Pilot Study on Consumer Preference, Intentions and Trust on Purchasing-Pattern for Online Virtual Shops

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***Abstract*—User behaviour about an item is a choice predicated on their perception of the item in order to satisfy the intent of such a purchase pattern/choice as made. With virtual stores to improve consumer coverage, monetization and ease of product delivery, users' trust is lowered with the non-delivery of advertised products as items purchased are often replaced with new/similar products. To resolve the issues of lowered consumer trust and preference for products purchased via online shops – each transaction reflects a user buying behaviour. This, if harnessed – will aid businesses to reshape their inventory to handle various challenges arising from feature evolution, feature drift, product replacement, and concept evolution. Our study seeks to resolve these issues via a Bayesian network with trust, preference and intent as features of the virtual store to investigate their effectiveness in the design and usefulness to promote e-commerce in Nigeria. Data consists of 8,693 records collected via Google Play Scraper Library for Jumia as retrieved from over 586 respondents. Expert evaluation ranked the design choice in the use of the parameters as high.**

***Keywords*—Consumer preference; consumer trust; purchasing-pattern; purchase intentions; online virtual shops**

I. Introduction

Data is quantified (i.e. pre-processed to remove unwanted feats called noise), and analyzed to reveal patterns/trends) [1]. Data is anything we can manipulate [2], and safely exist in either of its (un)structured forms [3], [4]. With the great volume of data generated for a variety of purpose(s) [5] – processed data yields a transaction of mining tasks [6] that unveils hidden relations and underlying feats of interest in the dataset [7], [8]. Today, the Internet with its plethora of tools, transforms many businesses with platforms that brings together buyer and seller [3], [4], provisions a veritable, traceable payment mode, and allows for effective goods/services delivery [9], [10]. This integration is made imperative/critical, the use of web-contents in business operations and functioning [11], [12], and to provide control schemes that continually improve consumer experience, and ensure improved service quality and delivery [13], [14].

With the digital revolution, the global economy is become more info-based and dependent [15]. Businesses of various forms are springing forth; And Nigeria as the most populous black nation [16] – was in 2021, ranked the 38th largest e-commerce market with a revenue of US$7.6 Billion [17], ahead of Pakistan. Nigeria is expected to experience a global growth rate of over 12% from 2023–2025 [18], [19] with an Internet penetration that stands at 55.4 percent for the nation's population with a total of 156million Internet users as of the January 2023 (Q1) [20], [21]. This survey by the Nigerian Bureau of Statistics holds for the use of e-commerce as consumers sell/purchase goods via electronic platform [22]. And in turn, has increased the sales volume of such e-commerce vendors to positively influence the growth of/in Small-Medium-Enterprise (SMEs). With e-commerce, SMEs can expand their distribution markets [23] via such a symbiotic relations and thus, increase monetization sales therein. Despite this plethora of positive effects, consumers still share doubts when transacting via online platforms. These can be attributed to fraudulent activities [24] from such online transaction(s) – as delivered items often differ from items ordered, identify theft, etc. [25]. Thus, issues of user trust in consumer preference and purchase intentions arise thus – in a vendor's quest to meet the consumer purchase pattern and needs [26], [27].

Another issue with online (virtual) shopping is the adoption rate in the growth of e-commerce [28] – as there still persists the issue of doubts amongst consumer transactions. The effective use of online platforms is a direct impact from the consumer purchase intent and purpose, which must be met [29]. Thus, this study seeks to evaluate and determine features that can influence a consumer's purchase intent and pattern by examining a known e-commerce (online) platform that is most frequently used by Nigerian consumers namely Jumia [30], [31].

II. Literature Review / Theoretical Framework

A. Literature Review: The Nigerian E-Commerce Market

Today, the nation Nigeria has a population of a little over 221,014,090 as of June 2023 based on the latest United Nations data from Worldometer. Nigeria has a Gross Domestic Product growth of US$506.6 Billion with an estimated growth of 2.41% [32], [33]. Her market is segmented thus: Beauty [34], Care [35], Consumer Electronics [36], Fashion [37], Drugs [38], Food and Beverages [38], Furniture/Homes (B2C and B2B) trends [39]. The market today, is driven and leverages on ICT-infrastructure, high internet penetration, and a growing number of card-based payment platforms – that hinges on the fact that her economy is fast embracing more cashless transactions with digital payment solutions adopted and adapted to suit the various needs of her citizens [40], [41]. With all her financial institutions adopting cashless, electronic transactions, there are a plethora of digital financial services platforms – to help consumer decisions and improve their purchasing pattern to satisfy their demands and needs therein [42], [43].

The Nigerian e-commerce market has contributed about 29 per cent globally – to e-commerce with a 30% increase in 2021, and penetration of digital payment solutions that encourage payment service providers onto the Nigerian e-commerce viable market [44]. The market is hampered in operation by the rise in phishing threats from fraudulent web acts [45], [46]. Excellent logistics can aid the effective creation of an e-market supply chain and management visibility, traceable goods/services delivery, and the overall consumer experience/satisfaction [47]. The restricted movement during the COVID-era lockdown [48], [49] witnessed many consumers shopping from home. This resulted in modified consumer behaviour, preference changes and a shift in the trust of product purchased and purchasing paradigm – and led to increased adoption in online (virtual) shops [50], [51].

B. Reviews on User Preference, Trust and Purchase Intents

A transaction often refers to the smallest, indivisible unit of data or information processing within a certain phenomenon or event [52]. Each transaction must either thus, succeed or fail as a complete unit. Transactions are basically processed using a transaction processing system (TPS) – which can also refer to a combination of hardware and software system that supports the processing of transactions. TPS also helps to sustain the smooth running of an organization or business by automating processes of managing large amounts of transactions handled on a daily basis [53]. This it does via accurately tracking of daily records, ensuring that transaction records, the require documents and its corresponding control procedures perform optimally [54], [55].

Transactional data are inherent in stream data, as grouping such data effectively yields a range of complications including: (a) the infinite length-size of data notes real-time data streams are continuous and transactions have no bounds, (b) concept drift is a common occurrence where a consumer shifts his/her decision to purchase a product, (c) concept evolution occurs if a new product acts as a close-substitute or replacement to a class of old products, and evolves the data stream, and (d) feature evolution is a recurrent process where various data-streams occur regularly during the text streams – wherever newer product features appear – with the corresponding increase in the data-streams [56]–[60].

Transactions are handled in real-time – making it tedious and difficult to manage. Items are purchased alone or as combination of itemset to form a basket. Virtual shops grants a consumer, the basket experience for which items are purchased directly in real-time via online platform [61], [62]. A consumer can also make a series of purchases – to yield an infinite number of changes in the buyer's preferences over time. This is referred to as concept drift in the consumer's purchasing pattern or behavior [63], [64].

C. Theories and Hypotheses for Consumer Purchase-Pattern

Resolving the issue(s) of preference, trust and intentions for purchasing pattern – we use association rules for transactions to generate the itemset(s); And thus, yield the purchasing pattern or behavior for a variety of customers. We adopt/adapt these theories using their corresponding (implied) relevance as thus:

- Theory of Reasoned Action emphasizes that behaviour very much depends on a consumer's attitude, choice and public perception. It posits that a consumer is influenced by their intentions, choices, and personal beliefs. These propagate as a shock to impact a consumer's decision; And align with [65]–[67] as in Fig. 1. Its relevance is that a consumer can buy items (online) with adequate confidence to use the tech due to its usage ease and hitch-free nature. This also impacts on intensity in use cum adoption of the system. When presented with expected results that are specific, a consumer can change his/her mind; And this impacts the action to be taken via such a decision, which yields an attitudinal and normative change in the user's trust and confidence in a product, and the overall experience with the product [68], [69]. Investigating if a consumer's action and attitude is tied to purchasing purpose/intention – seeks to ascertain if the consumer is rational when their choice is based on purpose, or if such action serves their best interest or their intentions and agrees with [70]–[72].

- Planned Behaviour Theory – states that attitude towards a behavior, subjective norms, and perceived control often shapes a consumer's behavioral intents and in turn, his/her actions. This theory improves the analytical capability of reasoned actions via the perceived control of behaviors. Since not all behavior is subject to a consumer's control – it is expedient we add perceived behavioral control which implies that irrespective of the action taken – a consumer's behavior is determined both by attitude, subjective norm, and perception/firm belief they are in control [73], [74].

- The Engel, Kollet, and Blackwell extend reasoned action by focusing on a consumer's mental state prior purchasing the product. It does so via planned set of behaviors as thus: (a) consumer absorbs item content via an advert, (b) s(he) processes the advertised content, and leans on experience to compare what-should-be versus what-is, and (c) s(he) then decides to either accept/reject the product purchase, a choice based on balanced insight via mental synthesis [75]. Manager must be equipped with appropriate data of the product to drive consumers to keep buying, and will push sales up. Such information about the underlying feats can cause a purchase shift in behavior. If a consumer is not adequately informed, s(he) rejects (i.e does not buy) so as to balance their data with the online data available. Thus, external shocks (i.e friends and item review ratings, be it fake or not) may influence the consumer to decide to either accept/reject the product [76], [77].

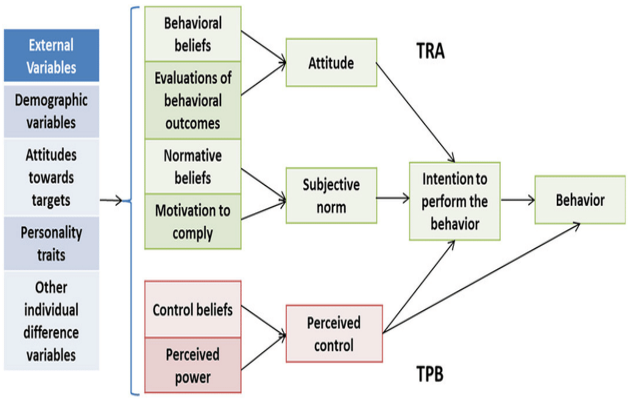

Fig. 1. The reasoned action theory (Source: [78], [79]).

D. Research Hypotheses

The hypothesis for the various features of interest include:

- Perceived Ease in Use is a degree in belief, confidence and trust a consumer places on the online platform vis-à-vis contents provided on the website. Thus, the consumer can easily navigate the platform with little or no challenge, to reflect the usage intensity and consumer interaction with the platform. And accounts for an overall satisfied consumer experience with access ease. It yields improved consumer-perceived usefulness and control [80]. Thus:

  H_1 = Perceived use ease impacts on perceived usefulness.

- Product Usefulness/Benefits is the degree/extent to which a platform improves a consumer's need to purchase as the more useful it is, the more transactions are performed, and the more benefits are harnessed. With faster transactions from their comfort [81] and usage easy – it yields user-satisfied and expected-content retrieval via the consumer-specific search [82] that improves overall experience to a user's benefit. This also impacts a user's purchase intents as the user also saves time with each transaction at lower cost, and greater access to a variety of product (types), and replacement products. The benefits experienced via online shops yield improved intentional buying and transactions, made by the consumer [83].

  H_2 = Perceived usefulness impacts on benefit → and consumer benefits → impacts consumer intentions

- Perceived Purchase Intentions – Product review are data points awarded to platforms by consumer in relation to a variety of items such as ease of use, product delivery, ability to find products with ease, etc. [84], [85]. These reviews are often poised to show a consumer's interaction with the online platform vis-à-vis a series of consumer satisfaction. These, help to improve confidence and trust, and also help to reduce a consumer's effort to learn navigation of the system. Their belief in the required ease to navigate the system is reflected in their intensity to use the system as well as their search for products whose results displays specific contents that are poised to satisfy the curiosity of the consumer. And thus, ensures the consumer's purchase intentions are met.

  H_3 = Perceived ease impacts consumer purchase intention

- Perceived Trust and Confidence – implies that the more a consumer interacts with an online platform, the more such a consumer concludes the great repute of such a store. This improves the perceived confidence and trust. Trust is quite critical in online purchasing patterns (since there is no face-to-face interaction). Trust guarantees that online stores will fulfill their obligation and care for the consumer(s). It is a vendor's responsibility to provide useful data, ensure consumer satisfaction for a complete transaction, and ensure the quality of products with safe delivery of products purchased. Thus, consumers attain usefulness from their trust in e-commerce platforms. And their confidence in the products delivered, in the vendor and online platforms, becomes imperative. Greater purchase intensity implies greater confidence and trust by the consumer in the online platform [86], [87].

- *H_4 = Consumer's confidence, trust and ease of use impact consumer's purchase intentions and pattern*

III. Methods and Materials

A. Data Collection and Gathering

Data were collected using Google Play Scraper Library for Python for the Jumia Online Shopping platform. A total of 8,693 records were collected in March 2023 – and retrieved from over 586 respondents. The scrapped records consist of personal data, user reviews, emails, posts, likes, shares, and replies – which is in agreement and as suggested by the study [88] in Table I.

TABLE I. Dataset Description, Data Types, and Format

Features	Data_Type	Format
Order_ID	Long Int.	1234
Customer_ID	Short Int.	1234
Customer_Name	Object	ABCD
Payment_Number	Long Int.	1234
Payment_Amount	Float	123.45
Transaction Time	Time	M:H:S
Order_Date	Time	D:M:Y
Deliveray_Date	Int	1234

B. Proposed Bayesian Network

Bayesian net of conditional probabilities for random events, is a learning mode that represents data as probability relations of a variable-set under uncertainty as directed acyclic graph and conditional probability tables of a random variable [89], [90] – given occurrence of its parent nodes. In relation to the degree of belief – it measures plausibility of an event given incomplete data [91], [92]. It states that the probability of an event A and is conditional on another event B is given by P(A|B) – and differs from the probability of B conditional on A as P(B|A). Thus: (a) it is a relation between events P(A|B) and P(B|A), (b) it computes P(A|B) given data of P(B|A), and (c) its outcome uses new data to update the conditional probability of event. So when given a sample space *s*, with mutually exclusive events ($A_1, A_2,\ldots,A_n$) – B can be any event from *s* with the probability P(B) > 0 [93], [94] and represented via the Eq. (1), which holds as:

$$P(A_k \mid B) = \frac{P(A_k)*P(B|A_k)}{P(A_1)*P(B|A_1)+..+P(A_n)*P(B|A_n)} \quad (1)$$

Bayesian networks are trained to learn the underlying feats via probability distribution for each node. It uses two learning modes: (a) structured discovery, learns the network structure and its adopted parameters based on observed inputs using hill climbing/Tabu-Search; and (b) probability distribution learning is done with algorithms like Bayesian network [95]. The model uses relation analysis to emphasize consumer purchase-pattern. The issues of preference, trust and buyer intentions, arises from a vendor's quest to meet the consumer's purchase pattern and needs [96], [97]. These, in turn yields concept drift, and justifies our adoption of user behavior theories that directly explains their corresponding relevance to our various research problem. To derive meaningful data via these theories, we visualized the consumers' behavior using a Bayesian network as in Fig. 2 so as to help us resolve the issue of feature drift, concept drift and concept evolution. Thus, using the hypotheses, we design the Bayesian network as thus:

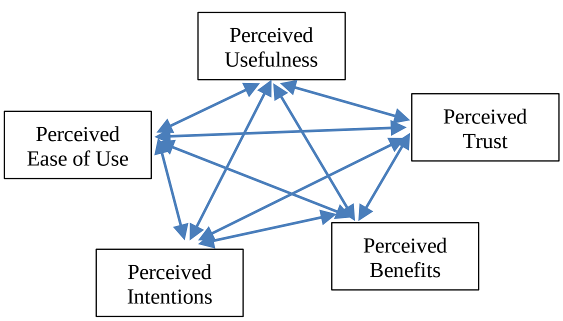

Fig. 2. Designing the model.

IV. Results and Findings Discussion

A. Performance Evaluation

System design in lieu of accountability, quality, and ethics for user-centric purchase-pattern to reflect various dimensions were re-purposed as [98] follows: (1) usefulness, (2) benefits, (3) purchase intents, (4) usage ease, (5) trust (as core features). With Eq. (1), we analyze the effectiveness E of the system as frequency of user's choice amongst its alternative(s) versus the total number of contents N. We further categorized into the following: (a) high is greater than 80%, (b) sufficient ranges between 71-80%, (c) moderate is between 55-60%, and (d) poor is below 55% [98], [99].

$$EP = [F/N] * 100 \quad (2)$$

The ranges high and sufficient – implying design parameters were met and does not require revision. Moderate requires some form of revision and implies that the use of the parameters is not reflective in the proposed system; while the category poor implies a complete revision of the parameters of choice. Thus, evaluation for both experts and participants yield Table I and Table II respectively.

Table II shows high and sufficient categories ranging above 85% for all the evaluated variables by the various experts. The implication of which, is that these components do not require revisions of any kind.

TABLE II. Experts' Evaluation on Variables Design

Parameters of Interest	1	2	3	4	5
Benefits	0.89	0.96	0.91	0.89	0.92
Usefulness	0.91	0.87	0.91	0.94	0.89
Usage Ease	0.75	0.89	0.79	0.89	0.91
Purchase Intentions/Purpose	0.92	0.92	0.86	0.85	0.90
User-Trust	0.91	0.90	0.93	0.98	0.89

Table III on participant evaluation shows the mean, standard deviation and dyadic interaction between the chosen variables, users and proposed system that leverages on the chosen feature of interest. Its mean values ranges implies that an effectiveness categorization interaction and use of the online platform ranges from over 90%. It also yields a dyadic interaction range that is above 95%.

TABLE III. Participants' Evaluation of Design Choice

Parameters of Interest	σ	µ	+Di
Benefits	0.27	0.94	0.89
Usefulness	0.27	0.87	0.89
Usage Ease	0.23	0.82	0.73
Purchase Intentions/Purpose	0.33	0.90	0.95
User-Trust	0.28	0.81	0.78

B. Result Findings

Adapting the model capabilities in [100], [101] – we model the outer layer as a sine qua non-effect of the study's reliability and validation of the research variables (i.e. benefits, perceived ease of use, perceived usefulness, trust and perceived purchase intentions/purpose). We compute model fitness of all variables as a criterion size for the problem space, which is thus – a good reflective parameter/feature to aid quick convergence. If model converges on a validity value with a fitness of 0.7 and above – it implies that model has good correlation. These keys reflect each variable in Table I: B = benefits, PEU = perceived ease of use, PU = perceived usefulness, PI = perceived purchase intentions/purpose, and T = trust, as seen in Table IV.

TABLE IV. CONFIDENCE VALUES OF SIMULATED DATA (C_{tt})

	B	PEU	PU	T	PI
B	0.627	0.638	0.915	0.534	0.613
PEU	0706	0.773	0.909	0.664	0.787
PU	0745	0.625	0.736	0.931	0.639
T	0745	0.661	0.677	0.951	0.659
PI	0.628	0.642	0.944	0.629	0.758

In Table IV, shaded cells are the parameters of interest. Thus, our model converges with the fitness values and scores as above. Recall, that if the value converges at a fitness of 0.7 and above indicates that model has a good correlation. Thus, shows that cells PEU(PEU), PU(PU), T(T) and PI(PI) have correlates and convergences good. This implies that features PEU, PU, PI and T are of great significance to consumer overall satisfaction – in designing an online/virtual platform. Designers must ensure the system is useful (i.e. delivers on the consumer's request correct contents for the searched products), intentional (i.e. meets the purchase intention of the consumer), trustworthy (i.e. consumer can trust the sites from which contents were displayed), and ease of use (i.e. system must be flexible).

C. Discussion of Findings

From the Bayesian computation as in Table III – the model yields an overall probability distribution value that is greater than 1,860 with a significance level of 5%. It becomes quite clear and explicit that [102], [103]:

- Perceived usefulness (PU) is impacts significantly both on the perceived ease of use (PEU), purchase intention (PI) and trust, and this agrees with [104].
- Trust (T) also impacts significantly on perceived ease of use (PEU), purchase intention (PI) and perceived usefulness, and it agrees with [105].
- Purchase intention (PI) was found to impact significantly on perceived ease of use (PEU), perceived usefulness (PU) and trust (T), and this agrees with [106], [107].
- Perceived usefulness was found to impact significantly on perceived ease of use (PEU), purchase intention (PI) and trust (T) parameters [108], [109], respectively.

We posit that other parametric feat can be used to investigate similar relations to unveil other (un)reasoned actions in lieu of a consumer's purchasing-pattern. This study will help and act as pivot for business owners to effectively design virtual platform cum shops, and to adequately manage challenges of product placement, features cum concept drift [110], [111] in relation to consumer purchase and consumption pattern. They will bear in mind that certain parameters impact majorly in the design of their virtual shops namely ease of use, intention, usefulness of system and consumer trust of products acquired and delivered.

V. CONCLUSION

The study aimed to analyze the Jumia e-commerce in lieu of the consumer purchasing intentions, perceived usefulness of the Jumia platform, consumer trust for Jumia, its ease of use by consumers, and overall consumer benefits (and experience) for the Jumia online virtual shopping platform. The study was only limited to the use of the Jumia platform by consumers vis-à-vis the experts and participants as adopted for the study. However, study could not ascertain the relationship cum immediate impact between the consumer benefits and other features/parameters not described herewith or under-studied [112].

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