EMPIRICAL INVESTIGATION OF FACTORS AFFECTING ONLINE SHOPPING BEHAVIOR

INTRODUCTION
Internet-based technology systems are critical in raising an online shopping store’s penetration and operating performance (Zhou et al., 2007). Internet applications offer online retailers the ability to transcend the restrictions of size, customer penetration and compete more efficiently with big, conventional retail businesses (Schilling, Shankar, 2019) if strategically used (Chesbrough, 2011). The internet strengthens the potential of online retail firms to engage as a strategic weapon with other businesses globally, provides the ability and chance for additional diverse individuals to start a business, and offers an easy way to make business transactions without being controlled to certain hours of operation (GieLens, Steenkamp, 2019; Melovic et al., 2020). Online shop is attractive to businesses because it upsurges profits. Advertising well done on the internet will bring the promotional message of such a new business to prospective buyers in any country in the world (Gupta, Singh, 2020; Azmi et al., 2021). In addition to trading products and services, online shops often establish a partnership between customers and businesses (Alkhamery et al., 2021; Broekhuizen et al., 2018; Chan, Astari, 2017).

Online shopping is becoming progressively common in Nigeria (Usman et al., 2019), particularly among middle-income earners, elites, technocrats, and students (Adamkolo et al., 2018; Ibrahim et al., 2019). Online businesses use the internet for advertising their goods, thereby promoting online shopping behavior. Online retailers advertise and offer their goods on beautifully crafted websites that allow shoppers to make windows shopping, search products, compare costs, order, drop products in the cart, pay and deliver products at their doorsteps. (Draper, 2019). In Nigeria, most internet retailers sell a wide variety of online goods and services (Olusanmi, 2019). Despite the growth of online shops in Nigeria yet, the penetration rate is low. For most Nigerians, the problem of transfers or sending money to an unknown entity you have never seen or encountered physically is strange. This is bound to be terrible for online stores in the country (Ugonna et al., 2017). In light of this, this study examines advertising, online risk, perceived usefulness, and reliability as factors affecting online shopping behavior among subscribers of online stores in Nigeria.
LITERATURE REVIEW

Online shopping
Shafiee and Bazargan (2018), Ladhari et al. (2019) posited that online shopping is a single, homogenous activity, selling goods and services through the internet. At the same time, Choi et al. (2019) stated that online shopping promotes online retailers before the transactional buying and logistics process. Online shopping is an electronic transaction system used by consumers in the background of business-to-consumer or business-to-business (Jaiswal et al., 2018). This illustrates that online shopping involves websites for retailers in which shopping is carried out in a simulated world without physical interaction between sellers and customers.

Rahi et al. (2017) posited that online businesses must plan and encourage user-friendly websites to attract and maintain users. Besides, they must ensure that customers get value for their cash, particularly for average and large online shops. The principal purpose of online shopping is to offer consumers a forum to share products and services with retailers. Lin et al. (2019) defined online shopping behavior as exploring, looking for, surfing for, or viewing a product to have details or correct information with the intention to buy on the web. According to Izogo and Jayawardhena (2018), Online shopping is the customers’ patronization of online businesses or department stores from the purchase level to the delivery stage. This means that all transactions between the online store and the client will be done in a virtual environment from the initial stage to the last series of transactions.

Advertising
According to Dahlen and Rosengren (2016), advertising is always associated with the brand, and a brand can be an authentic brand, an individual, or a cause. Advertising can influence consumers to buy a product or patronize services they have never tasted (BELK, 2017). The advertisement consists of all the actions involved in delivering a non-personal, verbal or visual, publicly endorsed message to an audience about the promotion by one or more media paid for by an identified supporter. Advertising influences lifestyle and buying behavior. Thus, for businesses to be well known, they have to invest in advertising. Advertising as a promotional technique gives a thoughtful tool in making a product popular and conditioners possible consumers to choose what to buy and what not to buy.

Researchers conducted empirical studies on the effect of advertising on online shopping behavior. For instance, the study was carried out by Senthil et al. (2013) to examine the consumer’s perception of advertising in online shopping and social media platforms. The findings show that consumers are skeptical about advertising on online shopping and social network sites. The result also revealed that consumers have a high degree of advertising rejection. Liaukonyte et al. (2015) examine the influence of Television advertising on online shopping. The results of the study revealed that advertising content plays a significant role in influencing online shopping. This evidence was further affirmed by researchers, such as Zhang et al. (2017) and Prashar et al. (2017).

Online risk
In the growth of online stores, online risk is seen as a severe obstacle (Lăzăroiu et al., 2020). Online risk can be defined as a consumer’s perception that they may suffer from unfavorable and unpredictable outcomes (WANG et al., 2019). One of the features of online risk is the unusual payment method, where the buyer and the seller never meet physically. This situation implies that the online shopping experience has specific risk characteristics specifically associated with it. These risks include worries over the delivery and return, lack of physical contact (Zhu et al., 2018), and being a victim of fraud (SAXENA et al., 2018), or exposure to a computer virus (INDIANI, FAHIK, 2020).

Online transactions are considered riskier than traditional transactions (ABYAD, 2017; NASIDI et al., 2021), although the perception of risk with the amount of internet experience is found to decrease (YOON et al., 2019). Internet experience also impacts online shopping behaviors, as substantial Internet users prefer to order more online than lighter users (LOKETKRAWEE, BHATIASEVI, 2018). Consequently, while the perception of the risks related to online shopping may increase with the Internet experience, it does not seem to impede its acceptance. Kumar and Bajaj (2019) Specify eight internet shopping-specific risk dimensions found from four
separate risk sources. A performance risk presented by the product itself is best defined as a disappointment that the goods did not work as fine as the consumer hoped they would.

**Perceived usefulness**

Perceived usefulness refers to how consumers think online retail firms could enhance value and effectiveness when patronizing online shopping. The process of decision-making on online shopping communicates the values and satisfaction they perceive while shopping (Al-ADWAN et al., 2020; MCLEAN et al., 2020). Perceived advantages of online shopping are potted as perceived usefulness (BADEGGI, MUDA, 2021; RUANGVANICH, PIRIYASURAWONG, 2019). Discovery’s low price and low charge of surfing online can help perceived usefulness. Perceived usefulness depends on the competence of technological characteristics consumers enjoyed from the online retail shops, especially personal services provided (ALKHAMERY et al., 2021; CUTSHALL et al., 2021).

**Reliability**

The degree to which a customer believes and trusts an online company’s services is referred to as reliability (AHMAD, ZHANG, 2020), which includes delivering the correct products or services after making payment from the online store (KAUSHIK et al., 2020). The specifics reliability has accuracy in billing, keeping accurate records, and delivering service at the designated period (WANG et al., 2020). Reliability is nearly associated with risk because it is a yardstick of consumers' perceptions of whether online firms can be counted on to deliver on their promises (MARKOWITZ, SHULMAN, 2021). The following hypotheses are formulated:

\[ H_1: \text{Advertising has a significant positive effect on online shopping behavior.} \]

\[ H_2: \text{Online Risk has a significant positive effect on online shopping behavior.} \]

\[ H_3: \text{Perceived Usefulness has a significant positive effect on online shopping behavior.} \]

\[ H_4: \text{Reliability has a significant positive effect on online shopping behavior.} \]

**Figure 1**: Research Framework

![Research Framework Diagram](image)

**Source**: Search data.
METHODOLOGY
This study adopted a quantitative approach in which a self-developed questionnaire was used
to gather data from consumers of online stores based in Nigeria. The items on the
questionnaire are graded on a ten-point Likert scale, with responses ranging from Strongly Disagree (SD) to Strongly Agree (SA). The questionnaire content was adapted from the prior studies (DEVARAJ et al., 2002; SEN et al., 2006; SMITH et al., 2011; TORKZADEH, DHILLON, 2002). The respondents of this research are subscribers of online stores who had previous experience of shopping for a product or services from an online store. An online sample size calculator was utilized to determine the sample size whereby a minimum of 375 consumers of the online store was obtained from the study population. Simple Random Sampling (SRS) techniques were used in this research.

The sample size was increased to 450 to avoid response bias and reduce sample error as recommended by (JIANG et al., 2016). Thus, 450 questionnaires were distributed to respondents; 372 questionnaires were filled out and returned. For the analyses of data, IBM SPSS Statistics version 24.0 and Smart PLS version 3.2.7 were used. PLS is an excellent match for this study because it is causal (HAMMOUDA, SALEM, 2020). A variance-based PLS-SEM approach was selected since it can handle all types of estimation models (i.e., reflective and formative models) that are used in the concept of this analysis.

Data analysis
This study employs the Harman et al. (2019) one-factor test to determine whether there is any
common method bias among variables. The researchers used the instructions and procedure
of Hair et al. (2017) to conduct the one-factor test. For this purpose, all measurement scale
objects were subjected to a principal component analysis with varimax rotation to detect some
single factor signs from factor analysis. Table 1 presents more details.

Table 1: Common Method Bias in Dataset – Harman’s One Factor Solution

| Component | Initial Eigenvalues | Extraction Sums of Squared Loadings |
|-----------|---------------------|-------------------------------------|
|           | Total               | % of Variance       | Cumulative % | Total          | % of Variance | Cumulative % |
| 1         | 12.433              | 37.675              | 37.675       | 12.433         | 37.675       | 37.675       |
| 2         | 6.260               | 18.970              | 56.645       | 6.260          | 18.970       | 56.645       |
| 3         | 2.422               | 7.340               | 63.986       | 2.422          | 7.340        | 63.986       |
| 4         | 1.475               | 4.469               | 68.455       | 1.475          | 4.469        | 68.455       |

Extraction Method: Principal Component Analysis

Source: Search data.

Measurement model analysis
The conceptual model for the study used both formative and reflective estimation models. The
formative measurement model was used for Online Shopping Behaviour, while the reflective
measurement model is used for Advertising, Online Risk, Perceived Usefulness, and Reliability.
Formative and reflective analysis models have distinct statistical prediction criteria (HAIR et al.,
2017). In formative calculation models, internal precision is a problem (CHEAH et al., 2018)
since formative measurement scale artifacts are more likely to represent a single source and
aren’t intrinsically highly correlated. On the other hand, reflective measurement model artifacts
must be correlated and represent critical outer loading values (HAIR et al., 2017). For this study,
both reflective and formative measurement models were checked separately. Hair et al. (2017)
guidelines were used to assess construct reliability and validity for both reflective and formative
measurement models and assess convergent validity and discriminant validity for formative
measurement models (i.e., Online Shopping Behaviour).
Reflective measurement models analysis

The procedures of Hair et al. (2017) were used to analyze the structures of reflective appraisal models (Advertising, Online Risk, Perceived Usefulness, and Reliability). To validate the reflective measuring models, both systems were tested for their reliability and validity. The findings revealed that both constructs had a factor loading value of 0.7 to 0.9, which is considered adequate. Both constructs had composite reliability (CR) and Cronbach’s alpha values higher than the 0.70 critical stage (TABER, 2018). Both structures' average variance extracted (AVE) values are higher than 0.50 critical values, as suggested by (HAIR et al., 2017). The total validity and reliability results for all constructs are shown in Table 2. In addition, as seen in Table 3, the discriminant validity was tested using the Fornell-Larcker criterion. Table 3 shows the discriminant validity of the structures used in the proposed estimation models by highlighting the square root of AVE, which is greater than the approximate correlation values. In general, these results follow all of the requirements for evaluating reflective measurement models’ validity and reliability.

In addition, Henseler et al. (2015) proposed the Heteromonotrait (HTMT) ratio of correlations as a new method for analyzing the discriminant validity of structures in measurement models. On average, an HTMT value greater than 0.85 indicates a potential issue with discriminant validity (Hair et al., 2017). This sample’s HTMT values were all just below the 0.85 thresholds, meaning that discriminant validity was not an issue. Another reference for the discriminant validity of reflective measuring frameworks was the cross-loading values of reflective constructs' markers. In contrast to other structures in the structural model, reflective measuring model indices should have a high level of accuracy. A complete list of cross-loading values for all measurements used in the structures of reflective measurement models can be found in Table 4. Table 4 shows that all measures (measurement scale items) have a higher loading on their respective underlying latent construct in reflective measurement models than any other construct in the model. As a result, these findings meet the cross-loading evaluation criteria and provide ample evidence for the discriminant validity of reflective measurement models, as illustrated in Table 5.

### Table 2: Validity and reliability of latent constructs

|                | Cronbach’s Alpha | Composite Reliability | Average Variance Extracted (AVE) |
|----------------|------------------|-----------------------|----------------------------------|
| Advertising    | 0.842            | 0.881                 | 0.516                            |
| Online Risk    | 0.809            | 0.862                 | 0.531                            |
| Perceived Usefulness | 0.936          | 0.947                 | 0.692                            |
| Reliability    | 0.93             | 0.942                 | 0.672                            |

**Source:** Search data.

### Table 3: Fornell-Larcker Criterion Analysis Discriminant Validity

|                | Advertising | Online Risk | Perceived Usefulness | Reliability |
|----------------|-------------|-------------|----------------------|-------------|
| Advertising    | 0.719       |             |                      |             |
| Online Risk    | 0.63        | 0.729       |                      |             |
| Perceived Usefulness | 0.63        | 0.659       | 0.832                |             |
| Reliability    | 0.631       | 0.61        | 0.794                | 0.82        |

**Source:** Search data.

### Table 4: Heteromonotrait (HTMT) Analysis Discriminant Validity

|                | Advertising | Online Risk | Perceived Usefulness | Reliability |
|----------------|-------------|-------------|----------------------|-------------|
| Advertising    | 0.787       |             |                      |             |
| Online Risk    | 0.708       | 0.72        |                      |             |
| Perceived Usefulness | 0.711      | 0.675       | 0.847                |             |
| Reliability    | 0.711       | 0.675       | 0.847                |             |

**Source:** Search data.
**Table 5**: Cross loadings among reflective measurement scale items.

|       | Advertising | Online Risk | Perceived Usefulness | Reliability |
|-------|-------------|-------------|----------------------|-------------|
| AD1   | 0.801       | 0.634       | 0.467                | 0.48        |
| AD2   | 0.757       | 0.584       | 0.439                | 0.409       |
| AD3   | 0.718       | 0.535       | 0.39                 | 0.402       |
| AD5   | 0.727       | 0.467       | 0.383                | 0.357       |
| AD6   | 0.696       | 0.529       | 0.498                | 0.468       |
| AD7   | 0.727       | 0.55        | 0.531                | 0.497       |
| AD8   | 0.586       | 0.373       | 0.448                | 0.546       |
| OR1   | 0.554       | 0.799       | 0.622                | 0.531       |
| OR2   | 0.649       | 0.887       | 0.542                | 0.527       |
| OR3   | 0.667       | 0.891       | 0.595                | 0.566       |
| OR4   | 0.51        | 0.772       | 0.467                | 0.429       |
| OR5   | 0.323       | 0.336       | 0.181                | 0.212       |
| PU1   | 0.553       | 0.556       | 0.788                | 0.803       |
| PU2   | 0.538       | 0.572       | 0.739                | 0.732       |
| PU3   | 0.535       | 0.519       | 0.834                | 0.594       |
| PU4   | 0.496       | 0.535       | 0.864                | 0.576       |
| PU5   | 0.522       | 0.549       | 0.865                | 0.616       |
| PU6   | 0.484       | 0.551       | 0.84                 | 0.635       |
| PU7   | 0.482       | 0.538       | 0.849                | 0.614       |
| PU8   | 0.576       | 0.557       | 0.867                | 0.686       |
| RE1   | 0.511       | 0.468       | 0.613                | 0.812       |
| RE2   | 0.462       | 0.406       | 0.613                | 0.759       |
| RE3   | 0.472       | 0.52        | 0.653                | 0.81        |
| RE4   | 0.517       | 0.463       | 0.637                | 0.81        |
| RE5   | 0.569       | 0.499       | 0.66                 | 0.81        |
| RE6   | 0.515       | 0.484       | 0.68                 | 0.81        |
| RE7   | 0.545       | 0.559       | 0.664                | 0.81        |
| RE8   | 0.541       | 0.585       | 0.683                | 0.81        |

Source: Search data.

**Formative measurement models analysis**

Formative constructs are evaluated differently than reflective constructs (HAIR et al., 2017). According to this logic, all formative measurement models are likely to represent an individual trigger for the underlying latent framework because formative measurements do not have a high correlation between measurement scale objects. Furthermore, for formative measurement models, the method for measuring convergent validity varies. This study uses one formative model as earlier discussed (i.e. online shopping behavior). The magnitude of the path coefficient (correlation) between formative and reflective structures, CS formative and CS reflective, was measured to determine convergent validity. The correlation coefficient between Y formative and Y reflective should be 0.80 or higher when determining the convergent validity of formative structures (HAIR et al., 2017). The path coefficient values between CS formative and CS reflective are higher than the 0.80 thresholds, meaning that they follow the criteria set by (FAROOQ et al., 2018).

Furthermore, the relative importance of indicators for their underlying latent construct was determined using formative indicator outer weights (relative value). The outer weights for all elements used in measuring the formative model of online shopping behavior are mentioned in Table 6. The significance of these outer weight values was also assessed using the parameters of (HENSELER et al., 2015). The findings reveal that all of the metrics in the formative measurement model have significant and positive outer weight values. It shows that all formative measurement model metrics adhered to the defined criteria for determining their significance and context. The suitability of formative structures is established based on the preceding discussion, and an overall analysis of reflective and formative measurement models yields adequate results, allowing the structural model to be assessed.
Table 6: Outer weights of items involved in formative constructs.

| Construct                  | Outer Weights | T Statistics (|O/STDEV|) | P Values |
|----------------------------|---------------|----------------|--------|
| OSB2 -> Online Shopping Behaviour | 0.812         | 1.539         | 0.124  |
| OSB3 -> Online Shopping Behaviour | 0.845         | 2.015         | 0.044  |
| OSB4 -> Online Shopping Behaviour | 0.882         | 2.008         | 0.045  |
| OSB5 -> Online Shopping Behaviour | 0.870         | 7.543         | 0.000  |
| OSB6 -> Online Shopping Behaviour | 0.872         | 0.255         | 0.799  |

Source: Search data.

Analysis of structural model

The R2 value, the statistical significance of the Q2 value, and the direction coefficient -values were used to measure the structural model’s overall explanatory capacity of constructs. Figure 1 illustrates the structural model’s output. Based on R2=0.324, these findings mean that the proposed model has a 32.40 percent predictive ability for online shopping behavior. Furthermore, the effect of advertising on online shopping behavior (= 0.148; t-value = 2.94; p = 0.003) is considered significant and positive, indicating that H1 is supportive. On the other hand, H2 (= -0.194; t-value = 3.66; p = 0.000) reported a negative effect of Online Risk on Online Shopping Behaviour. H3 supported the proposed effect of Perceived Usefulness on Online Shopping Behaviour (=0.382; t-value = 7.054; p = 0.000). Finally, a strong correlation between Reliability and Online Shopping Behaviour (= 0.236; t-value = 4.123; p = 0.000) supports H4. The findings are summarised in Table 7.

Table 7: Path Coefficients

| Construct                  | Original Sample (O) | Standard Deviation (STDEV) | T Statistics (|O/STDEV|) | P Values |
|----------------------------|---------------------|---------------------------|----------------|--------|
| Advertising -> Online Shopping Behaviour | 0.148           | 0.05                      | 2.94           | 0.003  |
| Online Risk -> Online Shopping Behaviour | -0.194          | 0.053                     | 3.66           | 0.000  |
| Perceive Usefulness -> Online Shopping Behaviour | 0.382           | 0.054                     | 7.054          | 0.000  |
| Reliability -> Online Shopping Behaviour | 0.236           | 0.057                     | 4.123          | 0.000  |

Source: Search data.
Our structural model’s R2 value is 0.324, as seen in Fig. 1, showing that the proposed conceptual model is insufficiently explanatory. It is essential to exercise caution here, as depending solely on the R2 value to aid a model is not a viable strategy (Hair et al., 2017). As a result, the structural model’s predictive relevance was assessed using the Stone (1974) Q2 test. If the Q2 value is greater than zero, the latent exogenous constructs in the structural model have predictive significance for latent endogenous constructs (Hair et al., 2017). As seen in Fig. 2, our model’s Q2 value is 0.219, supporting the study’s primary assumption that the endogenous framework (i.e., Online Shopping Behaviour) has a solid predictive significance.

Furthermore, the possibility of collinearity was investigated in any construct. According to the findings, collinearity was not an issue in our study. As a consequence, the overall predictive relevance of our proposed structural model was achieved.
Importance-Performance Map Analysis (IPMA)

Importance-Performance Map Analysis is a valuable PLS-SEM statistical tool that graphically extends conventional path coefficient estimates in a more practical manner (WONG, 2019). Hair Jr et al. (2016) argue that IPMA’s goal is to identify predecessors with low efficiency but high priority for the target constructs. According to the cumulative effect size (i.e. importance) of the identical predecessor construct, a one-unit point increase in the predecessor construct’s output will increase the goal of the construct’s performance. Online shopping behavior is a target construct in our context, and it is expected by four predecessor constructs (Advertising, Online Risk, Perceived Usefulness, and Reliability). We used IPMA for this study. The results are seen in Figures 3 and 4. “Reliability” has the highest significance score of 78.36 in the lower right corner of the value performance map; if reliability increases by one unit point, online shopping behavior will increase by 0.235. Furthermore, our findings revealed that online shopping behavior scored the lowest in terms of online risk and ads, with ratings of 69.634 and 70.926 respectively, showing that there is still room for improvement in these fields. Table 8 contains a complete set of importance-performance values for the reader’s convenience.

Table 8: Importance-Performance Map Analysis for Online Shopping Behaviour

| Latent Variable     | Performances | Importance |
|---------------------|--------------|------------|
| Advertising         | 70.926       | 0.178      |
| Online Risk         | 69.634       | -0.257     |
| Perceived Usefulness| 73.846       | 0.425      |
| Reliability         | 78.36        | 0.235      |

Source: Search data.
The Goodness of Fit (GoF)
The R2 value is commonly used to measure the model’s explanatory capability because PLS-SEM does not have overall Goodness of Fit (GoF) indices (Awang et al., 2015; Hair Jr et al., 2020). Tenenhaus et al. (2005) established the Goodness of Fit (GoF) index for PLS-SEM, which was used to determine model fit. The geometric mean value of the average communality score (AVE values) and the average R2 values (for endogenous constructs) was used to determine the Goodness of Fit (GoF), which is computed using the following equation: \( GoF = \sqrt{AVE \times R^2} \). The following cut-off values were given by Becker et al. (2012) for assessing the GoF study results: GoF medium = 0.25; GoFlarge = 0.36; GoFsmall = 0.1; GoFmedium = 0.25; GoFlarge = 0.36. Using the recommendations of (Henseler et al., 2015), we measured the Goodness of Fit (GoF) index for the model in this study which is seen below.

\[
GoF = \sqrt{AVE \times R^2} = \sqrt{0.324 \times 0.734} = \sqrt{0.2378} = 0.488
\]

| Average Variance Extracted (AVE) | R²  |
|----------------------------------|-----|
| Advertising                      | 0.516|
| Online Risk                     | 0.531|
| Online Shopping Behaviour        | 0.734| 0.324|
| Perceive Usefulness              | 0.692|
| Reliability                     | 0.672|

Source: Search data.

CONCLUSION
This study examined the factors that affect online shopping behaviors among consumers of online shops in Nigeria. A conceptual framework was used to assess the effects of variables using PLS analysis. The findings indicated that there is a significant positive effect of advertising and perceived usefulness on online shopping behavior. The results also showed a negative effect of online risk on online shopping behavior. Additionally, there is a positive relationship between reliability and online shopping behavior. The findings of this research could help online stores to make informed decisions on how to reduce risk and maximize sales by increasing confidence in consumers’ minds. Managers and online retailers can persuade customers to shop by using various online platforms such as social networking sites. Also, this research could create awareness among online shoppers, particularly Nigerians, regarding the benefits of online shopping innovations. This quantitative research is limited to a few factors affecting online shopping behavior in the Nigerian context, future research may adopt a qualitative approach to explore more factors.
REFERENCES

ABYAD, A. Importance of Consumer Trust in e-commerce. Middle East Journal of Business, 2017, 55 (4182), p. 1-5.

ADAMKOLO, M.; HASSAN, M.; PATE, A. Consumers' Demographic Factors Influencing Perceived Service Quality in e-Shopping: Some Evidence from Nigerian Online Shopping. Pertanika Journal of Social Sciences & Humanities, 2018, 26 (3).

AHMAD, W.; ZHANG, Q. Green purchase intention: Effects of electronic service quality and customer green psychology. Journal of Cleaner Production, 2020, 267, 122053.

AL-ADWAN, A. S.; KOKASH, H.; ADWAN, A. A.; ALHORANI, A.; YASEEN, H. Building customer loyalty in online shopping: the role of online trust, online satisfaction and electronic word of mouth. International Journal of Electronic Marketing and Retailing, 2020, 11 (3), p. 278-306.

ALKHAMERY, N.; ZAINOL, F. A.; AL-NASHMI, M. The Role of Dynamic Capabilities in Reconfiguring Operational Capabilities for Digital Business Transformation. The Journal of Management Theory and Practice (JMTP), 2021, 2 (1), p. 1-8.

AWANG, Z.; AFTHANORHAN, A.; MOHAMAD, M.; ASRI, M. An evaluation of measurement model for medical tourism research: The confirmatory factor analysis approach. International Journal of Tourism Policy, 2015, 6 (1), p. 29-45.

AZMI, N. J., HASSAN, I., AB RASHID, R., AZIZ, N. A., & NASIDI, Q. Y. (2021). Gender Stereotype in Toy Advertisements on Social Networking Sites. Online Journal of Communication and Media Technologies, 11(4), e202122.

BADEGGI, M. S.; MUDA, H. Issues and Challenges of Perceived Value and Service Quality on Student Loyalty among University Student in Malaysia. The Journal of Management Theory and Practice (JMTP), 2021, 2 (1), p. 26-29.

BECKER, J.M.; KLEIN, K.; WETZELS, M. Hierarchical latent variable models in PLS-SEM: Guidelines for using reflective-formative type models. Long Range Planning, 2012, 45 (5-6), p. 359-394.

BELK, R. W. Qualitative research in advertising. Journal of advertising, 2017, 46 (1), p. 36-47.

BROEKHUIZEN, T. L.; BAKKER, T.; POSTMA, T. J. Implementing new business models: What challenges lie ahead? Business Horizons, 2018, 61 (4), p. 555-566.

CHAN, A.; ASTARI, D. The analysis of content marketing in online fashion shops in Indonesia. Review of Integrative Business and Economics Research, 2017, 6 (2), 225p.

CHEAH, J. H.; MEMON, M. A.; CHUAH, F.; TING, H. Assessing reflective models in marketing research: A comparison between pls and plsc estimates. International Journal of Business and Society, 2018, 19 (1), p. 139-160.

CHESBROUGH, H. Open services innovation: Rethinking your business to grow and compete in a new era. John Wiley & Sons, 2011.

CHOI, D.; CHUNG, C. Y.; YOUNG, J. Sustainable online shopping logistics for customer satisfaction and repeat purchasing behavior: Evidence from China. Sustainability, 2019, 11 (20), p. 5626.

CUTSHALL, R.; CHANGCHIT, C.; PHAM, H.; PHAM, D. Determinants of Social Commerce Adoption: An Empirical Study of Vietnamese Consumers. Journal of Internet Commerce, 2021, p. 1-27.
DAHLEN, M.; ROSENGREN, S. If advertising won’t die, what will it be? Toward a working definition of advertising. Journal of advertising, 2016, 45 (3), p. 334-345.

DEVARAJ, S., FAN, M.; KOHLI, R. Antecedents of B2C Channel Satisfaction and Preference: Validating e-Commerce Metrics. Information Systems Research, 2002, 13 (3), p. 316-333.

DRAPER, N. A. The identity trade: Selling privacy and reputation online. NYU Press, 2019.

FAROOQ, M. S.; SALAM, M.; FAYOLLE, A.; JAAFAR, N.; AYUPP, K. Impact of service quality on customer satisfaction in Malaysia airlines: A PLS-SEM approach. Journal of Air Transport Management, 2018, 67, p. 169-180.

GIELENS, K.; STEENKAMP, J.B. Branding in the era of digital (dis)intermediation. International Journal of Research in Marketing, 2019, 36 (3), p. 367-384.

GUPTA, H.; SINGH, S. Evolution of guerrilla marketing as an emergent marketing strategy in global and Indian context. International Journal of Indian Culture and Business Management, 2020, 21 (2), p. 247-261.

HAIR, J.; HOLLINGSWORTH, C. L.; RANDOLPH, A. B.; CHONG, A. Y. L. An updated and expanded assessment of PLS-SEM in information systems research. Industrial management & data systems, 2017.

HAIR JR, J. F.; HOWARD, M. C.; NITZL, C. Assessing measurement model quality in PLS-SEM using confirmatory composite analysis. Journal of Business Research, 2020, 109, p. 101-110.

HAIR JR, J. F.; HULT, G. T. M.; RINGLE, C.; SARSTEDT, M. A primer on partial least squares structural equation modeling (PLS-SEM). Sage publications, 2016.

HAMMOUDA, Y. A.; SALEH, S. O. The Role of Corporate Social Responsibility Constructs in the Employees Job Satisfaction of Construction Industry at UAE. Psychology and Education Journal, 2020, 57 (9), p. 6467-6482.

HARMAN, M.; OVAYOLU, N.; UÇAN OVAYOLU, Ö. The effect of three different solutions on preventing oral mucositis in cancer patients undergoing stem cell transplantation: A non-randomized controlled trial: A Turkish study, 2019.

HENSELER, J.; RINGLE, C. M.; SARSTEDT, M. A new criterion for assessing discriminant validity in variance-based structural equation modeling. Journal of the Academy of Marketing Science, 2015, 43 (1), p. 115-135.

IBRAHIM, A. M. M.; HASSAN, M. S. H.; YUSUF, S. Factors determining e-shopping compliance by Nigerians. In Advanced methodologies and technologies in digital marketing and entrepreneurship, 2019, p. 219-232. IGI Global.

INDIANI, N. L. P.; FAHIK, G. A. Conversion of online purchase intention into actual purchase: the moderating role of transaction security and convenience. Business: Theory and Practice, 2020, 21 (1), 18-29.

IZOGO, E. E.; JAYAWARDHENA, C. Online shopping experience in an emerging e-retailing market: Towards a conceptual model. Journal of consumer Behaviour, 2018, 17 (4), p. 379-392.

JAISWAL, A. K.; NIRAJ, R.; PARK, C. H.; AGARWAL, M. K. The effect of relationship and transactional characteristics on customer retention in emerging online markets. Journal of Business Research, 2018, 92, p. 25-35.

JIANG, S.; WANG, C.; WEISS, D. J. Sample size requirements for estimation of item parameters in the multidimensional graded response model. Frontiers in Psychology, 2016, 7, 109.
KAUSHIK, A. K.; MOHAN, G.; KUMAR, V. Examining the antecedents and consequences of customers’ trust toward mobile retail apps in India. *Journal of Internet Commerce*, 2020, 19 (1), p. 1-31.

KUMAR, P.; BAJAJ, R. Exploring the influence of demographic factors on perceived performance risk among youth towards online shopping in Punjab. *International Journal of Business and Globalisation*, 2019, 23 (1), p. 47-68.

LADHARI, R.; GONTHIER, J.; LAJANTE, M. Generation Y and online fashion shopping: Orientations and profiles. *Journal of Retailing and Consumer Services*, 2019, 48, p. 113-121.

LĂZĂROIU, G.; NEGURITĂ, O.; GRECU, I.; GRECU, G.; MITRAN, P. C. Consumers’ Decision-Making Process on Social Commerce Platforms: Online Trust, Perceived Risk, and Purchase Intentions. *Frontiers in Psychology*, 2020, 11.

LIAUKONYTE, J. Exploring gender differences in online consumer purchase decision making: An online product presentation perspective. *Information Systems Frontiers*, 2021, 330.

MARKOWITZ, D. M.; SHULMAN, H. C. The predictive utility of word familiarity for online engagements and funding. *Proceedings of the National Academy of Sciences*, 2021, 118 (18).

MCLean, G.; OSEI-FRIMPONG, K.; AL-NABHANI, K.; MARRIOTT, H. Examining consumer attitudes towards retailers-commerce mobile applications—An initial adoption vs. continuous use perspective. *Journal of Business Research*, 2020, 106, p. 139-157.

MELOVIĆ, B.; JOCOVIĆ, M.; DABIĆ, M.; VULIĆ, T. B.; DUDIC, B. The impact of digital transformation and digital marketing on the brand promotion, positioning and electronic business in Montenegro. *Technology in Society*, 2020, 63, 101425.

NASIDI, Q. Y.; AHMAD, M. F. B.; HASSAN, I. Mediating Role of Social Media in the Relationship between Reliability, Perceived Usefulness on Online Shopping Behaviour: Building a Conceptual Framework. *INTERNATIONAL JOURNAL OF ACADEMIC RESEARCH IN BUSINESS AND SOCIAL SCIENCES*, 2021, 11 (2), p. 385 - 393.

OLASANMI, O. O. Online shopping and customers’ satisfaction in Lagos State, Nigeria. *American Journal of Industrial and Business Management*, 2019, 9 (06), 1446.

PRASHAR, S.; SAI VIJAY, T.; PARSAD, C. Effects of online shopping values and website cues on purchase behaviour: A study using S-O-R framework. *Vikalpa*, 2017, 42 (1), p. 1-18.

RAHI, S., YASIN, N. M.; ALNASER, F. M. Measuring the role of website design, assurance, customer service and brand image towards customer loyalty and intention to adopt internet banking. *The Journal of Internet Banking and Commerce*, 2017, p. 1-18.

RUANGVANICH, S.; PIRIYASURAWONG, P. Structural Equation Model of Acceptance Cloud Learning for Sustainability Usage in Higher Education Institutes. *International Journal of Emerging Technologies in Learning*, 2019, 14 (10).

SAXENA, R. P.; EGHBALI, P.; BEHESHTIAN, N.; KATTAN, S. An exploratory study on e-tailing in United Arab Emirates. *Journal of Empirical Research*, 2018, 8 (8), p. 291-306.
SCHILLING, M. A., SHANKAR, R. Strategic management of technological innovation. McGraw-Hill Education, 2019.

SEN, R.; KING, R. C.; SHAW, M. J. Buyers' Vchoice of Online Search Strategy and Its Managerial Implications. Journal of management Information Systems, 2006, 23 (1), p. 211-238.

SENTHIL, M.; PRABHU, N.; BHUVANESWARI, S. Customers’ perception towards advertising in the online shopping and social networking websites among Internet users in India’. AMET, International Journal of Management, 2013, 2 (1), p. 50-59.

SHAFIEE, M. M.; BAZARGAN, N. A. Behavioral customer loyalty in online shopping: the role of e-service quality and e-recovery. Journal of theoretical and applied electronic commerce research, 2018, 13 (1), p. 26-38.

SMITH, S. P.; JOHNSTON, R. B.; HOWARD, S. Putting Yourself in the Picture: An Evaluation of Virtual Model Technology as an Online Shopping Tool. Information Systems Research, 2011, 22 (3), p. 640-659.

STONE, M. Cross-validation and multinomial prediction. Biometrika, 1974, 61 (3), p. 509-515.

TABER, K. S. The use of Cronbach’s alpha when developing and reporting research instruments in science education. Research in Science Education, 2018, 48 (6), p. 1273-1296.

TENENHAUS, M.; VINZI, V. E.; CHATELIN, Y.M.; LAURO, C. PLS path modeling. Computational statistics & data analysis, 2005, 48 (1), p. 159-205.

TORKZADEH, G.; DHILLON, G. Measuring Factors that Influence the Success of Internet Commerce. Information Systems Research, 2002, 13 (2), p. 187-204.

UGONNA, I.; OKOLO, V.; NEBO, G.; OJIEZE, J. Effects of online marketing on the behaviour of consumers in selected online companies in Owerri, Imo State, Nigeria. International Journal of Business and Management Invention, 2017, 6 (6), p. 32-43.

USMAN, M. U.; KUMAR, P.; IBRAHIM, A. Determinants of Consumer Purchase Intention in the Context of Online Shopping in Kano State, Nigeria: A Conceptual Model. The 9th Interdisciplinary Annual National Conference of the College of Administration and Management Studies (CAMs), Hussaini Adamu Federal Polytechnic, Kazaure, Jigawa State, Nigeria on 4th-8th November 2019, November 2019.

WANG, M.; LI, X.; CHAU, P. Y. Leveraging image-processing techniques for empirical Research: Feasibility and Reliability in Online Shopping Context. Information Systems Frontiers, 2020, p. 1-20.

WANG, Y.; GU, J.; WANG, S.; WANG, J. Understanding consumers’ willingness to use ride-sharing services: The roles of perceived value and perceived risk. Transportation Research Part C: Emerging Technologies, 2019, 105, 504-519.

WONG, K. K.K. Mastering partial least squares structural equation modeling (PLS-Sem) with Smartpls in 38 Hours. iUniverse, 2019.

YOON, Y.; LI, Y.; FENG, Y. Factors affecting platform default risk in online peer-to-peer (P2P) lending business: an empirical study using Chinese online P2P platform data. Electronic Commerce Research, 2019, 19(1), p. 131-158.

ZHANG, Y.; TRUSOV, M.; STEPHEN, A. T.; JAMAL, Z. Online shopping and social media: friends or foes? Journal of Marketing, 2017, 81 (6), p. 24-41.

ZHOU, L.; DAI, L.; ZHANG, D. Online shopping acceptance model-A critical survey of consumer factors in online shopping. Journal of Electronic commerce research, 2007, 8 (1), 41.
ZHU, J.; GORAYA, M. A. S.; CAI, Y. Retailer-consumer sustainable business environment: how consumers’ perceived benefits are translated by the addition of new retail channels. *Sustainability*, 2018, 10 (9), 2959.

**Empirical investigation of factors affecting online shopping behavior**

Investigação empírica de fatores que afetam o comportamento de compras online

Investigación empírica de los factores que afectan el comportamiento de compra en línea

**Resumo**

Este estudo tem como objetivo examinar a publicidade, o risco online, a utilidade percebida e a confiabilidade como fatores que afetam o comportamento de compras online entre assinantes de lojas online na Nigéria. Esta pesquisa adotou uma abordagem quantitativa na qual foi utilizado um questionário auto-administrado para coleta de dados. Os entrevistados são compostos por 375 assinantes de lojas online que tiveram experiências de compras online prévias de uma loja online com sede na Nigéria. O estudo utilizou o Smart-PLS para análise de dados. Os achados revelaram que a publicidade e a utilidade percebida têm um efeito positivo significativo no comportamento de compras online. Por outro lado, o risco online tem um efeito negativo no comportamento de compras online. Além disso, há uma relação positiva entre confiabilidade e comportamento de compras online. Esta pesquisa pode ser uma diretriz valiosa para as empresas online tomarem decisões sobre como aumentar as vendas online. Além disso, esta pesquisa poderia avançar o conhecimento dos compradores online, particularmente nigerianos, em relação às compras online.

**Palavras-chave:** Publicidade na internet. Risco online. Compras online. Fiabilidade. Comportamento de compras.

**Abstract**

This study aims to examine advertising, online risk, perceived usefulness, and reliability as factors affecting online shopping behavior among subscribers of online stores in Nigeria. This research adopted a quantitative approach in which a self-administered questionnaire was used to collect data. The respondents consist of 375 subscribers of online stores who had prior online shopping experiences from an online store based in Nigeria. The study used Smart-PLS for data analysis. The findings revealed that advertising and perceived usefulness have a significant positive effect on online shopping behavior. On the other hand, online risk has a negative effect on online shopping behavior. Additionally, there is a positive relationship between reliability and online shopping behavior. This research could be a valuable guideline for online firms to make informed decisions on how to increase online sales. Additionally, this research could advance online shoppers’ knowledge, particularly Nigerians, regarding online shopping.

**Keywords:** Advertising internet. Online risk. Online shopping. Reliability. Shopping behavior.

**Resumen**

Este estudio tiene como objetivo examinar la publicidad, el riesgo en línea, la utilidad percibida y la confiabilidad como factores que afectan el comportamiento de compra en línea entre los suscriptores de tiendas en línea en Nigeria. Esta investigación adoptó un enfoque cuantitativo en el que se utilizó un cuestionario autoadministrado para recopilar datos. Los encuestados consisten en 375 suscriptores de tiendas en línea que tenían experiencias de compra en línea anteriores de una tienda en línea con sede en Nigeria. El estudio utilizó Smart-PLS para el análisis de datos. Los hallazgos revelaron que la publicidad y la utilidad percibida tienen un efecto positivo significativo en el comportamiento de compra en línea. Por otro lado, el riesgo en línea tiene un efecto negativo en el comportamiento de compra en línea. Además, existe una relación positiva entre la confiabilidad y el comportamiento de compra en línea. Esta investigación podría ser una guía valiosa para que las empresas en línea tomen decisiones informadas sobre cómo aumentar las ventas en línea.

**Palabras-clave:** Publicidad en internet. Riesgo online. Las compras en línea. Fiabilidad. Comportamiento de compra.