Leveraging AI to Study the Impact of COVID-19 on Consumer Online Purchase Behaviour: A Study of Konya

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ABSTRACT

The paper intends to address the impact of the COVID-19 crisis upon consumer online shopping behaviour, focusing on the factors that affect the decision making towards the choice of e-commerce platform. The study relies on interpreting answers received from the Konya Chamber of Commerce to a questionnaire applied online. The problem of choosing one e-commerce platform over another in terms of convenience, popularity, familiarity, benefits, and transparency is introduced. The study also investigates the main factors that influence different generations' behaviour towards choosing the online shopping platforms, product items, and respondents' willingness to support the local (Only from Konya) online retailers. The study implies AI techniques to find and identify the prospective customers most likely to shop from the local suppliers. An AI model has been developed that predicts the customers' likelihood of preferring regionally local suppliers over the nationwide counterpart. The trained model reported an accuracy of 0.91 on the testing set, which means that given the customer's data, the model predicts that 91% of the people are willing to buy from a local supplier. This model can be used for targeted advertisement for specific people at a specific time which improve the sales. The study adopts a descriptive research method and aims at describing the attitude of people living in Konya, represented by the members of the Konya Chamber of Commerce.

Keywords: Consumer behaviour, COVID-19, Turkey, Online shopping, e-commerce, Artificial Intelligence
JEL Classification: G1

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ÖZ

Bu makale, COVID-19 sağlık krizinin tüketicilerin çevrimiçi alışveriş davranışları üzerindeki etkisini ele almayı ve e-ticaret platformunun seçimine yönelik karar vermeyi etkileyen faktörlere odaklanmayı amaçlamaktadır. Çalışma, Konya Ticaret Odası'ndan çevrimiçi olarak uygulanan bir ankete verilen yanıtların yorumlanmasına dayanmaktadır. Kolaylık, popülerlik, aşinalık, faydalar ve şeffaflık açısından bir e-ticaret platformunu diğerine tercih etme sorunu ortaya çıkmaktadır. Çalışma aynı zamanda farklı nesillerin çevrimiçi alışveriş platformlarını, ürün öğelerini seçmeye yönelik davranışlarını ve katılımcıların yerel (Yalnızca Konya'dan) çevrimiçi perakendecileri destekleme istekliliğini etkileyen ana faktörleri de araştırmaktadır. Çalışma, yerel tedarikçilerden alışveriş yapma olasılığı en yüksek olası müşterileri bulmak ve belirlemek için yapay zeka tekniklerine işaret ediyor. Müşterilerin ülke çapındaki muadili yerine bölgesel olarak yerel tedarikçileri tercih etme olasılığını tahmin eden bir AI (Yapay Zeka) modeli geliştirilmiştir. Eğitimli model, test setinde 0,91 doğruluk bildirmiştir; bu, müşterinin verileri göz önüne alındığında, modelin insanların %91'inin yerel bir tedarikçiden satın almaya istekli olduğunu tahmin ettiği anlamına geliyor. Bu model, satışları artıran belirli bir zamanda belirli kişilere yönelik hedefli reklamlar için kullanılabilir. Araştırma betimsel bir araştırma yöntemini benimsemiş ve Konya Ticaret Odası üyeleri tarafından temsil edilen Konya'da yaşayan insanların tutumlarını betimlemeyi amaçlamaktadır.

Anahtar Kelimeler: Tüketici davranışı; COVID-19; Türkiye; Çevrimiçi alışveriş; e-ticaret, Yapay Zeka

JEL Sınıflandırma: G1

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1. INTRODUCTION

Since its outbreak in China in early January 2020, COVID-19 spread rapidly worldwide to affect 200 countries (WHO 2020). This had a significant impact on consumers and the retail sector across the globe (Feng & Fay, 2020; Evans, 2020). As a response to the initial outbreak, China was the first country to impose a mandatory nationwide self-quarantine between January 23 and February 9, 2020 (Bloomberg News, 2020). Other countries followed China by issuing movement control orders (MCO) to control the spread of the virus (Chinazzi et al., 2020; Hedgecoe et al., 2020).

In Turkey, the first official case diagnosed with COVID-19 was announced on March 11, 2020, which resulted in an immediate partial lockdown and gradually increased MCO. During Q2 2020, elderly citizens and youth, who constitute 40 per cent of the population, were under complete lockdown, while a mandatory lockdown for the entire population was applied on weekends and public holidays (Bostan et al. 2020).

Changes in consumer behaviour were one of the responses people displayed during the MCO period. The purchasing behaviour of consumers shifted from traditional sales areas to online channels (Pal and Bhadada, 2020; Gao et al., 2020). Even individuals who never used online shopping before being prompted to shop online as there is no alternative. A significant portion of those late adopters who were averse to shop online have inflowed into electronic markets after COVID-19.

In the Turkish context, social distancing and staying home boosted e-commerce. Compared to the same period in 2019, during March, April, and May 2020, online sales of food and supermarket products increased by 420 per cent, online sales of product groups such as household cleaning, household appliances, and childcare increased by 169 per cent, 102 per cent and 86 per cent respectively (Republic of Turkey Ministry of Trade, 2020).

Before Covid-19, relying on the internet for shopping had not been so ingrained in our day-to-day lives. A couple of decades ago, online shopping was a novelty, just as the internet itself still was. Most people were only buying hard-to-find records or evasive action figures on eBay. Consumers' adaptations to online shopping accelerated by the pandemic are not likely to end or reduce after the COVID-19 passes (Wolfinbarger & Gilly, 2001).

One of the main advantages of online shopping is that it offers greater flexibility in terms of time, location, and product variety (Rohm & Swaminathan, 2004). It is stated that the COVID-19 crisis jeopardized the development of e-commerce and moved it forward for at least three years. It should be highlighted that this is the first time in the history of e-commerce when people were left with no option but to shop online. Therefore, the increase in online shopping was inevitable. For example, the increase in grocery online shopping picked during the pandemic. The research indicates that new habits formed now will endure beyond this crisis (Hall et al., 2020).

Understanding the behaviours has been a long-sought out research avenue, and such information would go a long way in identifying the appropriate customers for a new product that a company wished to launch. Over the year's lots of interdisciplinary techniques ranging from sociology, behavioural psychology sciences have been used to enhance on or another aspect of marketing, and the latest to appear on the scene is Artificial Intelligence (AI). Over the years, AI has been employed in many aspects of business science like sales forecasting, inventory replenishment, market basket discovery (finding which items are frequently bought together), fraud detection, recommendation systems, etc. This study uses AI techniques to identify prospective customers that are most likely to buy from local suppliers.

This study aims to examine the problem of choosing one online platform over another and tried to understand what the main factors behind the decision are making of different generations. Also, participants were asked whether they would prefer the regionally local online shopping platform over the nationwide counterpart and what would be their expectation from such a platform and the reason for choosing it; based on the answers received the research devised an artificial intelligence (AI) model that predicts if a person is likely to prefer regional suppliers over the national counterparts.

Google trends for AI and Business Marketing is presented in Figure 1. As can be seen from the figure, the interest in incorporating AI in business marketing has been increasing steadily in recent years.

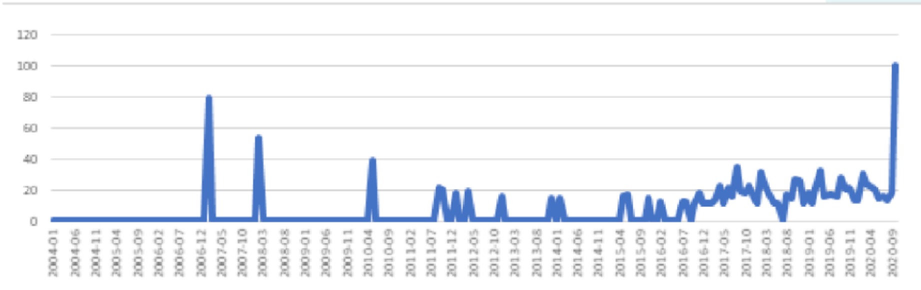

Figure 1. Artificial Intelligence and Business Marketing

Source: *Google trends*

The following points summarize the contribution of this research to the field of science:

- The problem of choosing one e-commerce platform over another in terms of convenience, popularity, familiarity, transparency, and benefits is introduced.
- The survey conducted to investigate the main factors that influence different generations' behaviour towards choosing online shopping platform and item groups which they purchased most. The questionnaire was held among Konya Chamber of Commerce members, which explains why the central mass is traders and businesspeople.
- The model that predicts the behaviour of a consumer towards the e-commerce platform selection is proposed.
- AI techniques are incorporated to segregate consumers for target advertising.

AI model that predicts if a person is likely to prefer local suppliers over the national counterpart is introduced.

The study adopts a descriptive research method and aims to describe the attitude of people living in Konya, represented by the members of the Konya Chamber of Commerce.

This paper is organized as follows. Section 2 reviews the related literature. Section 3 presents the methods, and empirical strategy. Section 4 discusses the main results, and Section 5 conclusion.

2. Literature Review

2.1 Changing Consumer Behaviour in Times of Crisis

A crisis is defined as an extremely dangerous or difficult situation, a time of confusion and suffering [1] or a moment during a severe illness when there is the possibility of suddenly getting better or worse . It is divided into various types such as sudden emerging crises (natural disasters, terrorist attacks, etc.) and slow emerging crises (product errors, scandals, bribery, administrative errors, etc.) (Arslan, 2009). When classified according to risks, crises are divided into three groups as controllable and known (economic, political, administrative, etc.), uncontrollable and unavoidable (natural disasters), and unknown and unexpected (terrorism, anthrax, etc.) (Ulutaş, 2010). In other words, crises can be seen because of natural disasters such as earthquakes, floods, fires, meteor strikes, or a technological disaster such as a computer virus that can swarm the whole world at once, or an epidemic disaster (Müftüoğlu, 2004). The research shows that crisis is a vital stressor that hurts the health of the general population (Lee et al. 2010; Giorgi et al. 2015; Wang et al. 2010; Evans-Lacko et al. 2013). One of the characteristics of stress is that it leads people to perceive that they currently lack control over their environment (Botti and McGill 2011; Cohen 1988).

On the other hand, consumption is a social, cultural, and economic process of choosing goods (Zukin & Maguire, 2004). Consumer behaviour changes during emergencies (Ballantine et al., 2014; Larson and Shin, 2018; Pantano et al., 2020; Sheu and Kuo, 2020). Therefore, consumers experiencing stress may show increased saving behaviour (hoarding), which assures them that monetary resources will be available when needed. Alternatively, consumers experiencing stress may show increased spending behaviour. Spending, however, is explicitly directed toward products the consumer perceives to be necessities (stockpiling). While saving allows consumers to reduce the unpredictability associated with an uncontrollable environment. Accounts of disaster-related shifts in consumption and consumer behaviour are often simplistically presented in terms of "panic buying" and "hoarding", including responses to COVID-19 (Peck, 2006, Pantano et al., 2020; Yuen et al., 2020). For example, the study conducted in the UK, the US, and Germany show that the expenditure on health and hygiene increased by 36%, 43%, and 33%, expenditure on the consumption of food and drinks increased by 32%, 31% and 22% and expenditure on household cleaning products increased by 30%, 40% and 18% in each country respectively. Whereas the spending on clothing and services such as hairdressing increased by only 4% and 5% in Germany, by 5% and 2% in the UK, and by 7% and 3% in the US (Statista, 2020).

2.2 The Impact of COVID-19 on Consumption

The COVID-19 pandemic has fundamentally changed the world as we know it. People are living differently, buying differently, and in many ways, thinking differently. Supply chains have been tested. Retailers are closing doors. Consumers across the globe are looking at products and brands through a new lens. The virus is reshaping the consumer goods industry in real-time, rapidly accelerating long-term underlying trends in the space of mere weeks. The research indicates that new habits formed now will endure beyond this crisis, permanently changing what people value, how and where they shop, as well as how they live and work (Accenture, 2020).

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[1] *Cambridge Dictionary https://dictionary.cambridge.org*

Wang et al. (2020) show that the current pandemic encourages many families to stockpile food and expand their fresh product reserves and that consumers are willing to pay more for fresh food reserves during the COVID-19 pandemic. The results from their regression analysis showed that motivations of "avoiding shortage" rather than " 'fight against rising food prices" have a significant effect on consumer decision about food stockpiling. This result suggests that a stable supply is more helpful than a stable price to reduce consumer food stockpile behaviour during the COVID-19 pandemic.

On the other hand, unusual retail consumer behaviour, such as hoarding toilet paper, was reported worldwide during March 2020 when the COVID-19 virus escalated into a pandemic (Miri et al. 2020; Laato et al. 2020). To understand the underlying motivation Laato et al. (2020) conducted an online survey in Finland. The study found a strong link between intention to self-isolate and intention to make unusual purchases, providing empirical evidence that the reported consumer behaviour is directly linked to the anticipated time spent in self-isolation. Their results revealed that exposure to online information sources results in increased information overload and cyberchondria. Information overload was also a strong predictor of cyberchondria. The perceived severity of the situation and cyberchondria had significant impacts on people's intention to make unusual purchases and voluntarily self-isolate.

Andersen et al. (2020) use transaction-level customer data from the largest bank in Denmark to estimate the change in consumer spending caused by the COVID-19 pandemic and the Danish economy's resulting shutdown. The authors found that aggregate spending was on average 27% below the counterfactual level without the pandemic in the seven weeks following the shutdown. The spending drop mainly was concentrated on goods and services whose supply was directly restricted by the shutdown, suggesting a limited role for spillovers to non-restricted sectors through demand in the short term. The spending drop was more considerable for individuals with more ex-ante exposure to the adverse consequences of the crisis in the form of job loss, wealth destruction, severe disease, disrupted consumption patterns and, most notably, for individuals with an ex-post realization of crisis-related unemployment.

2.3 Online Purchasing Behavior of Consumers during COVID-19

Consuming has become electronic today. With the emergence of social media, smart mobile devices, and tablet computers, consumption habits have rapidly switched to online platforms. Consumers can instantly access detailed information on products and services and quickly realize their purchasing behaviour without touching the products. Many consumers prefer to save time by shopping online. As online shopping is easy and not time-consuming, it enables consumers to purchase products in a short time with a few clicks without dealing with physical or traditional shops (Khan & Rizvi, 2012, p.32). However, before Covid-19, relying on the internet for shopping had not been so ingrained in our day-to-day lives. A couple of decades ago, online shopping was a novelty, just as the internet itself still was. Most people were only buying hardto-find records or evasive action figures on eBay.

Studies in the literature show that many factors affect the behaviour of consumers while shopping online. Considering the studies conducted, the primary and most important factors that cause or prevent consumers from purchasing a product online are privacy, security, trust, saving time, ease of use, and shopping pleasure. (Udo, 2001; Liu & Arnett, 2000; Harrison et al. 2002).
Nevertheless, few studies have examined whether and how people influenced by an epidemic change their behaviours in the adoption of e-commerce.

In Turkey, many decisions have been taken, and regulations have been made for citizens to stay at home by taking essential measures such as conducting jobs with minimum personnel in public and private institutions and converting education into distance education. Within the scope of the measures taken, consumers who will spend more time at home have chosen to create online orders and resolve their needs by delivering them home over the internet. Social distancing and movement control orders resulted in increased online shopping (Demiralp, 2020).

Figure 2 depicts some products' changes in online shopping during March, April, and May 2019 and 2020.

This research is based on the online survey conducted among 193 members of the Konya Chamber of Commerce, the sixth-largest chamber of commerce in Turkey and the first Chamber of Commerce established in Anatolia in 1882. Konya is the largest city with an area of 38.873 km2 and the seventh most populous city (2,232,374) of Turkey, where 60.6 % of the population is below 35 years old.

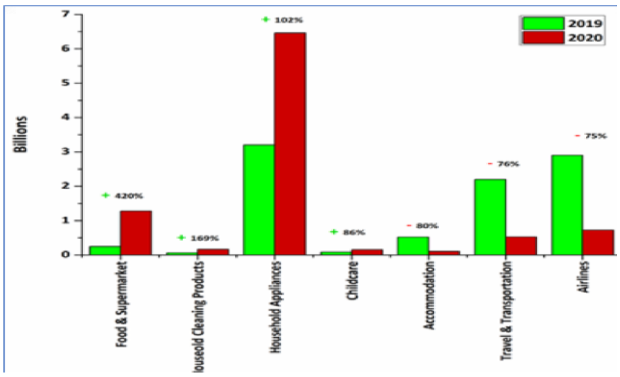


Figure 2. The Impact of Covid-19 on e-commerce in Turkey (March, April, May 2019 and 2020)
Source: Republic of Turkey Ministry of Trade

The change in online selling of food and supermarket products increased to TL 1.3 billion from the previous TL 168 million (+ 420%) in 2020. There is also an increase in online selling of product groups such as household cleaning (169 %), household appliances (102 %), and childcare (86 %). Simultaneously, online sales of product groups such as accommodation, travel, and transportation and airlines faced a decline. Accommodation shrunk 80% from TL 522 million in 2019 to TL 104 million in 2020. Travel and transportation faced a 76% decline from TL 2.2 billion in 2019 to TL 548 million in 2020. Online selling relating to the aviation sector encountered a shrinkage of 75%.

3. Methods

3.1. Data collection

The participants were asked to choose the online shopping platform they prefer and indicate the underlying reasons for their decision. Also, the participants were asked about their shopping behaviour during Covid-19 and the products they purchased online most during this period.

Active use of e-commerce platforms during Covid-19 harmed retail offline business owners due to the extensive use of online shopping, which resulted in unemployment and the closing of the retail business in the region (Konya). Introducing a local e-commerce platform can solve this problem as it enables the tradesman to re-gain the regular customer. Therefore, participants were asked if they would support a regionally local online shopping platform and the primary driving motivation behind this. The following subsection describes the results of the survey and the model.

Correlation between two variables is a quantitative measure of dependence between them and tracks the effect change in one variable that has triggered the changes in other variables. The value can be positive or negative. A positive correlation means that an increase in the variable also increases the variable, and a negative correlation means that an increase in the independent variable tends to decrease the independent variable. Finding out the correlation between variables in the survey is essential because it shows whether on e variable has a direct impact on another variable or not.

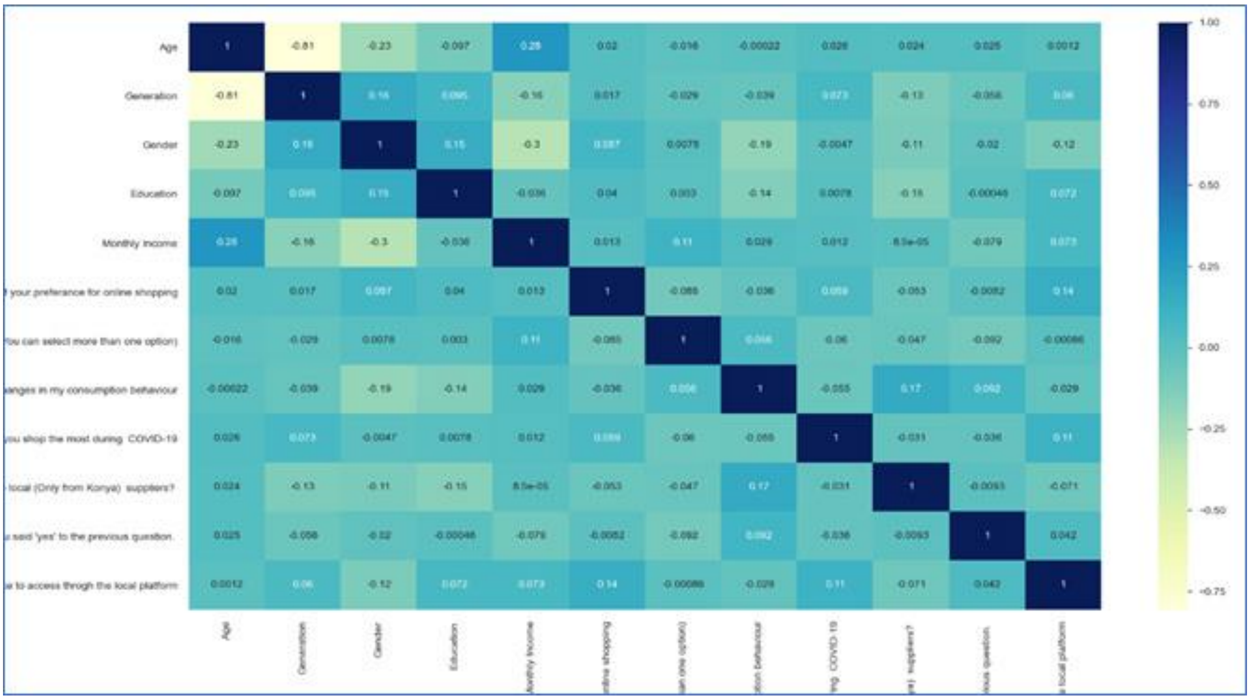
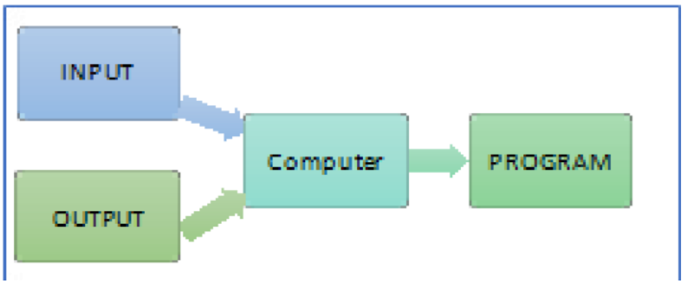


Figure 3. Correlation Matrix

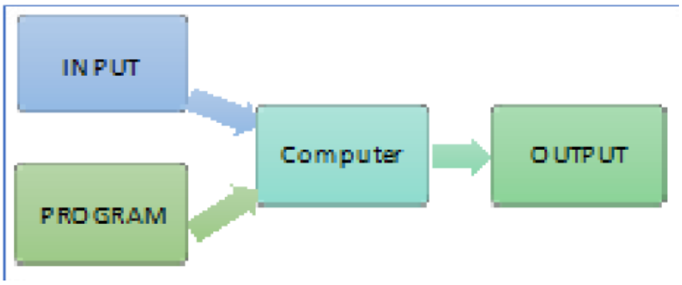
Figure 3 shows the correlation of all the variables (question asked during the survey) with one another. The correlation is the measure between -1 and 1. If the correlation is in +ve, then it means the variables are correlated with each other. However, if it is in -ve then the relationship between these variables is anticorrelated (Asuero, 2006). When the value of the correlation between two variables is above 70% (positive/negative), it is considered that these two variables have a significant impact on one another regardless of the relationship is correlated or anticorrelated. The main idea of conducting this analysis is to identify the correlation of variable(question) 'Would you prefer a platform which enables you to shop from the local (Only from Konya) suppliers' with other variables. From the figure, it can be noticed that no variable has a significant impact on the variable mentioned above. Thus, it was decided to imply an Artificial Intelligence (AI) algorithm, which will help predict whether a person will prefer a local platform over others.

3.2 Proposed AI Model

Machine Learning (ML) is a way of doing artificial intelligence wherein the Machine is trained to learn the patterns from the data without being explicitly programmed to so (Mitchell,1997). ML models enable a machine to learn from the data and make predictions on the future unseen data. . ML differs from the conventional programming in a way that in case of the conventional programming the Machine is programmed to produce an output from a given output, while as in Machine learning the input and output labels are used to make predictions about the model, that transform the inputs to outputs, as depicted in Figure 4.



a) Conventional Programming Paradigm



b) Machine Learning Paradigm

Figure 4. Different paradigms

ML techniques are broadly divided into two broad categories, i.e., supervised learning and unsupervised learning. In the supervised learning method, the model is trained by providing the 'labelled' data. Whereas in the unsupervised learning method, the model is not being supervised. Among many other types of supervised learning, 'decision trees' is one of them, where data is ceaselessly divided according to specific parameters. Decision trees are tree-like graphs with nodes representing the place where an attribute is chosen and a question is asked; edges represent the answers to the questions, and the leaves represent the actual output or class label (Quinlan,1986). Decision trees are used in non-linear decision making with a simple linear decision surface. The probability of a certain event to occur is measured by Entropy, also called Shannon Entropy is denoted by H(S) for a finite set S, which is the measure of the amount of uncertainty or randomness in data and defined as follows:

$$H(S) = -\sum_{x \in S}^{n} p(x)\log_2 p(x)$$

where it is assumed that 0log0=0.

The entropy is nonnegative and it shows the predictability of a certain event. If H(S) value is close to zero then there is less uncertainty while higher values imply high uncertainty. For instance, consider a coin toss whose probability of heads is 0.5, and the probability of tails is 0.5. Here the entropy is the highest possible since there's no way of determining what the

outcome might be. Alternatively, consider a coin that has heads on both sides, the entropy of such an event can be predicted perfectly since it was known beforehand that it'll always be beheaded. In other words, this event has no randomness hence it's entropy is zero.

Decision Trees can be used both for classification (where the target label is categorical) and regression (where the target label is quantitative). This research problem in essence is a classification problem, the aim was to predict if some person 'x' is likely to buy from a local supplier or not, hence for each person we predict a “YES” means a person is likely to buy from the local supplier and a “NO” mean very unlikely a person is going to buy from a local supplier.

Preparing Data

Like most ML techniques, Decision Trees works with quantitative data alone; however, the target labels can be qualitative. Since the data that was collected was primarily qualitative. So before any of the training or testing would have been done, the categorical data was converted to the numbers using a technique called Label Encoder. Once the data was transformed, the next step was to remove any imbalance in the dataset; our dataset was highly imbalanced, with 180 people responding with ‘yes’ to the target variable and only 16 responding with ‘no’. An imbalanced class problem has negative impact on the model. To reduce the class imbalance, the instances of the minority class has been synthetically produced by a technique called the Synthetic Minority Oversampling Technique (SMOTE).

Training and Testing Model

Once balanced data was obtained, the next step was to split a proportion of the data to train the model and spare a portion of to test the model; for this research problem, 70% of the total data was used to train the model and the remaining 30% was used to test the model. The trained decision tree is presented in Figure 5.

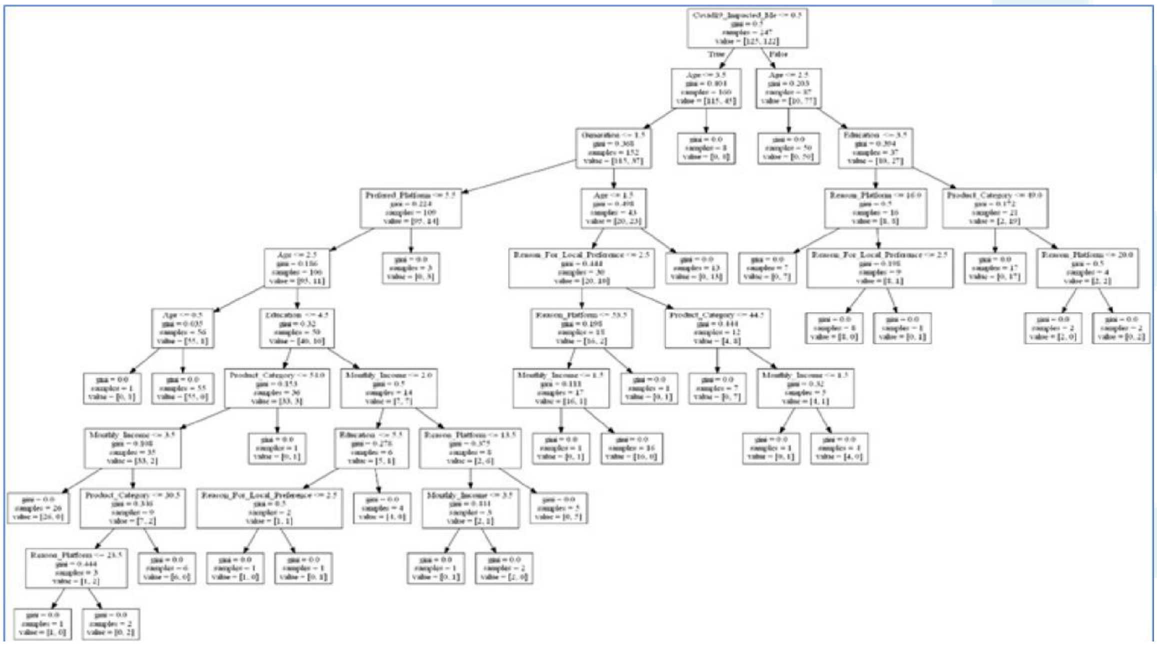


Figure 5. Decision Tree model for the data

The resulted model was tested on the testing data, and its performance was evaluated on the metrics derived from the confusion matrix, which a specific table layout that allows visualization of the performance of an algorithm, typically a supervised learning one.
Each row of the matrix represents the instances in a predicted class, while each column represents the instances in an actual class (or vice versa), as shown below. All correct predictions are located in the diagonal of the table (highlighted in bold), so it is easy to visually inspect the table for prediction errors, as values outside the diagonal represent them. In abstract terms, the confusion matrix is as follows:

		Actual class	
		P	N
Predicted class	P	TP	FP
	N	FN	TN

Accuracy: Accuracy of the model is the ratio of total correct instances over the total number of instances i.e., Accuracy=(TP+TN)/(TP+FP+TN+FN). Precision: Precision of the model is the ratio correct positive instances over the total number of positive predictions i.e., Precision=TP/(TP+FP). Recall: Recall of the model is the ratio of positive instances over the total number of actual positive instances i.e., Recall=TP/(TP+FN).

Results

Table 1 presents the classification report of the trained model. The decision variable for the proposed model was "WOULD YOU PREFER TO BUY FROM LOCAL SUPPLIER?". From the table it can be noticed that the total size of the randomly drawn test set was 107 for the decision variable. Out of 107 instances, there are 52 instances where people have opted "NO" and 55 instances where people have opted "YES". It can be noticed that the trained model was able to make prediction with an accuracy rate of 90% for the 'NO' cases and 91% for 'YES' cases.

Table 1: Classification Report of Trained Model

	Precision	Recall	F1-score	Support
NO	0.90	0.90	0.90	52
YES	0.91	0.91	0.91	55
Accuracy			0.91	107

Table 2 presents the confusion matrix of the proposed model on the test dataset. From the table it can been noticed that out of 52 "NO" instances, 48 were correctly classified as belonging to "NO" class while 4 were incorrectly classified as being "YES". Likewise out of the 55 "YES" instances 53 were correctly classified as being "YES" while 2 instances were incorrectly classified as being "NO".

Table 2: Classification Report of Trained Model

	Predicted	
ACTUAL	NO	YES
NO	48	4
YES	2	53

4. Findings

The majority (60.6 %) of the participants stated that COVID-19 resulted in significant changes in their This study aims to understand the online shopping behaviour of consumers in general and different generations in terms of the products purchased, the main motive behind choosing one e-commerce platform over another, and future expectations towards the introduction of the regionally local e-commerce platform in Konya. More than half (59%) of the respondents belong to Millenials, individuals born between 1977 and 1994, nearly 39% to Gen X, individuals born between 1966 and 1976, and only 2% belongs to Gen Z, the members of this generation were born between 1995 and 2012. The low number of representatives of Gen Z is explained by the fact that the survey was conducted among members of the chamber of commerce, and the age of these individuals (at the time of writing) is between 8 – 25 years old.
Figure 6 provides a generic composition of the respondents.

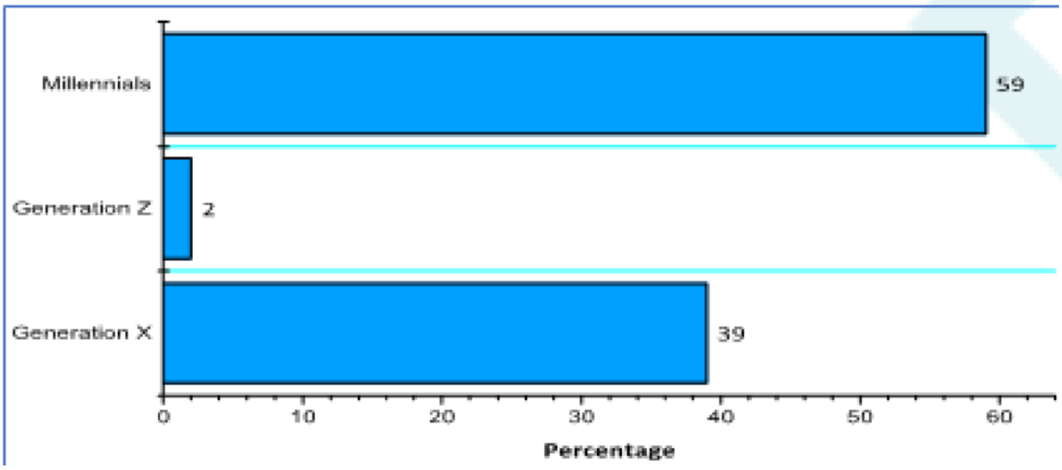


Figure 6. Breakdown of the respondents into generations

The majority (60.6 %) of the participants stated that COVID-19 resulted in significant changes in their consumption behaviour, shifting from traditional shopping to online. (See Figure 7).

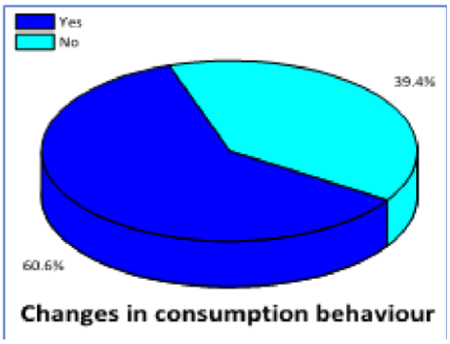


Figure 7. COVID-19 caused significant changes in my consumption behaviour.

Figure 8 displays the most demanded product items the respondents purchased online during the COVID-19

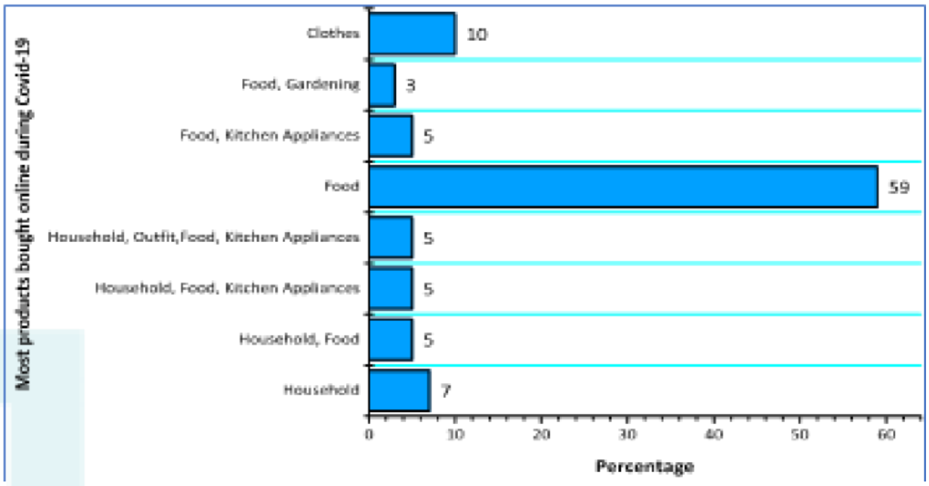
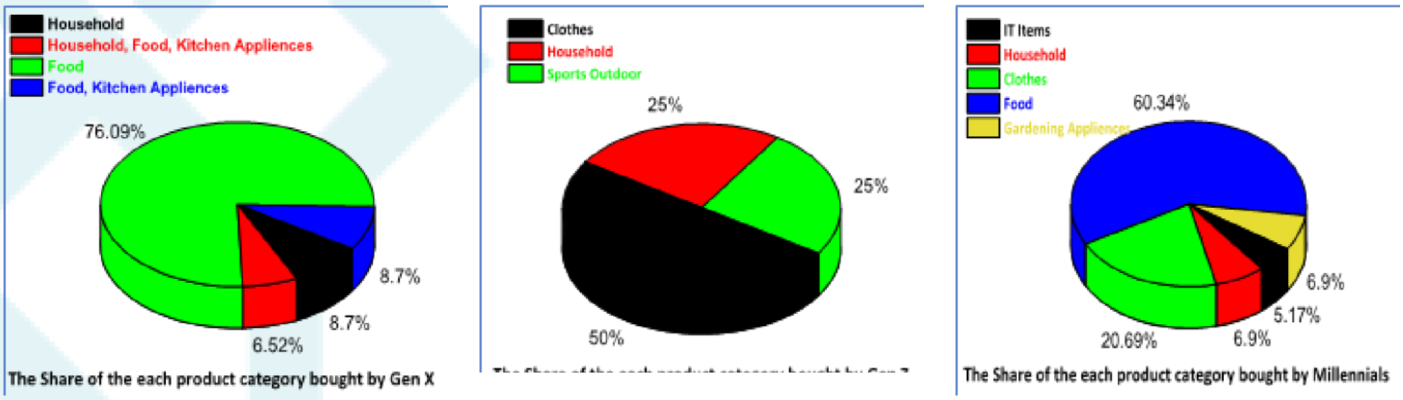


Figure 8. The items purchased online during COVID-19

Figure 9 presents the information regarding the items each generation has purchased the most.



a) Generation X online during

b) Generation Z online during

c) Millennials online during

Figure 9. Products purchased online during COVID-19 by different Generations

period.

Gen X and Millennials' top online shopping category was food, 76.09% and 60.34%, respectively. Interestingly, there is no demand for food among Gen Z respondents, most probably because they live with their parents and are not responsible for household support. Demand for household items is the highest among Gen Z (25%), followed by Millenials and Gen X with 6.90% and 6.52%, respectively. The clothing category appeared to be most purchased by Gen Z, so that 50% of the items Gen Z bought online during COVID-19 is the outfit, and 25% is sports items for outdoor activities. Another product categories are Information & Technology (IT) related products, gardening appliances, kitchen appliances and household items. Household constitutes 8.7% of online purchases for GenX and 6.9% for Millenials. From these charts, one can conclude that food was the top product category shopped online by Gen X and Millenials.

The aim of this research is to understand what drives the consumer to choose one e-commerce platform over another. There are six most popular online shopping platforms in Turkey, namely Amazon Tr, EPTTAVM, Gitti Gidiyor, Hepsiburada, N11, and Trendyol. Table 3 provides information for these platforms .2

Table 3. Most Popular E-commerce Platforms in Turkey

Ecommerce Platform	Country of Origin	Year of Establishment	Business Model	Export
Amazon Tr	USA	2018	B2C	Yes
EPTTAVM	Turkey	2012	B2C	No
Gitti Gidiyor	Turkey	2001	B2C	No
Hepsiburada	Turkey	1998	B2C	Yes
N11	China	2013	B2B-B2C	Yes
Trendyol	Turkey	2009	B2C	No

The participants were asked to choose the e-commerce platform they prefer for their online shopping activities. Figure 10 provides a summary of all generations.

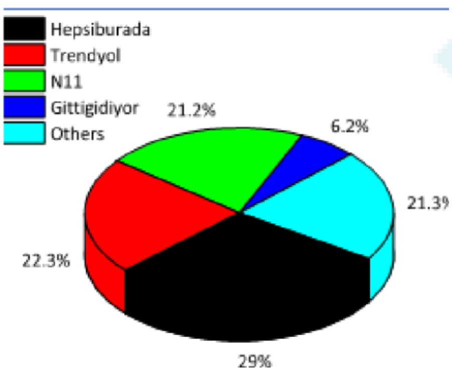
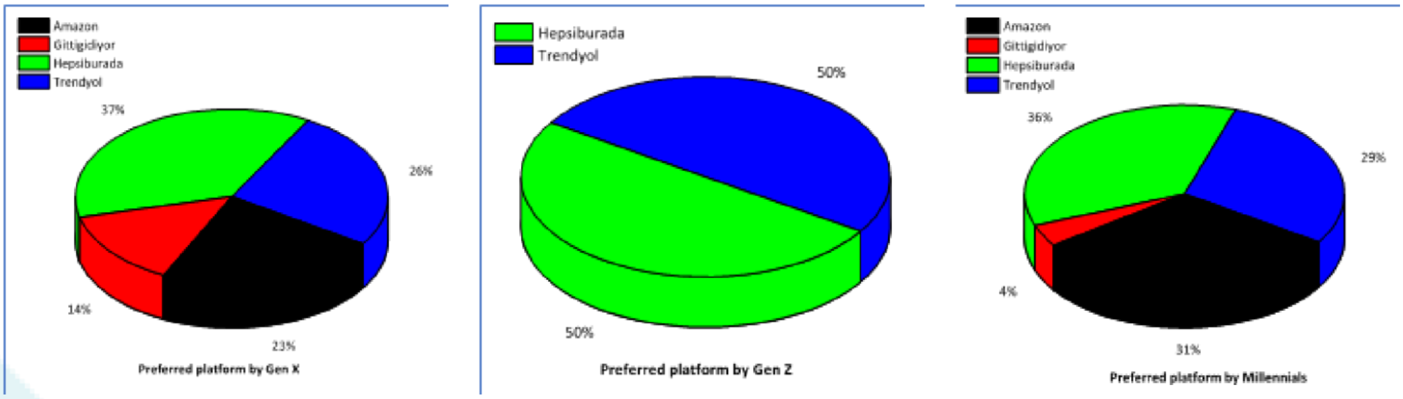


Figure 10. Most preferred platforms during the COVID-19

According to the pie chart, HepsiBurada, Trendyol, and N11 appeared to be the most preferred e-commerce platforms, with 29%, 22.3%, and 21.2%, respectively. Gitti Gidiyor is in fourth place with 6.2%. Figure 11 provides information regarding the preferred platforms chosen by different generations.

2 *Note that the platforms are listed in alphabetical order. Therefore, the position does not indicate any other factors, such as popularity or market capitalization.*



a) Generation X COVID-19 b) Generation Z c) Millennials

Figure 11. Preferred platforms of different generations

Among the four most preferred online shopping platforms, Hepsiburada is the most preferred one by all generations with the shares of 37%, 36% and 50% for Gen X, Millenials and Gen Z, respectively. The second most popular e-commerce platform among the participants is Trendyol. This platform is the choice of 50% of Gen Z, 29% of Millennials and 26% of GenX. Once the information has been collected on the most preferred e-commerce platforms, the participants were asked the main drivers behind their decision of choosing one platform over another (see Figure 12)

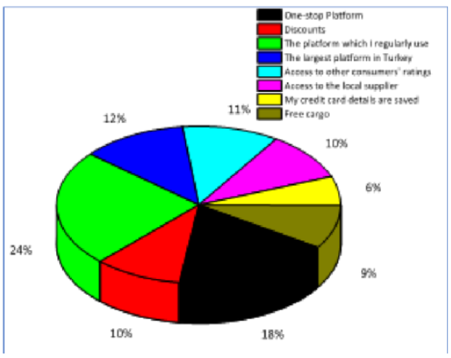


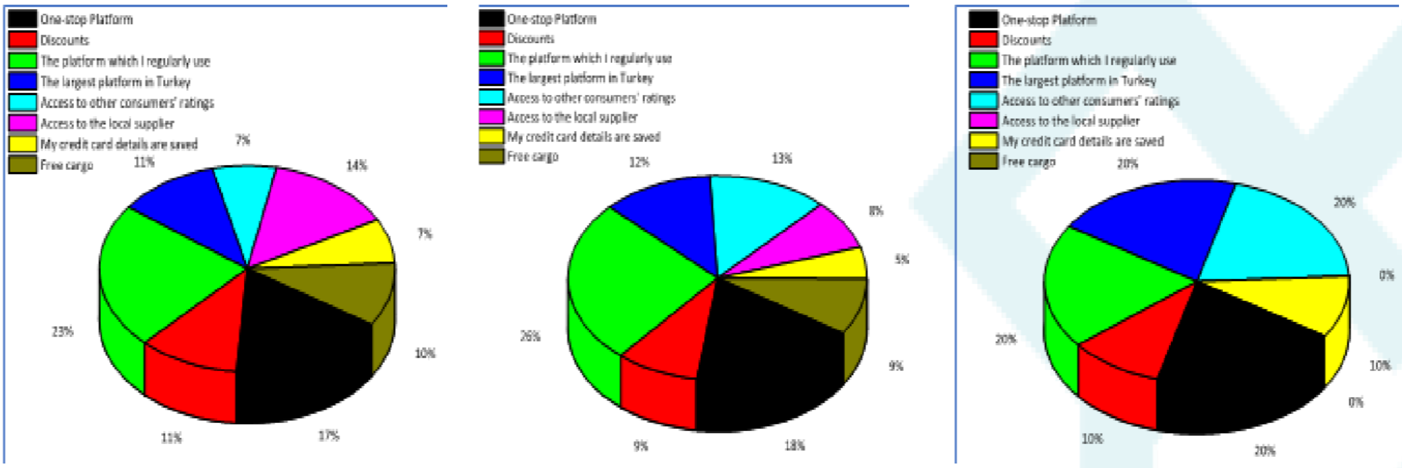
Figure 12. The reasons for the e-commerce platform selection

The pie chart illustrates the primary reasons that drive people to select one online shopping platform over another. At first glance, the main factor that motivates people to prefer one online shopping platform over another is convenience thus, 34% of the respondents stated that they choose the online shopping platform because they can find all their needs in one-stop, their credit card details are saved, and there is access to the local supplier which enables the delivery within the day of the order. The second factor, with 24%, is familiarity. People tend to stick to a platform that they always use and familiar to them. Nineteen per cent of the respondents stated that benefits such as discounts and free cargo influence their decision in online shopping platform selection. Popularity is the fourth factor; thus, 12% of the participants choose a platform because it the largest platform in the country. Moreover, finally, transparency plays an essential role in the decision of choice towards the e-commerce platform, so that 11 % of respondents value the feedback from other purchasers and users. Table 4 provides a summary of the factors that influence individuals' decision-making towards the selection of the e-commerce platform.

Table 4: The factors for e-commerce platform selection

Factor	Variable	(%)
Convenience	The one-stop platform, the consumer's credit card details are saved, access to the local supplier	34
Familiarity	The platform regularly used	24
Benefits	Discounts, free cargo	19
Popularity	The largest platform in the country	12
Transparency	Access to other consumers' ratings	11
Total		**100%**

Figure 13 describes a generic distribution of the decision-making process towards e-commerce platform decision.



a)Generation X b) Millennials c) Generation Z

Figure 13. The underlying factors for the e-commerce platform selection by different generations

Convenience is the most crucial factor in e-commerce platform selection among all generations, with 38%, 31%, and 30% for GenX, Millenials, and GenZ. The familiarity of the platform is the second motive (GenX - 23%, Millenials - 26%, GenZ - 20%) why people of all generations decide to shop from a particular e commerce platform. Informs of discounts and free cargo, benefits are most crucial for GenX (21%) followed by Millenials (18%), while only 10% of GenZ chooses an online platform due to this factor. Twenty per cent of Gen Z prefer a platform due to popularity and another 20% due to transparency. These factors appeared to be the least significant for Gen X and Millenials.

The participants were asked whether they would prefer the regionally local online shopping platform over the nationwide counterpart if available. The vast majority (92%) of the respondents stated they would prefer a regionally local platform that operates in Konya over the others. Figure 14 explains their motivation.

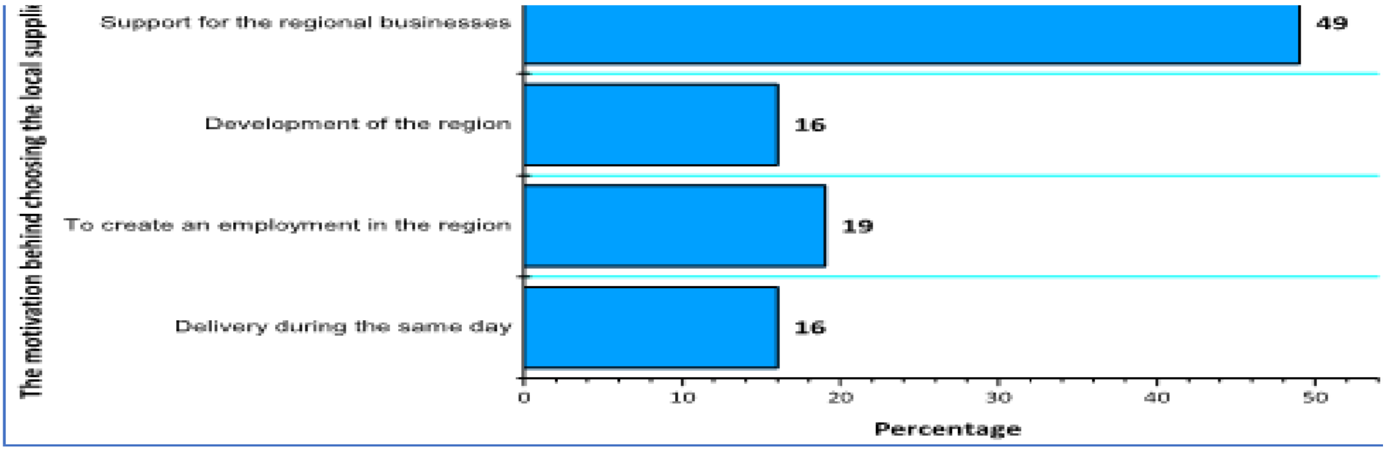
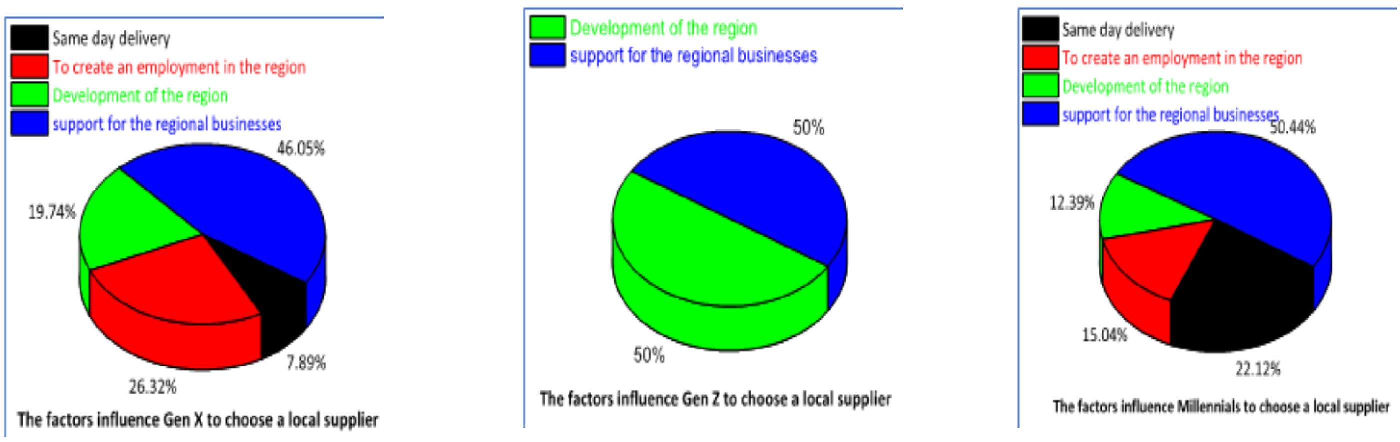


Figure 14. The motivation behind choosing the local supplier

According to the answers received, support for the regional businesses is the greatest motivation (49%) in choosing a local online shopping platform. Encouraging employment is the reason why 19% of the respondents would support the regionally local platform. On the other hand, 16% of the respondents would support the local supplier to develop the region, and another 16% to benefit from same-day delivery. This shows that 84% of the participants are interested in the development and job creation in the region. Figure 15 provides information on each generation's motive for choosing the local supplier.



a)Generation X b) Generation Z c) Millennials

Figure 15. Different Generation motive for choosing the local supplier

From Figure 15, it is clear that all three generations' main motive is to support the regional businesses. Job creation concerns are the primary catalyst to support the local supplier for Gen X (26.32 %) and Millenials (15.04 %), while this variable does not represent a concern for the Gen Z. Development of the region is the variable that appears to be the primary motive for 50% of GenZ, for 19.74% of GenX and the 12.39% of Millenials. Same day delivery is not vital for Gen Z, whereas 22.12% of Millennials stated they would support the regional supplier since they want their orders to be delivered within the same day.

5. CONCLUSION

The COVID-19 pandemic has fundamentally changed the world. COVID-19 has affected people in their day-to-day lives. Their way of living, buying products and way of thinking have been affected. Changes in consumer behaviour were one of the responses people displayed during COVID-19. Social distancing and movement control orders resulted in increased online shopping. The purchasing behaviour of consumers shifted from traditional sales areas to online platforms.

Prior to Covid-19, relying on the internet for shopping had not been so ingrained in day-to-day lives of common people. Especially older generations prefer to shop in traditional style. This study focuses on the impact of COVID-19 upon the online shopping behaviour of consumers, with the particular focus on the factors which affect the decision making towards the choice of one e-commerce platform over another. The study adopts a descriptive research method and aims to describe the attitude of people living in Konya, represented by the members of the Konya Chamber of Commerce.

The main reason why people choose an online platform is the *convenience* which is followed by *familiarity, benefits, popularity,* and *transparency.* At the same time, the key drivers appeared to be different for different generations. Most of the respondents will support the local (Only from Konya) online retailers with the motivation to support the development of the region and increase job creation. This study introduces the model which predicts the likelihood of a person to prefer regionally local supplier over the nationwide counterpart. The trained model reported an accuracy of 0.91 on the testing set, which means given the data of a customer, the model was able to predict correctly 91% of times if a person will buy from the local supplier of not. A potential drawback with the current system is that only one aspect was studied from the prism of Artificial Intelligence, this was mostly because the limited data that was accessible. A further extension to this work would be clustering the customers that share similar interest in the groups.

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