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ESTIMATING PERCEIVED RISK FROM CONSUMER PERSPECTIVE ON AN ECOMMERCE PLATFORM

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ABSTRACT

Online shopping has become part and parcel of our lives and more so as aggravated by the emergence of COVID-19 pandemic which necessitated need for social distancing and also work from home. This has led to unprecedented rise in online shops and consequently a myriad of alternatives for shoppers to consider before committing to a purchase. The myriad of alternatives has put a tall order on users in terms of information overload during decision making and as a result some to extent just rely on guesswork, putting them at a danger of losing income to unscrupulous vendors. It is prudent to have a way of evaluating the how trustworthy an online vendor is beforehand in order to assist the buyers to make meaningful decisions in time. In this study, we create a scale to estimate how trustworthy an online service provider is. We carry out a survey and then use factor analysis to come up with a model for estimating trustworthiness of an ecommerce platform from the consumer perspective. 2104 valid responses were attained from a total of 3,244 responses received from Google form whose link was shared directly to participant by reaching to them physically. The trust scale was then taken through reliability and validity tests. Confirmatory factor analysis yielded four components, which are security, privacy, deception and reliability. Cronbach's alpha is found to be 0.956. We will advance the research in order to establish the empirical impact of the scale on recommender systems on an e-commerce platform.

KEYWORDS: Trust, ecommerce, scale development, recommender systems, decision support.

1 INTRODUCTION

Technology has become pervasive in our day to day lives. This ranges from online shopping to embedded devices being inserted into our bodies to monitor health issues such as sugar level control. (Mishra & Rasool, 2019).

This increased reliance in technology on critical areas of life has necessitated the need to weed out unethical practitioners who may want to cause mayhem for other interests other than the welfare of the end consumer. Indeed it has cause a concern to ascertain trustworthiness between the service provider and service consumer.

For the case of ecommerce systems, this is even aggravated by the effects of COVI-19 such as the need to keep physical distancing and thereby prompting people to opt to online way of doing business, specifically working from home, and also shopping from home where possible (Tay, 2021). This has consequently led to an unprecedented mushrooming of online services such as e-commerce platforms as the vendors try to follow their customers to the online market. The net effect is that there is too much to choose from and therefore exposing the consumer to the problem of information overload and also disinformation (Soto-Acosta, Jose Molina-Castillo, Lopez-Nicolas, & Colomo-Palacios, 2014). This deters quality decision making and thereby opening a loophole for unscrupulous vendors to take advantage of the situation by abusing the digital marketing techniques, discussed in (Yasmin, Tasneem, & Fatema, 2015) to lure online consumers into engaging in dubious deals online.

Recommender systems have been used to eliminate the threat by helping users to choose a more suitable item in ecommerce platforms. Still the said tools suffer vulnerability posed by potential profile injection attacks, as discussed in (Burke, O'Mahony, & Hurley, 2011).

There is therefore an existential need that a trust parameter be developed, which can be incorporated in to the pipeline of artificial intelligence powered recommender system in order to weed out potentially untrustworthy items before the benign items can then be considered and one of them chosen for the user.

Several studies have tried to estimate ethical behaviours of an online retailer such as (Roman, 2007). The challenge here is that trust being a purely psychometric property and dependent on all factors that affect human behaviour (McLeod, 2018), including economic situation, then porting results from one context to the other is not a scientifically adequate solution, and it means that the data to estimate trust must be collected in a context specific and aware fashion.

We therefore constructed a model which can estimate trust from the consumer perspective in a developing country context and this trust parameter can be incorporated in recommendation pipeline of AI powered recommender system in order to improve cyber security assuredness from the consumer perspective at social engineering level as consumers shop online.

According to (Keith, 1960) the consumer is in the middle and not the company and so the company revolves around consumers and not the other way round so it is of uttermost concern that we get to consider how consumers perceive the presentation of services offered to them on ecommerce platforms.

Study in (Zait & Bertea, 2012)] discusses how to estimate perceived risk in ecommerce. The paper presents three methods which can be used to assess discriminant validity for multi-item scales. Q-sorting is presented as a method that can be used in early stages of research, being more exploratory, while the chi-square difference test and the average variance extracted analysis are recommended for the confirmatory stages of research. The paper describes briefly the three methods and presents evidence from two surveys that aimed to develop a scale for measuring perceived risk in e-commerce.

A study, (Kotler & Keller, 2006) defines satisfaction as a judgment between performance and expectation of a product and (Zeithaml & Bitner, 2003) defines satisfaction as “Satisfaction is the consumer fulfilment response. It is a judgement that a product or service feature, or the product of service itself, provides a pleasurable level of consumption-related fulfilment.” Indeed for the said satisfaction to be achieved by deliberately matching the expectation to the final customer’s experience, then it is desirable that the consumer’s expectations are known beforehand by the business, including their decision making which includes how they estimate the perceived risk before committing to a purchase.

In 2007, (Roman, 2007) developed a scale to measure ethics of an online retailer. The study uses structural equation modelling from survey, both exploratory and confirmatory and finds four constructs of ethics in online retailing, namely security, non deception, privacy, reliability. The study is carried out in developed country context and since the trust is a context specific phenomenon, in the sense that it is founded on past user experience, societal norms amongst other factors, the results cannot be directly ported to another context where these factors are different.

In 2011, Burke, Michael and Neil (Burke, O'Mahony, & Hurley, 2011) carried out a research on Robust Collaborative Recommendation algorithms. They outlined clearly the weakness of unaided collaborative recommendation algorithm and highlighted how exposed the algorithm is to manipulation to product nuke or product push by inserting fake profiles into the database, an attack known as profile attack. Recommender systems are software tools which are meant to suggest suitable items to active users amidst a myriad of alternatives.

A study about embedding trust into recommender systems was carried out in 2017 by (Yin, Wang, & Park, 2017) and it was found that the trust factor improves the prediction power of a recommender system. The data (Leskovec, 2003) used was however subject to deliberate human efforts and direct human labelling of trust values against each other. Even though this provide a proof of concept as a possible use of trust in marketing and particularly in recommender systems, the process that was used for data collection is open to bias and is also expensive in terms of human efforts involved.

Empirical effectiveness of digital marketing techniques has been demonstrated in the study carried out in (Yasmin, Tasneem, & Fatema, 2015). The power can still be misused by less trustworthy vendors in order to work in the exact opposite direction, which is to mislead the buyer to purchase something which is not in the buyer's best interest but the said untrustworthy vendor's best interest. There is therefore need to have a means of checking and balancing through some trustworthiness modeling.

Search advertising are also to some extent recommender systems because they customize their output to the user profiles and so if the profile database has been invaded then there is a danger that the output can be manipulated to mislead the end user and so there is also a need to institute some trust mechanism in the process. (Cornière, 2016) (Athey & Nekipelov, 2010) (Narayanan & Kalyanam, 2015) (Aggarwal, S, Pál, & Pál, 2009) (Ghose & Yang, 2009).

It is still possible to estimate trustworthiness of a service provider by providing a feedback form or questionnaire on the ecommerce platform as done by (Jumia KE, 2021) but this approach reactionary rather than deterrent.

Model development using factor analysis outputs several statistics as described described (Suhr, 2006) and the cut-off values for these statistics are suggested in (Kline, 2005).

Exploratory study on key factors that predict trustworthiness of an ecommerce platform had been carried out, part of which has been published in (Ngwawe, Abade, & Mburu, 2020) and resonates with that of (Roman, 2007) with the difference being that one is carried out in a context of developed nations while the other one in a context of a developing nation. The results of (Ngwawe, Abade, & Mburu, 2020) are summarized in table 1 below.

For this study, we choose to go with the approach proposed by (Roman, 2007) because this approach touches on ethical behavior of online retailer and this is a natural predictor of trust.

Table 1: Trust Elements in Ecommerce platforms from Consumer Perspective.

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 of 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 easy to understand.	True of false	Before purchase
Deception (L3)				
	D1	The language used in the site seems to	True of	Before and

		be exaggerating the features and benefits offered	false	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 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

2 To Construct Model For Measurement And Estimation Of Trust (Scale Development) Using Factor Analysis

2.1 Sampling Technique

Our target population was adults (people who have attained the age of eighteen years) and are currently living in Kenya. We used purposive sampling and carried out a sampled nation-wide survey as a confirmatory study to the exploratory study in (Ngwawe, Abade, & Mburu, 2020).

We sampled the counties according to old administrative provinces

We then took into consideration the counties with high income (the metropolitan counties), the counties associated with middle level income as well as the counties that are associated with low income. This consideration was founded on the fact that trusts in online services, which is a subset of ecommerce, and ecommerce is an economic affair will largely be affected by economic situation of the respondents. With this understanding, we sampled the counties in such a way that we ended up with counties associated with high income (the metropolitan counties), the counties associated with middle level income as well as the counties that are associated with low income. The categorization of the counties using economic situation was informed by the report of the Kenya National Bureau of Statistics on Counties (Kenya National Bureau of Statistics (KNBS), 2019). This is a body which was established by the act of parliament in 2006. The body is mandated with collecting, analyzing and disseminating statistics in Kenya, and is also the custodian of the Kenyan statistics.

It has offices both at the headquarters in Nairobi and in all the 47 counties.

Margin of error/Significance level (σ): 0.05 (5%)

Confidence level: 95%

Response distribution: 50%

Suggested sample size for each county: 377 (A target population greater than 20,000)

2.2 Data Collection Procedure

We created a questionnaire using Google Forms data collection tool. We then had research assistants physically on the ground reaching out to respondents, introducing themselves and the agenda of the study and then requesting the respondent to either accept the Google form link shared on Whatsap® so that the respondent could fill in the questionnaire on his own electronic device or just to provide questionnaire answers to the research assistant so that the research assistant could fill in the questionnaire using the research assistant's hand held electronic device such as a smart phone or tablet.

2.3 Responses

A total of 3,244 responses were received. After data cleaning which involved careful removal of incomplete records or records that clearly were not representative, we remained with a total of 2104 valid records. According to (Parasuraman, Zeithaml, & Malhotra, 2005), the required number of valid responses for this nature of SEM analysis is 2000 so this number is adequate. The responses were from adults cutting across all demographics.

2.4 Data Analysis

We used Confirmatory Factor Analysis test, which is a measurement part of SEM (Hox & Bechger, 2014) (Stein, Morris, & Nock, 2012) as the key statistical test.

Here we obtain several trust models, namely

1. One factor trust model
2. Two factor trust model
3. Three factor trust model
4. Four Factor trust model
5. Four factor with a second order factor trust model
6. Factor loadings, fit statistics, and data reliability.

2.5 Statistical tools used in data analysis

We used R Studio Statistical Program, (The R Foundation, 2021) as our data analysis program. Within this program, the following utility was of a great help in getting the fit statistics: FitMeasures function. This function is available in *lavaan* package (Rosseel, 2012). Other important R functions used are:

SemPaths from the *semPlot* package to get the path diagrams for our models.

Inspect function from *lavaan* package to get the factor loadings.

Cronbach. alpha function from *ltm* package to get the cronbach's alpha for measuring data reliability.

We report the results of this exercise in section 3

3. RESULTS

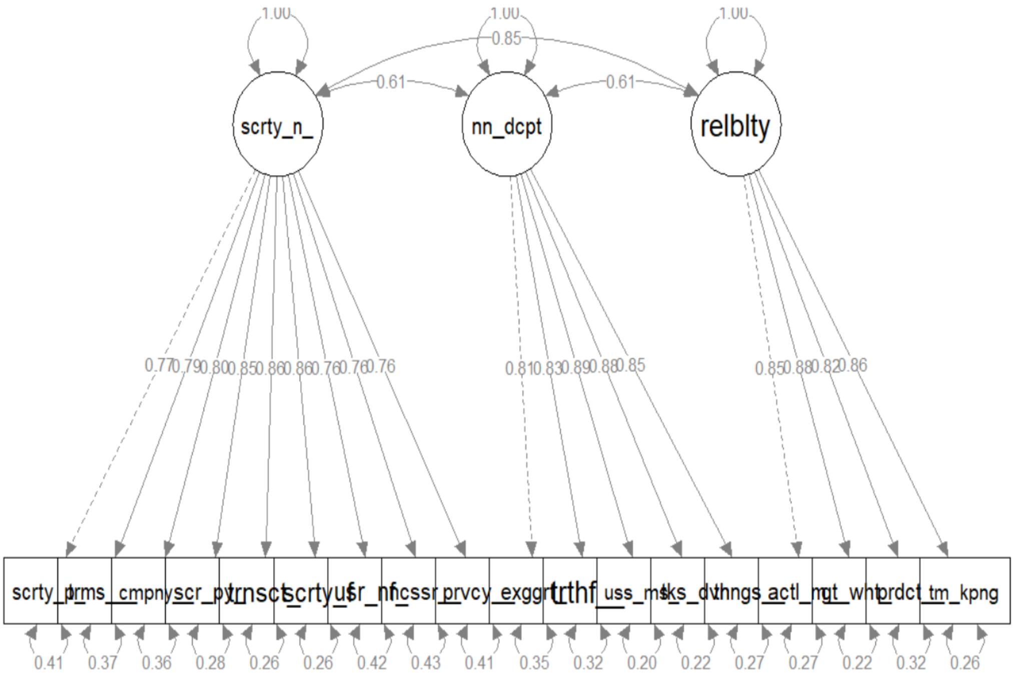

Figure 1: Four Factor Model path diagram - Security, non-deception, reliability, privacy.

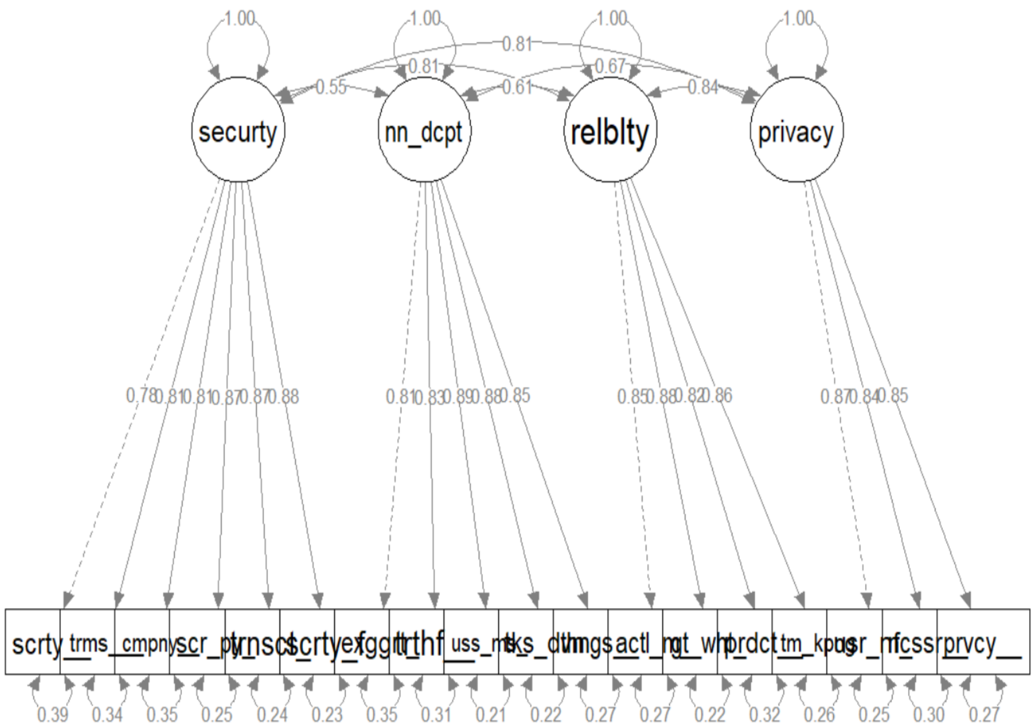

Figure 2: Three factor model path diagram – Privacy + Security, non-deception, reliability.

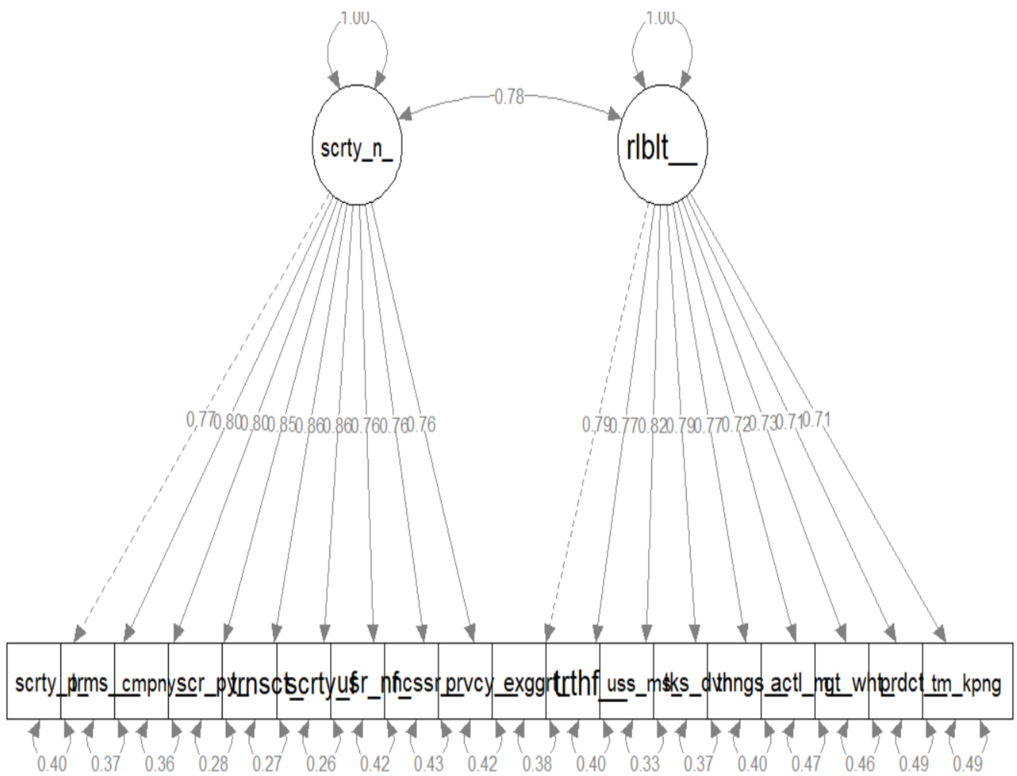

Figure 3: Two Factor Model Path Diagram – Security + Privacy, reliability + non-deception.

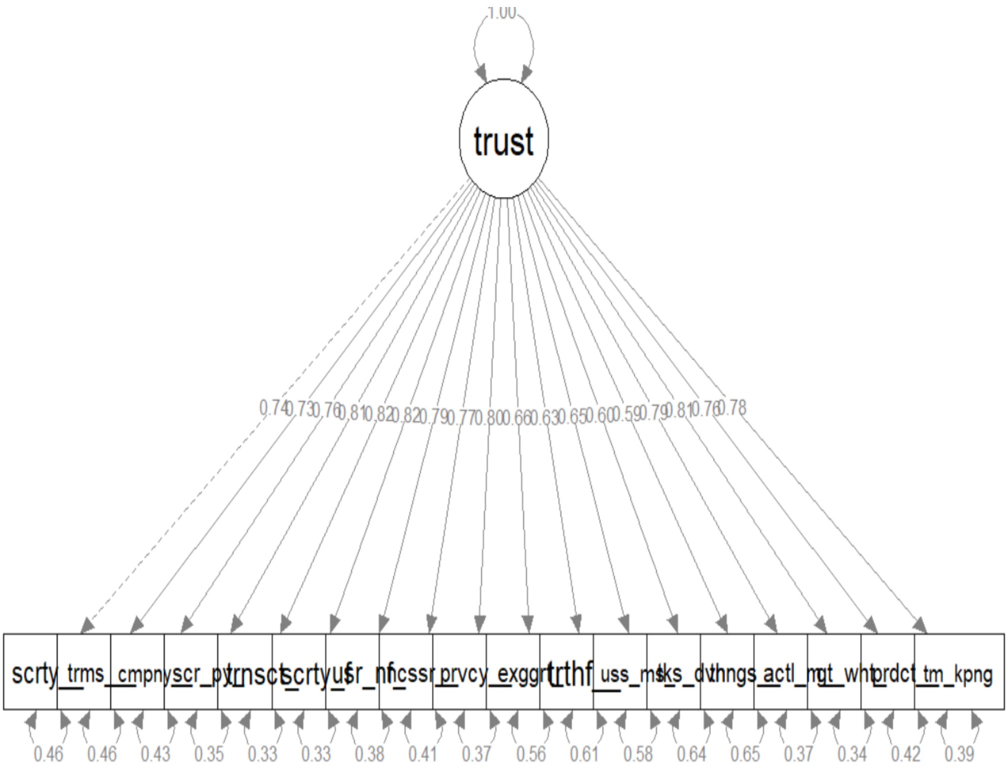

Figure 4: One factor model path diagram – Trust.

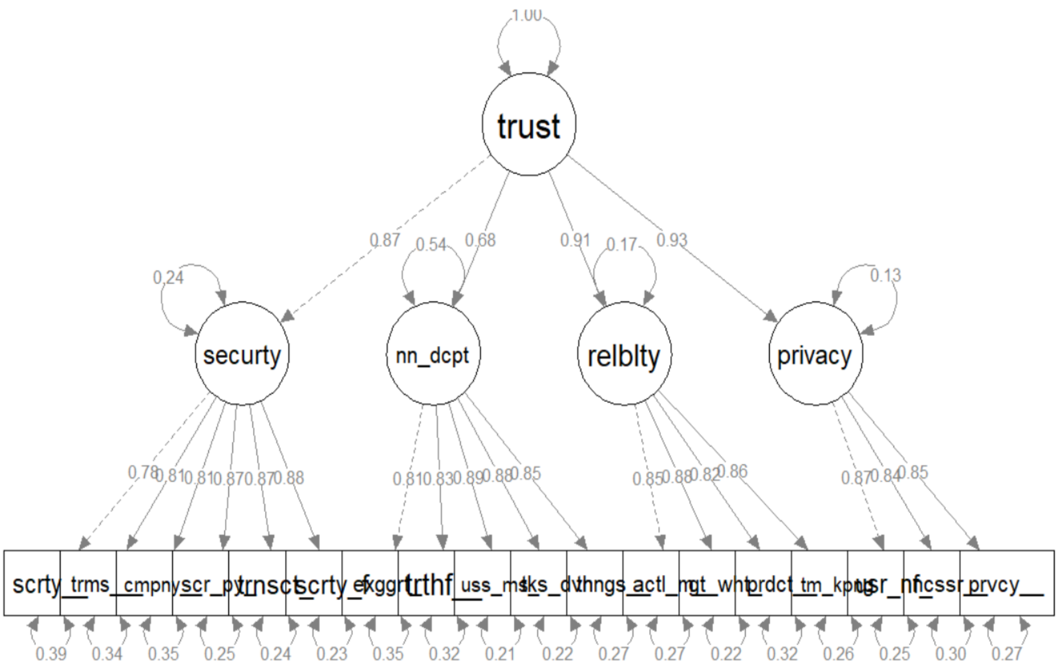

Figure 5: Four factors, one second-order model path diagram.

```
> library(ltm)
> cronbach.alpha(mydata)

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

Items: 18
Sample units: 2104
alpha: 0.956

> |
```

Figure 6: Cronbach's alpha.

Table 2: Models Fit Statistics for confirmatory factor analyses chart.

Item to Measure	Description	Cut off for good model fit	1 factor Model	2 factor Model	3 factor Model	4 factor Model	4 factor Model With 2nd Order Reflective	Passed
X^2	Chi-Square	p-value > 0.05	0.000	0.000	0.000	0.000	0.000	OK (Usually sensitive to large sample size, this is large sample size)
CFI	Comparative Fit Index	CFI ≥.90	0.733	0.786	0.919	0.961	0.959	OK
(N)NFI TLI	(Non) Normed-Fit Index Tucker Lewis index	NFI ≥ 0.95 NNFI ≥ 0.95	0.698	0.755	0.906	0.953	0.952	OK
RMSEA	Root Mean Square Error of Approximation	RMSEA < 0.08	0.178	0.160	0.099	0.070	0.071	OK
(S)RMR	(Standardized) Root Mean Square Residual	SRMR <0.08	0.102	0.106	0.054	0.033	0.036	OK

Table 3 Data Reliability.

Measure	Cut off for reliable data	Findings	Passed
Cronbach's / Coefficient Alpha	> 0.7	0.956	OK

Table 4: Convergent Validity.

Measure	Cut off for valid model	Findings	Passed
Convergent validity	Average Variance Extracted (AVE) > 0.5	Security: 0.704083333 Reliability: 0.744025 Privacy: 0.728333333 Non deception: 0.7268	OK OK OK OK

Table 5: Divergent Validity.

Measure	Cut off for valid model	Construct	Security	Reliability	Privacy	Non Deception	Passed
Convergent Validity	The Square Root of Average Variance Extracted (AVE) is greater than all the correlations between a construct and its counterparts.	Security	**0.839096737**				OK
		Reliability	0.81	**0.862568838**			OK
		Privacy	0.81	0.84	**0.853424474**		OK
		Non Deception	0.55	0.61	0.67	**0.852525659**	OK

DISCUSSION

In this work, we have presented models for estimating trust in ecommerce platform. We used Structural Equation Modeling (SEM) (Hox & Bechger, 2014), (Stein, Morris, & Nock, 2012).

We perform Confirmatory Factor Analysis test as an ongoing work from the Exploratory Factor Analysis (EFA) study done earlier, partly published in (Ngwawe, Abade, & Mburu, 2020) and resonating with (Roman, 2007) in terms of methodology, save for the context.

Here we produce path diagrams for models as follows:

1. One factor trust model
2. Two factor trust model
3. Three factor trust model
4. Four Factor trust model
5. Four factor with a second order factor trust model

We produce path diagrams for different number of factors because during EFA, there was some grey area in determining the correct number of factors to consider as can be seen on the scree test, where from the graphical solution was not agreeing with non graphical solutions to scree test in the sense that the point of inflection in the graph was at four factors where as the non graphical solutions such as parallel analysis, optimal coordinates, acceleration factor suggested two, two and one respectively. As a result, during this stage, we test all of the four possible cases and therefore we have here the path diagrams in figures 1, 2, 3, 4 and 5.

We then use statistics presented in table 2, in reference to the cutoffs suggested in (Kline, 2005) and determine that four is the number of factors to go with.

About the reliability of data used in the study, figure 6 shows the output of cronbach's alpha test for data reliability which is 0.956 and this is above the suggested cut of 0.7 for reliable data as summarized in table 3. We also present in the tables 4 and 5 the convergent validity and divergent validity and demonstrate how model passes the minimum requirements (Carlson & Herdman, 2012) (Zait & Bertea, 2012).

5. CONCLUSION

Having successfully created a scale in form of a model, the next phase is to run empirical study in order to perform a proof of concept. Here we will create an ecommerce platform and push it out to the users, the platform will have a questionnaire which the online shoppers will be requested to fill in order to help us gather data on the fly for this model. These data will then be used to estimate the trustworthiness of the ecommerce platforms with the help of the model and it is hypothesized that this will improve the robustness of the recommender system against several attacks that can be mounted against the mathematical properties of an artificial intelligence driven recommender system as discussed in (Burke, O'Mahony, & Hurley, 2011).

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