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Utilizing Deep Learning Neural Network to Predicting Factors Influencing Actual Purchase for Clothing Apparel during the COVID-19 Pandemic

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Abstract. The clothing industry has been increasing in revenue over the years. However, the buying behavior to actually purchase clothing has been affected during the COVID-19 pandemic. Due to the implemented lockdown and the strict health protocols, people have bought less materials. With that, this study utilized Deep Learning Neural Network using Python 3.8 to predict factors influencing actual purchase of clothing apparel during the COVID-19 pandemic. With 457 respondents, there were a total of 26,506 datasets. After data pre-processing, normalization, and optimization, a 95% average accuracy with 2.384 standard deviation was seen for social norm factor, followed by promotion, product, and perceived behavioral control. These factors were considered significant that affected actual purchase intentions for clothing apparel during the COVID-19 pandemic. The findings of this study could be utilized to entice customers to purchase clothing apparels during the COVID-19 pandemic. Lastly, the results and model utilized could be applied for clothing industries worldwide.

Keywords: deep learning neural network, actual purchase, clothing apparel, COVID-19 pandemic

1. Introduction

The increase of sales among the fashion industry was seen to be highly significant since 2014 [1]. Around $759 Billion CAGR was seen since 2014 globally [2]. From the global aspect, Ong et al. [1] indicated that the Philippines is one of the contributing factors that affected the increase of income for the fashion industry.

Despite the exponential growth of the clothing apparel industry, it was not excepted from the impact brought about by the COVID-19 pandemic. The buying behavior of consumers drastically affected the fashion industry [3] and was deemed underexplored among research fields.

Different studies [4-6] focused on the buying behavior of essential good such as medicine, food, and household supplies, even education [7,8]. However, businesses in general are affected during the COVID-19 pandemic and also affects livelihood due to their employees [9]. Tušl et al. [10] explained how COVID-19 impacted work and private lives of the people.

Ong et al. [11] explained how behaviors changed during the COVID-19 pandemic and has affected different businesses, even the fitness industry. Lockdowns were implemented worldwide, and the Philippines and New Zealand considered only opening the essential industries (e.g. supermarkets, pharmacy, hospitals, etc.) [11]. With the world slowly progressing from the pandemic, the need to explore buying behavior among consumers would be necessary to change business strategies and create promotions during the COVID-19 pandemic to situate the losses of the heavy lockdown implemented worldwide.

This study aimed to predict factors that influenced the buying behavior of Filipinos on clothing apparels during the COVID-19 pandemic. Specifically, this study utilized Deep Learning Neural Network (DLNN) as a machine learning algorithm for predicting the factors. DLNN has been utilized to predict factors affecting human behavior, forecasting, trends in economy, and image recognition [12]-[14]. It is an algorithm that is similar to the simple neural network, but utilizes more hidden layers for further processing and increase accuracy of prediction [15], [16]. Thus, DLNN was deemed to be highly advantageous for predicting human behavior.

2. Methodology

This study considered the framework (Fig. 1) and questionnaire (Table 1) from the study of Ong et al. [1]. The main factors considered were economic, technological, and political under macro-environmental factors. In addition, COVID-19, self-efficacy, and perceived severity were considered under the protection motivation theory. Moreover, attitude, subjective norm, perceived behavioral control, purchase intention, and actual purchase were factors under the theory of planned behavior. On the other hand, sub-factors under marketing mix were generalized as one latent. The data gathered involved 457 participants who voluntarily answered the online self-administered survey. To which, majority of the respondents were within 15-22 years old (31%), followed by 23-30 years old (47%) and older. Seventy percent of the respondents are currently in college, single (84%), and have monthly budget of $213 - $2500.

A total of 58 questions were administered and collated 26,506 datasets. Before applying DLNN, data pre-processing was done. To which, data cleaning utilizing correlation analysis using SPSS 25 was done. The removal of non-significant latent (p-value > 0.05; correlation value < 0.20) was considered. Out of 16 latent, only 9 were considered significant (product, place, promotion, economic and technical aspects, attitude, subjective norm [SN], perceived behavioral control [PBC], and purchase intention). Data aggregation was done to be utilized as the input layer for the DLNN.

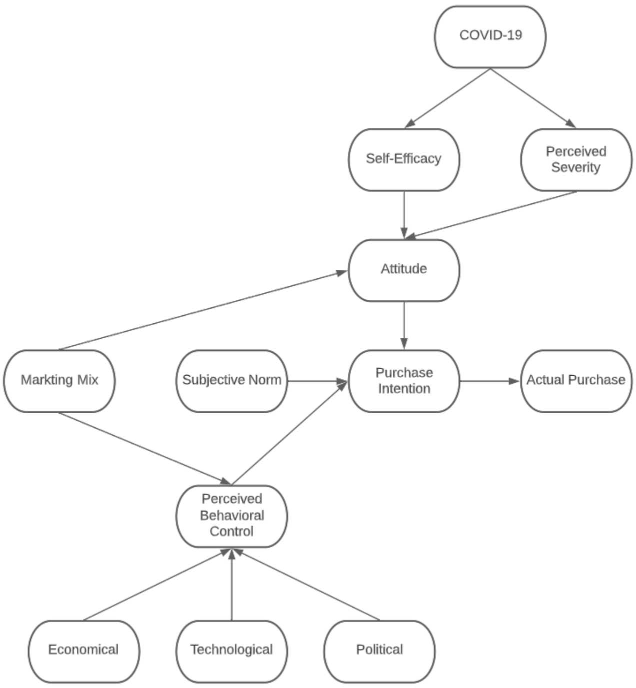

Fig. 1. Theoretical framework [1]

TABLE I. Questionnaire

CONSTRUCT		**MEASURES**
Marketing Mix	***Product***	Clothes offered must be the latest trends.
		Clothes offered must be high quality.
		The clothes that I need are always available.
		Clothes offered in different varieties or color influence my buying decision.
	Price	Retail price can influence purchase intention.
		I compare store prices when shopping.
		Charging lower prices than competitors is a must.
	Place	Need for Touch is necessary when purchasing clothes.
		I prefer shopping clothes in actual stores pre COVID-19.
		I prefer shopping clothes in actual stores during COVID-19.
		I prefer shopping clothes online pre COVID-19.
		I prefer shopping clothes online during COVID-19.
	Promotion	Brand Image influence purchase intention.

		Brand endorser/s influence buying behavior.
		Social Media posts can influence buying behavior.
		Social Media posts can influence brand image.
		Sale/Promos influence buying decision.
	People	Salespeople creates a positive impact with store/brand image.
		Salespeople recommendation influence buying decision.
		Salespeople has an impact on Customer Satisfaction
	Process	Maintaining stock availability influence buying decision.
		Maintaining stock availability has an impact on customer satisfaction.
		Store/Website design influence brand loyalty.
		Merchandise display inside the store influence buying decisions.
Macro Environmental Factors	***Economic***	COVID-19 has caused recession.
		The recession has affected my household.
		My purchase spending was reduced due to COVID-19.
		I prefer shopping clothes pre-COVID-19.
		I prefer shopping clothes due to COVID-19.
	Technological	I prefer online shopping for clothes.
		I obtain more information about the clothes when online shopping.
		I save more time when online shopping.
	Political	COVID-19 protocol prevention affects my buying behavior.
		Community quarantine declarations affects my buying decisions.
		Different preventive measures discourage me from shopping clothing apparel.
Protection Motivation Theory	**COVID-19**	I do understand the health risk from COVID-19.
		I do understand possible transmission of COVID-19.
		I am aware of the symptoms of COVID-19.
		I do understand health protocols for COVID-19
	Perceived Severity	I can be infected with COVID-19 when going to malls.
		I can be infected with COVID-19 when buying online.
		COVID-19 can lead to death.
	Self-Efficacy	I consider the clothes as sanitized before purchase.
		I can use the face mask as a preventive measure for COVID-19 when shopping.
		Disinfecting my purchase can prevent COVID-19
Theory of Planned Behavior	***Attitude Towards Behavior***	Purchasing clothing apparel is a good idea.
		Purchasing clothing apparel is a wise idea.
		Purchasing clothing apparel would be pleasant.
	Subjective Norm	People around me influence my purchasing behavior.
		My family and friends expect me to purchase clothing apparel.
		I value the opinion and feeling of my family and friends towards clothing apparel.
	Perceived Behavioral Control	I have the resource to purchase clothing apparel.
		I can participate in the decision-making process of purchasing clothing apparel.
		I am free to choose when purchasing clothing apparel
	Purchase Intention	I intend to purchase clothing apparel in my next purchase.
		I would like to purchase a clothing apparel.
		I would like to recommend to others to purchase clothing apparel.
		There are plenty of opportunities for me to buy a clothing apparel.
	Actual Purchase	I would highly purchase a clothing apparel during the COVID-19 pandemic.

Data normalization was done using Python 3.8 and parameter selection was done for running the DLNN. Sigmoid as the activation function of the hidden layers and output layers was considered [17]. The optimizer was adam [18], employing 150 epochs [19]. Different parameters were tuned for the optimization process such as the number of hidden nodes, number of hidden layers, and training and testing ratio (70:30 and 80:20). Ten runs for each combination was considered for the initial optimization [19].

3. Results

Final optimization was employed after determining the highest contributing factors for buying behavior (Table 2). It was seen that 4 out of 9 factors were significant (SN, product, promotion, and PBC). Based from the results, SN was seen to have the highest average accuracy of 95% with low standard deviation (StDev) of 2.384. This factor is deemed as the highest contributor to buying behavior during the COVID-19 pandemic.

The optimum DLNN following a feed-forward process is presented in Fig. 2. Based on the figure, it could be seen that 80 nodes in the first hidden layer and 20 nodes in the second hidden layer produced the best result of 95.00%.

The most significant factor would be SN, followed by promotion, product, and PBC. The highest significant factor is consistent with the results of Ong et al. [1], however the rest of the factors were not as highly significant. According to Fan et al. [20], structural equation modeling (SEM) would have inconsistencies when it comes to ranking of significant factors due to the causal relationship calculations considered for the model utilized. Since the model employed interrelationships among 12 latent variables, the standard coefficient may be lower due to the causal influence [20]. Thus, DLNN presents a more accurate result with 80% or more accuracy rate [21], [22].

TABLE II. Summary of Results

Latent	Node H	Ave Train	StDev	Ave Test	StDev	Decision
Product	80	23.32	3.208	91.96	3.402	Sig
Place	50	39.69	4.059	57.61	6.288	Not Sig
Promotion	40	30.03	2.529	92.39	2.034	Sig
Economic	80	31.27	8.945	58.48	1.721	Not Sig
Technical	80	31.89	3.349	48.04	3.637	Not Sig
Attitude	90	41.28	2.518	42.61	3.558	Not Sig
SN	80	14.06	2.780	95.00	2.384	Sig
PBC	80	42.68	4.496	61.69	4.674	Sig
Purchase Intention	90	42.38	3.763	25.00	4.548	Not Sig

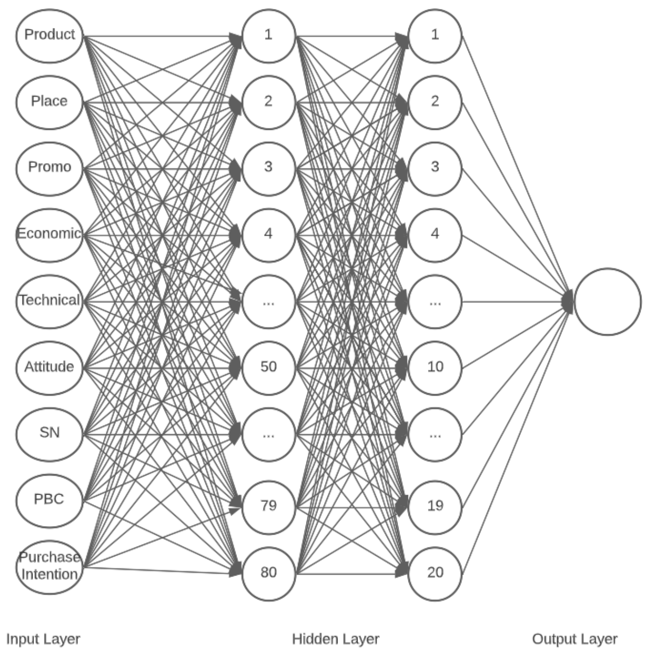

Fig. 2. Deep Learning Neural Network

4. Discussion

This study considered DLNN to predict factors influencing actual purchase for clothing apparel during the COVID-19 pandemic. With 95% accuracy with 2.384 StDev, SN was seen to have the most significant effect affecting actual purchase of clothing apparel, followed by promotion, product, and PBC.

When purchasing clothing apparel, the influence of friends and family affects an individual's decision [1]. It could also be seen that the impact based from other people's opinion and feeling affects a person's decision of purchasing a product, such as clothing apparels. Armitage et al. [23] explains how SN influences a person's purchasing intention. This is due to the fact that consumer's cognitive and emotional aspect would be affected by the people around them, even the ones selling the product [24]. To which, the individuals will have control over their behavior to purchase a product [1]. This justifies why PBC was considered a significant latent. Subsequently, if people have the means, option to choose, and resources, they will have a direct effect on actual purchase of clothing apparel.

Following which is the promotion and product, having a significant effect on actual purchase of clothing apparel. Based from the indicator of promotion, endorsement, product promotion, and sales would lead to a positive influence of an individual to actually purchase clothing apparel. Consequently, trend, availability, color choices, and quality were seen to be the indicators for products. Ong et al. [1] discussed how people are sensitive towards brand of a product. Sales and other types of promotion would also encourage people to actually purchase a product [25].

During the COVID-19 pandemic, businesses were greatly affected. Therefore, the findings of this study would contribute in helping to develop businesses by creating a lot of options, availability of products, create promotions, and have influences on their brand to enhance buyers. The utilization of social media and other platforms may increase brand recognition, spread promotional news and offers, and even utilize the platform to present available products. This will entice people to continue shopping despite the COVID-19 pandemic.

5. Conclusion

The challenge for businesses during the COVID-19 pandemic increased. The lockdown implemented across the world decreased sales and led to consider new strategies of different industries to enhance people's actual purchase. With that, this study considered predicting factors that influenced actual purchase of clothing apparels during the COVID-19 pandemic.

Utilizing DLNN, this study was able to predict SN as the highest contributing factor with 95% accuracy, followed by promotion, product, and PBC. It was seen that businesses such as clothing apparels should have high availability and option, widely promoted products, consider sales and promotions, and influence people to entice individuals to purchase during the COVID-19 pandemic. Following the study of Ong et al. [11], promotion based on monetary and non-monetary value such as influential promotion to purchase clothing due to environmental factors may be taken into consideration. Since SN was seen as the most significant factor, then promotion revolving about friendship and family may be considered to highlight how bonds may be formed. Since economic, environmental, and economics aspect are a challenge to the supply chain such as that of the clothing industry during the COVID-19 pandemic, it would be advised to build on promotion and product to highlight the purchasing intention and actual purchase of consumers [26]. Strategies such as reduce total cost and high marketing strategies could be built around the findings of this study.

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