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The impact of surge pricing on customer retention

Kun-Huang Huarng[a,*], Tiffany Hui-Kuang Yu[b]

[a] National Taipei University of Business, No.100, Sec. 1, Fulong Rd., Pingzhen Dist, Taoyuan City 324, Taiwan, ROC
[b] Feng Chia University, 100 Wenhwa Road, Seatwen, Taichung, Taiwan, ROC

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ABSTRACT

This study explores how satisfied customers are when they face surge pricing as well as how customer satisfaction affects customer retention. This study uses fuzzy set/Qualitative Comparative Analysis to generate relations and then qualitative analysis with structural associations to propagate the values and refine these relations. Both methods together generate proper relations for multi-layered problems. With data gathered from a group of executive MBA students in Taiwan, the empirical results show that loyal riders are more tolerable to surge pricing than non-loyal riders. Lastly, the evidence presents that customer satisfaction does not always positively affect customer retention.

1. Introduction

Taking ride-sharing company Uber as the case study, we explore how surge pricing impacts customer satisfaction, because its surge pricing is a popular mechanism for balancing demand and supply. Surge pricing also helps service providers gain more profits during the high seasons (Li, Moreno, & Zhang, 2015). However, one question arises: How do customers feel about surge pricing?

With the development of the Internet and related technologies, the sharing economy has experienced rapid growth, as exemplified by Uber (Uber 2019) in transportation, Airbnb (Airbnb 2019) in lodging, and others. These sharing economy platforms offer a channel to connect users with service providers like Uber's driver-partners and Airbnb's lodging owners. Uber helps connect riders with nearby driver-partners (Hall, Kendrick, & Nosko, 2015), and both sides access Uber's platform via its website and mobile App. If a rider requests a ride, then the Uber App calculates the fare based on time and distance to travel. When there are limited driver-partners available, Uber applies a surge pricing algorithm to balance demand and supply. The algorithm assigns a multiplier upon the standard fare to derive the "surge" fare.

To justify Uber's use of surge pricing, Hall et al. (2015) analyze a couple of events. One example is the rise in demand after a sold-out concert in New York in 2015. The results show that the surge pricing mechanism did help with the completion of the requested rides. The second event happened on New Year's Eve in 2014. There was a big rise in demand after midnight, but the driver-partners were reluctant to work, because the value of their leisure time at that point was high. Hence, in the absence of surge pricing, the gap between supply and demand became large. From both events, that study concludes without surge pricing that supply can be a total failure for matching demand.

Diakopoulos (2015) contrarily examines 4 weeks of data of five locations in Washington D.C. provided by Uber and concludes that in fact the surge pricing model did not create more supply, but instead only re-distributed the existing cars. In other words, under surge pricing, higher prices and better service quality for some places mean worse service quality in some other places. Various studies suspect that surge pricing does generate huge benefits to Uber (Kosoff, 2015; Stoller, 2014). Compared with static pricing, Zha, Yin, and Du (2018) find that the surge platform and drivers generally enjoy higher revenue, whereas customers may be made worse off during high surge periods. These reports offer some evidence to challenge the impacts of surge pricing.

There has been a long series of studies in the literature focusing on the design of pricing mechanisms to balance demand and supply (Alali, Elder, & Zhou, 2019; Bernstein, DeCroix, & Keskin 2019; Thorbecke, 2019). Miyazaki (2003) echoes that abundant existing literature presents how a seller sets the price, but what is lacking is the perception of customers' reaction to the price. In other words, there is a research gap in exploring the impact of surge pricing upon customers' retention.

It is still undetermined whether surge pricing really balances demand and supply, not to mention to what degree does price discrimination exist (Tanner, 2014). Some riders even consider price gauging stems from surge pricing (Surowiecki, 2014). We thus explore how satisfied riders are when they do in fact face surge pricing.

Customer satisfaction is an important direct or indirect factor on customer retention. Han, Kim, Lee, and Kim (2018) conduct a study on customers at luxury restaurants, finding that customer satisfaction is

* Corresponding author.
E-mail addresses: khhuarng@ntub.edu.tw (K.-H. Huarng), hkyu@mail.fcu.edu.tw (T.H.-K. Yu).

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prominent in determining retention. Mahmoud, Hinson, and Adika (2018) survey customers of mobile telecommunication operators, confirming that trust and conflict handling have an indirect significant effect on customer retention via customer satisfaction. Chen and Liu (2019) examine the relationship between customer satisfaction and retention, showing that a firm's competitive status moderates the effect of customer satisfaction on retention in the Taiwan mobile market. Díaz (2017) also shows in a mobile phone market that customer satisfaction strongly influences customer loyalty, and in turn loyalty is an important determinant of customer retention.

Fuzzy set/Qualitative Comparative Analysis (fsQCA) has been proposed and widely recognized among social science studies as a qualitative research method based on fuzzy sets and set theory (Ragin, 2009). FsQCA provides multiple relationships with combinations of different antecedents (independent variables) that show all the possible causal relationships leading to the outcome (dependent variable). Huarng (2015b) uses fsQCA to establish a configural theory for information and communication technology development. Huarng and Yu (2015) employ fsQCA to explore the combinations of antecedents for health care expenditure, providing results with strong predictive validity. Yu, Huang, and Huarng (2016) apply fsQCA to analyze the causal complexity of economic development by types of energy consumption.

To extend the application of qualitative analysis to problems of multiple layers, Huarng (2016) proposes qualitative analysis with structural associations, for which subsequent studies have used it to solve various problems. For example, Phung, Ly, and Nguyen (2019) utilize qualitative analysis with structural associations to explore brand equity in different cases of service marketing. Huarng and Yu (2019) apply this method to compare the different relationships on satisfaction and then on repurchase intention between Airbnb and physical hotels. Gentina, Huarng, and Sakashita (2018) use the method to compare mothers' and daughters' clothing co-consumption behaviors.

As we shall investigate how Uber's surge pricing affects customer satisfaction and then customer retention, the rest of the paper runs as follows. Section 2 reviews the relevant literature on surge pricing. Section 3 introduces fsQCA, qualitative analysis with structural associations, and the data and presents a survey conducted with a group of EMBA students at Feng Chia University, Taiwan, including frequent and non-frequent Uber riders. Section 4 shows the empirical results. Section 5 provides some managerial implication based on the empirical analysis. Section 6 concludes.

2. Theoretical framework

Many studies have worked on issues related to surge pricing for different purposes. In economics, studies have looked into the elasticity of labor supply when workers have discretion over how much they work. Hall and Krueger (2018) examine the labor market for Uber's driver-partners, based on both survey and administrative data. Uber's driver-partners seem attracted to the platform, because of schedule flexibility, the compensation, and the fact that earnings per hour do not vary much with the number of hours worked.

Studies have also investigated the positive impact of surge pricing in a two-sided market, but most are based on a single location (Castillo, Knoepe, & Weyl, 2017; Taylor, 2018). Cachon, Daniels, and Lobel (2017) find that the optimal contract significantly increases the platform's profit relative to contracts that have a fixed price, and although surge pricing is not optimal, it generally achieves nearly the optimal profit. They conclude that all stakeholders can benefit from the use of surge pricing on a platform with self-scheduling capacity. Ma, Xu, Meng, and Cheng (2020) focus on the ridesharing user equilibrium problem for an urban transportation network under the origin–destination (OD)-based surge pricing strategy. The results show that ridesharing under the OD-based surge pricing strategy reduces not only the travel cost for travelers, but also the deliberate detours. Fiat, Mansour, & Shultz (2018) compute surge prices and present that the rider-driver equilibrium maximizes social welfare, and riders revealing their true values is a dominant strategy.

Some studies consider the role of surge pricing in other applications. Chen and Sheldon (2015) find that price surges may result in driver idleness and cause drivers to leave the surge zone. Yang, Shao, Wang, and Ye (2020) propose a scheme integrated with surge pricing, such that riders pay an additional amount to a reward account plus the regular surge price during peak hours and then use the balance to support trips during off-peak hours. They find under some conditions that passengers, drivers, and the platform will be better off through this reward scheme. Guda and Subramanian (2019) suggest that even though such surge pricing reduces platform profit in the zone where it is used, it can increase total platform profit across zones.

Surge pricing in zones with excess supply may also be used to credibly inform workers about their need to move to adjacent zones or to minimize the number of workers leaving a zone. Hu, Hu, & Zhu (2019) rationalize the practice of short-lived sharp surge pricing (SSP) beyond the basic economic principle of demand and supply and show that it can benefit riders by causing many high-value riders to voluntarily wait out the initial surge period. They also identify another equilibrium pattern of a low initial price followed by a higher price (denoted as penetration surge pricing, PSP). They find that PSP equilibria are superior to SSP equilibria, but this requires platforms that share demand–supply information with drivers. Bikhchandani (2020) shows that charging a constant fee reduces intermediary profits, may amplify the surge in buyer prices, and may reduce the surge in seller prices during high demand periods.

Intelligent pricing mainly relies on the computational results of a computer algorithm. For example, Raju and Zhang (2010) introduce how Google, Priceline, and other leading companies use intelligent pricing to make more profits. Smart pricing, which considers differences in the costs of serving different segments and the different valuations of products by different segments, is a dynamic approach to pricing that requires accurate information about market demand and profit margins on each item sold (Bhattacharya & Friedman, 2001). Fleischmann, Hall, and Pyke (2004) apply smart pricing to manage a supply chain.

Regarding the conditions related to surge pricing, Tang and Yoo (2017) show that if consumers are not flexible in store choice, then two competitive firms should employ surge pricing. However, if consumers are flexible in store choice, then two competitive firms are open to apply surge pricing. If consumers are also flexible in time, then it is easier for the firm with the competitive advantage to use surge pricing. When consumers have store or time flexibility, then an increase in impatience benefits the firms. Greater impatience makes consumers more willing to avoid congestion and makes them less responsive to pricing. Consequently, it is more likely that firms will employ surge pricing and set a higher surge price. Following the literature, flexibility in time and flexibility in store choice are critical variables accompanying surge pricing. We thus present the first proposition:

Proposition 1. Flexibility in time and flexibility in store choice create various conditions for surge pricing.

The relationship between loyal customers and surge pricing is rather interesting. In a study of a ride-hailing transport service (Grab), Buruhanutheen, Kee, Malik, Yen, and Karlekar (2019) propose that Grab should offer promotions to loyal customers. However, another study shows that a car-sharing platform with a loyal customer base can charge higher prices yet still enjoy higher demand in equilibrium (Bernstein, DeCroix, & Keskin, 2019). For less loyal customers, Basu (2019) presents that customers can be confused and a bit annoyed with surge pricing during rush hours. Hence, loyal customers are a critical variable, too.

Regarding the relationship between surge pricing and customer satisfaction, Hoyer, Herrmann, and Huber (2002) use the prospect theory to convey a pricing policy for consumer satisfaction. Specifically, they examine how the attractiveness of an offer impacts and then combines with satisfaction toward a deal, customer service, and vehicle condition to determine satisfaction with vehicle purchase. Garbarino and Lee (2003) state that surge pricing is often considered unfair and hence damages customer trust. Antón, Camarero, and Carrero (2007) show that price unfairness has a strong effect on switching, both directly and indirectly, through satisfaction. Following the above literature, this study renders the next proposition.

Proposition 2. Customer loyalty and surge pricing affect customer satisfaction.

Studies also consider customer relationships when a firm configures pricing. Winer (2017) states that many managers emphasize costs and competition when setting prices. However, the same study points out that new pricing should incorporate customer value. Lewis (2005) introduces a new dynamic programming approach to customer relationship pricing and demonstrates that customer value is a key factor in pricing. Customer value gives an insurance company an opportunity to change its pricing strategy (Ryals, 2005). We thus have the third proposition.

Proposition 3. Customer satisfaction affects customer retention.

3. Methods

3.1. Data

This study prepared questionnaires for 4 conditions created by a combination of flexibility in time and flexibility in store choice (or service choice in Uber case). The data come from convenience sampling on a group of EMBA students at Feng Chia University, Taiwan. A prerequisite is that the students must have experiences of using Uber, whether frequent or non-frequent, and have faced different conditions. The total number of surveys is 106, and 89 of them are valid.

3.2. Antecedents and operational definitions

Following Proposition 1, flexibility in time and flexibility in store choice are used to create 4 conditions. Following Propositions 2 and 3, customer loyalty and surge are antecedents leading to customer satisfaction; and then customer satisfaction serves as an antecedent leading to customer retention.

To facilitate the empirical analysis, this study proposes the corresponding operation definition of each construct. To represent flexibility in time, this study uses Urgency to describe how urgent a rider is to catch a ride; 0 means “not urgent” and 1 means “urgent”. To represent flexibility in store choice, this study uses Decision to indicate a rider’s decision when s/he faces surge pricing, where 0 means “to take the ride” and 1 means “to switch to alternative vehicle”. Both antecedents are Boolean and form four conditions in the analysis, where Urgency and Decision can be either 0 or 1. The four conditions appear in Table 1.

This study uses Frequency to represent loyal customers. It describes how often a rider takes Uber, whose value ranges from 1 to 5, representing less than once per month, once per month, twice per month, once per week, and multiple times per week, respectively. The higher the value is, the more loyal the rider is. Surge represents the multiplier of the surge pricing, whose value ranges from 1 to 5, representing the same price as that of a taxi, 1.5 times the same price, 2 times, 2.5 times, and 3 times or above, respectively. The higher the value is, the higher is the multiplier.

Table 1
Four conditions.

Urgency	Decision	
	Take the ride (0)	Switch (1)
Not urgent (0)	Condition 1	Condition 2
Urgent (1)	Condition 3	Condition 4

Satisfaction represents customer satisfaction. It is the first level of outcome, representing how satisfied a rider is under either one of the four conditions and the combinations of antecedents. Its value ranges from 1 to 5, representing not very satisfied, not satisfied, neural, satisfied, and very satisfied. Retention represents customer retention (the second level of outcome). Its value ranges from 1 to 5, representing definitely not take again, probably not take again, neutral, probably take again, and definitely take again. It shows how a rider’s willingness to take Uber again in the future. Table 2 summarizes the definitions of these antecedents.

The antecedents are structured in a research framework as in Fig. 1. Based on the research framework, this study intends to show under four conditions (formed by Urgency and Decision) how customer satisfaction is affected by Frequency and Surge, followed by how customer retention is affected by customer satisfaction. All the measurements are calibrated into values between 0.0 and 1.0. The values of both outcomes range from 0.0 to 1.0.

3.3. Research methods

FsQCA uses fuzzy set and logic theory to analyze the relationships between independent variables (antecedents) and dependent variable (outcome). In fsQCA, the data (the survey answers range from 1 to 5) of a problem first need to be calibrated into values between 0.0 and 1.0 (Ragin, 2009) as follows: 1.5 or below is calibrated into 0.0; 3 is calibrated into 0.5; 4.5 or above is calibrated into 1.0; and the data with the other values are calibrated accordingly.

FsQCA generates a relation where X is a single antecedent and Y is the outcome, such as:

$$X \rightarrow Y$$

Aiming to solve a multi-layered problem, this study proceeds with the analysis in two steps. First, this study uses fsQCA to generate the candidate relations. There are two criteria to screen the relations generated by fsQCA: one is consistency (CO > =0.7), and the other covers the relations generated by at least 10 cases. This study accepts all the relations for the multi-layered problem when any one relation has CO ≥ 0.7.

Second, this study uses qualitative analysis with structural associations (Huarng, 2016) to propagate the values from a preceding layer to a subsequent layer. We define the value of the preceding layer by using the new consistency in Huarng (2015a) as:

$$\text{New consistency (NC)} = \frac{\sum_{i=1}^{n} \max[(1-\upsilon_{Xi}), \upsilon_{Yi}]}{n}, \quad \text{for } i = 1, n,$$

where υ_{Xi} is the calibrated value of the antecedent, and υ_{Yi} is that of the outcome for case *i*. In total, there are *n* cases.

To facilitate the interpretation of NC, this study sets 0.0 to 0.44 as negative, 0.45 to 0.55 as neutral, and 0.56 to 1.0 as positive. For example, 0.40 and 0.75 of Satisfaction means negative and positive customer satisfaction, respectively.

4. Empirical analysis

From the research framework, fsQCA generates three solutions: complex, parsimonious, and intermediate. This study consistently takes a parsimonious solution as the result. Urgency and Decision are either 0 or 1. Hence, both antecedents form 4 conditions. The analysis for each condition is summarized below.

Table 2
Definitions of the antecedents.

Antecedent	Value					
	0	1	2	3	4	5
Urgency (0 or 1)	not urgent	urgent				
Decision (0 or 1)	to take the ride	to switch				
Frequency (1–5)		less than once per month	once per month	twice per month	once per week	multiple per week
Surge (1–5)*		the same price	1.5 × the price	twice	2.5 × the price	triple or above
Satisfaction (1–5)		not very satisfied	not satisfied	neutral	satisfied	very satisfied
Retention (1–5)		strongly not take again	probably not take again	neutral	take again	strongly take again

* The same price means similar to what a taxi charges for the same trip.

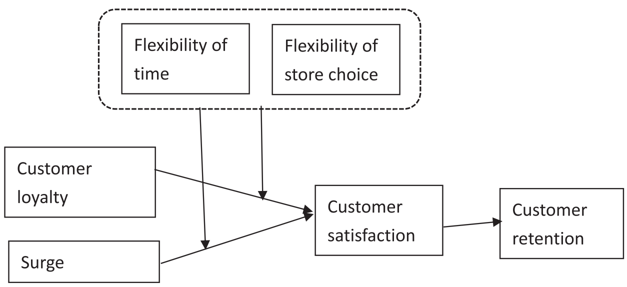

Fig. 1. The research framework.

4.1. Not urgent and take the ride

For customers who are not urgent and decide to take the ride, fsQCA generates only one relation with CO > = 0.7 for Satisfaction:

Surge → Satisfaction (CO = 0.78) (1)

Satisfaction → Retention (CO = 0.74) (2)

Following Boolean algebra, in Eq. (1), Frequency becomes “don't-care”. In other words, Eq. (1) is equivalent to:

Frequency AND Surge → Satisfaction (1a)

(NOT Frequency) AND Surge → Satisfaction (1b)

This study next uses qualitative analysis with structural associations for further analysis. Table 3 lists the analysis for Eqs. (1a) and (1b). In Table 3 the first column presents the number of possible relations (PR), the second column shows the number of cases matching the relation, and the next two columns are antecedents: NC for Satisfaction and Retention.

In Table 3, PR 1 comes from only one case, which is not qualified. The only relation qualified is PR 2 as follows:

(NOT Urgency) AND Take the ride AND
(NOT Frequency) AND Surge →
Satisfaction (NC=0.57) → Retention (NC=0.53) (3)

4.2. Not urgent and switch

For customers who are not urgent and choose to switch to an alternative vehicle, fsQCA generates one relation for Satisfaction:

Frequency → Satisfaction (CO = 0.52) (4)

Table 3
Not urgent and take the ride.

PR	#	Frequency	Surge	Satisfaction	Retention
1	1	P	P	0.88	0.50
2	11	N	P	0.57	0.53

Note: PR is the number of possible relations; # is the number of cases matching each PR.

Table 4
Not urgent and switch.

PR	#	Frequency	Surge	Satisfaction	Retention
1	13	P	P	0.44	0.59
2	6	P	N	0.44	0.75

Satisfaction → Retention (CO = 0.75) (5)

Eq. (4) is equivalent to:

Frequency AND Surge → Satisfaction (4a)

Frequency AND (NOT Surge) → Satisfaction (4b)

Qualitative analysis with structural associations similarly generates two possible relations listed in Table 4. In Table 4, PR 2 comes from only six cases, making it not qualified. Hence, the only relation qualified is PR 1:

(Not Urgency) AND Switch AND Frequency AND Surge →
Satisfaction (NC=0.44) → Retention (NC=0.59) (6)

4.3. Urgent and take the ride

For customers who are urgent and decide to take the ride, fsQCA generates two relations for Satisfaction:

(NOT Surge) → Satisfaction (CO=0.74) (7)

Frequency → Satisfaction (CO = 0.72) (8)

Sisfaction → Retention (CO = 0.80) (9)

Table 5 lists the possible relations. In Table 5, PR 2 and PR 3 match Eq. (7). However, PR 2 comes from only seven cases, making it not qualified which is not qualified. Hence, the only relation qualified is PR 3:

Urgency AND Take the ride AND (NOT Frequency)
AND (NOT Surge) → Satisfaction (NC=0.57) →
Retention (NC=0.64) (10)

In Table 5, PR 1 and PR 2 similarly match Eq. (8). PR 2 is again not qualified. Hence, the only relation qualified is PR 1:

Urgency AND Take the ride AND Frequency AND Surge →
Satisfaction (NC=0.53) → Retention (NC=0.56) (11)

Table 5
Urgent and take the ride.

PR	#	Frequency	Surge	Satisfaction	Retention
1	12	P	P	0.53	0.56
2	7	P	N	0.83	0.57
3	17	N	N	0.57	0.64

Table 6
Urgent and switch.

PR	#	Frequency	Surge	Satisfaction	Retention
1	1	P	N	0.12	0.88

Table 7
Summary of the relationships.

Urgency	Decision	
	Take the ride (0)	Switch (1)
Not urgent (0)	NOT Frequency and Surge → High Satisfaction → Neutral Retention	Frequency and Surge →Low Satisfaction → High Retention
Urgent (1)	Frequency and Surge → Neutral Satisfaction → High Retention NOT Frequency and NOT Surge → High Satisfaction → High Retention	N/A

4.4. Urgent and switch

For customers who are urgent and decide to switch, fsQCA generates one relation for Satisfaction:

$$\text{Frequency AND (NOT Surge)} \rightarrow \text{Satisfaction (CO=0.68)} \tag{12}$$

$$\text{Satisfaction} \rightarrow \text{Retention} \qquad (\text{CO} = 0.76) \tag{13}$$

In Table 6, PR 1 comes from only one case, making it not qualified. Hence, there is no relation generated. Table 7 summarizes all the relationships.

4.5. Discussion

From the above analysis, Proposition 1 forms 4 conditions for surge pricing. Proposition 2 shows that customer loyalty and surge pricing affect customer satisfaction, as supported by Eqs. (3), (6), (10), and (11). Proposition 3 presents that customer satisfaction affects customer retention in different directions, either positively or negatively, as supported by Eqs. (2), (5), (9), and (13).

5. Managerial implications

The empirical analysis herein offers evidence for managerial implications. For loyal riders confronted by surge pricing, when they have both flexibilities of time and store choice, their satisfaction is negative (Eq. (6)). Because these riders have better choices, they may complain about the existing services. Thus, their satisfaction turns negative. For the same group of riders, when they have no flexibilities in time and store choice, their satisfaction is neutral (Eq. (11)). When these riders have no choice, they have to settle with the existing services. Their satisfaction increases to neutral from negative. However, under both conditions the retention is positive, meaning that riders will take Uber again in the future. Both results imply that loyal customers can either get used to or tolerate surge pricing.

For non-loyal customers facing surge pricing, when they have the flexibility of time, but no store choice, they are satisfied with the existing services (their satisfaction is positive), but their retention drops to neutral, because of the surge pricing (Eq. (3)). For non-loyal customers with low surge pricing, when they have no flexibility in both time and store choice, their satisfaction is positive, and the retention is positive and higher than satisfaction due to the low surge pricing (Eq. (10)). Hence, non-frequent riders are sensitive to surge pricing.

The major difference between loyal and non-loyal riders lies on surge pricing. Uber can apply surge pricing, and its loyal riders will still return to the firm for services. However, surge pricing keeps non-loyal riders away. How to win back the non-loyal riders under surge pricing remains a challenge for Uber.

The literature clearly supports that customer satisfaction positively affects customer retention. This study thus provides evidence that positive customer satisfaction can lead to positive customer retention (Eq. (10)); positive to neutral retention (Eq. (3)); negative to positive retention (Eq. (6)); and neutral to positive retention (Eq. (11)). The evidences show that customer satisfaction does not always positively influence customer retention.

6. Conclusion

How does surge pricing affect customer satisfaction? How does customer satisfaction affect customer retention? After examining these questions, the empirical results we present herein support our propositions. Flexibility in time and flexibility in store choice form 4 conditions for surge pricing. The results show that customer loyalty and surge pricing affect customer satisfaction and that customer satisfaction affects customer retention in different directions.

For managerial implications, first, loyal customers are more tolerant of surge pricing. Conversely, non-loyal customers are more sensitive to surge pricing. How to apply surge pricing to keep existing customers and to attract new customers simultaneously is a continuous challenge for businesses.

This study also adds new knowledge to the relationship between customer satisfaction and customer retention. Though customer satisfaction can go down to negative, the corresponding retention can increase to neutral or positive. In other words, retention achieves a higher score than does satisfaction correspondingly. This strongly goes against the existing literature in which satisfaction always positively affects retention.

If customer satisfaction does not necessarily lead to customer retention, then how can we explain the above phenomena and what are the factors that may affect customer retention? Does that mean Uber can continue to use surge pricing in the future? Further studies can investigate these issues in greater depth.

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Kun-Huang Huarng received his Ph.D. from Texas A&M University, USA. He is a Vice President of National Taipei University of Business (NTUB), where he is also a Distinguished Professor, and a Professor of Creative Technologies and Product Design. Professor Huarng was awarded a Life Fellow by International Society of Management Engineers. He won the Outstanding Service Award Literati Network Award for Excellence from Emerald and was an Advisory Board Member of Emerald. His teaching and research interests include e-Commerce and Big Data analytics.

Tiffany Hui-Kuang Yu received her Ph.D. from Texas A&M University, USA. She served as the director of the Science and Technology Division at Taipei Economic and Cultural Office in Houston, USA for four years. She is currently a Consultant to the Office of the President and Professor of Public Finance, Feng Chia University, Taiwan. She is also the Principal Investigator, Network for International Student Advisor (NISA), Ministry of Education, Taiwan.