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A DUAL-CHANNEL SUPPLY CHAIN STRUCTURE ANALYSIS OF CONSUMER BEHAVIOR IN SHOPPING CHANNEL PREFERENCES

Olyvia Novawanda[1,*], Andi Besse Riyani Indah[2]
[1]Department of Industrial Engineering, Universitas Surabaya, Jalan Raya Kalirungkut, Surabaya 60293, Indonesia
[2]Department of Industrial Engineering, Universitas Hasanuddin, Jalan Malino No.8F, Gowa 92171, Indonesia
e-mail: olyvianovawanda@staff.ubaya.ac.id[1)], a.besseriyani@unhas.ac.id[2)]

ABSTRACT

Physical stores and online stores are one way that companies can continue to survive amidst competition by increasing profits from these two channels. Clothing is one of the textile commodities that is widely traded through physical stores and also online stores. This research identifies the factors that have the most significant influence on consumer preferences in choosing physical stores or online stores. Determining the factors involved adopts the results of previously conducted research. Based on existing research, there are several factors, namely Financial Risk, Performance Risk, Psychological Risk, Perceived Risk, Environment Quality, Service Quality, Internet Experience, and Switching Intention. From these variables, eight hypotheses were formed. All hypotheses from the model were processed using Structural Equation Modeling with SmartPLS 3 software, it was found that Financial risk has a positive effect on perceived risk (H1), Performance risk has a positive effect on perceived risk (H2), Performance risk has a positive effect on perceived risk (H3), Perceived risk has a positive effect on switching intention (H4), Environmental quality has a positive effect on switching intention (H5), and Need for touch has a positive effect on switching intention (H7) are accepted. Whereas Service quality has a positive effect on switching intention (H6) and Internet experience provides a moderating effect on the relationship of the need for touch and switching intention (H8) are rejected.

Keywords*: dual-channel supply chain, consumer behavior, switching intention*, SEM PLS

A. INTRODUCTION

In the current era of digitalization, e-commerce is something that is commonly found in everyday life. Electronic commerce or e-commerce is the trading of goods or services through electronic media. [1] explains e-commerce as financial and information transactions carried out on electronic media between an organization and the stakeholders related to it. One type of transaction in electronic media is a transaction between businesspeople and end consumers or, commonly referred to as B2C (Business to Consumer).

E-commerce is often used in the business-to-customer (B2C) model. In the B2C business model, producers distribute their products to consumers not only conventionally (offline) but also through online media to make them more effective and efficient. One implementation is the Dual Channel Supply Chain (DCSC) concept. Through the implementation of DCSC, business people can maximize profits by utilizing online and offline channels in marketing products to end consumers [2]. Various studies discussing DCSC have been around for a long time. Zhang et al. [3] analyzed pricing and guarantees in a dual-channel supply chain structure for manufacturers and retailers, and [4] investigated the effect of showrooming on the pricing and service of companies that sell their products through dual channels. [5] investigated consumer behavior when dealing with online and offline channels, especially for differentiated and homogeneous products. Research discussing consumer behavior in choosing shopping media is also emerging. This phenomenon of consumer switching when choosing shopping channels is called switching behavior. Switching behavior is a change or movement behavior of consumers when using a service provider to predict the occurrence of switching behavior; switching intention is used [6].

In this research, the Structural Equation Model (SEM) method was used to process and analyze the data. There are several reasons for the superiority of using SEM, including being able to analyze complex relationships between latent variables (not directly observed), allowing testing mediation and moderation effects in one model, and taking measurement error into account in the analysis, resulting in more accurate estimates [7].

This paper aims to evaluate factors that can influence consumer preferences to move from online to offline when buying clothes. In this research, the factors that influence consumer preferences to move in one direction, namely from online to offline channels, are analyzed. By knowing consumer preferences when buying clothing using the DCSC structure, it is hoped that companies operating in the apparel retail industry can increase customer trust, satisfaction, and service, help formulate strategies, and help companies not have to sacrifice their shopping channels.

B. LITERATURE REVIEW

The concept of managing a supply chain with two channels has received considerable attention in recent academic literature. Research has examined different areas, such as the influence of consumers' preference for low-carbon products on pricing choices [8], the incorporation of environmental considerations and digital solutions in supply chain management [9], and the value of supply chain integration in marketing through bibliometric analysis [10].

Research on consumer behavior in dual channel supply chain structures is also emerging. Consumer behavior in dual-channel supply chain is a complex subject that is influenced by a variety of factors. Studies have underscored the significance of consumers' low-carbon preferences in influencing pricing decisions [8], the influence of customer value creation on channel selection behavior in green supply chains [11], and the role of consumer-bounded rationality and loss aversion in supply chain coordination and pricing decisions [12] [13]. These papers highlight the importance of comprehending consumer behavior, preferences, and psychological factors in dual-channel supply chains.

C. RESEARCH METHOD

This paper evaluates the role of each factor that can influence consumer preferences in switching shopping channels from online to offline when shopping for clothes. Research conducted by [14] introduced a consumer switching intention model in the DCSC structure of clothing retailers by using a push-pull mooring (PPM) approach in identifying each factor. Push Pull Mooring (PPM) was introduced in 1885 and later became the theoretical basis for research on human migration behavior [15]. In line with research conducted by [16], which discusses the shift in customer behavior between the two shopping methods, the PPM framework is considered very relevant for providing in-depth insight and identifying influencing factors. This research adopts a switching behavior model based on research [14], and measures are carried out to determine the significant factors that influence customers' intention to switch from online to offline stores when buying clothes. Push factors are factors that motivate customers to leave online stores and switch to offline stores. Pull factors are positive factors in offline stores that can attract customers to choose offline stores while mooring factors are factors that can prevent or make this movement easier. This research uses structural equation model (SEM) analysis to measure factors that have a significant influence, apart from that, because the variables involved in the model are variables that cannot be observed directly or are latent variables.

According to [14], there are four factors that are classified as push factors that can influence consumer switching behavior, namely, financial risk, performance risk, psychological risk, and perceived risk. Pull factors consist of environmental quality, service quality, and need for touch (NFT), while what acts as a mooring factor is consumer experience in using the internet. The relationships between variables in the structural model are presented in Figure 1. below [14].

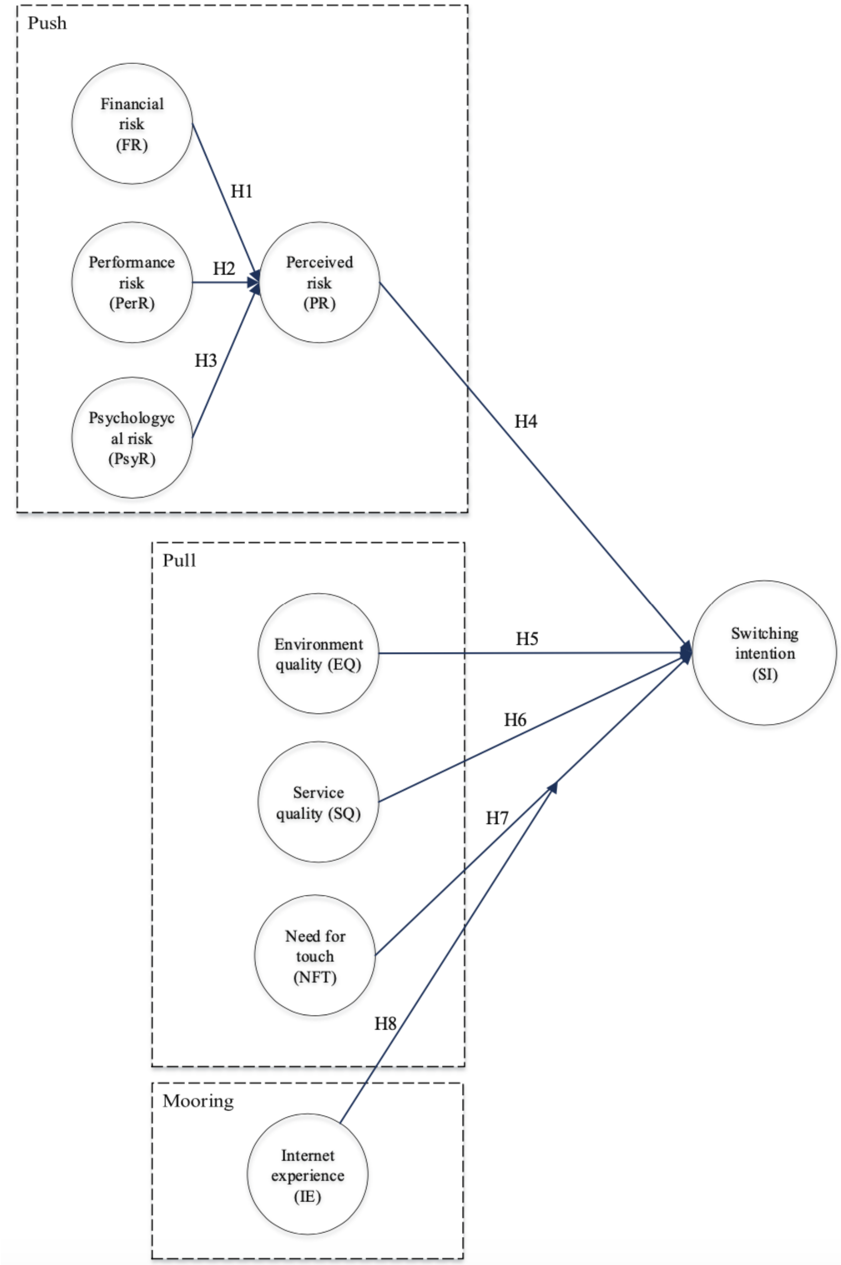

Figure 1. Online-Offline Structural Model

Based on the image above, research [14] formulated the following hypothesis.
H1: Financial risk has a positive effect on perceived risk.
H2: Performance risk has a positive effect on perceived risk.
H3: Psychological risk has a positive effect on perceived risk.
H4: Perceived risk has a positive effect on switching intention.
H5: Environmental quality has a positive effect on switching intention.
H6: Service quality has a positive effect on switching intention.
H7: Need for touch has a positive effect on switching intention.
H8: Internet experience provides a moderating effect on the relationship of the need for touch and switching intention.

The questionnaire was prepared based on the variables contained in the model. Next, the indicators for each variable are translated into questions in the questionnaire, which will be answered by each respondent. The questionnaire assessment in this study was carried out using a Likert scale technique. The Likert scale is used to measure attitudes, responses, and perceptions of a person or group of people towards a phenomenon [17]. This study uses an even Likert scale category to avoid middle values; this is because, in this study, the positive or negative attitudes of respondents are measured. The number of samples used is greater than or equal to ten times the total of the largest structural paths of one construct [18]. In this research, the questionnaire was aimed at consumers who had shopped for clothes in physical stores and online stores. The SEM model consists of a measurement model and a structural model. The measurement model is used to test the relationship between indicators that represent the latent variable being measured. Meanwhile, the structural model is used to test the relationship between latent variables.

a. Measurement Model Testing (Outer Model)
   The measurement test on SEM PLS is carried out by testing internal consistency and validity testing. The validity test consists of convergent validity and discriminant validity. This validity test is carried out to evaluate whether each latent variable has appropriate indicators and is able to define the variable.
b. Structural Model Testing (Inner Model)
   Structural model testing to show how good the proposed research model is by testing existing hypotheses. Structural model analysis with SEM was carried out by testing the coefficient of determination, effect size, predictive relevance, goodness of fit index, and hypothesis testing.

Data processing was carried out using descriptive statistical testing, testing the measurement model (outer model) and testing the structural model (inner model).

D. RESULTS AND DISCUSSION

A total of 313 respondents were involved in this research. In this research, it was found that age influences a person's choice of shopping channel; this is in line with research conducted [19]. SEM analysis was carried out using SmartPLS3 software. Testing of the measurement model (outer model) includes testing for internal consistency and validity (convergent validity and discriminant validity) with a threshold value of 0.7 [20]. Testing internal consistency values uses loading factor values (outer loading) and composite reliability values shown in Table 1. below.

Table 1. Loading Factor and Composite Reliability Values

Indikator	*Outer Loading*	*Composite Reliability*
FR1	0,864	
FR2	0,853	0,865
FR3	0,758	
PerR1	0,890	
PerR2	0,865	0,893
PerR3	0,816	
PsyR1	0,924	
PsyR2	0,892	0,932
PsyR3	0,899	
PR1	0,828	
PR2	0,883	0,898
PR3	0,879	
EQ1	0,839	
EQ2	0,832	0,877
EQ3	0,847	
SQ1	0,896	
SQ2	0,924	0,914
SQ3	0,826	
NFT1	0,898	
NFT2	0,894	0,942
NFT3	0,907	

NFT4	0,886	
IE1	0,764	
IE2	0,914	0,833
IE3	0,681	
SI1	0,890	
SI2	0,927	0,923
SI3	0,866	
Cut-off Value	≥ 0,7	≥ 0,7

From the table above it is known that all indicators are reliable, which is indicated by outer loading and composite reliability values exceeding 0.7. So, these indicators are considered capable of reflecting each latent variable. Validity testing is carried out at the indicator level with latent variables called convergence validity, and latent variable level validity testing is called discriminant validity testing. Convergence validity testing is carried out by calculating the Average Variance Extracted (AVE) value with a minimum value of 0.5 [21], the AVE value is in Table 2. Meanwhile, discriminant validity testing is carried out by looking at the Fornell-Larckel Criterion value. The Fornell-Larckel Criteria values can be seen in table 3.

Table 2. Average Variance Extracted (AVE) Value

Variable	*Average VarianceExtracted* (AVE)
EQ	0,704
FR	0,683
IE	0,627
NFT	0,804
PR	0,746
PerR	0,735
PsyR	0,820
SI	0,800
SQ	0,780

Based on [21], all AVE values are greater than 0.5, so it can be concluded that the relationship between the indicators and the latent variables is valid.

Table 3. Fornell-Larckel Criterion Values

	EQ	**FR**	**IE**	**NFT**	**PR**	**PerR**	**PsyR**	**SI**	**SQ**
EQ	0,839								
FR	0,458	0,826							
IE	-0,114	-0,125	0,792						
NFT	0,505	0,394	-0,030	0,896					
PR	0,496	0,632	-0,054	0,387	0,864				
PerR	0,552	0,674	-0,095	0,539	0,662	0,857			
PsyR	0,546	0,641	-0,106	0,567	0,711	0,793	0,905		
SI	0,470	0,572	-0,103	0,475	0,537	0,570	0,552	0,895	
SQ	0,594	0,444	-0,074	0,707	0,442	0,503	0,513	0,474	0,883

In discriminant validity testing, if the Fornell-Larckel Criterion value is greater than the correlation value between a particular latent variable and all other latent variables involved in the model, then the discriminant validity is declared valid or appropriate. From table 3. above, it can be seen that the correlation value of the latent variable is greater than the correlation with other latent variables, so validity is considered adequate.

Structural model testing was also carried out by testing the coefficient of determination (R^2), effect size (f^2), predictive relevance (Q^2), goodness of fit index (GoF), and hypothesis testing. The measurement of the coefficient of determination (R^2) value carried out on the endogenous latent variable ≥ 0,25 indicates a strong influence [22], the following table 4. shows the value of the coefficient of determination (R^2).

Table 4. Coefficient Determination Value (R^2)

Variable	R^2
PR	0,566
SI	0,401

From the table above, it is known that the (R^2).value is greater than 0.25, which means that the influence of the predictor variables on these two endogenous variables is strong. Next, to measure the influence of an independent variable on the dependent variable that is correlated with it, the effect size (f^2) is used.

Table 5. Effect Size Value (f^2)

Variable	Ukuran Pengaruh (f^2)
FR → PR	0.078
PerR → PR	0.017
PsyR → PR	0.148
PR → SI	0.141
EQ → SI	0.019
SQ → SI	0.006
NFT → SI	0.031
IE*ISB → SI	0.015

Another criterion used to evaluate structural models is predictive relevance (Q^2). If the value of Q^2, is greater than 0, this indicates that there is predictive relevance, while a value of Q^2, that is less than 0 means that there is no predictive relevance. The model shows predictive relevance, so the model can accurately predict data that is not used in evaluating the model [23]. The following table 6. displays the predictive relevance values of endogenous variables.

Table 6. Predictive Relevance Value

Variable	Q^2
PR	0,388
SI	0,296

From table 6. above, it can be seen that the Q^2 value exceeds 0, so it is concluded that this switching intention model can evaluate data that is not used to evaluate the model. The next step is to test the Goodness of Fit (GoF) of the model, which is used to validate the model as a whole. There are three levels of goodness of fit value criteria, namely 0,10 means small GoF, 0,25 medium GoF, and 0,36 large GoF. From the calculation results, the GoF value for this online-offline channel switching intention model is 0,600, which means that the entire model is valid.

The final step in the structural equation model analysis is hypothesis testing by measuring the significance of the influence between latent variables as seen from the path coefficient value (β), the calculated T value, and the P value of each relationship in the model which is presented in the following table 7.

Table 7. Path Coefficient Value, T value, and P value

Hypothesis	Path	Path Coefficient value (β)	T value	P value	Result
H1	FR → PR	0,257	4.236	0.000	Accepted

H2	PerR → PR	0,149	1.828	0.034	Accepted
H3	PsyR → PR	0,428	4.244	0.000	Accepted
H4	PR → SI	0,348	4.551	0.000	Accepted
H5	EQ → SI	0,141	1.890	0.030	Accepted
H6	SQ → SI	0,095	1.221	0.111	Rejected
H7	NFT → SI	0,196	2.549	0.006	Accepted
H8	IE*NFT → SI	-0.087	1.056	0.146	Rejected

E. CONCLUSION

Based on testing the questionnaire data, variables were obtained that influence consumer preferences for changing channels. In this online-offline channel switching intention model, it was found that Financial Risk (FR), Performance Risk (PerR), Psychological Risk (PsyR), Perceived Risk (PR), and Environmental Quality (EQ) influence consumer preferences to prefer offline stores compared to shopping for clothes via online platforms. Meanwhile, service quality (SQ) does not influence consumer preferences to switch to offline stores, nor was internet experience (IE) found that experience using online media will have a moderating effect on the relationship between need for touch (NFT) and switching intention (SI) variables.

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