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Abstract

The study focuses on developing a conceptual model to explore the factors influencing consumers' judgments in the decision-making process with a prime focus on personalized dynamic pricing (PDP). The study explored the judgmental impact of PDP on customer willingness to pay and mediating role of stickiness to the online store on PDP fairness and customer willingness to pay. The data was collected using a structured questionnaire administered among 256 students at a large university in India. SEM using AMOS software was used to analyze data. Price perception, involvement, product knowledge, and recommendation system positively impact price fairness of PDP, directly and indirectly influencing customer willingness to pay. Results also showed that stickiness to online stores fully mediates the relationship between price fairness of PDP and customer willingness to pay. Theoretically, the study contributes to pricing and marketing literature by identifying the antecedents of price fairness of PDP. For practitioners, this study signifies the importance of a robust recommendation system to stand out from the competition and provide deals to satisfy consumers. Specifically, the results emphasize the need to focus on stickiness to an online store to track consumer characteristics and customer value.

Keywords: Personalized dynamic pricing, stickiness to an online store, customer willingness to pay, recommendation system, price fairness.

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1. Introduction

Personalization of prices is gaining popularity as a viable pricing option in an online context (Priester et al., 2020). Personalized pricing improves a firm's profit by 19% compared to optimized uniform pricing and 86% compared with the firm's status quo pricing. Moreover, personalized pricing can benefit more than 60% of customers compared to the firm's uniform pricing (Dubé & Misra, 2019). Technological advancements and data analytics enable online retailers to adopt dynamic pricing strategies that help identify and track individual online consumers on a real-time basis (Priester et al., 2020).

Personalized dynamic pricing (PDP) is influenced by consumers' prior experience, interpersonal price comparison, date, time of purchase, gender, location, device used (Lastner et al., 2019), buyers' cultural differences, social norms in setting the price (Garbarino & Maxwell, 2010; Broeder & Wildeman, 2020) and the quantity purchased. Existing literature has studied the impact of PDP on consumer trust, loyalty, seller choice, price-setting mechanism, and competitor prices. Also, another stream of research focuses on regulatory implications of PDP, such as privacy concerns, legal concerns, societal and consumer welfare implications (Priester et al., 2020).

Customer perception of PDP can impact a firm's positioning and pricing strategies among its competitors (Krämer & Kalka, 2017). Hence this paper explores the role of price perception of PDP and its impact on customer willingness to pay in an Indian ecommerce context. Moreover, recent reports highlight the need for a comprehensive study on the advantages of PDP for consumers (Acquisti et al., 2016; Priester et al., 2020) and understanding PDP from the customer's perspective (Dubé & Misra, 2019). Our paper explores these research gaps. Objectives of this study are:

- To explore the role of price consciousness, involvement, product knowledge, and recommendation system in influencing price perception of PDP and customer willingness to pay
- To examine whether stickiness to online stores mediates the relationship between price perception of PDP and customer willingness to pay.

2 Literature Review

2.1 PDP and Price Fairness Perception

The first step of online shopping would be the entry of a search query by the consumer. The e-commerce platform displays a two-stage search result, for which the recommendation system considers the data comprising detailed browsing histories by each consumer. Ideally, a list of relevant products which a consumer can choose from appears. Second, consumers evaluate only a handful of products based on price, features, and reviews, which form the consideration set. Browsing data

from these two product/price search stages can be used by e-commerce firms to estimate consumer demand and provide personalization of the marketing mix (Dinerstein et al., 2018).

Following is an overview of how e-commerce firms use online consumer data to provide personalized dynamic pricing. Internet-based technology-mediated platforms enable e-commerce firms to track all individual customer activities. Online consumers are the source for data in analytics and recommendation system (Dinerstein et al., 2018). Firms need to comprehend how consumers select, use, and dispose of products and services to understand consumer behavior. The paper conceptualizes the consumer buying process in 3 stages: pre-purchase, purchase, and post-purchase (Lemon & Verhoef, 2016). We emphasize the series of activities in the pre-purchase phase, where a consumer pays attention to price during a product search in a platform. While shopping online, consumers use multiple modes to search prices of products (Dinerstein et al., 2018). E.g., a consumer looking to purchase a product online may check for the price listed in e-commerce platforms like Amazon, Flipkart, etc., or use comparison sites or price tracking tools like Keepa to track price fluctuations. Next, a consumer may sign in or not, view incognito mode, or ask friends/family to check for the price. Based on these activities, consumers form price perception.

Price perception is the evaluation of a specific price by consumers. "Fair" is a global measure of price acceptability (Lichtenstein et al., 1988). One stream of literature on price fairness literature explores factors influencing fairness perception and other consequences of fairness perception. Prior research has examined fairness perception of PDP in diverse contexts and its relationship with other constructs like customer's evaluation of price (reference price) and retailer price. The study adopts the definition by Xia et al. (2004) that defines price fairness as "customers' perceptions and their related emotions about how fair, acceptable, and reasonable the difference is between two prices."

The study draws from equity theory to explain how consumers perceive the price. It states that fairness depends on how much consumers are aware of and compare themselves with others' situations (Adams, 1965). Consumers would compare input or output with others to bring to or receive from the same setting. The theory explains price fairness in terms of equality, advantaged inequality (actual price is lower when compared to reference price), and disadvantaged inequality (actual cost is higher when compared to reference price). In advantaged inequality outcome, the actual price is lower than the reference price. Moreover, purchase history-based personalized dynamic price is fairer as consumers link the offered display price to their behavior based on purchase history (Priester et al., 2020). Hence, consumers justify the price received from the e-commerce store and consider it fair due to advantaged inequality.

3. Conceptual Model

Drawing from equity theory, the conceptual model is developed to include antecedents that influence the perception of PDP and its impact on willingness to pay mediated by stickiness to an online store. Existing literature provides evidence that price consciousness (Zielke & Komor, 2015), product knowledge (Chen et al., 2019), involvement (Koufaris et al., 2001), and recommendation system (Hazee et al., 2017) influence PDP judgments of consumers in the decision-making process. Hence, the study uses these variables in the conceptual model.



Figure 1: Proposed model and hypotheses

3.1. Price Consciousness

Consumers prefer online shopping due to convenience and relatively lower prices than an offline store. The intention to find out the lower price is defined as price consciousness, and it impacts consumer price perception (Zielke & Komor, 2015). Through their cognitive process, consumers perceive the price of a product and convert them into meaningful information. Price consciousness helps consumers evaluate price cues (Lichtenstein et al., 1988). In the PDP context, consumers view, track, encode the price displayed in an online store and assign meaning to the price to make it more personal or psychological. One of the antecedents for psychologically consumers accepting the product's price is price consciousness. Technology has enabled consumers to search for lower prices and better deals. Hence, we posit:

H1: Price consciousness will play a positive role in influencing price perception of PDP

3.2. Product Knowledge

Product knowledge is defined as the familiarity and expertise of a product (Rao & Sieben, 1992). Familiarity depends on the purchase, use, or experience of a product. The ability to perform product-related tasks is expertise. Highly knowledgeable consumers fully process product information, including price. They perceive the product to have high quality will be willing to pay more. Consumers acquire product knowledge through product descriptions and visual aids. Consumer product knowledge influences their purchase decisions (Chen et al., 2019). Based on this, we posit:

H2: Product knowledge will play a positive role in influencing price perception of PDP

3.3. Product Involvement

Consumer involvement in a product impacts its price acceptability. The degree to which the product is essential to the buyer is product involvement (Zaichkowsky, 1985). Product involvement positively influences information search behavior. When product involvement is high, consumers dedicate a significant amount of time and effort to decide on their choice. In an online context, involvement impacts consumers' decision to return to the store (Koufaris et al., 2001). Highly involved online consumers read through the product description, browse the image gallery, and watch demo videos (Sheth & Unnikrishnan, 2020). The impact of involvement on price perception varies depending on the type of product purchased, either durable or convenience goods. Hence, we posit,

H3: Product involvement will play a positive role in influencing price perception of personalized dynamic price.

3.4. Recommendation System

A recommendation system is defined as a system that generates a personalized, optimized experience for a customer selected from discrete options (Burke et al., 2011). A personalized pricing recommendation system provides price personalization using customer data such as preferential data and purchasing histories. Algorithms predict customers' preference patterns based on preferential data. Consumer preference patterns and purchase histories determine price discounts. The precision and prediction accuracy of the recommendation system impact consumers' reliability on the recommendation system and influence consumer purchase decisions (Burke et al., 2011). Consumers using an e-commerce platform should consider the reliability of other consumer behavior because the behavior of other users also impacts personalization (Hazee et al., 2017). Consumers can get reliable recommendations and price personalization which influence consumer willingness to pay (Lee & Rha, 2016). Hence, we posit:

H4: Recommendation system will play a positive role in influencing price perception of personalized dynamic price.

3.5. Impact of PDP on Willingness to Pay

In today's digital world, consumers interact with firms through a myriad of touchpoints comprising multiple media and channels (Lemon & Verhoef, 2016). Hence, switching between stores and price information is readily available at minimal search cost. Considering the dynamic nature of PDP, the product's price could vary multiple times within a day. When price difference exists, price perception is affected, influencing willingness to pay (Basaran & Buyukyilmaz, 2015; Sheikh & Basti, 2015). The study identifies consumers' willingness to pay as an outcome of consumers' perception of personalized dynamic pricing. Thus, we posit:

H5: Price perception of PDP will play a positive role in influencing customers' willingness to pay.

3.6. Stickiness to Online Store (SOS) on Customer's Willingness to Pay

Digitally influenced consumers in India search for at least 2-3 weeks before making their purchase decision (Sheth & Unnikrishnan, 2020). This behavior can influence the personalization of services by online retailers, where consumers may be aware or unaware of what they do during the pre-purchase phase (Jain et al., 2019). Before making a purchase, potential shoppers browse more than 20 product pages for a few categories and 50 to 60 product pages for specific product categories like mobile phones and women's ethnic wear, and they spend less than 9 minutes per visit on an e-commerce platform in India (Sheth & Unnikrishnan, 2020). Stickiness is a critical success factor. It helps e-commerce platforms to measure the duration of each visit, helps retain online customers and prolong their period during each stay. Personalization in online services results in a higher level of enjoyment that further leads to increased intention to stay longer and to use or purchase from the online store, thereby leading to customer willingness to pay. SOS is used to measure the frequency and duration of the visit by a consumer. Next, to find out the impact of stickiness on an online store, we study its role as a mediator on WTP and price perception of PDP (Roy et al., 2014). Hence, we posit:

H6: In a PDP context, stickiness to an online store will mediate the effect of price perception of PDP and customer willingness to pay.

4. Research Methodology

4.1. Sample and Data Collection

The study used data collected from students at a large university in India for hypothesis testing. Students are the most innovative and active users of websites, apps, and online shoppers (Gefen et al., 2003). Wang et al. (2001) state that using students as the sample for online studies is justified because they are the same as online customers for their psychological processes. Moreover, students have access to the internet and use them for communication and transaction purposes hence justified for using them as in sample online research and e-retailing studies. To check

whether the personalized dynamic pricing phenomenon exists during the study period, we conducted a price tracking exercise using multiple accounts with different browsing characteristics (Richard et al., 2016). Within half an hour, we noticed different prices for consumers, as shown in Table 1 below. The study used the information in Table 1 to describe the scenarios while asking participants to respond to our survey.

S No	Date	Timestamp	Customer account type	Price displayed	Offers suggested
1	17.1.2019	11.32 am	Without Signing In	Rs.37,999	2 offers
2	17.1.2019	11.34 am	New user	Rs.37,999	2 offers
3	17.1.2019	11.33 am	Intermittent shopper with low purchase value	Rs.37,999	3 offers
4	17.1.2019	11.36 am	Regular customer with high purchase value	Rs.39,200	1 offer
5	17.1.2019	11.38 am	Non-regular customer with high purchase value and purchased the same model	Rs.39,200	1 offer

Table 1: Price tracking of personalized	dynamic p	ricing from a	a leading e-
commerce website in India			

The respondents were asked to go through the given scenario and respond to the questionnaire. The scenario adapted and modified from Richard et al. (2016) read as follows, "Imagine you planned to purchase an Air conditioner and to search for a model. Your friend purchased a model a few days back for Rs. 38,500. Interested in buying the same model, you check for the price and ask your family members to see the price displayed. You see the price as shown in Table 1. How would you perceive the price displayed? Based on your perception, kindly fill the questionnaire". The students responded to the survey based on their online shopping experience on a five-point Likert scale. Data were collected through online Google forms questionnaire and pen and paper from April 2019 to September 2019 from 500 respondents, out of which 280 completed the survey. Twenty-four responses were removed because of incomplete responses. Finally, 256 valid responses were accepted with a response rate of 51%. The demographic profile of the sample size (256) comprised 59.7% male and 40.3% female respondents and belonged to the age group of 18-32 years.

4.2. Research Instrument

Measure for price consciousness adopted from Lichtenstein et al. (1993) consists of 3 items modified for our study. Product knowledge has three items adapted from Brucks (1985). Involvement consists of 5 items (Zaichkowsky, 1985). Recommender system (5 items) measures from Lee and Rha (2016) and price perception measure

consist of 3 items adopted from Xia et al., 2004. Measures for willingness to pay consisted of 3 items (Richards et al., 2016), and stickiness to online store consisted of 3 items from Lin (2007). All items were pilot tested on a sample of 31 and had a high-reliability score with Cronbach's alpha coefficients above the recommended level of 0.7. Table 2 shows the measurement instrument.

4.3. Data Analysis and Results

Data assessed for normality assumption using Maximum Likelihood (ML) estimation revealed that kurtosis and skewness of variables in the study were between -1.117 to 1.393 and -1.012 to 0.933 respectively and well within the recommended acceptable range of \pm 1.96 for ML estimation (Bollen & Stine, 1992).

4.3.1. Measurement Model

A two-stage structural equation modeling used AMOS 22.0 to test the measurement model and analyze the structural model (Anderson & Gerbing, 1988). Confirmatory factor analysis (CFA) confirmed construct validity of the constructs using the bootstrapping method with n = 2,000 at 90% confidence level, and bias-corrected intervals were executed. Table 2 summarizes CFA results. We modeled factors using the ML approach. The model had excellent reliability with fit indices χ 2= 337.1, d.f. = 197, p-value = .000, RMSEA = 0.41, SRMR = 0.053, CFI = 0.972 which is well within the recommended cut off limit (RMSEA < 0.06, SRMR < 0.08, CFI > 0.95). Thus, the model shows a good fit (Hu & Bentler, 1999). Other fit indices (NFI = 0.93, AGFI = 0.94) were also high, showing a good fit.

Scale items	Factor loadings (λ)	Cronbach alpha (α)	Composite Reliability	AVE	Mean	SD
Price consciousness	0.70				2 75	0 77
lam more willing to take extra effort to find lower prices	0.76				3.75	0.77
I believe the time it takes to find low prices is worth the effort.	0.82	0.85	0.86	0.65	3.94	0.84
I believe that money saved by finding lower prices is worth the time.	0.79				3.79	0.93
Product knowledge						
The product information given on a retailer	0.89				2.33	0.91
website is clear enough to me. It is clear to me how the product works.	0.98	0.92	0.75	0.53	2.39	0.90
I know exactly what the product is.	0.85				2.41	0.89
Involvement I would be interested in reading information about how the product is made.	0.68				3.83	0.94

Table 2: Measurement model results

I would be interested in reading the consumer reviews and checking price comparison sites about this product I compare product characteristics among brands. I think there are great differences among brands. I have the most preferred brand of this product.	0.77 0.66 0.89 0.78	0.88	0.84	0.56	4.02 3.69 3.93 3.89	0.88 0.99 0.84 0.88
Recommender System Through recommender system, I can get personalized prices tailored to my interests and needs. I can get personalized prices tailored to my activity contexts. I can get personalized prices tailored to my shopping patterns. I can reduce my time and effort in finding the shopping information I need. I can get shopping information more easily and conveniently.	0.80 0.76 0.91 0.87 0.78	0.90	0.88	0.57	3.49 3.46 3.66 3.55 3.57	0.81 0.85 0.87 0.95 1.02
Price perception of PDP Personalized dynamic pricing is fair. Personalized dynamic pricing is acceptable. Personalized dynamic pricing is reasonable.	0.76 0.66 0.63	0.82	0.85	0.62	3.72 3.75 3.86	0.83 0.74 0.92
Willingness to pay I am willing to pay the price displayed on a retail website I am willing to pay the price displayed based on my preferences I am willing to pay the price displayed based on my purchase and browsing history	0.82 0.89 0.83	0.85	0.87	0.68	3.69 3.66 3.77	0.89 0.85 0.83
Stickiness to an online store I intend to continue using an online store for shopping. I intend to purchase from an online store in the future. I spend more time on a retail website than other comparable websites I visit a retail website more frequently than other comparable websites I spend more money on a retail website than on other comparable websites	0.94 0.91 0.73 0.67 0.58	0.91	0.88	0.69	3.33 3.32 3.47 3.50 .53	0.92 0.95 1.04 0.95 1.08

Note: *** Statistically significant at p < 0.001

The convergent validity was measured by examining the parameter estimates. The item to total correlation values range from 0.75 to 0.88, and the average variance

extracted (AVE) ranges from 0.53 to 0.65, thereby showing high convergent validity (Fornell & Larcker, 1981). Also, the average variance extracted of the factors exceeded the squares of its correlation with other constructs, showing discriminant validity of the measures (Fornell & Larcker, 1981).

	RS	PC	РК	I	PP	SOS	WTP
Recommender system (RS)	0.75						
Price consciousness (PC)	0.01	0.81					
Product knowledge (PK)	0.17	-0.03	0.73				
Involvement (I)	0.01	0.59	-0.13	0.77			
Price perception of PDP (PP)	0.12	.03	0.42	0.09	0.83		
Stickiness to online store (SOS)	0.18	0.43	0.34	-0.56	0.20	0.79	
Willingness to pay (WTP)	0.35	0.23	0.02	0.35	0.25	0.54	0.75

Table 3: Discriminant validity

4.3.2. Common Method Bias

The study took several precautions to minimize common method variance (CMV) impact. First, the study did not collect personal information to ensure the anonymity of responses. Second, a five-point Likert scale format to reduce the commonalities in scale endpoints and anchoring effects. Harman's single-factor test was used to examine potential common method bias (Podsakoff et al., 2012). In a one-factor solution, our data had 24.65% of an eigenvalue which is lesser than the recommended critical value of 50%. This result confirms that our model is free from common method bias and CMV is not a significant problem in this study (Podsakoff et al., 2012).

4.3.3. SEM Results

Using AMOS 22, the structural model represented in Figure 1 was tested. Table 4 shows the results. Structural model had good fit indices with $\chi 2 = 386.512$, df = 161, $\chi 2/df = 2.400$, RMSEA = .055 (RMSEA < 0.06), SRMR = 0.068 (SRMR < 0.08) and CFI = 0.968 (CFI >0.95) with all indices higher than the recommended cut off values. Other fit indices NFI = 0.93, AGFI = 0.94 also showed a good fit. The results were analyzed and found to support all our hypotheses. Results indicated that price perception has a significant positive impact on price perception of PDP ($\beta = 0.12$, p<0.01), thereby supporting H1. Product knowledge has a significant positive impact on price perception determine the price perception of PDP ($\beta = 0.11$, p<0.05), supporting H2.



Figure 2: Structural Model with Beta Coefficients of Direct and Indirect Effects

Note: *p <0.05; **p<0.01; ***p<0.001

Involvement has a significant positive impact on price perception of PDP ($\beta = 0.16$, p<0.01), supporting H3. The recommender system significantly affects price perception on PDP ($\beta = 0.48$, p<0.001), thereby supporting H4. The results showed a significant positive impact of price perception of PDP on WTP ($\beta = 0.47$ p<0.001), thereby supporting H5. SOS causally affects WTP. We calculated the mediating parameters in a model simultaneously. We adopted a user-defined estimand in AMOS to test the hypothesized indirect effect (Gaskin, 2016). As predicted, SOS plays a mediating role in impacting willingness to pay ($\beta = 0.28$, p<0.001), supporting H6. The results show that stickiness mediates the relationship between price perception of PDP and willingness to pay.

Hypotheses	Path coefficient	t- value	Result
H_1 : Price Consciousness \rightarrow Price perception of PDP	0.12 **	2.69	Supported
H_2 : Product Knowledge \rightarrow Price perception of PDP	0.11 *	2.01	Supported
H_3 : Involvement \rightarrow Price perception of PDP	0.16 **	2.85	Supported
H ₄ : Recommender System $ ightarrow$ Price perception of PDP	0.58 ***	8.96	Supported
H_5 : Price perception of PDP \rightarrow WTP	0.47 ***	7.76	Supported
H_6 : Price perception of PDP → Stickiness to an online store Stickiness to online store → WTP	0.44 *** 0.31***	7.90 5.32	Supported

Table 4. Hypotheses and results

Note: *p <0.05; **p<0.01; ***p<0.001

Table 5 mentions the mediation result. The t-value of the mediation is significant, with a value of 8.09. The indirect effect with a value of 0.13 lies well within the lower and upper cut-off confidence interval of 0.09 to 0.18. Thus, showing full mediation.

Path tested	Direct	Indirect effect	Indirect effect confidence level		p-	Conclusion
	mediator		Lower	Upper	value	
Price perception of PDP \rightarrow Stickiness to online store \rightarrow WTP	0.29 (8.09)	0.13	0.09	0.18	0.001	Full Mediation

Table 5. Mediation results

Note: Values presented are regression coefficients - t-values in parentheses

5. Discussion

Results showed that the recommendation system appears to have a more significant direct influence on price fairness of PDP and an indirect impact on willingness to pay. Collectively, price consciousness, product knowledge, involvement, recommendation system combines to influence price fairness perception to influence further willingness to pay mediated through SoS. Much of the knowledge gained from existing offline retailing research applies to the online retailing context (Jiang & Rosenbloom, 2005). Overall, the results showed support for all hypotheses. It can be observed from data analysis that our model had a good fit.

There are some interesting findings of this study to be pointed out consistent with previous studies. Price is an essential factor in consumer decision-making and the purchase process. Therefore, it largely influences fairness perception and consumer behavioral outcomes. The results showed price consciousness directly affects the perception of price fairness of PDP and indirectly influences willingness to pay. Our results are consistent with past studies that provide empirical evidence that PDP impacts the fairness perception of consumers. As expected, product knowledge had a significant association with price fairness of PDP, which in turn is related to customer willingness to pay (Chen et al., 2019). Similarly, involvement has a significant association with price fairness of PDP, which in turn is related to customer willingness to pay (Malar et al., 2011).

6. Implications

6.1. Theoretical Implications

The study adds the role of the recommender system to the extant research. To enable retailers to provide personalized prices, the role of the recommender system is vital. 35% of revenue generated from Amazon.com was through recommendations

based on sophisticated algorithms and predictive models (Mackenzie et al., 2013). Consumers' reliability on the recommendation system, precision, and prediction accuracy plays a vital role in influencing purchase decisions. The study links the function of the recommender system in directly influencing the price fairness of PDP and an indirect influence on willingness to pay. The key finding of the research is that the recommender system is vital among other antecedents for the price fairness of PDP evident from a higher t-value (8.96).

Consumer loyalty in the e-marketplace is complex. Hence stickiness to online stores has to be considered. Drawing parallels from the study of Beatty and Smith (1987), an involved consumer will spend a lot of time and effort to find their product and price offered through the online store by visiting the online store site frequently. Not many studies have studied the mediating role of SoS on price fairness and willingness to pay (Roy et al., 2014). This finding is a welcome addition to literature seeking to understand the role of stickiness in customers' willingness to pay. It is important because customer stickiness to online stores signifies a psychological attachment to visiting those sites (Roy et al., 2014). Also, the results show the full mediation effect of SoS on price fairness and willingness to pay.

Finally, our study provides a significant contribution to pricing literature. Most of the existing studies had focused on studying how price and pricing strategies affect consumer purchase decisions in a traditional economy setting. At the same time, this paper focused on examining consumer characteristics influencing price personalization and how it impacts customer fairness perception.

6.2. Managerial Implications

This paper explores customer willingness to pay as the vital outcome in a PDP context. It also investigates the mediating role of stickiness to the online store on customer willingness to pay. We have included antecedent that affects the price fairness of PDP. In addition, this study offers important insights for companies to understand online consumer behavior. Understanding how consumers perceive personalized dynamic pricing in an electronic marketplace is vital. It impacts decision-making at a micro-level in marketing management and a macro-level in policy decision-making by organizations and regulators. First, the results found that online shoppers will feel special and acknowledged to receive a personalized price, resulting in a willingness to pay.

Given the phenomenal growth of online retailing accelerated by external factors such as pandemics and competition among leading players (Sheth & Unnikrishnan, 2020), enticing consumers is one of the critical requirements for an online retailer to sustain intense competition and prevent switching behavior among consumers. Also, about 74% of online buyers do not have a brand fixed before they start searching for their product and most of the consumers search for around 2 to 3 weeks on an online platform (Jain et al., 2019). Firms can use this search duration window to attract consumers by providing personalized offers through recommendation systems. Data

captured through stickiness to an online store can aid firms in arriving at customized offers. Second, information on the product sought should be readily available on the site so that consumers can browse through and decide without any search frictions. Visual aids detailed product information to help consumers understand the products is essential. These aids can improve consumer knowledge and involvement towards the product (Ford et al., 2018). This aspect can also be addressed by having clear and visual assistance to product description.

Over time, customer characteristics and determination of customer value potential keep evolving. A reliable method to periodically evaluate customer value measures is necessary for managers to track changing customer characteristics. In ecommerce, platform stickiness can be used to assess customer value by looking at the frequency and duration of visits and the number of purchases the consumer has made. Thus, it is evident that the antecedents chosen for study in this paper provide insights into customer value co-creation and price fairness of PDP.

7. Limitations and Future Research

While this research has some significant contributions, it has its limitations too. For instance, it did not consider the role of risk attitude on personalized pricing, which may have affected the perception of fairness. Future research can study the part of risk attitude among consumers to understand various pricing cues and explore its impact on consumers' real buying behavior. Studies can do further experimental investigation on the influence of norms and price transparency on customer perception of fairness (Güngör & Bilgin, 2011; Kaynak & Eksi, 2011; Arcuri, 2020). Analyzing how firms can arrive at the segmentation base of PDP, its impact on personalization-privacy and trust can also be explored. Lastly, future studies could be extended to identify potential consequences of unfair perception of personalized price, looking into the intervening effects of personalized social media advertisements and personalized prices. The dynamic nature of PDP and impulse purchase behavior can be explored further (Naikoo et al., 2021).

References

Acquisti, A., Taylor, C., & Wagman, L. (2016). The Economics of Privacy. *Journal of Economic Literature*, 54(2), 442–492. <u>https://doi.org/10.1257/jel.54.2.442</u>

Adams, J. S. (1965). Inequity in Social Exchange. *Advances in Experimental Social Psychology*, 267–299. <u>https://doi.org/10.1016/s0065-2601(08)60108-2</u>

Anderson, J. C., & Gerbing, D. W. (1988). Structural equation modeling in practice: A review and recommended two-step approach. *Psychological Bulletin*, *103*(3), 411–423. https://doi.org/10.1037/0033-2909.103.3.411

Arcuri, M. C. (2020). General Data Protection Regulation (GDPR) implementation: What was the impact on the market value of European financial institutions? *Eurasian Journal of Business and Economics*, 13(25), 1–20. <u>https://doi.org/10.17015/ejbe.2020.025.01</u>

Basaran, U., & Buyukyilmaz, O. (2015). The effects of utilitarian and hedonic values on young consumers' satisfaction and behavioral intentions. *Eurasian Journal of Business and Economics*, *8*(16), 1–18. <u>https://doi.org/10.17015/ejbe.2015.016.01</u>

Beatty, S. E., & Smith, S. M. (1987). External search effort: An investigation across several product categories. *Journal of Consumer Research*, *14*(1), 83. <u>https://doi.org/10.1086/209095</u>

Bollen, K. A., & Stine, R. A. (1992). Bootstrapping goodness-of-fit measures in structural equation models. *Sociological Methods & Research*, 21(2), 205–229. https://doi.org/10.1177/0049124192021002004

Broeder, P., & Wildeman, N. (2020). The color red for emotion in cross-cultural e-commerce. *Eurasian Journal of Business and Economics*, 13(25), 75–89. <u>https://doi.org/10.17015/ejbe.2020.025.05</u>

Brucks, M. (1985). The effects of product class knowledge on information search behavior. *Journal of Consumer Research*, *12*(1), 1. <u>https://doi.org/10.1086/209031</u>

Burke, R., Felfernig, A., & Göker, M. H. (2011). Recommender Systems: An overview. *Al Magazine*, *32*(3), 13–18. <u>https://doi.org/10.1609/aimag.v32i3.2361</u>

Chen, J., Wang, H., & Gao, W. (2019). How do goal and product knowledge specificity influence online channel choice? A polynomial regression analysis. *Electronic Commerce Research and Applications*, *35*, 100846. <u>https://doi.org/10.1016/j.elerap.2019.100846</u>

Dinerstein, M., Einav, L., Levin, J., & Sundaresan, N. (2018). Consumer price search and platform design in internet Commerce. *American Economic Review*, *108*(7), 1820–1859. https://doi.org/10.1257/aer.20171218

Dubé, J.-P., & Misra, S. (2017). Personalized pricing and consumer welfare. *NBER Working Paper Series*, Working Paper: 23775. <u>https://doi.org/10.3386/w23775</u>

Ford, D. L., Ziegler, L. L., Fang, R., & Holmes IV, O. (2018). Exploring knowledge sharing in a professional network: A Central Eurasian case. *Eurasian Journal of Business and Economics*, *10*(20), 1–22. <u>https://doi.org/10.17015/ejbe.2018.021.01</u>

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, *18*(1), 39–50. <u>https://doi.org/10.1177/002224378101800104</u>

Garbarino, E., & Maxwell, S. (2010). Consumer response to norm-breaking pricing events in ecommerce. *Journal of Business Research*, *63*(9-10), 1066–1072. <u>https://doi.org/10.1016/j.jbusres.2008.12.010</u>

Gaskin, J. (2016) "My Indirect Effects" User-Defined Estimand for AMOS from Gaskination's StatWiki.

Gefen, D., Karahanna, E., & Straub, D. W. (2003). Trust and TAM in online shopping: An integrated model. *MIS Quarterly*, 27(1), 51-90.

Güngör, Ö. M., & Bilgin, Z. F. (2011). Customer's Advisory, Organizational Openness, and Capability: The Locus of Value Creation. *Eurasian Journal of Business and Economics*, *4*(7), 81–97.

Hazée, S., Delcourt, C., & Van Vaerenbergh, Y. (2017). Burdens of access: understanding customer barriers and barrier-attenuating practices in access-based services. *Journal of Service Research*, 20(4), 441-456. <u>https://doi.org/10.1177/1094670517712877</u>

Hu, L., & Bentler, P. M. (1999). Cut-off criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling: A Multidisciplinary Journal*, 6(1), 1–55. <u>https://doi.org/10.1080/10705519909540118</u>

Jain, N., Sanghi, K., and Pateriya, A. (2019). "Digital Powers Consumer Durables: A \$23Bn opportunity by2023". Available at: <u>https://www.bcg.com/en-in/digital-powers-consumer-durables-a-23-bn-opportunity-by-2023</u>

Jiang, P., & Rosenbloom, B. (2005). Customer intention to return online: Price Perception, attribute-level performance, and satisfaction unfolding over time. *European Journal of Marketing*, *39*(1/2), 150–174. <u>https://doi.org/10.1108/03090560510572061</u>

Kaynak, R., & Eksi, S. (2011). Ethnocentrism, Religiosity, Environmental and Health Consciousness: Motivators for Anti-Consumers. *Eurasian Journal of Business and Economics*, 4(8), 31-50.

Koufaris, M., Kambil, A., & Labarbera, P. A. (2001). Consumer behavior in web-based Commerce: An empirical study. *International Journal of Electronic Commerce*, *6*(2), 115–138. https://doi.org/10.1080/10864415.2001.11044233

Krämer, A., & Kalka, R. (2017). How digital disruption changes pricing strategies and price models. In A. Khare, B. Stewart, & R. Schatz (eds.), *Phantom Ex Machina* (pp. 87-103). Springer <u>https://doi.org/10.1007/978-3-319-44468-0_6</u>

Lastner, M. M., Fennell, P., Folse, J. A., Rice, D. H., & Porter, M. D. (2019). I guess that is fair: How the efforts of other customers influence buyer price fairness perceptions. *Psychology & Marketing*, *36*(7), 700–715. <u>https://doi.org/10.1002/mar.21206</u>

Lee, J.-M., & Rha, J.-Y. (2016). Personalization–privacy paradox and consumer conflict with the use of location-based Mobile Commerce. *Computers in Human Behavior, 63,* 453–462. https://doi.org/10.1016/j.chb.2016.05.056

Lemon, K. N., & Verhoef, P. C. (2016). Understanding customer experience throughout the customer journey. *Journal of Marketing*, *80*(6), 69–96. <u>https://doi.org/10.1509/jm.15.0420</u>

Lichtenstein, D. R., Bloch, P. H., & Black, W. C. (1988). Correlates of price acceptability. *Journal of Consumer Research*, 15(2), 243. <u>https://doi.org/10.1086/209161</u>

Lin, J. C.-C. (2007). Online stickiness: Its antecedents and effect on purchasing intention.Behaviour& InformationTechnology,26(6),507–516.https://doi.org/10.1080/01449290600740843

MacKenzie, I., Meyers, C., and Noble, S., (2013). How retailers can keep up with consumers. Available at: <u>https://www.mckinsey.com/industries/retail/our-insights/how-retailers-can-keep-up-with-consumers</u>

Malär, L., Krohmer, H., Hoyer, W. D., & Nyffenegger, B. (2011). Emotional brand attachment and brand personality: The relative importance of the actual and the ideal self. *Journal of Marketing*, 75(4), 35-52. <u>https://doi.org/10.1509%2Fjmkg.75.4.35</u>

Naikoo, M. W., Peer, A. H., Ahmed, F., & Ishtiaq, M. (2021). Monetary policy and Housing Prices Dynamics in India. *Eurasian Journal of Business and Economics*, 14(27), 47–61. https://doi.org/10.17015/ejbe.2021.027.03

Podsakoff, P. M., MacKenzie, S. B., & Podsakoff, N. P. (2012). Sources of method bias in social science research and recommendations on how to control it. *Annual Review of Psychology*, *63*(1), 539–569. <u>https://doi.org/10.1146/annurev-psych-120710-100452</u>

Priester, A., Robbert, T., & Roth, S. (2020). A special price just for you: Effects of personalized dynamic pricing on Consumer Fairness Perceptions. *Journal of Revenue and Pricing Management*, *19*(2), 99–112. <u>https://doi.org/10.1057/s41272-019-00224-3</u>

Rao, A. R., & Sieben, W. A. (1992). The effect of prior knowledge on price acceptability and the type of information examined. *Journal of Consumer Research*, *19*(2), 256. <u>https://doi.org/10.1086/209300</u>

Richards, T. J., Liaukonyte, J., & Streletskaya, N. A. (2016). Personalized pricing and Price Fairness. *International Journal of Industrial Organization, 44,* 138–153. https://doi.org/10.1016/j.ijindorg.2015.11.004

Roy, S. K., M. Lassar, W., & T. Butaney, G. (2014). The mediating impact of stickiness and loyalty on word-of-mouth promotion of retail websites. *European Journal of Marketing*, *48*(9/10), 1828–1849. <u>https://doi.org/10.1108/ejm-04-2013-0193</u>

Sheikh, S. M., & Basti, M. (2015). Customer satisfaction in business to consumer (B2C) ecommerce: A comparative study of Turkey and Pakistan. *Eurasian Journal of Business and Economics*, 8(16), 73–100. <u>https://doi.org/10.17015/ejbe.2015.016.05</u>

Sheth, A. & Unnikrishnan, S. (2020, June 16). *How India shops online*. Bain & Company, Inc. <u>https://www.bain.com/insights/how-india-shops-online/</u>

Wang, Y-S., Tang, T-I. and Tang, J-E.E. (2001). An instrument for measuring customer satisfaction toward web sites that market digital products and services, *Journal of Electronic Commerce Research*, *2*(3), 89-102.

Xia, L., Monroe, K. B., & Cox, J. L. (2004). The price is unfair! A conceptual framework of Price Fairness Perceptions. *Journal of Marketing*, *68*(4), 1–15. <u>https://doi.org/10.1509/jmkg.68.4.1.42733</u>

Zaichkowsky, J. L. (1985). Measuring the involvement construct. *Journal of Consumer Research*, 12(3), 341. <u>https://doi.org/10.1086/208520</u>

Zielke, S., & Komor, M. (2014). Cross-national differences in price–role orientation and their impact on retail markets. *Journal of the Academy of Marketing Science*, *43*(2), 159–180. https://doi.org/10.1007/s11747-014-0379-4