Predicting Trustworthiness of an E-Commerce Platform From the Consumer Perspective

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Abstract

Internet shopping has become part and parcel of our day to day lives. Coupled with COVID-19 pandemic and the necessity to keep social distancing, many people have resorted to online shopping as a way of reducing potential exposure to the deadly virus. Online vendors have tried to follow the trends and put up online shops in unprecedented numbers. These myriad of alternatives have given room to unscrupulous vendors to also sneak in their products with an intention to defraud inexperienced online buyers. This massive number of online shops makes it impractical for an average user to assess with certainty which shop is trustworthy and which one is potentially fraudulent. In this study, we carry out a research to establish the indicators of trust in an e-commerce platform from the consumer perspective. We carry out a survey, focus group discussions and in-depth interview with a community within a public university to establish the factors they consider to conclude that an e-commerce platform is trustworthy or otherwise. We the use Exploratory Factor Analysis (EFA) and Principal Component Analysis (PCA) as our data analysis procedures. For EFA, we obtain uniqueness, factor loadings, scree plot, Eigen values, parallel analysis, optimal coordinates, and acceleration factor. For PCA, we obtain PCA Importance of Components, Loadings, Scree Plot, and biplot. We also obtain a Cronbach' alpha of 0.959 which indicates reliable data. Further research will involve creating a model from these results which can be used as a trust adjustment factor for autonomous use in artificial intelligence driven recommender system in ecommerce platforms.

Keywords : Decision support, e-Commerce, recommender systems, scale development, trust

I. INTRODUCTION

Improved ICT technologies coupled with the general drop in prices of electronic devices which can be used to access online services have led to a massive online presence, coupled with the COVID-19 pandemic which requires people to keep physical distance, thereby pushing them to work, shop, and socialize online.

This has indeed come with its own challenges. The massively online phenomenon has led vendors to try to maximize reach by following people and also placing their products online and they have placed their products online massively. This has led to a myriad of alternatives, thereby bringing along the burden of choice or information overload to the online users. This is a situation where users have too much information to analyze in order to make a worthwhile decision. Indeed it is not practical for an average user to assess all possible options unaided and they tend to optimally purchase online. Unscrupulous vendors are now taking advantage of the information overload and tease online users or a group of online users into buying items, which indeed is not in the best interest of the online user, and this has come along with trust issues within the eCommerce space.

Trust is a psychometric property which can only be perceived from a set of its indicators but cannot be measured directly as a single quantity.

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Trust, which can be considered as a perceived risk in pursuing a deal varies from context to context since it is dependent on other factors such as social norms, past experiences, as well as economic situation of the parties involved in the deal [1]. As such, the trust elements from research which have been carried out in a different context might not be naturally suitable to drop in replacement when ported to a context with different characteristics as far as the contributing factors, mentioned earlier are different. Indeed, a similar research had been carried out in European context [2]. However, there is no evidence that the scale developed applies to another context such as the African context. In this research, we seek to identify the indicators of trust from consumer perspective in the African context.

II. RELATED WORK

(1) Scale for measuring the ethics of an online retailer

In [2] the researchers used structural equation modelling to construct and validate a scale for measuring ethics of an online retailer. Ethics imply reliability and is therefore, closely related to trustworthiness. He ended up with four constructs; however, there is still need to repeat the experiment in a different target context.

(2) Trust based in sociology

In [3], the researchers experimented with success, the inclusion of trust into recommender system and found that trust improves prediction accuracy measured by both Mean Absolute Error and Root Mean Square Error. The data he used however, is not only old but required deliberate human efforts to estimate trustworthiness another user in the network [4].

(3) Robust Collaborative Recommendation

In [5] the researchers conducted a study on Robust Collaborative Recommendation algorithms. They outlined clearly the weakness of unaided collaborative filtering recommendation algorithm. Recommender systems are tools which are meant to alleviate information overload by helping users choose an item amidst a myriad of alternatives. This study highlighted how exposed collaborative filtering recommendation algorithm is to manipulation such as by product nuke or product push which involve inserting fake profiles into the database, an attack known as profile attack.

(4) Effectiveness of Digital Marketing

In [6] the researchers carried out an empirical study on the effectiveness of Digital Marketing Techniques. They collected empirical data on digital marketing and analyzed it using various statistical tools and techniques. The study demonstrated the importance of digital marketing for both marketers and consumers, so it is a worthwhile idea save for potential abuse by possible manipulations. For example, Pay Per Click advertising is a way of using search engine advertising to generate clicks to your website rather than earning those clicks organically. This generation of clicks involves automatic bidding for display space in the web page that the website visitor is reading, or ranking in the search engine results page with the background idea that the more conspicuous the advertisement space is on the web page or the higher the ranking in the search engine results page, the more likelihood that the web page visitors will click on a link which directs them to the target online shop and higher the likelihood is to make a sale. If left for pricing only as the factor determining the score, then a malicious vendor can outbid benign vendors, but with a malicious intention.

(5) Sponsored search or search advertising

Sponsored search or search advertising enables advertisers to target consumers based on the query they have entered. To some extent, these sponsored searches qualify as recommender systems. This is because the shopper considers the ranking and positioning of the sponsored search results on the webpage as one of the indicators of the superiority of a product. The following studies on sponsored searches have focused on maximizing the advertisers' profit but with not much regards to the ethics or trustworthiness of the service to be offered. This approach therefore, still requires the need to look for a way to incorporate a trust parameter to remain existential [7], [8], [9], [10], [11].

(6) Measuring trustworthiness by a feedback form on E-Commerce platform

It is also possible to estimate trustworthiness of a vendor by providing shoppers with a feedback form to report their experience and assess the satisfaction by comparing the expectation against the actual experience with the vendor such as the method taken by [12]. However, this is reactionary rather than deterrent measure and will allow for zero day attacks to go through and only protects users after a few reported successful penetrations.

III. GENGERATING FACTORS OR INDICATORS THAT PREDICT TRUST

We propose to construct trust measurement parameters from the indicators commonly used when evaluating trustworthiness of a vendor in a brick and mortar shop and in a context aware fashion.

We seek to investigate the factors that a natural buyer considers when assessing the trustworthiness of a seller with the aim of porting this knowledge into computing for the purpose of autonomously estimate trustworthiness of an online vendor and filter out those who do not meet a set threshold before products are ingested into recommender systems for consideration during the recommendation process.

(1) Item generation

In generating the items, we first pick the foundation ones from literature [2]. We then refine the items through in-depth interviews and focus group discussion.

(2) Focus group discussion questions

The following were the focus group discussion questions:

(a) Have you purchased an item online at any time in your life?

(b) If you have purchased an item online, what was the motivation? If not yet, then please explain if you can one day purchase an item online or possibly what is the hindrance?

(c) When did you purchase your first and last items online?

(d) How was the online shopping experience?

(e) Were there any noteworthy concerns?

(f) Is there any kind of products (goods or services) that you cannot consider buying online?

(g) Would you please identify the exact website where you purchased your last item from and also, if possible, let us know why you chose that website?

Trust was then defined (to the participants) as the belief that the online retailer will fulfill his obligation and then a list of dimensions of trust from literature were shown to the participants

(h) From the list of dimensions of online ethics, which ones did you find on the website where you last made your online purchase?

(i) In the list of dimensions of trust construct shown, in your opinion, what do you think should be added?

(j) From the list of dimensions of trust construct, in your opinion, what do you think is not representative of trust construct and should be removed?

(3) Focus group composition

There were seven members in each of the focus groups and these had been invited from one of the leading universities, comprising of faculty members, non-faculty members, as well as students. Some of the members had purchased items online and therefore, were familiar with the online experience while some of the members had not purchased items online. It was important to understand the online shopping experience for those who had purchased items online and also understand the reasons others had not. There was both a facilitator as well as a note taker in each focus group discussion. The facilitator also played the role of the moderator.

The composition of each focused group discussion was:

- Handpicked students only
- Randomly selected students
- Selected faculty members only
- Selected non-faculty members only
- A mixture of selected students, selected faculty, and selected non-faculty members.

The key contributing factor to the selection criteria was willingness to participate and a balance between those who had purchased items online and those who had not.

Other contributing factors were demographic factors such as:

- Gender
- Age
- Income
- Specialty

Each focus group session consisted of 6-12 members. The focus group sessions which involved students were deliberately made bigger because it was presumed that when students outnumber faculty members, they naturally consider the discussion a student level affair than in the opposite case.

(4) Focus group process

Each of the focus group discussions was held within the university premises where all members were familiar with and comfortable with. Each session was planned for two hours and even though we tried to get responses for each of the questions from each of the participants, there were deliberate efforts to make the process as informal as possible in order to allow members to participate as freely as possible and contribute towards the discussion maximally.

(5) Focus groups termination

The focus group discussions were iterated until the theory saturation was attained, this is when no more new knowledge was being generated after a certain number of the focused group discussions had been conducted.

(6) In-depth interviews composition

The participants of the in-depth interviews consisted of members of the faculty. The interviews were brought to an end after attainment of theory saturation, which is when no more new knowledge was coming in after the number of participants had been interviewed.

(7) In-depth interview questions

The in-depth interview questions were similar to the focus group discussion questions listed earlier, only that it targeted experts from whom we sought to get slightly more information.

(8) In-depth interview process

In the interviews, the process involved first defining trust as the belief that the online retailer will fulfill his obligation. Then a list of dimensions of trust from literature was shown to the participants.

The participant was then invited to provide their inputs. The interviewer ensured that at the end of the in-depth interview the interviewees had responded to all the questions in the focus group questions.

This approach was taken because it was necessary to have the interview process flow as naturally as possible in order to capture the maximum from the interviewees.

(9) In-depth interviews termination

The in-depth interviews were iterated until the theory saturation was attained, this is when no more new knowledge was being generated after a certain number of in-depth interviews had been conducted.

(10) Item generation outcome

In total, we performed 6 focus group discussions and 6 in-depth interviews.

At the end of focus group discussions and in-depth interviews, 61 items were finally generated from the literature, the focus group discussions and in-depth interviews.

(11) Items thematic review

These items were then submitted to a panel of expert judges (members of faculty from the school of business) who after reviewing the items, agreed to retain only the items listed in Table I.

These remaining items were then used to prepare a questionnaire for the Exploratory Factor Analysis, herein called the first study.

(12) The first study (Exploratory Factor Analysis and Principle Component Analysis)

Sample and data collection : We conducted a survey on people who had never purchased an item online as well as those who have with the help of Google forms. We used Google forms because according to Best and Krueger [13] online surveys offer a more efficient and convenient form of data collection. In the Google form, there was an introduction section, where the purpose of the survey was described, and thereafter the participants were invited to fill in the e-questionnaire.

IV. DATA ANALYSIS

We used Exploratory Factor Analysis (EFA) and Principal Component Analysis (PCA) tests as the key statistical tests [14].

Exploratory Factor Analysis produces maximum likelihood factor analysis while Principal Component Analysis produces an unrotated Principal Component Analysis.

For EFA, we obtain uniqueness, factor loadings, scree plot, Eigen values, parallel analysis, optimal coordinates, and acceleration factor.

For Principal Component Analysis, we obtain PCA Importance of Components, Loadings, Scree Plot, and the distance biplot.

Statistical Tools

We used R Program [15] as our data analysis program. Within this program, the following functions were used:

The **factanal( )** function which produces maximum likelihood factor analysis.

The **princomp()** function which produces an unrotated principal component analysis.

```
> loadings(fit) # pc loadings

Loadings:
```

	Comp.1	Comp.2	Comp.3	Comp.4	Comp.5	Comp.6	Comp.7	Comp.8	Comp.9	Comp.10	Comp.11	Comp.12	Comp.13	Comp.14	Comp.15	Comp.16	Comp.17	Comp.18	Comp.19
security_policy_understandable	0.232	0.232	0.272	0.162				0.151		0.571	0.184		0.344	0.213	0.149	0.149	0.343	0.267	
terms_and_conditions_displayed	0.228	0.250	0.310	0.178			-0.148	0.277	0.130		-0.291	0.352	-0.273	0.115		-0.343	-0.460		
company_owner_information	0.230	0.126	0.334	-0.218		-0.146	0.325	0.180	0.201	-0.413	0.221	-0.390	-0.220	0.328		0.181		0.101	
secure_payment_methods	0.245	0.240				-0.229	-0.194	-0.293		-0.176	-0.182		-0.160	-0.343	-0.346		0.343	0.492	
transaction_details	0.247	0.202		0.141	0.108	-0.107	0.119		0.253	-0.248	-0.245	-0.221	0.472	-0.259	0.305	-0.292	0.103	-0.348	
security_features	0.242	0.230	0.139		0.165	-0.227	-0.237	-0.239	-0.256		0.172	0.116	-0.203	-0.103	0.101	0.436		-0.550	
user_information_used	0.250			-0.105	-0.413	0.327	0.116	-0.100			0.319	0.132	-0.196		-0.249	-0.412	0.336	-0.317	
necessary_information_only	0.238	0.138		-0.162	-0.477			-0.403	-0.409		-0.118		0.261	0.202	0.177		-0.358	0.210	
privacy_policy_presented	0.248				-0.171	0.501		0.178	0.266	0.160	-0.136	-0.262		-0.447		0.399	-0.231		
exeggerates_benefits	0.212	-0.243	0.247	0.149	0.227	0.368	0.289	0.240	-0.523	-0.305		0.257		-0.179			0.106		
truthful_about_offering	0.207	-0.281	0.147	-0.364	0.240		-0.580				0.307	-0.199	0.228			-0.308	-0.140		
uses_misleading_tactics	0.225	-0.366		0.366	-0.253	-0.203			0.121		0.147					0.106			0.711
takes_advantage	0.208	-0.368		-0.298			-0.160		0.160		-0.564		-0.170	0.307	0.238	0.115	0.373		
things_not_needed	0.192	-0.358		-0.130	0.347		0.477	-0.397	0.152	0.381				-0.132	-0.169	-0.105	-0.253		
abnormal_pricing	0.225	-0.358		0.396	-0.252	-0.231					0.153								-0.700
actual_amount_billed	0.217		-0.345	-0.376	-0.159	-0.461	0.186	0.531	-0.211	0.170				-0.207					
get_what_ordered	0.243		-0.353		0.216	0.132			0.162	-0.183		0.261	0.369	0.362	-0.529	0.215		-0.109	
products_looked_available	0.231		-0.371	0.365	0.198				-0.315	0.169	-0.115	-0.533	-0.288	0.278		-0.172			
time_keeping	0.230		-0.464		0.214				0.202	-0.140	0.308	0.315	-0.220		0.533			0.262	

	Comp.1	Comp.2	Comp.3	Comp.4	Comp.5	Comp.6	Comp.7	Comp.8	Comp.9	Comp.10	Comp.11	Comp.12	Comp.13	Comp.14	Comp.15	Comp.16	Comp.17	Comp.18	Comp.19
SS loadings	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Proportion Var	0.053	0.053	0.053	0.053	0.053	0.053	0.053	0.053	0.053	0.053	0.053	0.053	0.053	0.053	0.053	0.053	0.053	0.053	0.053
Cumulative Var	0.053	0.105	0.158	0.211	0.263	0.316	0.368	0.421	0.474	0.526	0.579	0.632	0.684	0.737	0.789	0.842	0.895	0.947	1.000

Fig. 1. Principal Components Analysis – Loadings With Abnormal Pricing

```
> summary(fit) # print variance accounted for
Importance of components:
```

	Comp.1	Comp.2	Comp.3	Comp.4	Comp.5	Comp.6	Comp.7	Comp.8	Comp.9	Comp.10	Comp.11	Comp.12	Comp.13	Comp.14	Comp.15
Standard deviation	3.3701654	1.4158104	0.94856576	0.74994360	0.72577871	0.68223344	0.66725380	0.61912826	0.59495324	0.56761305	0.55251477	0.51880122	0.49107121	0.47663569	0.44559574
Proportion of Variance	0.5977903	0.1055010	0.04735668	0.02960081	0.02772393	0.02449697	0.02343303	0.02017473	0.01862997	0.01695708	0.01606698	0.01416604	0.01269215	0.01195693	0.01045029
Cumulative Proportion	0.5977903	0.7032913	0.75064796	0.78024877	0.80797270	0.83246967	0.85590270	0.87607743	0.89470740	0.91166448	0.92773146	0.94189749	0.95458965	0.96654657	0.97699687

	Comp.16	Comp.17	Comp.18	Comp.19
Standard deviation	0.424430181	0.359375518	0.34478395	0.0942964213
Proportion of Variance	0.009481104	0.006797409	0.00625663	0.0004679903
Cumulative Proportion	0.986477971	0.993275380	0.99953201	1.0000000000

Fig. 2. Principal Components Analysis – Importance of Components or Communality (Variance accounted for), With Abnormal Pricing

TABLE I.
TRUST ELEMENTS IN ECOMMERCE PLATFORMS FROM CONSUMER PERSPECTIVE IN AFRICAN CONTEXT

Constructs of Trust	Items/Indicators of the Constructs			
		Items to Measure	How to Measure	When to Measure
Item's Variable Name	S/N	Item Description		
Security (L1)	S1	The security policy clearly stated and can be understood without any form of ambiguity.	True of false	Before purchase
	S2	The terms and conditions are displayed in a page which appears before the purchase takes place.	True of false	Before purchase
	S3	There is clear information about the legal owner of the site.	True of false	Before purchase
	S4	The payment methods provided in the site are secure and cannot be repudiated.	True of false	Before purchase
	S5	There is a facility for confirming details before payment.	True of false	Before purchase
	S6	Security features of the site such as the SSL are OK.	True of false	Before and after purchase
Privacy (L2)				
	P1	There is a clear explanation on how collected information will be used.	True of false	Before purchase
	P2	The site does not collect personal information in excess of what is needed to complete the transaction.	True of false	Before and after purchase
	P3	Privacy policy statement is clearly provided and is easy to understand.	True of false	Before purchase
Deception (L3)				
	D1	The language used in the site seems to be exaggerating the features and benefits offered.	True of false	Before and after purchase
	D2	It is not entirely truthful about its offerings.	True of false	Before and after purchase
	D3	The site uses misleading tactics to convince consumers to buy its products.	True of false	Before and after purchase
	D4	This site takes advantage of less experienced consumers to make them purchase.	True of false	Before and after purchase
	D5	This site attempts to persuade you to buy things that you do not need.	True of false	Before and after purchase
	D6	The site items are abnormally priced as compared to other sites.	True of false	Before and after purchase
Reliability/				
Fulfillment (L4)	R1	The prices shown at the checkout page are actually the amount deducted on card.	True of false	Before and after purchase
	R2	When you order something, you actually end up getting it and there is no possibility of other stories emerging along the line.	True of false	Before and after purchase
	R3	The products which are displayed on the site are indeed available for sale and are not just a means to lure the buyer into a conversation and negotiations and then the products are sourced or brokered from elsewhere.	True of false	Before purchase
	R4	Keep time when dealing with customers.	True of false	Before and after purchase

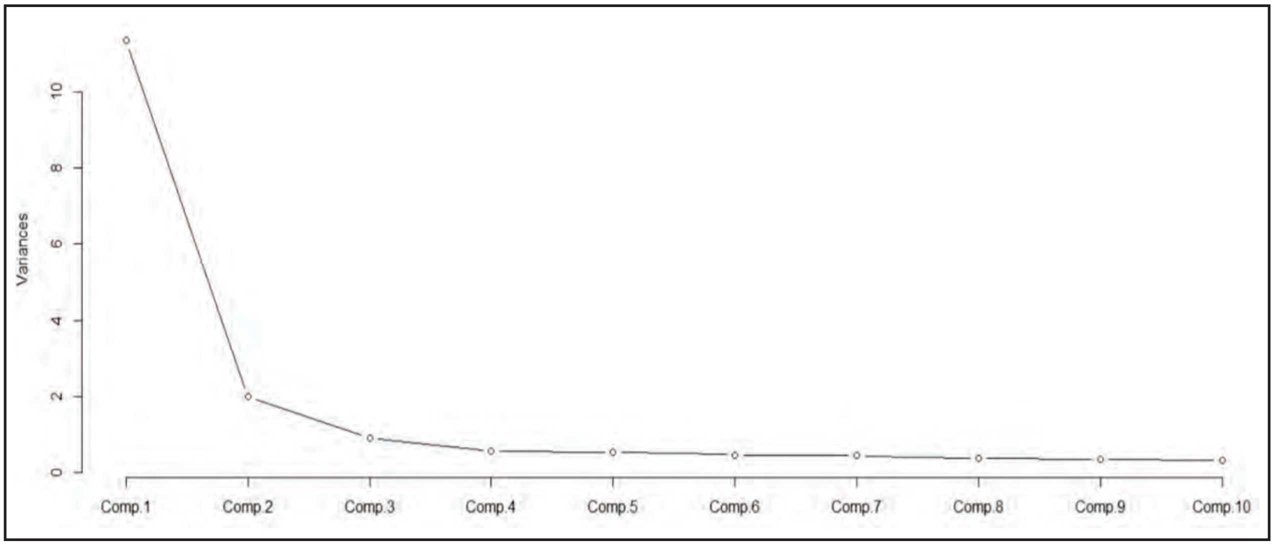

Fig. 3. Principal Components Analysis - Scree Plot, With Abnormal Pricing

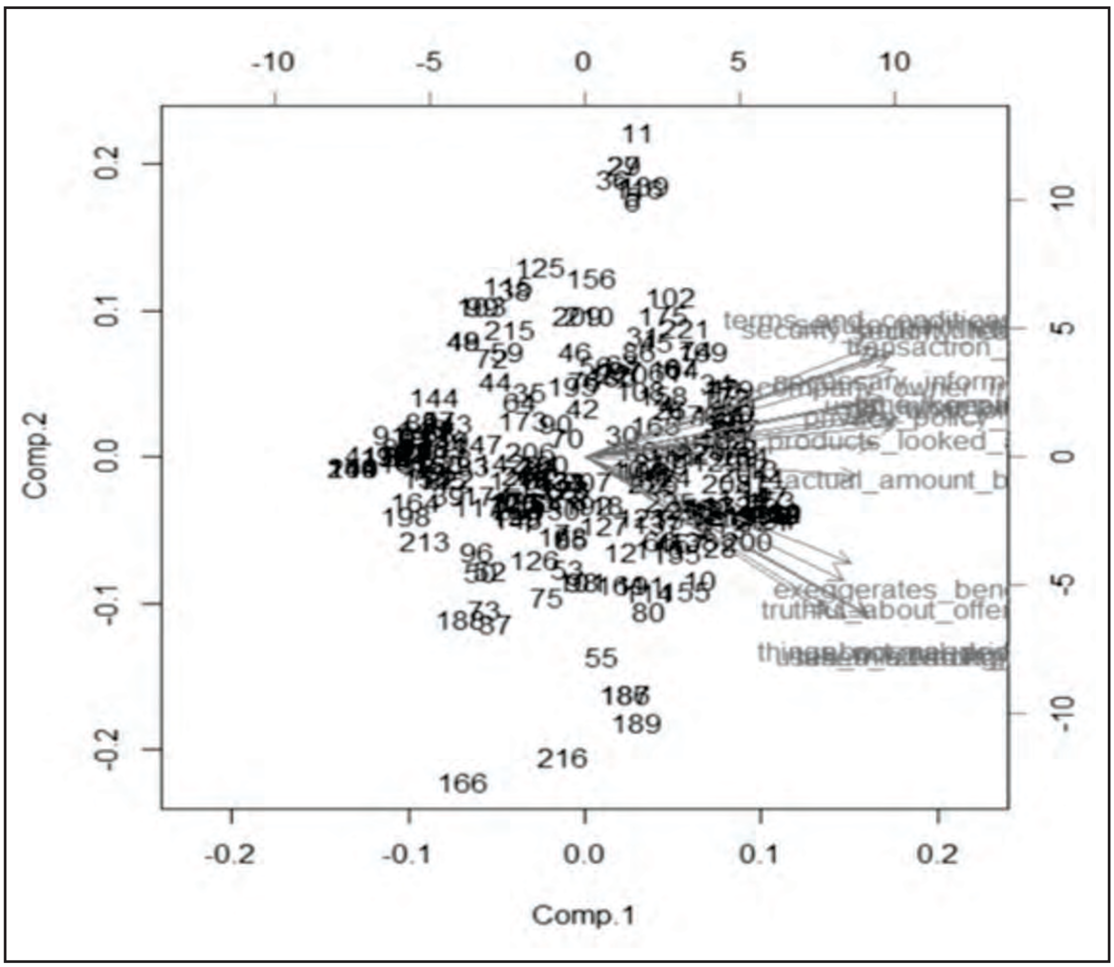

Fig. 4. Principal Components Analysis - Distance Biplot With Abnormal Pricing

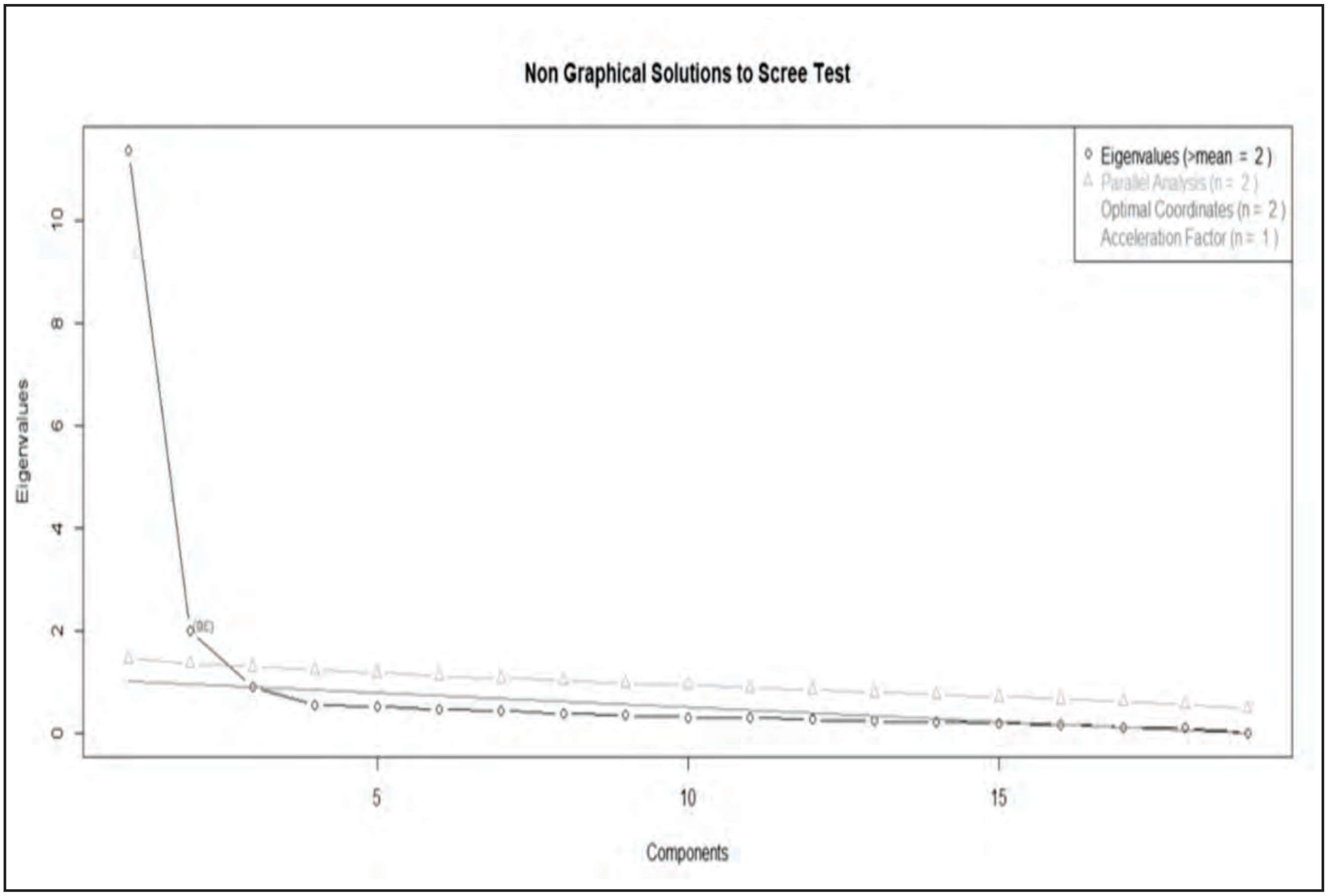

Fig. 5. Exploratory Factor Analysis - Eigenvalues (Scree Test) With Abnormal Pricing

```
> print(fit, digits=2, cutoff=.5, sort=TRUE)

Call:
factanal(x = mydata, factors = 4, rotation = "varimax")

Uniquenesses:
security_policy_understandable terms_and_conditions_displayed     company_owner_information          secure_payment_methods           transaction_details
                          0.25                           0.23                          0.33                            0.22                          0.24
             security_features          user_information_used    necessary_information_only        privacy_policy_presented           exeggerates_benefits
                          0.23                           0.31                          0.36                            0.31                          0.42
      truthful_about_offering          uses_misleading_tactics                takes_advantage               things_not_needed               abnormal_pricing
                          0.36                           0.01                          0.21                            0.40                          0.00
          actual_amount_billed               get_what_ordered       products_looked_available                     time_keeping
                          0.45                           0.22                          0.33                            0.21
```

Fig. 6. Exploratory Factor Analysis - Uniqueness, With Abnormal Pricing

Loadings:

	Factor1	Factor2	Factor3	Factor4
security_policy_understandable	0.80			
terms_and_conditions_displayed	0.83			
company_owner_information	0.71			
secure_payment_methods	0.75			
transaction_details	0.72			
security_features	0.77			
user_information_used	0.61			
necessary_information_only	0.62			
privacy_policy_presented	0.57			
exeggerates_benefits		0.63		
truthful_about_offering		0.71		
uses_misleading_tactics		0.73		0.59
takes_advantage		0.83		
things_not_needed		0.72		
abnormal_pricing		0.71		0.62
actual_amount_billed			0.50	
get_what_ordered			0.69	
products_looked_available			0.60	
time_keeping			0.75	

	Factor1	Factor2	Factor3	Factor4
SS loadings	5.66	4.29	3.04	0.90
Proportion Var	0.30	0.23	0.16	0.05
Cumulative Var	0.30	0.52	0.68	0.73

Fig. 7. Exploratory Factor Analysis – Factor Loadings Table With Abnormal Pricing

> summary(fit) # print variance accounted for

Importance of components:

	Comp.1	Comp.2	Comp.3	Comp.4	Comp.5	Comp.6	Comp.7	Comp.8	Comp.9
Standard deviation	3.2924354	1.3895884	1.00079794	0.79803248	0.66944856	0.60255945	0.57692310	0.56629626	0.54957153
Proportion of Variance	0.6022295	0.1072753	0.05564425	0.03538088	0.02489785	0.02017099	0.01849113	0.01781619	0.01677938
Cumulative Proportion	0.6022295	0.7095048	0.76514908	0.80052996	0.82542781	0.84559880	0.86408993	0.88190612	0.89868550

	Comp.10	Comp.11	Comp.12	Comp.13	Comp.14	Comp.15
Standard deviation	0.52578763	0.48891728	0.48455265	0.46025397	0.45601899	0.44190416
Proportion of Variance	0.01535848	0.01328001	0.01304396	0.01176854	0.01155296	0.01084885
Cumulative Proportion	0.91404398	0.92732399	0.94036795	0.95213649	0.96368945	0.97453830

	Comp.16	Comp.17	Comp.18
Standard deviation	0.421346888	0.379322412	0.369989081
Proportion of Variance	0.009862956	0.007993638	0.007605107
Cumulative Proportion	0.984401255	0.992394893	1.000000000

Fig. 8. Principal Components Analysis – Importance of Components or Communality (Variance Accounted for) Without Abnormal Pricing

> loadings(fit) # pc loadings

Loadings:

	Comp.1	Comp.2	Comp.3	Comp.4	Comp.5	Comp.6	Comp.7	Comp.8	Comp.9
security_policy_understandable	0.225	0.180	0.367		0.584		0.295		0.142
terms_and_conditions_displayed	0.224	0.249	0.398		0.302	-0.137		-0.273	
company_owner_information	0.235	0.176	0.284		-0.157	0.177	-0.599	0.356	0.425
secure_payment_methods	0.250	0.226	0.117	0.122	-0.399		0.185	-0.122	-0.173
transaction_details	0.251	0.213		0.150	-0.317			-0.215	
security_features	0.251	0.198	0.165	0.152	-0.347		0.210	0.134	-0.198
user_information_used	0.247		-0.119	-0.532		0.137		0.149	
necessary_information_only	0.241		-0.112	-0.536	-0.135	0.195	0.384	0.176	-0.101
privacy_policy_presented	0.247		-0.165	-0.410		-0.224	-0.207	-0.497	
exeggerates_benefits	0.223	-0.315	0.125		0.169	0.125	-0.415		-0.717
truthful_about_offering	0.218	-0.347	0.128			-0.641		0.184	
uses_misleading_tactics	0.224	-0.376							
takes_advantage	0.212	-0.423			-0.139	-0.107	0.176	-0.154	0.311
things_not_needed	0.207	-0.410		0.132		0.450	0.114		0.234
actual_amount_billed	0.246		-0.317	0.147	0.176	-0.179	0.126	0.554	
get_what_ordered	0.253		-0.307	0.164		-0.244	-0.115		0.126
products_looked_available	0.238		-0.348	0.294	0.221	0.292		-0.178	
time_keeping	0.242		-0.400	0.198			-0.119	-0.125	0.128

	Comp.10	Comp.11	Comp.12	Comp.13	Comp.14	Comp.15	Comp.16	Comp.17	Comp.18
security_policy_understandable	0.130		0.381					0.207	0.330
terms_and_conditions_displayed			-0.542			-0.111		-0.307	-0.367
company_owner_information	-0.243			-0.128	0.101				0.126
secure_payment_methods			-0.166		-0.415	-0.128		-0.171	0.592
transaction_details	0.103	0.450	0.273			0.407	0.435	-0.133	-0.191
security_features		-0.345	0.216	0.107	0.166	-0.216	-0.162	0.423	-0.410
user_information_used	0.191	-0.323	-0.125	0.321	-0.421	0.253	0.237	0.115	-0.133
necessary_information_only		0.205	-0.112	-0.433	0.327		-0.156		
privacy_policy_presented	-0.236		0.398	0.141		-0.350	-0.168		
exeggerates_benefits	0.136			-0.141		-0.144		0.113	0.131
truthful_about_offering		-0.239	0.199	-0.317	-0.113	0.310		-0.227	
uses_misleading_tactics	-0.301		-0.159	0.557	0.243	0.391	-0.340		0.116
takes_advantage			-0.271		0.116	-0.277	0.530	0.359	0.105
things_not_needed	0.291		0.185		-0.297	-0.247	-0.224	-0.319	-0.248
actual_amount_billed	-0.159	0.255		0.313		-0.336	0.200	-0.274	
get_what_ordered	0.338	0.383	-0.223	-0.113	-0.188	0.103	-0.393	0.426	
products_looked_available	-0.558	-0.201		-0.332	-0.227	0.145			-0.112
time_keeping	0.414	-0.435			0.481			-0.233	0.192

	Comp.1	Comp.2	Comp.3	Comp.4	Comp.5	Comp.6	Comp.7	Comp.8	Comp.9
SS loadings	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Proportion Var	0.056	0.056	0.056	0.056	0.056	0.056	0.056	0.056	0.056
Cumulative Var	0.056	0.111	0.167	0.222	0.278	0.333	0.389	0.444	0.500

	Comp.10	Comp.11	Comp.12	Comp.13	Comp.14	Comp.15	Comp.16	Comp.17	Comp.18
SS loadings	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Proportion Var	0.056	0.056	0.056	0.056	0.056	0.056	0.056	0.056	0.056
Cumulative Var	0.556	0.611	0.667	0.722	0.778	0.833	0.889	0.944	1.000

Fig. 9. Principal Components Analysis – Loadings Without Abnormal Pricing

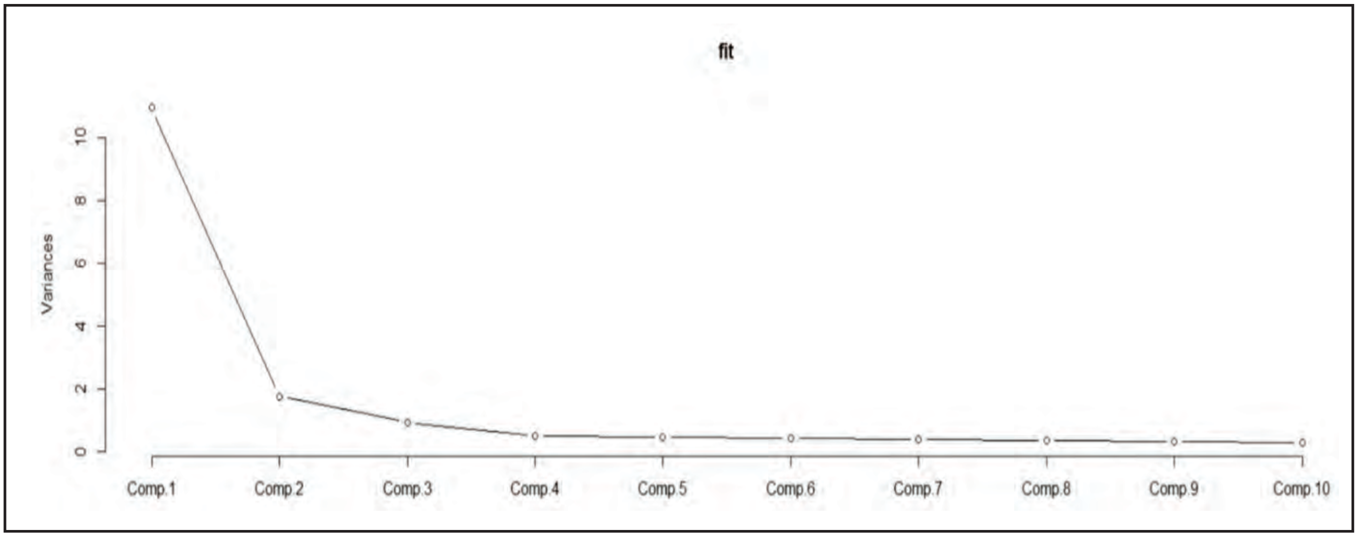

Fig. 10. Principal Components Analysis - Scree Plot Without Abnormal Pricing

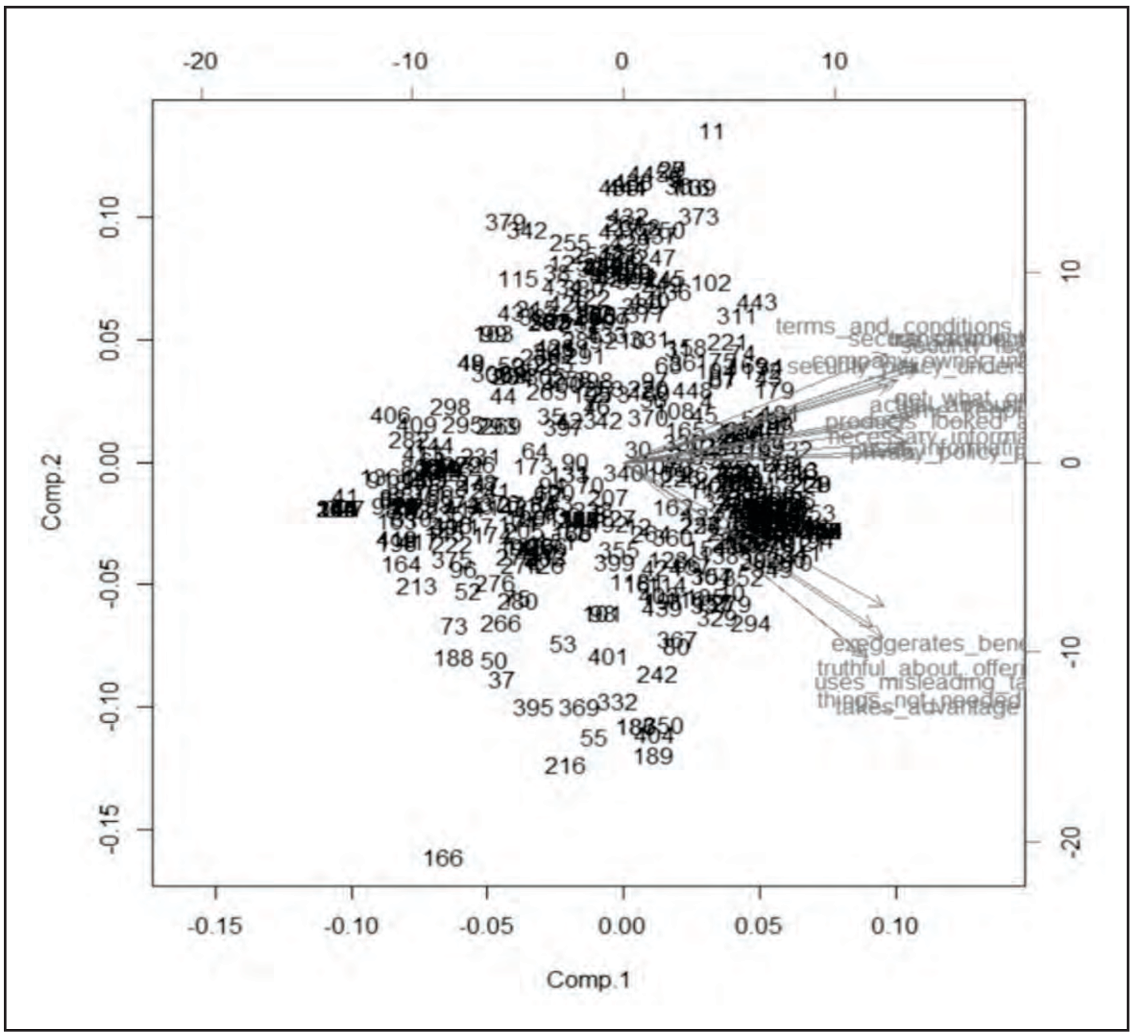

Fig. 11. Principal Components Analysis - Distance Biplot Without Abnormal Pricing

```
factanal(x = mydata, factors = 4, rotation = "varimax")

Uniquenesses:
security_policy_understandable terms_and_conditions_displayed    company_owner_information    secure_payment_methods    transaction_details    security_features
                          0.27                           0.23                         0.34                      0.21                   0.24                 0.22
         user_information_used     necessary_information_only      privacy_policy_presented        exeggerates_benefits   truthful_about_offering   uses_misleading_tactics
                          0.00                           0.32                         0.29                      0.40                   0.37                 0.28
               takes_advantage               things_not_needed           actual_amount_billed          get_what_ordered  products_looked_available          time_keeping
                          0.24                           0.37                         0.23                      0.22                   0.29                 0.26
```

Fig. 12. Exploratory Factor Analysis - Uniqueness Without Abnormal Pricing

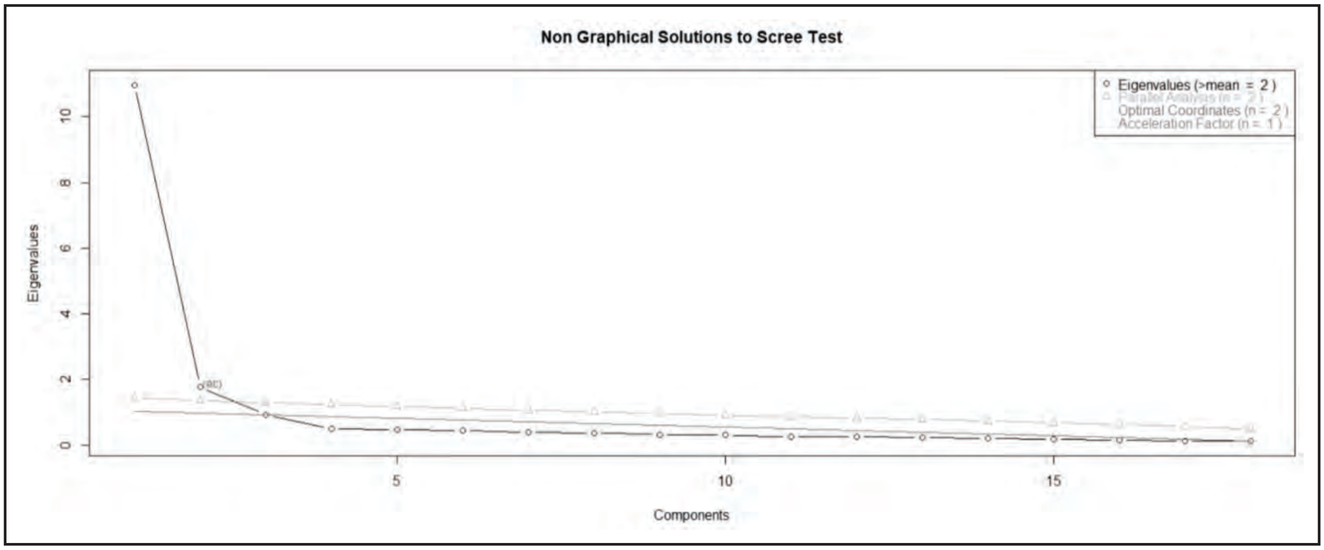

Fig. 13. Exploratory Factor Analysis - Eigenvalues (Scree Test) Without Abnormal Pricing

```
Loadings:
                               Factor1 Factor2 Factor3 Factor4
security_policy_understandable 0.76
terms_and_conditions_displayed 0.81
company_owner_information      0.68
secure_payment_methods         0.73
transaction_details            0.70
security_features              0.76
necessary_information_only     0.56
privacy_policy_presented       0.51
exeggerates_benefits                   0.67
truthful_about_offering                0.71
uses_misleading_tactics                0.75
takes_advantage                        0.82
things_not_needed                      0.75
actual_amount_billed                           0.69
get_what_ordered                               0.70
products_looked_available                      0.68
time_keeping                                   0.72
user_information_used                                  0.68

               Factor1 Factor2 Factor3 Factor4
SS loadings       5.01    3.92    3.42    0.87
Proportion Var    0.28    0.22    0.19    0.05
Cumulative Var    0.28    0.50    0.69    0.73

Test of the hypothesis that 4 factors are sufficient.
The chi square statistic is 195.06 on 87 degrees of freedom.
The p-value is 2.89e-10
```

Fig. 14. Exploratory Factor Analysis – Factor Loadings Table Without Abnormal Pricing

```
> library(ltm)
Loading required package: MASS
Loading required package: msm
Loading required package: polycor
> cronbach.alpha(mydata)

Cronbach's alpha for the 'mydata' data-set

Items: 18
Sample units: 448
alpha: 0.959
```

Fig. 15. Data Reliability

V. RESULTS

The results are shown in Fig. 1 to Fig. 15.

VI. DISCUSSION

In this work, we have presented the indicators that indicate trust in e-commerce platforms from consumer perspective in the African context.

We used EFA and PCA tests as the key statistical tests. For Exploratory Factor Analysis, we obtained uniqueness, factor loadings, scree plot, Eigen values, parallel analysis, optimal coordinates, and acceleration factor.

For Principal Component Analysis, we obtained PCA Importance of Components, Loadings, Scree Plot, and the distance biplot.

In EFA, we are usually keen to find underlying factors that contribute to certain observed variables. In turn, these variables can be used to predict the presence of such factors in a reversed manner. The variables are therefore called indicators of the underlying factor and what this means is that varying the indicator contributes to some variation or variance in the underlying factor which it indicates. Indeed, the more variance in the underlying factor is observed by a variation in the surface variable/indicator, the more significant that indicator is. As a result, the total variance of an underlying factor can be represented by Eq. (1):

$$\textit{Total Variance} = \textit{Common Variance} + \textit{Unique Variance} + \textit{error} \qquad (1)$$

In Eq. (1), common variance is the variance accounted for by many indicators combined. The Unique variance is the variance which is unique to a particular indicator whereas error term is the term associated by some error not necessarily as a result of actual relationship between the underlying factor and its indicator, such as error in measurements. In our results, this unique variance is represented by Fig. 6 and Fig. 12. As can be seen in Fig. 6, the uniqueness of the indicator “abnormal pricing” is indeed 0.00, and is very much close to that of use of misleading tactics, which indicates that indeed the two are very high correlated and an indicator that one of them is not as significant when estimating trustworthiness of an e-commerce platform, an indicator that one might need to be done away with.

We also have factor loadings for EFA in Fig. 7 and Fig. 14. As can be seen in Fig. 7, there is still a problem of cross loading, which does not occur in Fig. 14. The next parameter we report under EFA is the Sree test in Fig. 5 and 13. These indicate the Eigen values, parallel analysis, optimal coordinates, and acceleration factor. As can be seen in Fig. 5, there is really no clear point of inflection in the plot as can be seen clearly in Fig. 13 that the point of inflection is indeed at four factors. This is consistent with literature. The Eigen values, parallel analysis, optimal coordinates, and the acceleration factor are however, the same in both figures, which paints some element of greyness and necessitates further research as some analysts may argue that both figures are meaningful. However, we go with the results of Fig. 13 because indeed it agrees with literature and also with the opinion of the thematic review panel, both of which suggest that four factors are adequate for this data. Scree test helps a researcher to estimate the number of factors to retain Exploratory Factor Analysis. However, due to the subjectiveness about the actual or acceptable point of inflection (sometimes the graph has multiple points of inflection!), non-graphical solutions to Scree test have been suggested and these include the Eigen values, parallel analysis, optimal coordinates, and the acceleration factor. We do not discuss these in this paper because they are all consistent and their meanings can be inferred from literature [16, 17].

About Principal Component Analysis, even though most studies choose to either carry out either PCA or EFA because the two scientific/statistical procedures usually talk to answer different research questions, the two procedures are not mutually exclusive in the sense that a researcher may want to excavate underlying factors which are contributing to the values of some set of observed variable, which is a structural question while still maintaining the desire to exercise dimensionality reduction, which is a measurement question on the observed variables for certain reasons such as to reduce the length of a questionnaire or a need which is related to resource constraint whatsoever, then the researcher will perform Principal Component Analysis in order to determine the most important variables/components to retain. As such we sought to carry out both procedures and report both the results in one go.

For the Principal Components Analysis, we obtained PCA Importance of Components, Loadings, Scree Plot, and the distance biplot.

Fig. 2 and Fig. 8 show the PCA Importance of components or Communality (variance accounted for), with abnormal pricing and without abnormal pricing respectively. As can be seen in Fig. 2, the variance accounted for by component 19 is indeed negligible as compared to the rest of the components. This means that component 19 is not contributing meaningful amount of variance and therefore, dropping it from the list of variables does not result in losing a meaningful amount of information present in the original data. Fig. 8 looks better in terms of how each of the 18 components contribute relatively a balanced amount of variance and therefore, all are worth retaining.

Another indicator of weight of component, in absolute value is the PCA loadings, shown in Fig. 1 and Fig. 9. PCA loadings are equivalent to correlations between observed variables and components. As can be seen in Fig. 1, component 19 has only two items loading onto it. These are abnormal pricing and use of misleading tactics. In Principal Component Analysis, negative loading implies a negative correlation. It can be seen that component 19 is problematic since only two variables load onto it, which are the use of misleading tactics and the use of abnormal pricing. From the thematic expert review panel, these two items are supposed to be scored in the same direction since in their view, use of abnormal pricing to tease buyers is indeed a manifestation or an instance of or a case of use of misleading tactics. Therefore, we dropped the use of abnormal pricing from the list of variables and after running the analysis again, Fig. 9 gives a better output where all items have meaningful loadings to all the remaining components.

The graphical PCA scree plots in Fig. 3 and 10 also agree with the EFA scree plots in Fig. 5 and 13 that four components can adequately represent the information contained in the original data. For the same reason as that already discussed for the EFA scree plot, again it is not very clear where the graph screes at for Fig. 3, but it is clear from Fig. 10 that it screes at four components.

Another parameter reported here is the distance biplot shown in Fig. 4 and Fig.11. This is a type of scatter plot which graphically represents the position of each variable score on a two dimensional axis of the first two principal components. Each score is represented by a vector representing the direction and the magnitude of effect that a variable has on the final estimation. The visual biplot is a tool which can be used to quickly get a glance of the most important variable that contributes to a certain direction, just by looking at the variable with the longest vector whose direction is towards the desired direction.

We used Cronbach's alpha, shown in Fig. 15 to ascertain the reliability of the data used in this study. The Cronbach's alpha cut off for reliable from the literature is 0.7. Fig. 15 shows a Cronbach's alpha value of 0.959 which confirms that we used reliable data in the study.

Therefore, we present the residual elements of trust in Table 1, which describes the trust constructs, their indicators, when to measure the said indicator, and also how to measure the indicator.

VII. CONCLUSION

In this research, we have been able to identify the indicators of trust in a step by step approach in the African context. The results of this work can be used by shoppers as a benchmark for evaluating trustworthiness of online vendors so to reduce the exposure to risk of losing income (or even lives) that has been posed by untrustworthy vendors.

Also, the results of this work can be applied by e-commerce platform developers targeting the African market to help them align their services with the expectation of end users in order to maximize the values of their eCommerce platforms.

VIII. FURTHER RESEARCH

As can be seen from the discussion, the Scree test is not giving a very clear cut off of the desired number of variables/components to retain and this naturally invites the need for a further confirmatory Factor Analysis stage.

Also, still there is a need to automate the process of evaluating the trustworthiness of e-commerce platforms. This will incorporate the Confirmatory Factor Analysis and also fitting the data into a model which will help us get variable coefficients of each of the element or factor mentioned in Table I so that we can use Structural Equation Modelling to construct a scale for estimating the trustworthiness of an e-commerce platform as a single aggregate.

This will help in filtering out untrustworthy services in e-commerce platforms and help shield the shopper from fraud and can also be embedded into Artificial Intelligence driven recommender systems pipelines. This will be particularly paramount when curbing potential abuse of mathematical properties recommender systems such as profile injections which is an attack to trick a recommender system to recommend an item to an active user, when indeed that item is not the most suitable one to the active user, just to attain some interests that the attacker intends to achieve, many at times commercial gain.

In other words, this will help to improve the robustness of the recommender systems in question. More about robust recommender systems can be read about in [5].

AUTHORS' CONTRIBUTIONS

Edwin O. Ngwawe came up with the concept and also designed the research; Elisha Abade assisted with the refinement of data collection tools while Stephen Mburu assisted with insights in data analysis.

CONFLICT OF INTEREST

The authors certify that they have no affiliation with or involvement in any organization or entity with financial or non-financial interests in the subject matter or materials discussed in this manuscript.

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REFERENCES

[1]S. McLeod, "Maslow's hierarchy of needs," SimplyPsychology, 2007. [Online]. Available: https://www.simplypsychology.org/maslow.html

[2] S. Roman, "The ethics of online retailing: A scale development and validation from the consumers' perspective," *J. Bus. Ethics, 72,* pp. 131–148, 2006, doi: 10.1007/s10551-006-9161-y.

[3] C. Yin, J. Wang, and J. H. Park, "An improved recommendation algorithm for big data cloud service based on the trust in sociology," *Neurocomputing,* vol. 256, pp. 49–55, 2017, doi: 10.1016/j.neucom.2016.07.079.

[4] J. Leskovec, "Epinions social network," Stanford Univ., 2003. [Online]. Available: https://snap.stanford.edu/data/soc-Epinions1.html

[5] R. Burke, M. P. O'Mahony, and N. J. Hurley, "Robust collaborative recommendation," In F. Ricci, L. Rokach, B. Shapira, P. Kantor, P. (eds) *Recommender Syst. Handbook,* 2011, Springer, Boston, MA. https://doi.org/10.1007/978-0-387-85820-3_25.

[6] A. Yasmin, S. Tasneem, and K. Fatema, "Effectiveness of digital marketing in the challenging age: An empirical study," *Int. J. Manage. Sci. Bus.*

Admin., vol. 1, no. 5, pp. 69–80, 2015, doi: 10.18775/IJMSBA.1849-5664-5419.2014.15.1006.

[7] A. D. Cornière, "Search advertising," *Amer. Econ. J.: Microeconomics,* vol. 8, no. 3, pp. 156–188, 2016. [Online]. Available: ttps://www.jstor.org/stable/43948892

[8] S. Athey and D. Nekipelov, "A structural model of sponsored search advertising auctions," Sixth Ad Auctions Workshop. New Haven: Yale Univ.," pp. 1–72, 2011. [Online]. Available: https://eml.berkeley.edu//~nekipelov/pdf_papers/paper16.pdf

[9] S. Narayanan and K. Kalyanam, "Position effects in search advertising and their moderators: A regression discontinuity approach," *Marketing Sci.,* vol. 34, no. 3, pp. 309–472, 2015, doi: 10.1287/mksc.2014.0893.

[10] G. Aggarwal, S. Muthukrishnan, D. Pál, and M., Pál, "General auction mechanism for search advertising," In *Proc. 18th Int. Conf. World Wide Web,* pp. 241–250, 2009.

[11] A. Ghose and S. Yang, "An empirical analysis of search engine advertising: Sponsored search in electronic markets," *Manage. Sci.,* vol. 55, no. 10, 1605–1622, 2009. http://dx.doi.org/10.1287/mnsc.1090.1054

[12] Jumia. (March 29, 2021). Rate & review. Accessed: March 29, 2021 https://www.jumia.co.ke/customer/reviewsratings/detail/?sku=

[13] Best, S.J. and Krueger, B., "New approaches to assessing opinion: The prospects for electronic mail surveys," *Int. J. Public Opinion Res.,* no. 14, pp. 73–91, 2002. https://www.semanticscholar.org/paper/New-Approaches-to-Assessing-Opinion%3A-The-Prospects-Best-Krueger/431805dd74246bc58dc40818d60b18d305b4a222

[14] D. D. Suhr, "Principal Component Analysis vs. Exploratory Factor Analysis," *SUGI 30 Proc.,* 2009. https://citeseerx.ist.psu.edu/viewdoc/summary?doi=10.1.1.456.4679

[15] The R project for statistical computing. R-Project. [Online]. Available: https://www.r-project.org/

[16] J. Ruscio and B. Roche, "Determining the number of factors to retain in an exploratory factor," *Psychological Assessment,* vol. 24, no. 2, pp. 282–292, 2012, doi: 10.1037/a0025697.

[17] R. D. Ledesma, P. Valero-Mora, and G. Macbeth, "The scree test and the number of factors: A dynamic graphics approach," *Spanish J. Psychology,* 1–10, 2015, doi: 10.1017/sjp.2015.13.

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