The Implications of Smart Tip Nudging: A Data-Driven Behavioral Economic Study

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Abstract

Tipping phenomenon has been widely observed with broad social-economic impacts. Digital nudging using 'default tip options' on iPad-like payment devices is increasingly adopted by the service providers, in order to increase the size of the tip that can greatly impact service industry worker's income. The current practice is to use one set of standard 'default tip options' regardless of whatever kind of service to be delivered. This paper proposes a data-driven approach to designing smart tipping nudge that enables customized 'default tip options' tailored to varying tendency of different services for potentially high or low tip amounts. For a behavioral economic analysis of the tipping behavior, we apply prospect-theoretic value functions to model the tip amount as the consumer perceived value of service quality. A field experimental study in a fast-causal business is reported to demonstrate the potential of the proposed data-driven approach to smart tip nudging.

Keywords
Behavioral economics, Prospect theory, Tipping behavior, Incentive design, Service delivery system.

1. Introduction
Tipping phenomenon has attracted a large body of studies in behavioral economics and experimental psychology. Diverse tipping practices are observed from culture to culture or country to country (Saayman and Saayman, 2015). It is reported that tipping in the United States food industry alone accounted for a $46.6 billion economic value (Azar, 2011), whilst 3 out of 4.7 million food servers employed in the USA earn some portion of their income from tips (Miller, 2010). With broader social-economic impacts, tipping has profound implications for labor economics as well as economics of information and management strategies (Azar, 2003).

Numerous literature has been devoted to understanding various social-demographic variables that affect people's tipping behaviors (Lynn, 2006). For example, Green et al. (2003) find that the percentage of tips decreases with the bill size, which coincides with an economic concept of free-riding (Nelson, 2017). A situation where tipping is involved typically consists of two main parties that affect the prevalence or size of the tip: the consumer or demand side and the service provider or supply side (Azar, 2007). On the demand side, age, gender, education, culture, mood, and other variables can impact the size of the tip given. Regardless, tipping is a behavior that is motivated more by the positive results rather than being restricted by the negative results of not tipping. There are no consequences for not tipping, so the action of tipping is a way to express gratitude on top of the base cost of the product. On the supply side, attitude, appearance, and other variables can impact the size of the tip received.

A nationwide tipping field study based on 40 million Uber trips reveals that both consumer traits and service provider traits contribute to the amount of tip given, while demand-side variables matter more (Chandar et al., 2019). The study finds that the knowledge of certain patterns in the tipping behavior can be used to maximize tips. While service providers cannot change the consumer's traits, the service provider can manipulate certain aspects of their service operations to gain a larger tip. For example, service providers can provide faster or cleaner service, greet the customers,

or compliment the customers. They can also alter other features like playing happy music to lift customers' moods and setting 'default tip options'. Depending on those traits, service providers can maximize their given tip (Chandar et al., 2019).

An emerging trend, owning to the increase in technological innovations, is that there are more and more service providers nowadays implementing electric payment systems that adopt point of sale iPads or handhold terminals to offer 'default tip options' rather than relying on traditionally handwritten tips (Warren et al., 2021). As shown in Figure 1, many fast-casual service providers, such as a diner, a coffee shop, or a cab driver, use a touchpad for credit card payment or mobile payment systems (e.g., ApplePay or GooglePay) to display a menu or buttons with default options of tip amount, e.g., 0% (No Tip), 10%, 15%, 20%, and "Other (allowing consumers to custom tip amount)". With the increase in electronic checkouts, 'default tip options' also enhance the user experience of the consumers when they tip.

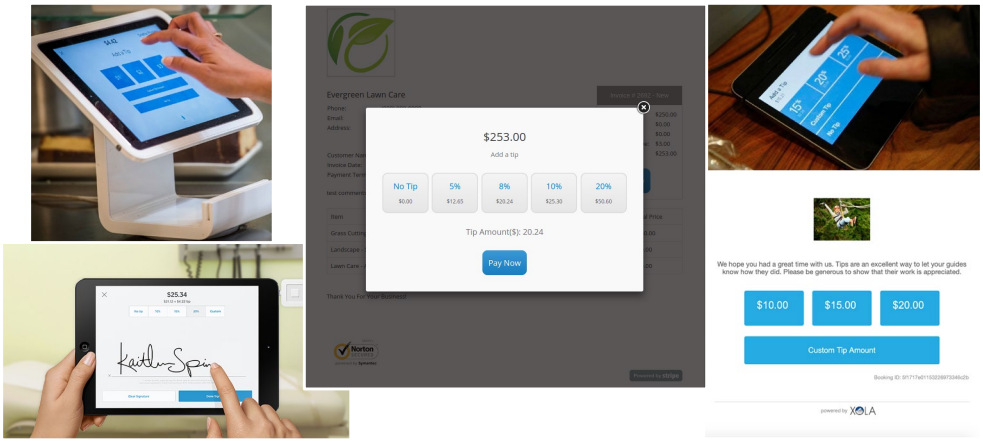


Figure 1. Examples of 'default tip options' on the screen

By offering certain 'default tip options', consumers may be pressured to choose certain options. Anchoring customers at higher tip options may cause consumers to tip more (Zarrabian, 2019) as they may feel guilty if they do not tip at all. The same is true when a "no tip" option is given, because of the social norm reason for tipping (Azar, 2007). While higher 'default tip options' may lead to more tips, customer satisfaction may decrease as they pay an unexpectedly high amount of money on top of the good or service and taxes. Consumers are also less likely to rate the place as fair or appropriate, or they are less likely to recommend the place to others. It is thus imperative to design a smart tipping mechanism with 'default tip options' that can leverage the interests of both the consumers and the service providers.

Towards this end, this paper examines how 'default tip options' affect the prevalence and size of the tip, and in turn how this knowledge can be used to maximize the prevalence and size of the tip through digital nudging. For a behavioral economic analysis of the tipping behavior, we apply prospect-theoretic value functions to model tip amount as the consumer perceived value of service quality, a data-driven approach is proposed to design smart tipping nudge to enable customized 'default tip options' tailored to varying tendency of different services for potentially high or low tip amounts. Therefore, smart tip nudging leads to better user experience on the consumer side, while bringing better chance of higher tips on the supply side.

2. Literature Review

2.1 Behavioral Economic Studies of Tipping Behaviors

Tipping is a behavior involving a direct exchange between the consumer and service provider. Unlike other exchanges, tipping is dictated by custom rather than explicitly stated procedures. Because there are no rules stating how much a consumer should tip or when and where they should not tip, these traits are patterns in tipping behavior and are not guaranteed that the consumer would tip. There are stereotypes of certain cultures or demographics that would not tip, but ultimately, service providers never really know which customers would tip or not (Saayman and Saayman, 2015). Whyte's study (1948) claims that tipped employees tended to believe that tipping was responsible for their feelings of inferiority to the customer. However, it is not necessarily the case. More often, tipped employees perceive a greater

relationship between pay and performance (Shamir, 1983) and will often increase their performance for a bigger tip. Since tips account for more than half of service providers' earnings (Tung, 2018), it further supports that service providers link tips to performance quality.

Because giving something up is more painful than the pleasure derived from receiving it, an individual acting in his or her own self-interest would never tip. However, tipping is a popular consumer behavior that is found in various forms and industries. So why do individuals tip if it is irrational? There are three main reasons as to why individuals tip (Nelson, 2017). One, tipping is the social norm. Because it is so common, individuals want to conform to the norm and tip to avoid feeling embarrassed or guilty by not tipping. Two, tipping is an incentive for the service provider to continue providing good service or improve future service. A bigger tip could be used as motivation for the service to be faster, more careful, or more intricate. Three, tipping is used to directly reward the service provider.

Tipping is a challenge for economic modeling. Economists are more receptive to the idea that the utility of individuals may depend on social norms and feelings (Rabin, 1998). Recently, the tendency to consider emotions more seriously is likely to continue (Thaler and Sunstein, 2008). Nevertheless, models that incorporate social norms or feelings in the agent's utility are still controversial. Many economists criticize such models by the claim that, if we allow agents to care about social norms and feelings, everything can be explained.

Originating in the late 18th and early 19th centuries, classical economics focused on the idea that free markets are self-regulating. Classical economists believed that humans were rational and assumed that individuals have stable preferences and engage in maximizing behavior (Pesendorfer, 2006). However, Kahneman and Tversky (1979) argued that when presented with various options under the conditions of scarcity, individuals would choose the option that maximizes their own individual satisfaction rather than the rational choice, i.e., a new model coined as prospect theory.

Prospect theory, also known as the loss-aversion theory, states that decisions are not always optimal, and individuals make decisions based on perceived gains and losses (Kahneman and Tversky, 1979). While classical economics assumes that all individuals are rational, prospect theory directly counters it. Prospect theory consists of two stages: an editing stage where heuristics are applied in decision making and an evaluation stage where statistical analysis is used to analyze risky alternatives. The decision making in the editing stage can be affected by wording, order, or the way the choices are presented. These ideas helped create a new field in economics, i.e., behavior economics, that studied the effects of various factors on the decisions of individuals and institutions (Tversky and Kahneman, 1992).

Certainty, isolation effect, and loss aversion are the main factors that influence decision making in prospect theory. Individuals show a strong preference for the option with certainty because they have more trust in options that are more familiar with them. Additionally, individuals tend to view wealth in relative terms rather than absolute terms. They also tend to discount very small probabilities even if the risk is high. Finally, individuals view losses as more impactful than gains.

2.2. Tip Nudging and Choice Architecture Design

Nudging is a term based on the heuristics work of Kahneman and Tversky (1979) that is used to indirectly encourage individuals to act or believe in a certain way. The term was popularized by Thaler and Sunstein (2008). Thus, tip nudging refers to indirectly persuading customers to tip. For example, using iPad to suggest tip amounts with default options can be regarded as a means of digital nudging.

Recently, nudge theory has gained much popularity in order to understand, assist and manage individuals' decision making and behaviors. Rather than being based on the rational individual's behavior, it accepts that individuals have specific attitudes, knowledge, and capabilities (Hummel and Maedche, 2019). Because of this, nudge theory is very relevant to leadership, motivation, change management, and aspects of personal and self-development (Meske and Amojo, 2019).

The effect of nudges can vary from positive to negative, sometimes backfiring or causing unintended consequences (Abdukadirov, 2016). Positive nudges can include a scavenger hunt game to encourage a child to clean his or her room or an allowance to complete chores. Negative nudges can include false advertisement or misleading information. As individuals often seek more discovery than would be relevant (Brod, 2021), so nudges can be very influential on an individual's decision making.

The notion of a choice architect connects strongly to the philosophy of nudge theory (Mertens et al., 2022). It emphasizes that change is enabled by designing choices for people, which encourage them to make decisions, ideally towards positive helpful outcomes (Thaler and Sunstein, 2008). A choice architecture is about designing different ways in which choices can be presented to consumers such that the impact of that presentation on consumer decision making leads to better experiences for the customers, employees, and other stakeholders (Parikh and Parikh, 2017). In behavioral economics research, the role of a choice architecture is consistent with the concept of framing effect in psychology, i.e., a cognitive bias in which people react to a particular choice in different ways depending on how it is presented (Gonzalez et al., 2005). The reference point phenomenon in prospect theory is an instance of the framing effect.

Choice architecture framing plays an important role in designing default choices. People are more likely to stay with the default choice if presented with options, as the energy and time to consider options has been done at a previous time (Herrmann et al., 2011). An example of a recurring default is a person that made a choice previously, after taking the time to consider the options at that time, and then chooses that choice once again, simply because they have approved it previously. For instance, when one returns to a restaurant, he may choose the same thing he ordered before if he enjoyed it, rather than considering all the options again.

In business, opting in and opting out of services are examples of default choice architecture at work. When asked to opt into receiving a newsletter, people will more likely stay with the default of not receiving a newsletter. This works the other way around too. If the default position is that everyone is opted in to receive a newsletter, and they are asked to opt-out, people will more likely remain opted in.

Likewise, service providers can alter certain features to nudge customers to tip more or more often. Because tipping accounts for a large economic value, small changes in tipping behavior can have largescale revenue impacts. This framing effect inspires the significance of smart tip nudging by taking advantage of any aspect of choice architecture that alters behavior in a predictable way, without forbidding options or significantly changing economic incentives. Digital nudging exemplifies when we design websites, app interfaces, and other digital products we shape how people think. How we present choices impacts what people will decide to do. Many elements of user-experience design play a role in the architecture of choices online.

3. Prospect Theoretic Modeling of Consumer Tipping Preference

The prospect theory model shows how an individual perceives gains and losses by replacing the utility function over states of wealth with a value function over gains and losses relative to a reference point. (Tversky and Kahneman, 1992). It exhibits an s-shaped graph with losses and gains on the x-axis with respect to certain reference point on the y-axis. As an individual moves along the graph, the curve starts steep then levels out. However, the slope on the loss/negative value side is steeper since individuals weigh losses more than gains. Therefore, we propose to model consumer tipping preference based on a subjective value function of prospect theory, as the following:

$$T = v(Q) = \begin{cases} \left(Q - Q^{Ref}\right)^{\alpha}, & Q - Q^{Ref} \geq 0 \\ -\lambda\left(Q^{Ref} - Q\right)^{\beta}, & Q - Q^{Ref} < 0 \end{cases} \qquad 0 < \alpha, \beta < 1, \lambda > 1 \tag{1}$$

where α and β are free parameters that vary between 0 and 1, modulating the curvature of the subjective value function and indicating the risk attitude of the customer. For α , the larger the value, the more risk-seeking the customer tends to be. For β, the larger the value, the more risk-averse the customer would be. Moreover, λ specifies aversion to unpleasant outcomes, meaning customers' perception on those service levels that are below the reference point, with larger values expressing more aversion and sensitivity to unpleasant perception of the service.

As shown in Figure 2, tip amount T in terms of percentage of the bill size is defined as the customer perceived value of a quality service delivered to him by the service provider. The connection between service quality and tip sizes is a strong market phenomenon albeit in a peculiar type of market without rigid enforcement of obligations, as shown by an analysis of 286 survey studies examining the relationship between service and tips (Bodvarsson and Gibson, 1999). Moreover, service level Q (%) is used as the metric by which a particular service is measured, which is widely

practiced in the service industries. Service level provides the expectations of quality and service type and also remedies when requirements are not met.

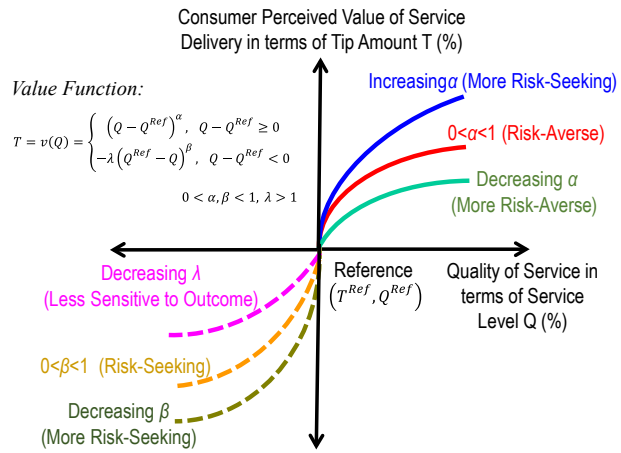


Figure 2. Tip amounts correlated to quality of service in line with a prospect theory value function

The consumer perceived value in terms of tip amount T (%) of the quality of service delivered with a service level Q (%) can be defined as a subjective value function, $T = v(Q)$. The perceived value of service quality is identified relative to a certain service level that gives a neutral perception and acts as a reference point. For example, the reference may correspond to a fair service level that deserves 0% tip amount. Hassenzahl and Tracinsky (2006) point out that human perception necessitates dynamic, context-dependent internal states of consumers, which involve both instrumental and emotional aspects. It is likely that the reference point varies among different respondents. To hedge against this problem, we can set up individual reference points for individual value functions for customer heterogeneity and take a grand mean as the reference point for all the customers within one market segment for customer homogeneity.

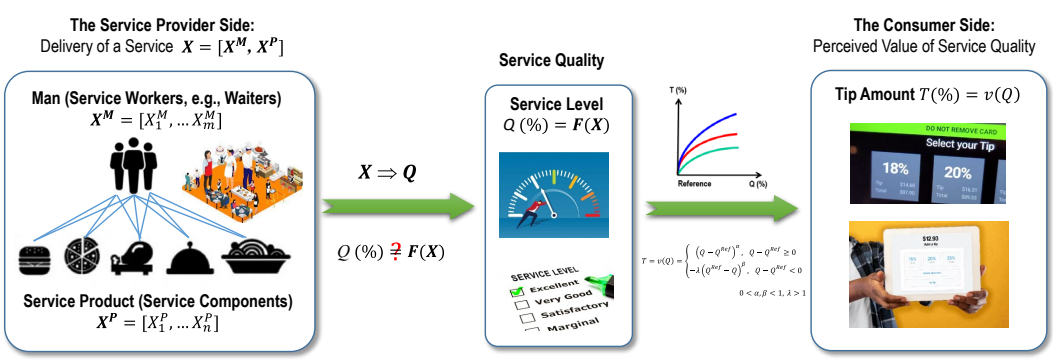


Figure 3. Fulfillment of a service delivery process resulting in perceived value of service quality by the tip amount

While the consumer side receives a quality service and perceives its value as $T_i(\%)$, the service level of the service $Q_i(\%)$ is resulted from delivery or fulfillment of a particular service that comprises the service workers who do the service jobs, $\boldsymbol{X^M} = [X_1^M, \dots X_m^M]$, and the specific service product, $\boldsymbol{X^P} = [X_1^P, \dots X_n^P]$, that is consisted of a number of service components. These service components could be physical items of the service product (e.g., starters/entrees on the menu), or multiple steps of the service process in order to deliver the product (e.g., check in/out), or even the key service performance indicators (e.g., cycle time). In addition, X_i^M indicates if the service worker i provides the service, and m is the number of service workers. Also X_j^P indicates the product comprises the j-th product or service component instances out of a large set of available component choices with a total number of n. Figure 3 illustrates such a service delivery and value fulfillment process towards the tip award at the end of the process.

The prospect theoretic model reveals the fundamental decision-making mechanism underlying the tipping behavior. It essentially entails of a cascading two stage mapping process to fulfill the service value that finally deserves tips. The first stage takes place on the supply side, that is, the service provider commits certain manpower and resources to create the ordered service that yields a level of service quality. Then the second stage follows to map the fulfilled service quality to what the consumer would perceive as a tip amount. Understanding of such a mapping mechanism of tipping behaviors sheds light on developing insights into the design of tip nudge with better user experience.

4. Data-Driven Smart Tipping Nudge Design

In practice, in order to establish various parameters of the service quality and prospect value functions, tremendous efforts are necessary to set up user experiments and conduct comprehensive data collection and analysis. For our digital tip nudging case, we propose a pragmatic approach using nowadays advanced data-driven analysis techniques to circumvent the costly experiment and parameter tuning process by exploiting large data of sales transactions available owing to employment of electric payment systems widely in the fast-causal service sector. For this purpose, machine learning techniques are particularly useful for achieving smart tipping nudge design, as elaborated below.

Figure 4 shows the framework of the proposed data-driven approach, regarding how historical sales transaction data are utilized to analyze and identify underlying mapping patterns between the service delivered and the corresponding tip amounts in the past. As shown in the figure, one particular transaction record $\{\boldsymbol{X_i}, T_i\}$ contains two segments of information regarding the supply and consumer sides, respectively. The delivered service record instantiates a vector of the specific service worker and the associated product and service components conducted for this particular service, i.e., $\boldsymbol{X_i} = [X_i^M, \boldsymbol{X_i^P}]$, meaning that a waiter X_i^M (e.g., Mr. David) did this job (e.g., serving a dinner) that comprised multiple items $\boldsymbol{X^P} = [X_1^P, \dots X_n^P]$ (e.g., that dinner included a beer, a ribeye steak and a salad). For this particular dinner service, that customer finally paid a tip amount T_i, say $T_i = 14\%$, to Mr. David.

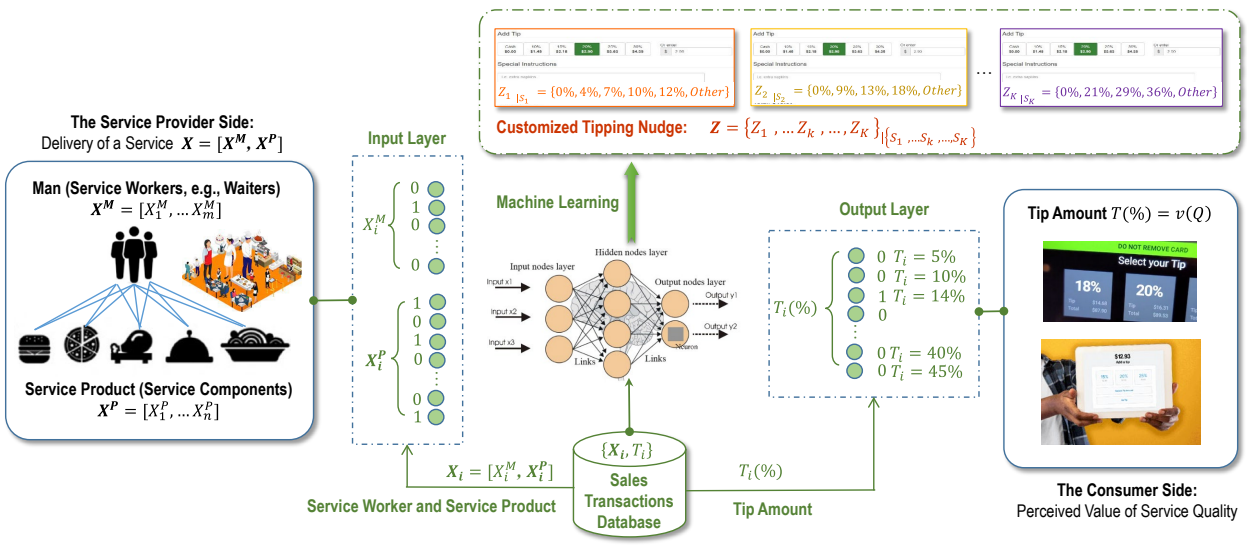


Figure 4. Data-driven smart tip nudging through analysis and learning of historical tip transactions

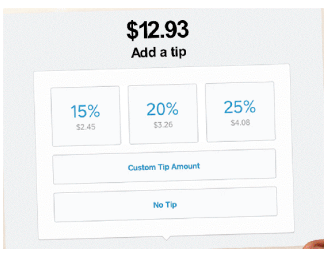
To identify the tipping patterns from a large dataset of past transaction records, machine learning techniques can be applied to classify different categorizes of services $\{S_1, \dots S_k, \dots, S_K\}$ that tend to yield typically high or low tip amounts. For example, some star waiters and waitresses along with those best sellers among the service products always received higher than average tips. Likewise, a few inexperienced waiters and waitresses mostly received below average tips, in particular when serving some basic items on the menu ordered by the customers.

As shown in Figure 4, the model inputs are delivery of service data $\boldsymbol{X_i} = [\boldsymbol{X_i^M}, \boldsymbol{X_i^P}]$, servers and served items for the order i, in the sales transactions database. Correspondingly, the model output is the tipping amount $T_i(\%)$ for that order. In the context of tip nudging, several tip values can be suggested. Therefore, nudge recommendations become a classification problem. Since the inputs involve both the service worker and service product factors, the mapping of

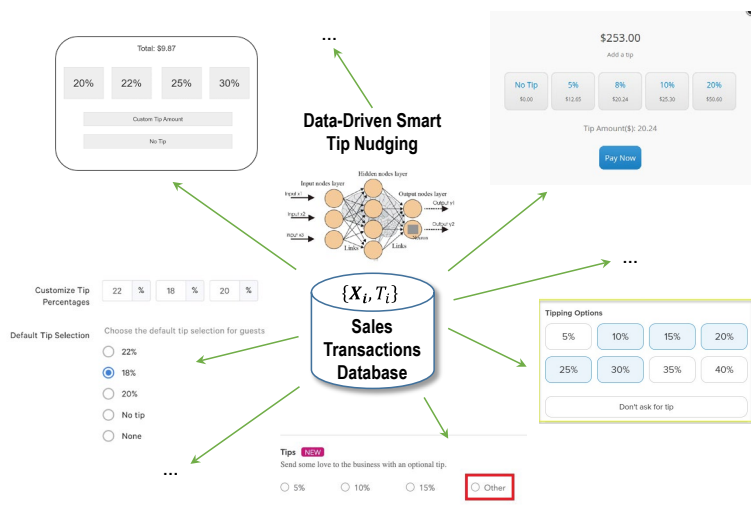
$\boldsymbol{F}(\boldsymbol{X}) \rightarrow T$ is not guaranteed to be linear and is therefore learned through a multilayer neural network, which is a non-parametric model with more a complex structure compared to the regression approach.

After classification and identification of tip patterns, clustering analysis can be conducted for those salient service-tipping categories. For each category S_k , tendency for potential tips that will be higher or lower than average can be predicted accordingly, and in turn an appropriate tipping nudge $Z_{k\ |S_k}$ can be defined for that category, e.g., $Z_{k\ |S_k} = \{0\%,\ 9\%, 13\%, 18\%, Other\}$. Throughout the smart tip nudging decision making process, domain knowledge regarding the particular problem context of the specific business also should come into play. For example, during the peak hours, the waiting time for order fulfillment may be expected to take longer than usual. During this situation, the 'default tip options' prompted to the customers can be compromised a bit, e.g., {0%, 4%, 9%, 14%,19%, Other}, instead of {0%, 5%, 10%, 15%, 20%, Other}.

For instance, Mr. David is one of the star waiters in the restaurant who always delivered 5-star service and were well paid with higher than average tips in the past. Similarly, a house steak is among the best sellers on the menu, and usually leading to higher tips as well. If a customer happens to be served by Mr. David and happens to order this house steak, then the payment iPad will prompt a customized 'default tip options', e.g., $Z_{K\ |S_K} = \{0\%,\ 21\%, 29\%, 36\%, Other\}$, which is tailored to this particular 'high-end' service provided, when the customer is about to pay his check. Similarly, if a 'low-end' service if provided, which implies a low likelihood of receiving more tip, the system should smartly prompt 'default tip options' more conservatively, e.g., $Z_{1\ |S_1} = \{0\%,\ 4\%,\ 7\%, 10\%, 12\%, Other\}$.



(a) As-is model: Current practice of standard 'default tip options' regardless of whatever kind of service delivered



(b) To-be model: Customized 'default tip options' tailored to varying tendency of different services for potentially high or low tip amounts

Figure 5. Using standard 'default tip options' versus smart tipping nudge

The end result of smart tip nudging is shown in Figure 5. Figure 5(a) shows the as-is model of prevailing practice in the market, in which only one set of standard 'default tip options', e.g., {No, 10%, 15%, 20%, Other} is used, regardless of whatever kind of service to be delivered. This totally ignores the fact that different service workers exhibit varying competency in anchoring to a higher tip amount. Likewise, a basic service like handing a muffin versus a more complex job like preparing an espresso milk shake inherently implies different service value added, and in turn perceived as an extra by paying a tip amount.

On the other hand, the proposed to-be model, as showing in Figure 5(b), aims to improve the current practice of one set of standard 'default tip options' with tailor-made choice architectures. Smart tipping nudge enables customized 'default tip options' that are tailored to varying tendency of different services for potentially high or low tip amounts. The adaptability of a smart tipping nudge conforms to the common consumers' perception on paying tips as revealed by the prospect-theoretic model. Therefore, it leads to better user experience on the consumer side, while bringing a better chance of higher tips on the supply side.

5. Experiment and Pilot Test Results

5.1 Neural Network Model

In this study, a 4-layer neural network is developed. To fit the data into the neural network, the input data $[\boldsymbol{X^M}, \boldsymbol{X^P}]$ are flattened into a one-dimensional array as the input layer, with the size being the sum of the number of service workers and the number of service products $|\boldsymbol{X^M}| + |\boldsymbol{X^P}|$. The hidden layers are fully connected layers. The output layer is an array indicating different tip percentage values, with the size being the number of tip percentages $|T|$. The model structure is shown in Table 1 (the size of the input layer and the output layer corresponds to the dataset in Section 5.2). The model structure is illustrated in Figure 6.

Table 1. Neural Network Model Structure

Layer (Type)	Output Shape	Number of Parameters
Input Layer	36	0
1st Fully Connected Layer (ReLU)	30	1116
2nd Fully Connected Layer (ReLU)	23	720
Output Layer (Softmax)	12	299

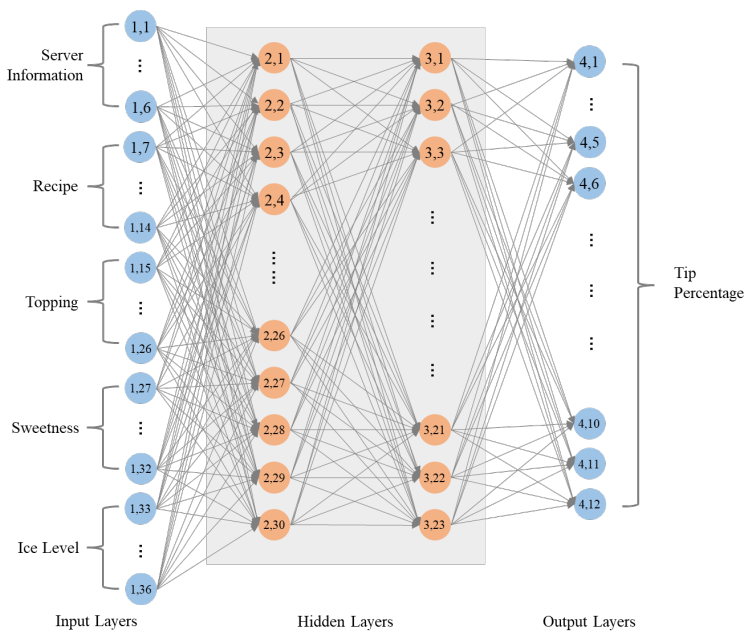


Figure 6. A 4-layer neural network structure

Here ReLU is the activation function for hidden layers:

$$f(z) = \begin{cases} z, z > 0 \\ 0, else \end{cases} \tag{2}$$

$$z = Wy + b \tag{3}$$

where W is the weights of previous neurons to the current neuron, y is the value matrix for previous neuron values, and b is the bias. The training uses backpropagation, and the loss function uses the categorical cross entropy loss. Furthermore, Softmax is chosen as the activation function of the output layer for multi-class classification, which is formulated to calculate the probability of each tip percentage:

$$P(Y = j) = \frac{e^{z_j}}{\sum_{i=1}^{|T|} e^{z_i}} \tag{4}$$

5.2 Field Experiment and Data

Our field experiment was conducted in a local bubble tea shop located in Sandy Springs, Georgia in the USA. It is a typical food business offering fast-causal service, for which quick turnaround time and direct service of a large variety of receipts make 'default tip options' using iPad a perfect instrument to elicit tips. While a cup of bubble tea itself seemingly does not cost much, the tip amount in terms of percentage is not low at all, probably due to less sensitivity of the customers towards a relatively small bill size. Due to large variations in adding many different toppings and specifying different sweetness and ice levels on top of dozens of drink receipts, almost every bubble tea order is custom made by the tender, and as a result many people pay tips.

The shop delivers around 200 orders per day. We collected 10,000 transaction records in recent two months from the sales database. After disguising the shop's proprietary information and customers' personal information, we organized 6,000 pseudo data for testing our smart tip nudging approach, in the format shown in Table 2.

Table 2. Pseudo dataset for the bubble tea shop case

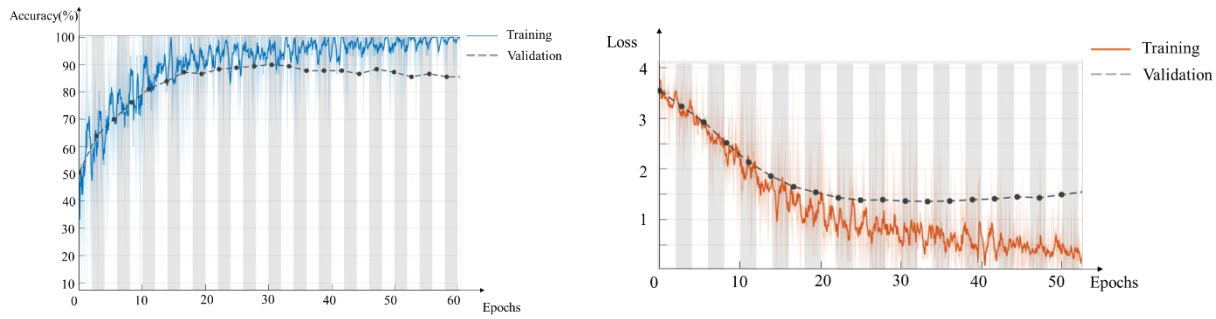
					Sales Transaction Record (Order #)					
					1	2	…	3	…	…
The Service Provider Side	Delivery of a Service $\boldsymbol{X} = [\boldsymbol{X^M}, \boldsymbol{X^P}]$	Service Worker $\boldsymbol{X^M} = [X_1^M, \dots X_m^M]$		Tender Alex	0	0	…	0	…	…
				Tender Bert	1	0	…	0	…	…
				Tender Cathy	0	0	…	1	…	…
				Tender David	0	1	…	0	…	…
				…	…	…	…	…	…	…
		Service Product (Service Components) $\boldsymbol{X^P} = [X_1^P, \dots X_n^P]$	Drink Recipe	Classic black milk tea	0	0	…	0	…	…
				Mango green tea	1	0	…	0	…	…
				Hawaii fruit tea	0	0	…	1	…	…
				Thai milk tea	0	1	…	0	…	…
				…		…	…	…	…	…
			Topping	Crystal boba	0	0	…	0	…	…
				Mini pearl	1	0	…	0	…	…
				…	…	…	…	…	…	…
				Lychee jelly	0	1	…	0	…	…
				…	…	…	…	…	…	…
				Vanilla ice cream	0	0	…	1	…	…
				…	…	…	…	…	…	…
				Aloe vera	0	0	…	0	…	…
				Pudding	0	0	…	0	…	…
				…	…	…	…	…	…	…
			Sweetness	120%	0	0	…	0	…	…
				100%	0	0	…	1	…	…
				80%	0	0	…	0	…	…
				50%	1	0	…	0	…	…
				30%	0	0	…	0	…	…
				0%	0	1	…	0	…	…
			Ice	More	0	0	…	1	…	…
				Regular	1	0	…	0	…	…
				Less	0	0	…	0	…	…
				No	0	1	…	0	…	…
The Consumer Side	Perceived Value of Service Quality	Tip Amount $T(\%)$		0%	0	0	…	0	…	…
				1%	0	0	…	0	…	…
				…	…	…	…	…	…	…
				6%	0	0	…	0	…	…
				…	…	…	…	…	…	…
				10%	1	1	…	0	…	…
				11%	0	0	…	0	…	…
				…	…	…	…	…	…	…
				14%	0	0	…	0	…	…
				15%	0	0	…	1	…	…
				…	…	…	…	…	…	…

5.3 Result and Analysis

To validate the proposed approach, the pseudo dataset is used for neural network training and testing. The database consists of 6,000 transactions and 48 attributes, including 6 service workers, 8 drink recipes, 12 toppings, 6 sweetness levels, 4 ice levels, along with 12 tip percentage values.

The dataset is split into training, validation, and testing sets with a 6:2:2 ratio for model training. The training curve is shown in Figure 7. After around 34 epochs, the model reaches around 88.74% accuracy on the testing dataset, suggesting the proposed neural network-based data-driven approach is effective for tip nudging design.

It should be noted that the model has overfitting issues after 40 epochs, suggesting this model complexity is enough to explain factors and patterns that influence the tip behavior with given data. Factor analysis can be further conducted to find significant factors and to simplify the model. In the meantime, other data, like service transaction time, can be included as additional factors that enable the tip nudging mechanism with more context-awareness.



(a) Accuracy Curve (b) Loss Curve

Figure 7. Neural network training curve

To test the significance of the resulted smart tipping nudge, we organized a focus group with 20 participants to run a controlled experiment, as shown in Table 3. Each participant responded to each scenario (standard/smart nudge) by ordering one type of drinks each time. Overall each participant placed 6 orders of 3 types of drinks twice. Each drink type received 20 orders for the standard or smart nudge scenario, totaling 40 orders. After randomly 6 runs of the experiment, the statistics of average tip amount for the standard and smart nudge cases are 12.34% and 17.86%, respectively. The experiment concluded that the smart nudge outperform the standard nudge case.

Table 3. Experiment of smart tip nudging

Testing Drink Service Category	Tip Nudging Experiment		Result (Average Tip Amount)
Classic black milk tea (Low-end)	One set of standard 'default tip options'	{No, 10%, 15%, 20%, Other}	12.34%
Matcha boba tea (Mid-end)	Smart tipping nudge with customized 'default tip options' tailored to each Low-/Mid-/High-end category	Low-end: {No, 8%, 12%, 18%, Other}	17.86%
Handmade tars (High-end)		Mid-end: {No, 10%, 15%, 20%, Other}	
40 Customer orders for each category		High-end: {No, 13%, 18%, 22%, Other}	

6. Conclusions

There are varying perspectives on the correlation between tipping and service quality in the literature. While some studies suggest the connection between service quality and tip sizes is tenuous at best (Lynn, 2001), other studies conclude the opposite (Bodvarsson and Gibson, 1999), or argue if it is because of a weak relationship or just weak measurement (Lynn, 2003). Our prospect-theoretic modeling finds out that the process of delivering a service results in fulfillment of service value added and this is perceived as the prevalence of tipping. In addition, the tip size is correlated to quality of service in line with a prospect theory value function. These behavioral economic findings shed light on developing insights into the underlying mechanism of the tipping behavior.

The prevailing behavioral economic and experimental psychology studies on the tipping behavior are mainly empirical and focus on understanding human social factors that affect tipping. There are limited formal guidelines or

methodologies on how to mitigate various factors towards increasing tips. We approach this issue from an engineering design perspective through smart tip nudging. Designing a smart tipping nudge improves the current practice of using one set of standard 'default tip options' regardless of whatever kind of service delivered. The end result is envisioned to be customized 'default tip options' tailored to varying tendency of different services for potentially high or low tip amounts. This is conducive to better user experience on the consumer side, while bringing better chance of higher tips on the supply side.

Traditional tipping behavior research is dominated by experimental studies, in which limited sample sizes or subjective surveys tend to be biased and difficult to generalize or even validate the findings. The proposed data-driven approach indicates the great potential to embrace data analytics, machine learning and AI technologies, given pervasive connectivity, massive data and smart sensor technologies widely available in nowadays business operations. For example, data-driven parameter tuning lends itself to be a promising means to enhance the prospect-theoretic value function formulation to model irrational decision making underlying a number of social-economic phenomena.

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