



ORIGINAL ARTICLE

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Association rule mining approach: evaluating pre-purchase risk intentions in the online second-hand goods market

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Abstract

Research background: A considerable amount of research has been conducted on the riskiness associated with online transactions in general. However, few studies have paid particular attention to the risk of online second-hand goods transactions. We, therefore, argue in this paper that, while online transactions pose several risks to consumers, the addition of second-hand goods intensifies the risks to the user. As the risk factors brought about by the online second-hand goods transactions persist, the magnitude of such risk inherent in the customer in question has not clearly emerged.

Purpose of the article: This paper aims at eliciting the magnitude of risky components aligned with the tendency to connect online in search of second-hand goods. Again, providing insight into demographic variables in relation to the pre-purchasing risk factors; averting customers to connect online in search of second-hand goods stands as one of the key reasons for the present study.

Methods: The research adopts a data mining algorithm, notably the Association rule mining to glean relevant patterns in the data accrued from the Czech Republic, premised on risk components governing the online buying behaviour of second-hand goods. To this end, a simple random technique was adopted to gauge the views of e-shoppers in the Czech Republic on online second-hand goods transactions; with 329 out of 411 respondents eligible for our analysis.

Findings & Value added: The results of the association rule technique have revealed that respondents within the gender frame are both adamant to hook-up online, in spite of the fact that they have shopped online, yet do not think of looking at second-hand goods sites because of some risky influence inherent in them, even if the respondent is an ordinary personal-user of online transactions. In all these developments, the research concludes that the second-hand industry needs to redesign the websites with much attention to reinforce stringent measures that will give better assurance of the risk factors, which will tend to avert the customer from connecting via the Internet in pursuit of second-hand goods.

Introduction

The market for second-hand goods has become a recognized component in the Gross Domestic Products (GDP) computation in most economies around the world, be it developed or developing the economy. For instance, in 2015, the second-hand goods market in Canada added a sum of \$36 billion to the economy (CBC, 2016) representing a 2.2% share of the annual GDP. Likewise, in the United States, the market for second-hand goods produced an annual sales figure of \$9 billion in 2007 registering an increase of 20% from the figures recorded in 2002.

In Europe, there continues to be a booming market for second-hand goods, particularly in the automobile industry, antiques, vintage items and electronic goods in general. For instance, a recent statistic of the online second-hand goods transactions showed that Spain has accrued a whopping sum of 28 billion euro as a boost to its economy in 2017 (Statista, 2018). In the Czech Republic, this view is of no exception, thus recording an increasing market for second-hand goods along the length and breadth in the country. Accordingly, there is an estimated number of retail companies amounting to over 127,117 since 2013 (Czech Statistical Office, 2016). It cannot be denied that about 32% of these retail companies are operating on used goods. More so, the revenue generated out of the whole retail store to GDP was 882,515 million Czech crowns in 2013, and expected to increase more in the years ahead (Czech Statistical Office, 2016), hence, it cannot be gainsaid that the total sale generated in 2013 has about 27% from the sale of used goods to the revenue computation of GDP in the Czech Republic.

With this emerging figures quoted, it is imperative to deduce that the advent of electronic commerce platforms provides the medium for the sale of second-hand goods. As a matter of fact, the Internet with its online platform sales has even triggered the consumption of online-based second-hand and refurbished goods. This stems from the fact that consumers can make several comparisons, and arrive at the best alternative to choose from, with little cost attached to the product in question. The idea of second-hand vendors connecting online to publicize their product in order to enhance daily sales is fast gaining momentum in developed economies, as elaborated earlier. For instance, in the Czech Republic, where the present study has been carried out, there are a number of second-hand goods outlets that have transitioned to online platforms to boost their daily sales. Some of these websites in the Czech Republic that deal solely in second-hand goods include aukro.cz, Basoz.cz, etc. It must be noted that these websites are increasing at a constant pace across the length and breadth of the Czech Republic, given the purported benefits attained by second-hand vendors.

Despite the potential benefits associated with the acquisition of online second-hand goods, consumers still hesitate to connect online in the quest to acquire second-hand goods. We, therefore, argue in this paper that while online transactions pose several risks to the consumer, the addition of second-hand goods, exacerbates the risks to the end-user. In spite of the several risk factors brought about by the online second-hand goods transactions and the associated risk intentions to embark on online transactions of second-hand goods, scientific research in the area is very limited. Additionally, there is a gap between academic research and industrial settings in having a deeper understanding of the pre-purchasing risk attributes averting e-shoppers to embark on online transactions of second-hand goods; arguing that the internet is not going into extinction anytime soon.

This paper is bent on generating more research and to elicit the magnitude of such risky intentions on or before the initiation of online transaction purposely on second-hand goods. In addition, scant knowledge is presently available on how online consumers perceive the second-hand online transactions as been risky, and more so less is known about such associated risks towards buying second-hand via online. While some studies have sought to investigate some risky scenarios of second-hand transactions purported on babies (see Waight, 2015), no studies have empirically measured the associated risk intentions reflecting on the tendency of the consumer attitudes geared towards the second-hand goods transactions in the Czech Republic, which this study sought to reveal. Hence, elucidating these gaps in the literature will unearth and assist both researchers and practitioners to appreciate the key associated risk factors that could affect the decision of e-shoppers

to connect via the Internet in search of second — hand goods in the Czech Republic. Therefore, this study aims to fill these gaps by addressing two research questions:

1. *What is the influence of perceived risk factors on the decision to purchase second-hand goods online?*
2. *How are risk factors associated with the penchant to purchase second-hand goods online?*

The rest of the paper is organized as follows: First, state-of-the-art online transactions in the online second-hand market are provided. Second, the Association Rule Mining employed in this study is discussed, and the data collected analysed. Finally, the empirical results are presented with the conclusions of the study.

State-of-the-art in the second-hand market and online transactions

Second-hand goods as defined by Lane *et al.* (2009) are the ones that are purchased by or perhaps relocated to another user. A second-hand good is often attributed to a good that is not in the same shape as when it was originally purchased before relaying to the current user (Charbonneau, 2008). In as much as the good in question has been used by someone or first owner and handed over to second-hand retailers (market), it leaves its original position as it was purchased. This gave birth to a higher proliferation of such second-hand market businesses that we see today, mostly touted as affordable, ready to go, and with different varieties of goods situated there. The second-hand market is made up of all consumers' durable neglected, sold or bartered with or without any transitional party, after discarding by the consumers (Lin & Chang, 2013). Second-hand retailers are mostly made up of physical stores like vintage shops/boutiques, consignment stores, charity shops among others. Lately, second-hand markets are seen as informal and are attributed to small or mid-sized business enterprises (Hansen, 2004; Williams & Paddock, 2003) shapeless retail setups (Gregson & Crewe, 2003), and a beneficial market in the developing part of the world (Mhango & Niehm, 2005).

On the contrary, the Internet, as an influence on consumer behavior cannot be overlooked. This stems from the fact that the upsurge of Internet penetration within the entire marketing arena in the past few decades have brought in its wake, relentless desire of consumers to embark on transac-

tions online. Alturkestani (2004) states that transactions or shopping online could be defined as the way and manner customers use the Internet to search for information that relates to a particular product, and also to make trade-offs with the mind-set of finalizing a purchase transaction. Online shopping or transactions, deals with how Internet users, in general, make retail purchases with the aid of internet connectivity (Swinyard & Smith, 2003). To Donthu and Garcia (1999), numerous studies of active researchers have provided empirical evidence which indicates that customers who shop online are more likely to behave differently in terms of the overall shopping decisions as compared to those who shop through the conventional brick and mortar style.

The extent and rate at which consumers are keen on purchasing online have been measured by previous studies. According to Lian and Lai (2002), the extent of consumer's passion and zeal to purchase online stems from the fact that customers are more likely to return to their respective websites of purchase within the next three months or during the year from the initial purchase, consequently growing or increasing their online purchase. Again, online shoppers stand the chance of enjoying multiple forms of convenience in the form of less physical effort, flexibility in terms of shopping, leniency in responding to promotions as well as advertisement, and finally, accompanied by some user-friendly websites. After all, convenience is measured when customers make use of the Internet to make purchases. Furthermore, specific websites with discounts on sales and other information on some particular websites which induce consumers' willingness to purchase online may be recommended by other online shoppers (Kukar-Kinney *et al.* 2016).

According to Corbitt *et al.* (2007), previous literature has, on the contrary, detailed that customers who embark on online purchasing are less likely to reduce the anxiety due to the risk of financial cost. Similarly, it was discovered by Gupta *et al.* (2004) that such customers are less likely to be risk-averse more than the traditional brick and mortar customers. In all these developments, there has not been any robust tool or the methodology that will be adopted in this present study. The general consensus from researchers alike governing the rampant outburst of second-hand market on the globe nowadays demands that researchers espouse on a technique to intrinsically find out the value proposition of customers in that business, more so when the business is bent on trading online. That is to emphasize that the risky components inherent in the consumer must be unveiled to assist the growth of the second-hand industry. In the subsequent section, the theoretical underpinning of the concept the Association rule theory is provided with its mathematical scenarios behind it.

Research methodology

Association rule mining and conceptual framework of the study

Massive volumes of user-generated data have recently invigorated the zeal of businesses to elicit the value proposition of their respective customers. The generated transaction-type databases are mined with rigorous algorithm to find out the patterns of consumer buying behaviour. One such algorithm is the Association Rule Mining (ARM) which is seen under the umbrella of the Data mining algorithm. The main objective of the ARM is to identify items clustered in the transaction database with the view to tracking and digging out valuable associations as well as interesting relations embedded in such large datasets (Agarwal & Skrikant, 1994). The impact of the ARM methodology helps retail businesses analyse a large dataset with the intention of discovering groups of products or service that tends to be purchased simultaneously. In a broader sense, it helps to learn more about the purchasing pattern of customers (Houstma & Swami, 1995). To put it simply, the ARM takes the surge of ‘what goes with what effect’. Since the last two decades, this algorithm has been widely used by renowned researchers in academia and the industry in general, mostly in the field of marketing. However, a full-blown application of the ARM methodology could be attributed to Agrawal *et al.* (1993). The seminal works of Agrawal and Skrikant (1994) helped with fine-tuning the algorithm into a well-known concept for utilization in academia. We must emphasize that other renowned scholars (Park *et al.*, 1997; Dehase & Toivonen, 2001) cannot be left out as championing the cause of the ARM methodology into the mainstream research seen today. The ARM has been designed in a suitable manner, feasible for different datasets. By extension, this algorithm is made up of two stages before its application. The reliability, robustness, and strength of the ARM produced in many research areas and academic disciplines give credibility to its significant and accurate usage in any research endeavor (Shmueli *et al.*, 2007).

Traditionally, the ARM mining is represented by $X \geq Y$, showing when the two products (X and Y) were purchased. X then becomes the antecedent, while Y is represented as the consequent, indicating that X influenced the purchase of Y.

The association rule analysis follows the methodical steps below. The mathematical foundation of the ARM is primarily centred on the terminologies below: With regard to the present study, the a priori algorithm as a taxonomy of the Association is used. The Association rule theory as championed by (Agrawal & Skrikant, 1994) is defined in the following:

Definition 1: Let $I = \{i_1, i_2, \dots, i_n\}$ be a set of n binary attributes called items.

Definition 2: Let $D = \{t_1, t_2, \dots, t_m\}$ be a set of transactions referred to as the database.

Each transaction in (D) has a unique transaction ID and contains a subset of the items in I .

An AR mining assumes the form $X \Rightarrow Y$, where X and Y are item sets and are satisfied $X, Y \subseteq I$. Example, $\{\text{Coffee, Milk}\} \rightarrow \{\text{Bread}\}$. The right-hand side of the rule (Y) is termed the antecedent or the premise and the left-hand side, the consequent or the conclusion.

In extracting or generating rules for analysis, we selected the variables of interest in mining the relevant relationship patterns. Variables of interest were converted into a transactional data format to aid association rule mining. Three vital metrics form the bases and deployment of association rules. These are measures of support, confidence and lift.

Support:

The support of an association rule $X \Rightarrow Y$ is the percentage (%) of transactions in the database that contains both X and Y . Mathematically, $\text{Support} = (\text{freq}(X, Y))/N$ where N is the number of transactions.

Confidence:

The confidence (Φ) for an association rule ($X \Rightarrow Y$) is the proportion attributed to the number of transactions that are made up of $X \cup Y$ assigned to the number of transactions that comprises X . This is shown mathematically as,

$$\text{Confidence } (\Phi) = (\text{freq}(X, Y)) / (\text{freq}(X))$$

Lift:

The lift of an association rule is the fraction of the support of (X, Y) to the support of (X) and the support of (Y) . In practice, the lift looks at the left-hand side rule and finds the percentage of chance of Y appearing would increase.

$$\text{Lift} = (\text{support}(X, Y)) / (\text{support}(X) * \text{support}(Y))$$

Over the last two decades and in line with its standard application, the ARM analysis has been adopted for many academic disciplines in a variety of areas within academia and industry, as earlier indicated. For example, Khan and Parkinson (2018) used the ARM to convert event log entries into an object-based model which animatedly assisted in extracting an associative rule, Kwarteng *et al.* (2016) measured the associations in online shoppers' data in the Czech Republic, whilst Domadiya and Rao (2019) also made use of the ARM in a novel way to build the knowledge centre for disease prevention, which eases the healthcare provider as sequel to earlier treatment and stoppage. Again, the ARM was adopted to identify the signs and risk factors for three hostile diseases, namely: cardiovascular disease, hepatitis, and breast cancer with reverence to the rare association rules. The ARM has different classifications apart from the most known Apriori algorithm. These include the Frequent-Pattern Growth algorithm and the Éclat algorithm (Zaki *et al.*, 1997). The following section explains the implementation of the rules generated from Step1: Pre-processing and Step 2: Rule generation (see Figure 1)

Step 1: Pre-processing

Data collection

A questionnaire was adopted as a data collection instrument, prepared with the aid of Google docs application software. However, the distribution of questions was administered through the length and breadth of the Czech Republic. Hence, the study specifically adopted the probability sampling technique. With regard to data collection, some selected students from the Tomas Bata University in Zlin, the Czech Republic; mostly Bachelor students assisted in distributing the questionnaire to different regions in the Czech Republic, as earlier stipulated. A token of reward was given to these students for their immense contributions in terms of data collection. A simple random technique was adopted for the study within 2 months range of time span used in collecting data for the study (Between November 2018–January 2019).

A total of 411 questionnaires were distributed, 329 of which were eligible to being valid for the analyses. We must emphasize that the entire questionnaire was prepared in two linguistic forms, the English and the Czech format. It was so because the researchers wanted to do away with unnecessary ambiguity of the questions. The questionnaire was, however, pilot-tested with Bachelor students in our 'Management I' class, where it was revealed that some of the questions were not properly situated and hence

turned to be repeated. As a matter of urgency, they were all corrected and pre-tested again with the Advanced Management and Marketing subject of our Bachelor students. This time, the error rate was meager and even such an error was attributed to the way and manner some students attempted to answer the questions, as some of them just filled some part and left other ones unfilled. Some respondents were also filling almost every section of the questionnaire. We must also emphasize that the data used in this study was culled from one of the author's Ph.D. thesis.

Data Processes/cleaning

The data cleaning/processing phase involved a number of stages to arrive at the requisite data needed for further application. First, encoding was initiated purposed on deleting unnecessary fields from the original data. This was backed by the notion of maintaining a definite binary item. This was adhered to desist from errors in the event of running the data with the RapidMiner software. Subsequently, repeating of the data-set was scanned and checked. This, however, was preceded by deleting the repeated data into one complete data ready for initiation. Next, consistency validation was subjected to the accrued data, thus binary attributes were deemed necessary for the Association rule mining implementation.

Data Repair

This stage involved the data consistency as earlier mentioned, thus where the accrued data was keenly monitored to ensure inaccuracies. We must emphasize that much of the repairs are fixed as a result of encoding and decoding redoubtable rules in the previous step, thus through data processing. However, to ensure a potent rule in the end, variables that are deemed proper to initiate the generations are arranged. Subsequently, the entire binary dataset is stored as CSV, as earlier stipulated.

Step 2: Rule Generation and Results

Conducting Association rules

The idea behind ARM is to determine all possible rules between items as an indication of true dependence. Hence, the RapidMiner studio 2.3 software was deployed in generating rules for further deliberations (see Table 1 and 2).

Selection of rules

Given the abundance of the rules retrieved, the rationale is eliciting the rules that indicate a strong dependence between the antecedent and the consequent (see Shmueli *et al.*, 2010). In addition, to ensure a potent rule from our set of all possible rules, we made use of the confidence and the lift ratio. These indicators were meant to ascertain the strength of the rules generated.

Results and discussion

The ARM naturally lends itself to many rules, depending on the number of transactions in the database and the threshold set on some variable measures. However, to ensure the selection of interesting, potent and redoubtable rules from a set of all possible rules, certain constraints are often used as measures of significance. Largely, two of the best-known of these constraints are support and confidence, where the minimum thresholds are set on their resulting values. The support is a fraction of transactions that contain both the antecedent and the consequent whereas confidence measures how often items in the consequent appear in transactions that contain the antecedent. It must be noted that when associations between three or more attributes are found, for example, Cheese, Bread, → diaper, the confidence percentages are computed based on the two attributes being found in the third. Other metrics such as Lift, Laplace, Gain, etc. are additional indicators that demonstrate the strength of the rules' relationships (Shmueli *et al.*, 2010). According to the basic principles underlying the validity, accuracy, completeness as well as the reliability of the Association rule mining technique, the technique is vouched or guaranteed with the magnitude (percentages) of the aforementioned metrics; thus, confidence, support, lift of the rules (Chena *et al.*, 2016). Tables 1 and 2 present some key findings of association rules of the data-set governing pre-purchasing risk intentions in the online second-hand goods transactions.

As can be seen from both tables (Table 1 and 2), binary attributes automatically retrieved from the association centred on two specific consequents, namely: Do risk factors influence the decision to purchase second-hand goods and the type of online user? It must be noted, with reference to the conceptual framework of the study (see Figure 1), that in generating association rules, data with binary variables are deemed fit for efficient output interpretation. To do this, data was retrieved and saved as CSV in an excel file. The missing data was quickly replaced with values, but as earlier

indicated, attributes with binary variables were selected from the entire data set to initiate and generate an association between such variables in tandem with the objective of the present study. The rationale behind association rules is to foremost examine all salient rules embedded in a pool of datasets, specifically between items in an if-then format. In lieu of this and with respect to the present study, the generated rules seek to establish the antecedent and consequents of the data retrieved. It must be emphasized that one of the shortcomings of association rules is the utmost profusion of rules that are generated. Therefore, a need arises to reduce these rules to a small set of vital rules, as has been done in this study by concentrating on the rules with stronger rules.

In line with the above explanation and from both Tables 1 and 2, it can be seen that for each of the rules generated, the confidence of more than 90% was ensured. The findings from this section shed more light on the association of risk factors as an influential decision for customers not to engage in the online transactions precisely of used/second-hands goods and the type of an online customer as both consequents of our analysis. The first#2 rule indicates that when a customer has shopped online before and decides not to purchase any used good, then it is so because there is an iota of risk factors averting him/her to embark on online for such used goods. Then the overriding risk factor or reason for such customers dwells on the premise of risk as an influence of that decision. This decision, as a consequence, is accompanied by a 96% confidence, indicating a higher association between the antecedent and the consequent.

Consequently, in rule#1 of the same Table 2, when a personal use as a binary attribute of the type of online customer pause to make transactions online, yet decides to ignore the used goods sections, on the premise of some risky scenarios running in his/her minds which will even go a long way to influence the type of second-hand good should there be, then there can be a conclusion that, those perceived risk factors influenced the customers' decision not to embark on the online transactions of used goods. This rule, however, is supported by a 100% confidence with the support of 7.29%. This intent signifies that Czech online customers' being adamant in relocating used goods online stems from some risk factors ingrained in the minds of the customer in question. This is synonymous with the previous finding of the thesis that confirmed some iota of risk components that will avert the customer from hooking up online in search of used goods (Bryan, 2016). Hence, second-hand vendors in the Czech Republic should take measures to eradicate the fear psychological trauma coupled with health implications with a stringent assurance of no risk considering these two

variables. These two variables have been stated because rules generated specifically point to used goods as a risk factor preventing the customer.

Similarly, in rule #5, it can be implied that when a male customer who often connects via the Internet and does not think of initiating second-hand good, then the intervening effect is attributed to the fact that such a male customer perceived some risk factors that thwart his decision for such a transaction with a confidence of 96%, which is a true reflection of such a male customer. With higher confidence and sizable support coming from this rule, it thus becomes leverage for second-hand vendors in the Czech Republic to address the risk issues that might avert males' customers not to engage in such transactions.

Again, Rule 1# from Table 1 shows that when a customer decides to abandon second-hand transactions online with the intentions geared towards, financial, psychological, security or health-wise, then the overruling sense in this scenario is that indeed this type of customer is a personal user of the computer in the Czech Republic. This decision is supported by 9.1%, accompanied by 97% confidence that this rule is attested in the database. In the same vein, judging from rule #3 from the same Table 2, when a female Czech customer had bought a second-hand well online before, but was careful with the type of such a second-hand good even though she is not under the influence of any risk, such as financial, security, etc. then, this type of customer is a personal user and not a business user. This rule, however, is associated with higher confidence of 96%, with a higher support of 24%. This implies that anytime a female Czech customer decides to buy second-hand goods online, then indeed this decision is borne out of no risk, yet very circumspect with the kind of second-hand or particular second-hand good. This rule is given an indication to the second-hand vendors to redesign their websites in a peculiar manner, to meet and provide confidence in the customer. For instance, the websites of shopping sites of brand new goods should not be designed in the same way as those the second-hand ones, ranging from the information that will be present there, thus, assurance of other metrics that will lure the customer in those businesses should be initiated.

Alternatively, Rule 4# indicates that when a male personal user in the Czech Republic has shunned the initiation of second-hand goods online due to the fact that risk components influenced that type of second-hand good, he/she intended to patronize, probably, books, vintages, etc. then, the superseding cause of this decision is highly attributed to the influence of some risk factors occupying 100% in the database. This means that for a male Czech personal user of the internet to disregard second-hand goods as a result of some types of such goods then indeed there is a bit of risk in

that decision of the customer in question. This stems from the fact that some second-hand goods are likely to pose a higher risk to the customer, for instance second-hand garments are more than expected to put fear in the customer. This claim has been seconded by the works of Chipambwa *et al.* (2016), even though their work was not premised on the risk of online second-hand transactions.

Conclusions

There has been a rapid growth of online shopping across the globe as far as migration to online buying and selling platform is concerned. This swift shift from traditional transactions to the era of information system (digital world) has indeed transformed the nature of activities, specifically among marketers and consumers and other related business transactions. It cannot be gainsaid that online shopping has come to stay mainly because of the advent of the Internet. Online shopping as an innovative marketing strategy has come with a series of benefits to both the seller and the buyer. Many studies have dealt with its numerous benefits to the business environment, amongst them include fast transaction, product search, price information, location of the product, conveniences of transaction, among others. Yet, many consumers or online shoppers feel unsafe when it comes to online transactions, precisely when the said good is a second-hand one.

In spite of the aforementioned importance attached to online shopping, little or insignificant research has been done in relation to the relative significance (risk) associated with pre-purchase risk in online shopping. In this present study, the ARM technique was harnessed to analyse the pre-purchasing sentiments that run through the minds of the customer as he/she decides to embark on an online transaction of second-hand goods specifically.

The ARM technique used in this study was meant to glean relevant information from the accrued data, so far as the risk intentions of the customer is concerned. This approach is broadly swayed from the traditional deductive means of falsifying existing theories, hence bent on logically eliciting the magnitude of risk inherent and associated with the penchant of online customers to engage in the second-hand goods transactions. The Association rule mining technique did not only assist in mining patterns from the data, but also provided us with the metrics of measuring the severity of such risks. The consequent or the antecedent in making justifiable decisions was accompanied by its associated metrics, such as the support, confidence, and lifts. In this respect, the research has provided insight into

some factors such as; demographic variables in relation to the pre-purchasing risk factors averting customers to connect via online in search of second-hand goods.

The research established that second-hand industry needs to redesign their websites with much attention to reinforce stringent measures that will give better assurance of the aforementioned risk factors which will tend to avert the customer from connecting online in pursuit of second-hand goods. This could be executed by taking into consideration what inherently runs through the minds of the customer towards engaging in such transactions, of which this study has sought to reveal. Although this research model cannot be overly described as the best view in tackling pre-purchase risk intentions in the online second-hand goods or transactions, it could give a broader understanding regarding the pre-purchase intentions consumers attached to online shopping. The empirical analysis of this current study would go a long way to assist especially, vendors and shoppers trading online for better seller-buyer satisfaction and business sustainability. This point reinforces the notion that second-hand vendors who have transitioned on the online platform do not need to entirely concentrate on their internal activities, but to look at other metrics that will avert the online customer is not patronizing their business.

Additionally, in the academic literature, adequate knowledge derived from the analyses would broaden the concept of online shopping and consumer behavior from the marketing perspective. However, the limitation of the paper could be attributed to the sample size as being small, taking into consideration the scope of demography of the study. It appears that the study has a narrow scope of results interpretation in a sense that the attention of the research theme was given only to users or potential users of second-hand goods in the online space. Future research directions could need more respondents of this kind of research. Again, the authors suggest that a subsequent study of this nature can be geared toward a specific kind of second-hand goods such as textiles(clothes), books, among others. In addition, a comparative study could be done to substantiate the same pre-purchase risk factors against un-used goods (new goods). It is also worth noting that few studies have attempted to look at the pre-purchasing risk factors or intentions from the customers' point of view and that this study shed a limitation of scanty academic work in that area.

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Annex

Table 1. Binary attributes of the data set towards the type of an online customer

<i>Rules</i>	<i>Antecedent (X)</i>	<i>Consequent (Y)</i>	<i>Support %</i>	<i>Confidence %</i>	<i>Lift %</i>
#1	{second. hand. goods. Online. =No, Do. risk. factors. Influence=Yes, Any.of.the.risk. factors. =Yes}		9.1	97	1.06
#2	{Gender=Female, Do. Risk. Factors. influence=Yes, Any.of.the.risk.factors.=Yes}		20	95	1.05
#3	{Gender=Female, shop. Online. =Yes, second. Hand. Goods. online. =Yes, Do. risk. factors. Influence=Yes, Influence.the.type.of. second. Goods=Yes, any.of.the.risk.factors.=No}	=Yes,	24	96	1.06
#4	{shop. Online. =Yes, second. hand. goods. Online. =No, Do. Risk.factors. influence=Yes, Influence.the.type.of. second. Goods=Yes, Any.of.the.risk.factors.=Yes}		7.2	96	1.06
#5	{Gender=Female, shop. Online. =Yes, second. hand. goods. Online. =Yes, Influence.the. type. Of. second. Goods=No, Any.of.the.risk.factors.=No}		6.3	95	1.05
#6	{shop. Online. =Yes, second. hand. goods. Online. =Yes, Do. Risk.factors. influence=Yes, Influence.the.type.of. second. Goods=Yes,		31	97	1.07
#7	{Gender=Male, shop. Online. =Yes, Second.hand. goods. Online. =Yes, Do Risk factors. influence=Yes, Influence.the.type.of. second. Goods=Yes, Any.of.the.risk.factors.=Yes}		9.1	97	1.07

{Type. Of. online. Customer=Personal user}

Table 2. Binary attributes of the data set towards risk factors (intensions) influencing customer decision

<i>Rules</i>	<i>Antecedent (X)</i>	<i>Consequent (Y)</i>	<i>Support %</i>	<i>Confidence %</i>	<i>Lift %</i>
#1	{Type. Of. online. Customer=Personal user, second. hand. goods. Online. =No, Influence.the.type.of. second. Goods=Yes, Any.of.the.risk. factors. =Yes }	{Do. risk. factors. Influence=Yes }	7.9	100	1.39
#2	{shop. Online. =Yes, second. hand. goods. Online. =No, Any.of.the.risk.factors.=Yes }		7.6	96	1.33
#3	{Type. Of. online. Customer=Personal user, second. hand. goods. Online. =No, Influence.the.type.of.second.goods=Y es }		7.2	97	1.33
#4	{shop. Online. =Yes, second. hand. goods. Online. =No, Influence.the. Type.of.second.goods=Yes }		7.5	95	1.37
#5	{Gender=Male, Type. Of. online. Customer=Personal user, second. Hand. Goods. online. =No, Influence.the. Type.of.second.goods=Yes }		7.5	100	1.39
#6	{Gender=Male, shop. Online. =Yes, second. hand. goods. Online. =No Influence.the. Type.of.second.goods=Yes }		7.6	96	1.34
#7	{Gender=Female, shop. Online. =Yes, Type. Of. online. Customer=Personal user, second. Hand. Goods. online. =No, Influence.the. Type.of.second.goods=Yes }		7.4	96	1.33
#8	{shop. Online. =Yes, Type. Of. online. Customer=Personal user, second. hand. goods. Online. =No, influence. The. type. Of. second. Goods=Yes Any.of.the.risk.factors.=Yes }		7.2	96	1.32

Figure 1. Conceptual Framework for the study (Research Process)

