usefulness, trust, recommendation intention, and manipulation concerns. The collected data were coded and analyzed using IBM SPSS Statistics version 27. [18-19] Reliability assessment yielded a Cronbach's alpha of 0.850 for 11 items, confirming excellent internal consistency. The Anderson-Darling test evaluated distributional normality, while Ordinary Least Squares (OLS) regression analysis examined predictive relationships between variables, specifically investigating how AI accuracy influences trust and how trust affects recommendation intentions.

## Results and Discussion

Table 1. Demographic Characteristics

| Characteristics | Frequency | Percentage (%) |
|---|---|---|
| Age | | |
| Under 18 | 24 | 4.8% |
| 18-30 | 214 | 42.5% |
| 30-40 | 194 | 38.6% |
| 40-50 | 61 | 12.1% |
| 51 above | 10 | 2% |
| Gender | | |
| Male | 287 | 57.1% |
| Female | 215 | 42.7% |
| Prefer not to say | 0 | 0 |
| Marital Status | | |
| Single | 162 | 32.2% |
| Married | 208 | 41.4% |
| Divorced | 67 | 13.3% |
| Windowed | 59 | 11.7% |
| Prefer not to say | 7 | 1.4% |
| Education Level | | |
| High School or below | 33 | 6.6% |
| Diploma Certificate | 104 | 20.7% |
| Bachelor's degree | 168 | 33.4% |
| Master's degree | 147 | 29.2% |
| Doctoral degree | 51 | 10.1% |
| Occupation | | |
| Student | 65 | 12.9% |
| Employed (Private Sector) | 157 | 31.2% |
| Employed (Government)/ | 99 | 19.7% |
| Business Owner | 101 | 20.1% |
| Unemployed | 71 | 14.1% |
| Retired | 10 | 2% |

This table 1shows the demographic profile of respondents shows that the majority fall within the 18–30 (42.5%) and 30–40 (38.6%) age groups, indicating a predominantly young and middle-aged sample. Males (57.1%) slightly outnumber females (42.7%). In terms of marital status, most respondents are married (41.4%), followed by single individuals (32.2%). Educational attainment is relatively high, with most participants holding a bachelor's (33.4%) or master's degree (29.2%). Occupationally, private-sector employees (31.2%) form the largest group, followed by business owners (20.1%) and government employees (19.7%), reflecting a largely working professional population.

Table 2. Reliability Statistics

| Reliability Statistics | | |
|---|---|---|
| Cronbach's Alpha | Cronbach's Alpha Based on Standardized Items | N of Items |
| .850 | .850 | 11 |

This table 2 shows the reliability analysis indicates strong internal consistency of the measurement scale. The Cronbach's alpha value of 0.850, both for raw and standardized items, exceeds the acceptable threshold of 0.70, demonstrating high reliability. With 11 items included, the scale is considered consistent and suitable for further statistical analysis. 50 words

| Table 3. Assessment of Normality Using the Anderson–Darling Test | | | |
|---|---|---|---|
| Variable | A–D Statistic | Critical Value (5%) | Normality Decision |
| Accuracy | 24.47373 | 0.781 | Not Normal |
| Cost | 26.60318 | 0.781 | Not Normal |
| Ease of use | 28.9307 | 0.781 | Not Normal |
| Engaging | 24.76565 | 0.781 | Not Normal |
| Logical | 22.16668 | 0.781 | Not Normal |
| Match product info | 23.23869 | 0.781 | Not Normal |
| Enjoyable | 22.53881 | 0.781 | Not Normal |
| Helpful / Future use | 31.32785 | 0.781 | Not Normal |
| Recommendation | 21.38559 | 0.781 | Not Normal |
| Trust | 22.6885 | 0.781 | Not Normal |
| Manipulation concern | 20.76224 | 0.781 | Not Normal |

Table 3 presents The normality test results indicate that none of the study variables follow a normal distribution. For all constructs, including accuracy, cost, ease of use, engagement, logical recommendations, product information matching, enjoyment, future use, recommendation, trust, and manipulation concern, the calculated A–D statistics are substantially higher than the critical value of 0.781 at the 5% significance level. As a result, the null hypothesis of normality is rejected for all variables. These findings confirm the presence of non-normal data patterns, suggesting that non-parametric or robust statistical techniques are more appropriate for subsequent analyses and interpretation.

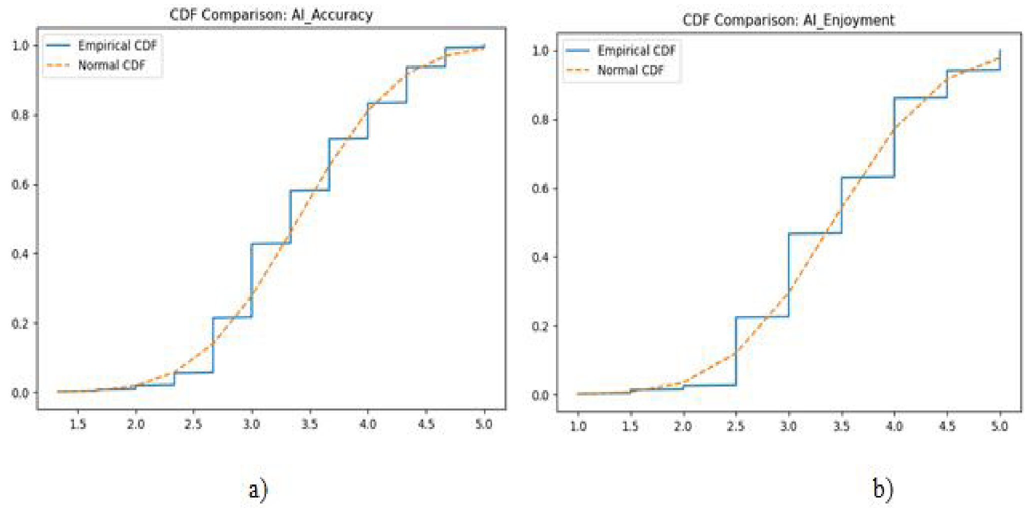


**Figure 1:** Cumulative Distribution Function (CDF) Analysis of a) AI Enjoyment and b) AI Accuracy

Figure 1 illustrates a) CDF Comparison for AI Accuracy: The empirical CDF for AI accuracy (1.5–5.0 range) deviates from the normal distribution, showing fewer low values and clustering in the 2.5–3.5 region. The curves converge at higher accuracy levels, indicating that while generally approaching normality, the data exhibits significant departure in lower and central ranges. b) CDF Comparison for AI Enjoyment: The empirical CDF for enjoyment ratings demonstrates discrete clustering and step-wise behavior rather than smooth normality. The distribution exhibits fewer low-enjoyment responses and concentrates in the moderate-to-high range (2.5–4.0), suggesting categorical preferences or rating bias rather than continuous normal distribution.

**AI Trust as Predictor of Recommendation Intention**

| Table 4. Ordinary Least Squares (OLS) regression | |
|---|---|
| Item | Value |
| Dependent Variable | Recommendation Intention |
| Model | OLS |
| Method | Least Squares |
| No. Observations | 503 |
| Df Model | 1 |
| Df Residuals | 501 |
| R-squared | 0.000 |
| Adjusted R-squared | -0.002 |
| F-statistic | 0.2361 |
| Prob (F-statistic) | 0.627 |
| Log-Likelihood | -604.32 |
| AIC | 1213 |
| BIC | 1221 |

| | |
|---|---|
| Covariance Type | nonrobust |
| Durbin–Watson | 1.302 |
| Omnibus | 5.629 |
| Prob(Omnibus) | 0.060 |
| Jarque–Bera (JB) | 5.557 |
| Prob(JB) | 0.0621 |
| Skew | -0.226 |
| Kurtosis | 2.752 |
| Condition No. | 19.1 |

Table 4 presents the OLS regression model estimating Recommendation Intention as the dependent variable using 503 observations. The model shows a very low explanatory power, with an R-squared value of 0.000 and an adjusted R-squared of −0.002, indicating that the predictor does not explain variation in recommendation intention. The F-statistic (0.2361, p = 0.627) is not statistically significant, confirming poor model fit. Diagnostic statistics suggest no severe violations of assumptions, with acceptable skewness, kurtosis, and near-normal residual distribution. Overall, the results indicate that the model does not significantly predict recommendation intention.

Table 5. Regression Coefficients

| Variable | Coef | Std. Error | t | p-value | 95% CI (Lower) | 95% CI (Upper) |
|---|---|---|---|---|---|---|
| Constant | 3.3938 | 0.207 | 16.363 | 0.000 | 2.986 | 3.801 |
| AI_Trust | 0.0337 | 0.069 | 0.486 | 0.627 | -0.103 | 0.170 |

Table 5 Shows that the regression coefficient table shows the effect of AI_Trust on Recommendation Intention. The constant (intercept) is 3.394, which is statistically significant (p < 0.001), representing the baseline recommendation intention when AI_Trust is zero. The coefficient for AI_ Trust is 0.034, but it is not statistically significant (t = 0.486, p = 0.627), and its 95% confidence interval (-0.103 to 0.170) includes zero. This indicates that AI_Trust does not have a meaningful or significant impact on recommendation intention in this model.

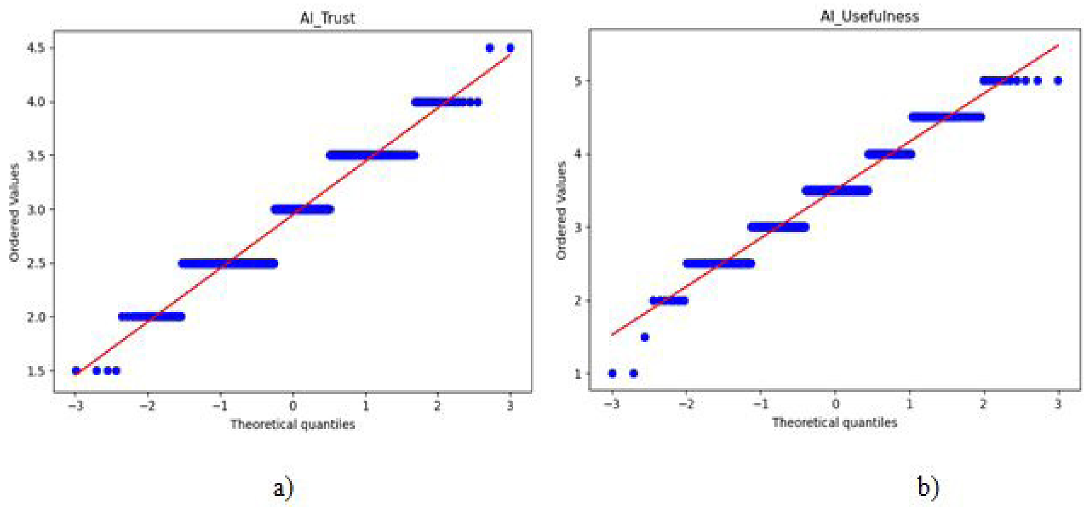


**Figure 2:** Normality Assessment of a) AI Trust and b) AI Usefulness

Figure 2 presents the a) Q-Q Plot for AI_Trust: The Q-Q plot reveals substantial deviation from normality in trust ratings. Data points cluster at discrete intervals (1.5, 2.0, 2.5, 3.0, 3.5, 4.0, 4.5), forming horizontal bands rather than following the diagonal reference line. Lower quantiles fall markedly below the theoretical normal line, indicating left-tail compression. This pattern demonstrates that AI trust data is ordinal with clustering characteristics, strongly deviating from continuous normal distribution assumptions. b) Q-Q Plot for AI_Usefulness: The Q-Q plot for usefulness ratings demonstrates substantially better agreement with theoretical normality compared to trust ratings. Data points closely follow the diagonal reference line across most quantiles, indicating approximate normality. Minor deviations appear at distribution extremes (lower and upper tails), suggesting slight departures at the margins. Overall, usefulness ratings approximate a normal distribution more convincingly, with continuous rather than discrete clustering patterns evident throughout the range.

### AI Accuracy as Predictor of AI Trust

Table 6. Ordinary Least Squares (OLS) regression

| Item | Value |
|---|---|
| Dependent Variable | AI_Trust |
| Model | OLS |
| Method | Least Squares |
| No. Observations | 503 |
| Df Model | 1 |
| Df Residuals | 501 |
| R-squared | 0.014 |
| Adjusted R-squared | 0.012 |

| | |
|---|---|
| F-statistic | 7.021 |
| Prob (F-statistic) | 0.00831 |
| Log-Likelihood | -379.10 |
| AIC | 762.2 |
| BIC | 770.6 |
| Covariance Type | nonrobust |
| Durbin–Watson | 1.902 |
| Omnibus | 3.784 |
| Prob(Omnibus) | 0.151 |
| Jarque–Bera (JB) | 2.955 |
| Prob(JB) | 0.228 |
| Skew | 0.055 |
| Kurtosis | 2.641 |
| Condition No. | 19.2 |

Table 6shows that OLS regression results for AI Trust indicate that the model is statistically significant, with an F-statistic of 7.021 ($p = 0.008$), suggesting that the predictor has a meaningful influence on AI trust. However, the explanatory power remains low, as reflected by an R-squared value of 0.014, indicating that only a small proportion of variance in AI trust is explained. Diagnostic measures show acceptable model validity, with a Durbin–Watson value of 1.902 indicating no serious autocorrelation and normality tests (Omnibus and Jarque–Bera) supporting approximately normal residuals.

Table 8. Regression Coefficients

| Variable | Coef | Std. Error | t | p-value | 95% CI (Lower) | 95% CI (Upper) |
|---|---|---|---|---|---|---|
| Constant | 3.2481 | 0.118 | 27.611 | 0.000 | 3.017 | 3.479 |
| AI_ Accuracy | -0.0899 | 0.034 | -2.650 | 0.008 | -0.157 | -0.023 |

Table 8 presents the regression results examining the effect of AI Accuracy on AI Trust. The constant is positive and statistically significant ($\beta = 3.248$, $p < 0.001$), indicating a moderate baseline level of AI trust. AI Accuracy shows a significant negative relationship with AI trust ($\beta = -0.0899$, $t = -2.650$, $p = 0.008$). The 95% confidence interval (−0.157 to −0.023) excludes zero, confirming the robustness of this effect. This finding suggests that increases in perceived AI accuracy are associated with a slight but statistically meaningful decrease in users' trust in AI systems.

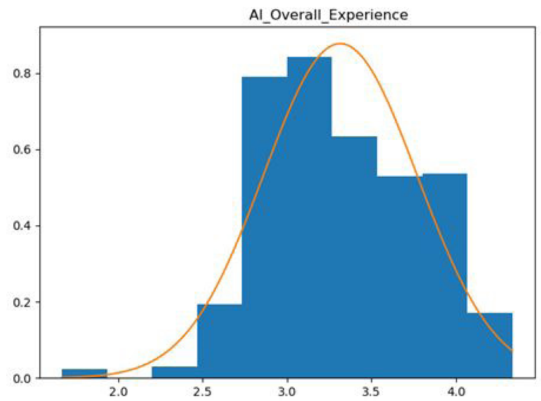


**Figure 3:** AI Overall Experience Distribution

Figure 3 illustrates the histogram displays the frequency distribution of overall AI experience ratings overlaid with a fitted normal distribution curve (orange line). The data spans approximately 1.8 to 4.2 on the rating scale, exhibiting a multimodal pattern with prominent peaks around 3.0–3.2 and 3.5–4.0. The distribution shows higher concentration in the 3.0–3.5 range, representing the modal region. The empirical histogram reveals notable deviations from the fitted normal curve, particularly with a broader, flatter distribution tail extending toward higher values (3.5–4.2) than the normal model predicts. The left tail (below 2.5) remains relatively sparse, suggesting few respondents reported very low overall experience.

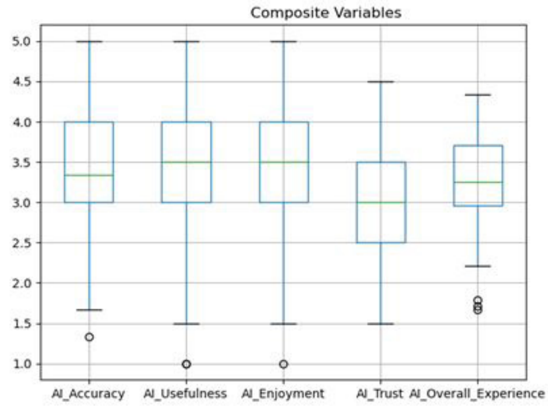


**Figure 4:** Distribution of Composite AI Perception Variables

Figure 4 presents the box plot comparison reveals distinct distributional characteristics across five AI-related composite measures. All variables span approximately 1.5–5.0, yet exhibit notable differences in central tendency and spread. AI_Accuracy, AI_Usefulness, and AI_Enjoyment display similar median values (3.0–3.5) with substantial interquartile ranges, indicating moderate variability. AI_Trust exhibits a slightly higher median (≈3.4) with comparable spread. AI_Overall_Experience shows a lower median (≈3.2) with narrower interquartile range, suggesting more concentrated responses. Outliers appear across all measures, primarily in lower ranges (1.0–1.3), indicating occasional extreme low ratings. The consistent presence of whisker extensions above the third quartile reveals right-skewed tendencies. Overall, AI_Trust demonstrates the most positive ratings, while all measures indicate generally favorable user perceptions with comparable variability patterns.

## Conclusion

This empirical investigation into AI-powered shopping assistants reveals complex and counterintuitive relationships between user perceptions, trust, and behavioral intentions that challenge conventional assumptions in artificial intelligence retail applications. Drawing from a diverse sample of 503 respondents predominantly comprising young to middle-aged professionals, the study achieved robust measurement reliability (Cronbach's $\alpha = 0.850$) while uncovering significant theoretical and practical implications. The most striking finding contradicts prevailing wisdom: AI accuracy demonstrates a statistically significant negative relationship with user trust ($\beta = -0.090$, $p = 0.008$), suggesting that increased perceived accuracy paradoxically diminishes rather than enhances trust. This unexpected inverse relationship indicates that accuracy alone cannot serve as the primary driver of trust formation in AI shopping contexts. Potential explanations include the "uncanny valley" effect where excessive accuracy triggers user suspicion, concerns about data privacy and manipulation when systems appear too precise, or inflated user expectations that accurate systems fail to meet in other experiential dimensions. Furthermore, the complete absence of significant predictive power from AI trust to recommendation intention ($R^2 = 0.000$, $p = 0.627$) reveals a fundamental disconnect between trusting AI systems and willingness to recommend them. This finding challenges the theoretical assumption that trust directly translates into advocacy behavior, suggesting that additional mediating factors—such as perceived usefulness, enjoyment, social norms, or personal innovation characteristics play critical roles in shaping recommendation intentions. The non-normal distributions across all measured variables indicate that user perceptions of AI shopping assistants are categorical and clustered rather than continuously distributed, reflecting discrete preference patterns and potential rating biases.

These distributional characteristics necessitate careful methodological consideration in future research designs. Practically, these findings urge retailers and AI developers to adopt holistic optimization strategies that balance accuracy with transparency, explain ability, user control, and emotional engagement. The complexity of trust formation and behavioral intention in AI shopping contexts demands multidimensional approaches that extend beyond technical performance metrics to encompass psychological, social, and contextual factors influencing user acceptance and advocacy.

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