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Factors Influencing Consumer Behavior and Prospective Purchase Decisions in a Dynamic Pricing Environment—An Exploratory Factor Analysis Approach

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Abstract: The rapid advancements in information and communication technology during the third industrial revolution of the late 20th century has marked the beginning of a new era in the retail sector with the introduction of E-commerce. The dawn of the new century witnessed industry 4.0, revolutionizing all areas of online business by bringing in novel opportunities and possibilities. Despite the progress in technology, the determination of correct pricing on online selling platforms still remains a very complex task. The adoption of big data technology has enabled online sellers to make real-time price changes of high magnitude and proximity. However, with increasing awareness among buyers regarding modern pricing strategies, it is necessary to examine probable changes in consumer behavior when exposed to dynamic pricing scenarios. This study investigates the factors that influence consumer behavior, and their prospective online purchase decisions in a dynamic pricing context, through an exploratory factor analysis approach. A primary research survey was conducted, and 178 samples were finalized for data analysis through a series of web surveys completed by respondents in India. This study identifies, measures and classifies 27 research items into variables, namely shopping experience, privacy concerns, awareness about dynamic pricing, buying strategy, fair price perceptions, reprisal intentions and intentions for self-protection. These seven factors could be used to explain consumer behavior in a dynamic pricing situation.

Keywords: dynamic pricing; E-commerce; industry 4.0; big data; consumer behavior; India

1. Introduction

Since the third industrial revolution, information and communication technology has become widespread and the E-commerce sector has shown tremendous growth which outpaced the growth of the traditional retail business sector. The worldwide sales of the retail E-commerce sector recorded 2.3 trillion US dollars in 2017, and is expected to rise around 4.88 trillion dollars by 2021 (Statista 2018). As per the Indian Brand Equity Foundation report, business in the Indian E-commerce sector alone was worth 15 billion US dollars in 2016 and is expected to reach 63.7 billion dollars by 2020. According to the PwC report on E-commerce in India (PwC Report 2014), online retail and online marketplaces are the fastest growing segments within the E-commerce space, and these are more than doubling in size every two years. Books, apparel, accessories and electronics constitute about 80% of the products sold through eTailing. India is also witnessing increasing adoption of smartphones, tablets and 4G services, which has widened the online consumer base. This, combined with a larger number of homegrown eTail companies, innovative business models and a young customer base willing to spend online, has led to a vibrant eTail market in India.

India is among the fastest growing economies in the world, with a significantly large percentage of young and internet-savvy consumers. As a result, it has become a target for global E-commerce businesses. The Indian economy is driven mainly by a young demographic market segment, with around 75% of internet users in the 15 to 34 years age group. Their presence online is substantially driven by peer pressure, rising education and aspirations, and growing interest in global fashion and lifestyle trends. Although internet penetration is lower by percentage in India, its absolute size is comparable to larger markets, such as the United States and those in Europe, and it is quickly catching up with the online market size of China. Additionally, favorable government policy, which allows 100% FDI in business to business (B2B) E-commerce, is expected to boom the E-commerce market of India further in the coming years (IBEF Report 2017). The growth in the E-commerce sector in India is due to many contributory factors, including a rise in the number of internet users, adoption of modern technology and alternative payment methods offered by E-commerce sellers (Harish 2017). All of these factors, in conjunction with a rise in confidence in doing business in India, makes the market very attractive for large foreign players and portfolio investors who are witnessing slower growth elsewhere. The latest development in the large saga of investment is the takeover of the homegrown Indian eTail giant Flipkart by Walmart.

The growth of E-commerce business received an impetus globally with the advent and spread of industry 4.0, a term first used in 2011 by the Fraunhofer-Gesellschaft institute. The German Federal Government identify industry 4.0 as a synthesis of internet of things and cyber physical systems, interacting and cooperating with each other and with the humans within the system (Kagermann et al.; Ślusarczyk 2018). Industry 4.0 is characterized by highly automated factories, warehouses, products and services, etc. (Stock and Seliger 2016). The newest form of industrial revolution is digitalizing each and every aspect of business, including logistics, purchases, supply chain and sales processes, which will result in E-commerce accruing 90% of the global commercial transactions in the near future (Geissbauer et al. 2016).

Foreseeing the growing opportunities, the E-commerce sector in India is attracting many global players. International companies have brought forth advanced and sophisticated technological capabilities in the areas of consumer analytics and recommendation systems, which have already become a challenge for local companies. Stiff competition has given way to both price and non-price competition among companies. One of the most commonly practiced pricing strategies in the E-commerce sector is the dynamic pricing strategy, which, in economic terms, is an individual level pricing strategy based on real-time information (Haws and Bearden 2006).

Dynamic pricing is not an entirely novel concept. It is the most modern form of price discrimination. Price discrimination is an age-old practice employed by sellers to sell their products at different prices (Krugman 2000). In traditional markets, sellers are able to decipher the ability of customers to pay, which enables them to make tailor-made prices for each customer. For stores in the online marketplace, information about consumer identity was uncertain until the advent of big data analytics. With big data analytics, it is possible to gather and know a great deal about the prospective and actual customers without meeting them physically. Firms can now change prices more rapidly and offer tailor-made, targeted advertisements for individual online consumers, as well as tailor a price for an individual customer based on their income, spending habits, past purchases, online reviews and social media engagements, etc. Dynamic pricing has now become a norm in the E-commerce sector as the menu cost in the internet market is minimal. The cost of changing prices in internet marketing is negligible and online sellers can easily experiment with different prices to obtain a larger profit margin (Victor and Bhaskar 2017).

In order to make the best out of the dynamic pricing strategy, retailers require information about prospective consumers, such as their behavior, and the strategies of competitors. The internet of things and big data have made it possible for online sellers to use available information for chalking out tailor-made prices for both actual and prospective customers (Cox 2001). A number of studies have shown that when consumers are dissatisfied with the magnitude and proximity of the price changes, they resort to spreading negative comments about sellers and engage in behaviors which damage the brand name of sellers (Garbarino and Lee 2003; Kannan and Kopalle 2001; Kung et al. 2002; Kovács and Kot 2016; Victor and Bhaskar 2017).

Though there are numerous studies carried out in the area of E-commerce, there is a dearth in understanding about consumer traits in dynamic pricing environments; an area of growing interest in eTailing in India and globally. Gaining a better understanding in this area would empower eTailers to generate better strategies for dynamic online pricing, in order to gain a competitive advantage without hurting or losing their customer base.

Thus, the aim of this study was to investigate, measure and classify factors which influence consumer behavior and their prospective online purchase decisions, in a dynamic pricing context, through an exploratory factor analysis model.

2. Research Background

Industry 4.0 has transformed ordinary machines into intelligent systems, sensing and collecting necessary inputs required by themselves without human interventions, thereby improving the overall performance in a much more efficient manner. Industry 4.0 has made real-time data monitoring possible, enabling sellers to make price and output variations in accordance with changes in a wide range of factors (Vaidya et al. 2018). Dynamic pricing with the aid of big data is an efficient pricing strategy, facilitating variation in price mooted by complex algorithms.

In the past few decades, dynamic pricing has become a very common pricing strategy in many industries. It is considered a profitable strategy for airlines, hotels, cruises and rental cars, etc. (Kimes 2002; Duman and Mattila 2003; Sahay 2007). Not only does this pricing strategy offer huge profits, but it also helps to manage shortages in supply and in reallocating demand to the most suitable time periods (Sahay 2007). Dynamic pricing has become more common with the prevalence of internet marketing driven by big data analytics. It is an individual-level price discrimination strategy in which the prices differ based on customer, location, product or time (Kotler and Armstrong 2010). Dynamic pricing is commonly defined as the buying and selling of goods where prices adjust freely in accordance with the demand and supply at the individual transaction level. Retailers, especially eTailers, have the potential to use the latest available information to form the best prices for consumers.

Until the 1960s, the economic models and thoughts on consumer behavior relied on the assumption of rationality. It was assumed that consumers were always rational in their purchases and therefore bought products which gave them maximum satisfaction (Le and Liaw 2017). The economic, sociological, psycho-analytic and learning models developed prior to 1979 show that consumers exhibited a conservative behavioral pattern in buying products (Kahneman and Thale 2006). The period of global economic crisis in 2008 resulted in consumer behavior tending towards a defensive one as they bought fewer products than they usually did (Le and Liaw 2017). The popularity of online marketing gave way to internet of things to play a bigger role in purchase decisions, as people began using the internet to order products and compare prices and features of products they were interested in. The modern customer has a wide range of products to choose from, further complicating the decision-making process and consumer behavior (Trifu and Ivan 2014).

The dynamic pricing strategy has been adopted by sellers with an intention to maximize their revenue with the aid of big data. Many business to consumer (B2C) and business to business (B2B) companies in the E-commerce sector have already adopted the dynamic pricing strategy (Elmaghraby and Keskinocak 2003). It is relatively easy to apply the dynamic pricing strategy in E-commerce due to the ease of access to consumer data. Using big data analytics techniques, it is possible to more accurately segment consumers into much smaller units, enabling online sellers to provide tailor-made advertisements and prices for each customer. It is also possible to vary prices for every sale offer (Kung et al. 2002). From the theoretical aspect of the transaction cost theory in E-commerce (Devaraj et al. 2002; Williamson 1979), online firms that use data analytics for products and price recommendations have benefited greatly by improving the market transaction cost efficiency, managerial transaction cost efficiency, and time cost efficiency. The most modern technology, which uses cookies and clickstream data, etc., allows sellers to make real-time price changes at minimum cost by analyzing the customer traffic, customer demographics, and preference data, etc. (Elmaghraby and Keskinocak 2003; Mak et al. 2018).

The aspiration for successful and agile business plans promoted business intelligence, which was mooted by the internet of things and big data within the organizations. This enabled businesses to obtain useful customer information, thereby allowing for efficient decisions through identification of opportunities and threats, particularly by keeping an eye on customers, suppliers and competitors in real-time (Olszak and Zurada 2015; Oláh et al. 2018). One of the most important developments which evolved with the application of big data analytics was that customers became actively involved in the pricing decisions in the online market. Advanced search engines, web crawlers, shopbots and novel E-commerce models, and group buying, etc., provide customers with opportunities to be a part of the price determination process (Kung et al. 2002).

Consumer behavior has been a major subject of market research since the beginning of the 21st century. Studies have mainly focused on the behavior and attitudes of consumers towards different brands, offers, sellers and business strategies (Mokrysz 2016). Deksnyte and Lydeka (2012) discuss the factors which form a proper dynamic pricing strategy. The research points out customer behavior and characteristics, fair prices, market structure, product demand, and perception of product value as some of the most important factors which help in forming the right prices. One of the most important concerns of the consumers with regard to dynamic pricing is their price fairness perception (Kimes 2002; Sahay 2007). The perceived price fairness primarily depends on the amount of information that sellers unveil to the buyers (Choi and Mattila 2009).

A number of studies have reported consumer dissatisfaction due to high magnitude and rapid proximity of price changes, which leads to the spreading of negative information, buying from competitors or engaging in other actions which deteriorate the reputation of sellers (Dai 2010). Research has shown that increased revenues obtained from the dynamic pricing strategy will prevail only in the short run if a consumer cannot perceive a difference in the service received, as the consumer will view the situation as unfair (Kimes 2002). Hence, despite the potential gain from dynamic pricing, if consumer sentiments are not well understood and taken care of, the dynamic pricing strategy could have an adverse effect for an online firm.

After reviewing previous literature that attempted to study some facets of consumer behavior in an online purchase environment, several research items were adapted for measurement in this study. Firstly, Le and Liaw (2017) paper on big data and its impact on consumer behavior employed items such as user's ability to find useful information from the website, as well as their perception on how their privacy is safeguarded. For this research, several new, self-developed items were also refined in regards to online shopping experience and privacy concern measures, which were thought to better capture these constructs. Altogether, six items were adapted or newly developed in an attempt to measure consumers' online shopping experience and privacy concerns in a dynamic pricing environment.

Dai (2010) research, on the other hand, offered several measures for price fairness perception, reprisal intentions and self-protection intentions. In total, 12 items were adapted and self-developed to measure consumers' price fairness perception, reprisal intention and self-protection intention, for testing in this research.

This study also introduces nine new items to supplement some of the above items and to measure consumers' awareness about dynamic pricing and their online buying strategies in a dynamic pricing environment. These items were developed by the authors based on expert opinion and experience in online marketing research. All 27 items are presented in Table 1.

Table 1. Items used in the questionnaire.

Items	Measurement	References
1	I am able to search useful information in the e-shopping website	(Le and Liaw 2017)
2	Shopping Website can recommend substitute goods for the product I wish to buy	
3	The results provided are quick and fit my needs	
4	I believe product recommendation is very useful to me	
5	I fear that my personal information about payment method may be stolen	
6	I fear that my personal information may attract the attention of cyber criminals	
7	The price I paid was fair	(Dai 2010)
8	The price I paid was questionable	
9	The price I paid was justified	
10	I am satisfied with the price and purchase decision	
11	I will say negative things about the online retailer's pricing policy to others	
12	I will switch to the competitors of this online retailer after my experience with their pricing policy	
13	I will complain about the online retailer's pricing policy through online social networking channels such as Facebook, Twitter etc.	
14	I will complain to governmental agencies regarding the online retailer's pricing policy	
15	I will buy fewer products from this online retailer in the next few years	
16	I will stop buying products from this particular online retailer	
17	I will buy more products from this retailer in the next few years regardless of their pricing policy	
18	I will continue to buy the same product from this online retailer if I need it in the future	
19	I feel offended when online shopping websites use my personal information for product recommendations and changing prices	[Own Construction based on Expert Opinion]
20	I am not interested in sharing my personal information including browser history with online shopping websites to get personalized product recommendations	
21	I will consider the changing prices as an opportunity to buy products at lower prices	
22	I am aware that the shopping websites use the information collected for personalized product recommendations and advertisements	
23	I will motivate my friends and family to track the prices to avoid paying higher prices	
24	In future, I will track the price of the products which I intend to buy for a few days before purchase	
25	I will use some software applications or browser extensions to track the changes in the price of the product	
26	I am aware that the shopping websites collect personal information through browser cookies	
27	I am aware that the shopping websites use the information collected for making changes in the price of the products	

3. Materials and Methods

3.1. Sample Size

There are varying opinions regarding the sample size for a factor analysis. Disparities in studies with regard to the sample size is noted by Hogarty and Hines (2005). Some researchers suggest that the minimum sample size should be at least greater than 100 for factor analysis (Hair et al. 1995).

The survey data was collected from internet-savvy college students in South India. All participants had previous experience in using the internet and purchasing online. Many studies have demonstrated the viability of collecting data from students, especially for studies with an interest in online shopping (Gefen 2002; Kuo et al. 2009; Zhang et al. 2011). A purposive and intuitive sampling technique was used to choose the right respondents in order to include only those who had previous experience with online shopping. A total of 201 students participated in the study, with 16 responses being removed due to incomplete information and seven responses being removed for inserting inconsistent or conflicting inputs. The remaining 178 sample responses were finalized for analysis. The respondents fell into the age group of 20–27. The sample population comprised of 101 males and 77 females. All had made at least one online purchase in the last year. The total number of online purchases made ranged between 1 and 20. This outcome further asserts that the younger populace in India have strong online participation and are actively purchasing online.

3.2. Data Collection Procedure

The survey was conducted in the month of June 2018 at the computer labs of Saintgits Institute of Management, Kerala. A structured online survey was created using Google Forms and was distributed online to the respondents. They were first asked to navigate to the website www.amazon.in and add products to the cart without buying them. This was to provide the respondents some exposure to an online selling platform which rigorously uses big data analytics in personalizing product offerings and pricing mix. A previous study (Le and Liaw 2017) used a similar approach to study the positive and negative impacts of big data on purchase decisions. The products added by the respondents into their carts also validated the assumption that the primary products that would be shopped for online are apparels and electronics. A report by Ernest and Young (EY India E-commerce Report 2016) showed that the common denominator in a large majority of online shopping carts of men and women across different age categories was apparels and phones.

3.3. Analytical Approach

An exploratory factor analysis (EFA) method was used in the analysis to determine the number and nature of factors which explain the covariance structure of the data. EFA is a statistical model which explores the relationship pattern between the latent outcome measures (factors) and observed outcome measures (items) (Gerbin and Hamilton 1996; Litavcova et al. 2015). A factor means a list of items which are grouped together based on the loadings. These items are interrelated and define the given latent construct. Unrelated items are considered as items which do not belong to the group and do not explain the construct, and therefore need to be deleted (Munro 2005).

R Programming (RStudio) was used to do all the statistical estimations and tests. *psych* and *GPA rotation* packages were used to conduct the exploratory factor analysis and other reliability tests in R.

3.4. Measurement

The questionnaire used for this study was composed of two main parts. The first part of the questionnaire included questions to collect socio-demographic details of the respondents. The second part consisted of a hypothetical purchase scenario in which the respondents were exposed to a real price change and were asked to rate their reactions on the 27 items of measurement with regard to the dynamic pricing environment. The Likert scale, ranging from 1 = strongly disagree to 5 = strongly agree, was used to collect the responses.

4. Results and Discussion

Bartlett's sphericity test was applied to check whether the correlation matrix was an identity matrix. The p value for the Bartlett test was below 0.05, confirming that the data frame under consideration was not an identity matrix. The Kaiser-Meyer-Olkin (KMO) test of sample adequacy was conducted to check whether the sample collected was adequate. Hair et al. (2010) suggests that if the KMO value is greater than 0.6 and Bartlett's test of sphericity is significant, then factorability of the correlation matrix can be assumed; which, in other words, means the dataset is suitable for factor analysis. The value of KMO was found to be 0.67, which indicated that the dataset could be used for factor analysis.

With a valid Bartlett and KMO test score, we were able to proceed with the exploratory factor analysis. A wide range of methods are available for conducting a factor analysis, including the "maximum likelihood", "minimum residual", "principal axis", "weighted least squares", and "generalized weighted least squares", etc. For this study, the principal axis method was used. This method is very similar to the principal component analysis, with pre-specified priors consisting of a matrix of squared multiple correlations among variables. The principal axis method is one of the most commonly used methods for exploratory factor analysis (Tabachnick and Fidell 2001; Thompson 2004; Henson and Roberts 2006).

A parallel analysis was conducted to identify the number of items to be retained. The parallel analysis results suggested seven factors should be retained, and thus we proceeded with the factor analysis using seven factors. The rotation method used in this study was varimax. The ordinary least squares method (OLS) was used, with the factoring function fm = "minres". OLS method provides results using the 'maximum likelihood method', which does not assume multivariate normal distribution and finds the results through an iterative eigen decomposition, such as a principal axis. The output table showing factor loadings is given below in Table 2.

Table 2 shows the loadings of items on different factors. As per the parallel analysis results, the number of factors to be included for the analysis was seven, namely shopping experience (SE), buying strategy (BS), privacy concerns (PC), awareness about dynamic pricing (DP), fair price perceptions (FP), reprisal intentions (RI), and intentions for self-protection (SP). In Table 2, the number shown within the parenthesis indicates the serial number of the item, while the three-digit alphanumeric code indicates the acronym of the seven constructs, with the first two characters identifying the construct and the last digit identifying the item number within the construct. The items that were retained after the EFA with their respective construct names are attached in Appendix A as Table A1.

The items with insignificant loadings were eliminated in the first place, and only 21 out of 27 items were retained for further analysis. Items named SE2(2), FP2(8), SP1(15), SP2(16), RI1(11) and RI4(14) were removed. The cumulative variance observed was 0.51, which means that the seven factors explain 51% of the variance in the subject. For the factors MR3 and MR7, only two items were loaded. Raubenheimer (2004) suggests that if the scale uses only one factor, a minimum of four items should be loaded while scales with more than one factor identified with as little as two items are considered acceptable, in accordance with the type of the study conducted. In this study, the loadings of the factors MR3 and MR7 were high enough, which was important as these two factors pertained to the items concerning the reactions of consumers after the purchase, which were quite different from the rest of the items. Table 3 given below shows the residual test results.

Table 2. Factor pattern matrix for rotated loadings.

Item Names		MR3	MR4	MR2	MR6	MR5	MR1	MR7	h2	u2	com
Buying Strategy	**BS1 (24)**	−0.06	**0.57**	0.08	0.16	0.12	−0.11	0.16	0.51	0.589	1.6
	BS2 (25)	−0.12	**0.54**	−0.02	0.11	0.04	0.07	0.06	0.43	0.669	1.3
	BS3 (23)	0.13	**0.76**	0.09	0.22	0.00	−0.08	−0.05	0.65	0.347	1.3
	BS4 (21)	−0.01	**0.59**	0.16	−0.01	−0.04	0.03	0.03	0.58	0.618	1.2
Awareness of Dynamic Pricing	**DP1 (26)**	−0.05	0.12	0.13	**0.70**	0.01	−0.08	−0.04	0.54	0.464	1.2
	DP2 (27)	0.00	0.11	0.12	**0.73**	0.00	−0.06	0.03	0.56	0.443	1.1
	DP3 (22)	0.08	0.27	−0.02	**0.44**	−0.03	0.10	0.12	0.40	0.698	2.0
Fair Price Perceptions	**FP1 (7)**	0.03	0.02	0.13	−0.07	**0.66**	0.09	−0.11	0.47	0.525	1.2
	FP3 (9)	−0.10	0.05	0.08	0.01	**0.75**	0.12	0.17	0.62	0.379	1.2
	FP4 (10)	−0.01	0.02	0.09	0.05	**0.46**	0.11	−0.16	0.46	0.744	1.5
Shopping Experience	**SE1 (1)**	**0.85**	0.00	−0.02	−0.02	−0.06	−0.01	0.07	0.74	0.261	1.0
	SE3 (3)	**0.61**	−0.09	−0.03	0.03	−0.02	0.06	0.27	0.46	0.538	1.5
	SE4 (4)	**0.78**	0.00	−0.17	0.00	0.01	−0.01	0.04	0.64	0.357	1.1
Privacy Concerns	**PC1 (5)**	−0.05	0.00	**0.59**	0.23	0.13	−0.06	−0.04	0.42	0.576	1.5
	PC2 (19)	−0.03	0.18	**0.63**	0.03	0.07	0.17	0.06	0.46	0.535	1.4
	PC3 (20)	−0.02	0.06	**0.60**	−0.01	−0.01	−0.07	−0.10	0.48	0.618	1.1
	PC4 (6)	−0.15	0.07	**0.65**	0.06	0.20	−0.07	−0.05	0.50	0.504	1.4
Intentions for Self Protection	**SP3 (17)**	0.14	0.07	−0.10	0.07	0.03	−0.15	**0.55**	0.40	0.632	1.4
	SP4 (18)	0.18	0.13	−0.02	−0.01	−0.20	0.09	**0.75**	0.66	0.345	1.4
Reprisal Intentions	**RI2 (13)**	0.08	0.11	0.01	−0.08	0.14	**0.98**	−0.01	1.00	0.004	1.1
	RI3 (14)	−0.02	−0.09	−0.05	0.00	0.16	**0.46**	−0.04	0.45	0.753	1.4
		MR3	**MR4**	**MR2**	**MR6**	**MR5**	**MR1**	**MR7**			
SS Loadings		1.93	1.80	1.78	1.49	1.41	1.30	1.23			
Proportion Variance		0.09	0.08	0.08	0.07	0.06	0.06	0.07			
Cumulative Variance		0.09	0.17	0.25	0.32	0.38	0.44	0.51			
Proportion Explained		0.18	0.16	0.16	0.14	0.13	0.12	0.11			
Cumulative Proportion		0.18	0.34	0.50	0.64	0.77	0.89	1.00			

Note 1: Factor analysis using method = minres; Call: fa (r = x, nfactors = 7, rotate = "varimax", fm = "minres"); Standardized loadings (pattern matrix) based upon correlation matrix. **Note 2:** h2 shows communality. Significant factor loadings are in boldface. Reverse scored items are shown with negative signs.

Table 3. Residual test results.

Indicators	Values						
Root Mean Square of the Residuals (RMSR)	0.03						
Tucker Lewis Index (TLI)	1.00						
Root Mean Square Error of Approximation (RMSEA)	0.024						
	MR3	MR4	MR2	MR6	MR5	MR1	MR7
Correlation of (regression) scores with factors	0.91	0.87	0.85	0.84	0.85	1.00	0.83
Multiple R square of scores with factors	0.84	0.75	0.72	0.71	0.72	0.99	0.69
Minimum correlation of possible factor scores	0.67	0.50	0.44	0.42	0.45	0.99	0.39

The root mean squares of residuals (RMSR) value of 0.03 was in the range of acceptance as this value is close to zero. The root mean square index was 0.024, showing a good model fit as the value is well below 0.05. The Tucker–Lewis index (TLI) here was 1.00, while the cut off for TLI is 0.9.

The factors shopping experience (MR3), buying strategy (MR4), privacy concerns (MR2), awareness about dynamic pricing (MR6), fair price perceptions (MR5), reprisal intentions (MR1), and intentions for self-protection (MR7) all had significant loadings.

The factor MR3, named as shopping experience, explained 18% of the total variance. The items loaded to this factor were related to the usability of the shopping websites, usefulness of the search results and product recommendations provided by the shopping websites. This finding is in line with previous web usability research findings that highlighted the importance of web usability in determining user satisfaction (Nathan and Yeow 2009, 2011). The factor loadings for the items in MR3 ranged from 0.78 to 0.85.

The factor MR4, named as buying strategy, explained 16% of the total variance. The items loaded on this factor were related to the probable strategies that might be taken by the consumers after being exposed to a dynamic pricing scenario. Tracking the prices before purchase, using software to track prices and advising friends and family to track before purchase were the items loaded on this factor. The factor loadings ranged between 0.54 and 0.76.

The factor MR2, named as privacy concerns, explained 16% of the total variance. The items loaded were related to the concerns regarding the usage of personal information by the companies for personalized product recommendations (0.65) and prices (0.63), and fear that personal information including payment methods will be stolen (0.59) and may attract the attention of cyber criminals (0.60).

The items loaded on factor MR6, named as awareness about dynamic pricing, included awareness of customers about website cookies which collect personal information (0.70), awareness about using the collected data for product recommendations (0.73) and price changes (0.44). This factor explained 14% of the total variance. All item loadings were above threshold, and hence none were removed after the EFA.

The factor MR5, named as fair price perceptions, explained 13% of the total variance. This factor included items probing the attitude of people regarding the fairness of price they paid, if the price was justified and their satisfaction with the price they paid. Here, the factor loadings ranged between 0.46 and 0.75.

The factor MR1, named as reprisal intentions, explained 12% of the total variance. The items loaded to this factor were related to the intentions of people to take revenge against the seller, including complaining via posting on social media (0.48) and buying from the competitors (0.98). The item on tendency to say negative things about the online retailers to others had very low factor loading, and hence it was removed after the EFA. This is probably because users are more online savvy these days and complaining online via social media is more natural for them to show their reprisal of an online vendor.

The last factor MR7, named as intentions for self-protection, explained 11% of the total variance. The items loaded were related to the measures taken by the respondents to protect themselves from high fluctuations in prices. The items probed the desire of consumers to buy again from the same seller after being exposed to a dynamic pricing scenario (0.75), and their intention to stop purchase from the seller thereafter (0.55). Items with low loadings that were removed after the EFA included the measure of user intention to buy less—or stop buying altogether—from the online retailer. Interestingly, these items did not achieve the loading threshold, which indicates that users do not altogether shun an online seller due to a single previous price fluctuation experience.

Internal Consistency and Reliability of the Model

Internal consistency checks the correlation within the items in an instrument, and shows how well the given items fit to a conceptual model (Nunnally and Bernstein 1994; Devon et al. 2007). Cronbach's alpha is one of the most commonly used methods to test the reliability and internal consistency of the test items (Trochim and Donnelly 2006). Nunnally and Bernstein (1994) suggest that if there are two or more subscales in an instrument, Cronbach's alpha should be calculated for the individual subscales, as well as the entire scale as a whole. The *psy* package in R includes the Cronbach's alpha test. Table 4 gives the Cronbach's alpha for all 21 test items.

Table 4. Cronbach's alpha test.

Reliability Analysis							
Call: alpha(x = x, check. keys = TRUE)							
raw_alpha	std.alpha	G6(smc)	average_r	S/N	ase	mean	sd
0.73	0.73	0.82	0.11	2.7	0.034	3.6	0.42
lower	alpha	upper	95% confidence				
0.68	0.73	0.80	boundaries				

The raw alpha for the 21 items measured here was 0.73, which is satisfactory. This confirms the internal consistency and reliability of the model. According to Nunnally (1978), the minimum level of reliability for a model depends on how the model is being used. Lance et al. (2006) suggests that the requirement of having a Cronbach's alpha value above 0.70 for every measurement scale is an urban legend. The Cronbach's alpha for the subscales identified were all above 0.70, except MR3 (reprisal intentions), which had an alpha score of 0.68. Many researchers support the value of Cronbach's alpha ranging between 0.65 and 0.70 as acceptable. The Cronbach's alpha values for the subscales are given in Table 5.

Table 5. Cronbach's alpha test for the subscales.

Factor Number	Cronbach Alpha
MR1	0.72
MR2	0.80
MR3	0.68
MR4	0.71
MR5	0.75
MR6	0.77
MR7	0.70

5. Limitations and Future Research

Despite meeting the objectives that were set out for this research, there are a few limitations that were encountered during the study. This research investigated the impact on dynamic pricing in the Indian online retail context and, hence, the results are better suited to the Indian E-commerce industry. These findings may not be directly generalizable to other countries and regions due to differences in terms of economy, culture and technology. Furthermore, since the respondents belonged to the age group of 20–27, the results of this study may not be generalizable to the whole population of India. However, considering the size and growth of the Indian market and the share of youngsters in the total population, this limitation is not believed to discount the findings of the study. Additionally, the constructs that this study has identified and tested could be adapted by future research for testing in other regions and market and age segments.

Though the sample size selected for this research was found to be acceptable, a larger sample size could have resulted in a more convincing assessment of the behavioral and attitudinal perceptions towards dynamic pricing in an online environment. Furthermore, all of the respondents were from a similar age group, internet savvy and sufficiently educated. However, as this research is focused on the eTail customer, this is not a very significant limitation as this consumer segment constitutes about 75% of the Indian eTail market.

It is recommended that future research should carry out empirical tests on causal relationships between the constructs identified in this study and consumers' continual intention to purchase online, despite their awareness of online dynamic pricing.

6. Conclusions

This study has identified, measured and classified various online dynamic pricing environment measures into seven factors which could influence consumer behavior and prospective purchase decisions in a dynamic pricing situation. The results of the exploratory factor analysis identified shopping experience, awareness about dynamic pricing, privacy concerns, buying strategy, fair price perceptions, reprisal intentions and self-protection intentions as factors which could have a significant influence on consumer behavior and their prospective purchase decisions.

This study, in agreement with previous studies, points out that dynamic pricing decisions must be made carefully by figuring out their impact on consumer reactions. The results of this study, which pertain to an Indian population, also have implications for global players in the E-commerce sector. Sellers are keenly observing developments in the online business industry in rapidly growing economies like India and China. The Indian economy, driven mainly by young people, has already become a favorite destination for global players, such as Amazon and Walmart, etc. The Indian eTail marketplace has attained a critical mass, with a couple of large, established home-grown and foreign players further developing this market. With greater focus on digital India, this makes the Indian marketplace a very attractive place for more global players to enter.

With very high growth trajectory, there is a need for increased understanding of customer behavior and their reaction to dynamic pricing, in order to better address their privacy concerns, improve their perception of online pricing as not being deceitful, and increase their awareness of the positives of dynamic pricing as a win-win for both the buyer and seller. This will help to address reprisal attitudes and self-protection measures, such as completely avoiding the online channel or spreading negative comments, which could be very detrimental to the brand or the medium as a whole.

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Appendix A

Table A1. Items retained after Factor Analysis.

Variables	Items	Measurement	References
Shopping Experience	SE1 SE3 SE4	I am able to search useful information in the e-shopping website The results provided are quick and fit to my needs I believe product recommendation is very useful to me	(Le and Liaw 2017)
Awareness about Dynamic Pricing	DP1 DP2 DP3	I am aware that the shopping websites collect personal information through browser cookies I am aware that the shopping websites use the information collected for personalized product recommendations and advertisements I am aware that the shopping websites use the information collected for making changes in the price of the products	[Own Construction based on Expert Opinion]

Table A1. *Cont.*

Variables	Items	Measurement	References
Privacy Concerns	PC1 PC2 PC3 PC4	I am not interested in sharing my personal information including browser history with online shopping websites to get personalized product recommendations I feel offended when online shopping websites use my personal information for product recommendations and changing prices I fear that my personal information about payment method may be stolen I fear that my personal information may attract the attention of cyber criminals	(Le and Liaw 2017)
Price Perception	FP1 FP3 FP4	The price I paid was fair The price I paid was justified I am satisfied with the price and purchase decision	(Dai 2010)
Buying Strategy	BS1 BS2 BS3 BS4	In future, I will track the price of the products which I intend to buy for a few days before purchase I will use some software applications or browser extensions to track the changes in the price of the product I will consider the changing prices as an opportunity to buy products at lower prices I will motivate my friends and family to track the prices to avoid paying higher prices	[Own Construction based on Expert Opinion]
Reprisal Intentions	RI2 RI3	I will complain about the online retailer's pricing policy through online social networking channels such as Facebook, Twitter etc. I will complain about the online retailer's pricing policy through online social networking channels such as Facebook, Twitter etc.	(Dai 2010)
Self-Protection Intentions	SP3 SP4	I will buy more products from this retailer in the next few years regardless of their pricing policy I will continue to buy the same product from this online retailer if I need it in the future	(Dai 2010)

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