Using Variability in Default Tip Options as a Form of Smart Nudging

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0. Personal Statement

I was never a STEM-oriented person. I like to think it was because I had talent in another subject that took my attention away from STEM, but it was more likely due to the humbling experience of going to an academically challenging high school that turned my love for science and math into the stress of finishing mountains of homework and fear of failing back-to-back assessments. I couldn't picture myself pursuing a career in STEM when I obviously wasn't good at it.

I bounced from subject to subject, taking various non-STEM-related classes to find my interest. Music bore me, literature made no sense half the time, and Spanish required me to use more brain cells than I had. It seemed like I would end up majoring in a subject I disliked until I took AP Psychology during my junior year. While the kid next to me used the class to catch up on his sleep, I was engrossed in the material, taking notes on every little thing in each lecture. By the time the fall semester was over, I knew that I wanted to do something psychology related in the future.

My dad is a professor, so research papers were his life. When he introduced the idea of writing a paper to my brother and me, my brother gagged in response while my eyes lit up. I've always loved creating things, so the idea of writing a research paper seemed like a perfect way to actually follow through on my interests rather than admire them from afar. With my dad's guidance, I contacted a research assistant professor at the Georgia Institute of Technology and introduced myself. I combined my interest in psychology, natural understanding of economics, and job in the food service industry to research tipping and how default tip options on an electronic payment system can affect the amount a customer tips.

During the process of writing my paper, I realized that I would have to utilize mathematical formulas and figures to convey my research rather than explain through analogies and anecdotes (my usual M.O.). It was also a different side of math that I had to learn. Rather than following a pre-existing theorem, I had to come up with my own equation with its own variables to describe my model. While I was still in my "STEM is too difficult for me" phase, I recognized that my research still involved STEM. The electronic payment systems were technology, the neural network models were engineering, and the equations and data I used were math. I realized that STEM wasn't as black-and-white as individual subjects but woven into everyday life. Through my project, I realized that my hatred towards science and math was petty, and I began to love STEM again.

While research is a vast field with no superior figure setting strict rules and orders, use the freedom to your advantage. Pick a topic you're interested in, find an issue or problem related to it, then find an idea that fixes or improves the issue. For example, one of my friends interested in computer science decided to research on the lack of female representation in the field and led a case study to help increase female representation by increasing interest in computer science among teenagers. Another tip is not to be afraid of failure. Even if your research doesn't achieve its intended results, other researchers may use your findings as inspiration or a starting point for their own research. Research may seem like a daunting task at first, but all you need is an interest, an idea, and motivation to bring your solution to life.

1. Introduction

The phenomenon of tipping has attracted a large body of study 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) while 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 literatures have 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 decrease with the bill size, coinciding with the 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. On the supply side: attitude, appearance, and other variables can impact the size of the tip received. 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.

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, but demand-side variables matter more (Chandar et al., 2019). The study finds that the knowledge of certain patterns in 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, due to the increase in technological innovations, is that there is an increase in service providers 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 for 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.

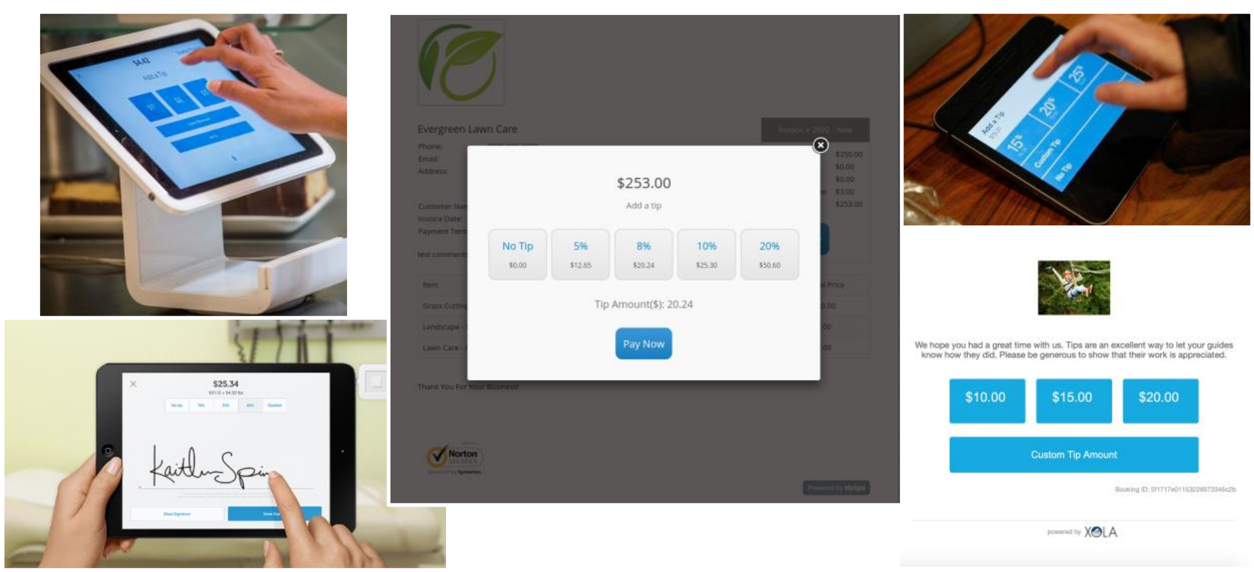


Figure 1. Examples of default tip options on electronic payment systems

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. Due to the social norm of tipping (Azar, 2007), consumers are more likely to avoid the "no tip" option when given. While higher default tip options may lead to more tips, consumer 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 service providers.

Towards this end, this research aims to examine 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. Focusing on a behavioral economic analysis of tipping behavior, this research develops 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 the varying tendencies 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. Problem Formulation: Prospect Theoretic Modeling of Consumer Tipping Preferences

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

While classical economics assumes that all individuals are rational, prospect theory 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: behavior economics, studying the effects of various factors on the decisions of individuals and institutions (Tversky and Kahneman, 1992).

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 a 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, this research proposes to model consumer tipping preference based on a subjective value function of prospect theory as:

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

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 consumer. 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 $\boldsymbol{T}$ in terms of percentage of the bill size is defined as the consumer's perceived value of a quality service delivered to him by the service provider. The connection between service quality and tip size is a strong market phenomenon albeit in a peculiar type without rigid enforcement of obligations, shown by an analysis of 286 survey studies examining the relationship between service and tips (Bodvarsson and Gibson, 1999). Moreover, service level $\boldsymbol{Q}$ (%) is used as how a particular service is measured. Service level is widely practiced in the service industries since it provides the expectations of quality, service type, and remedies when requirements are not met.

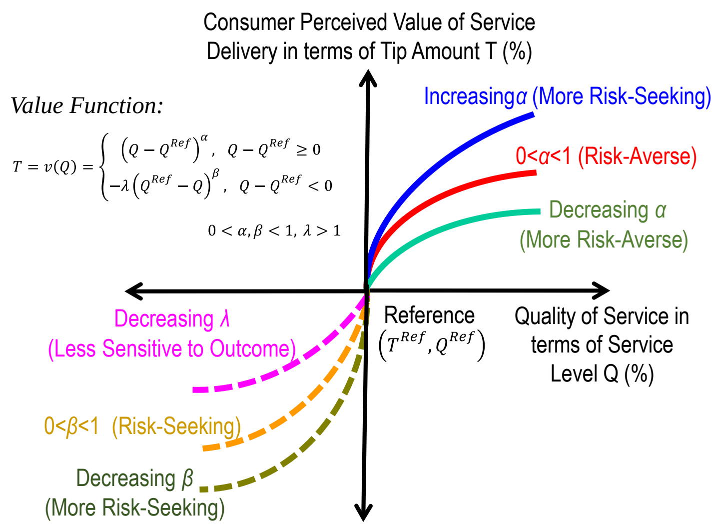


Figure 2. Tip amounts correlated to quality of service in line with a prospect theory value function

The consumer's 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, involving both instrumental and emotional aspects. Thus, it is likely that the reference point varies among different respondents. To solve this problem, individual reference points can be set up 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.

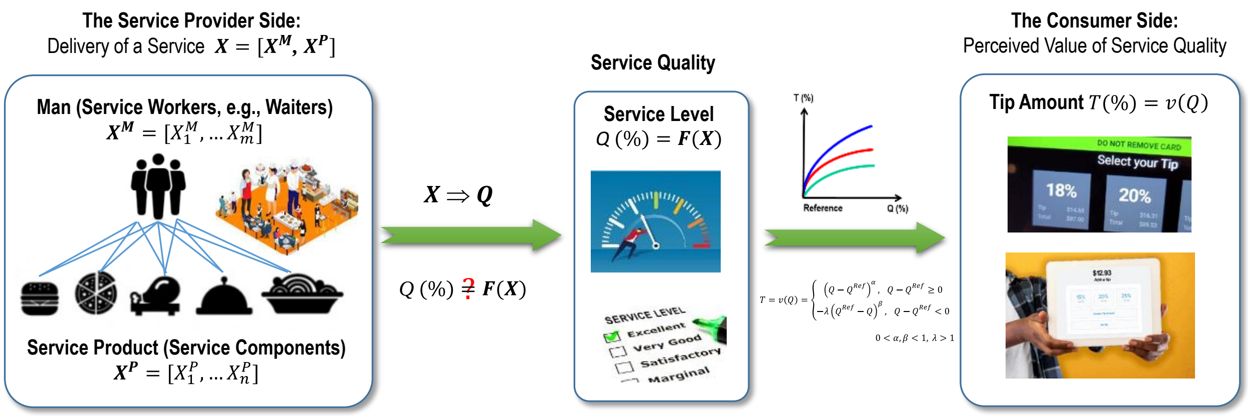


Figure 3. Fulfillment of a service delivery process resulting in perceived value of service quality by the tip amount

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 the delivery or fulfillment of a particular service that comprises the service workers who do the service jobs, $\boldsymbol{X^M} = [X_1^M, \ldots X_m^M]$, and the specific service product, $\boldsymbol{X^P} = [X_1^P, \ldots X_n^P]$, 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 the service worker i provides the service, and m as the number of service workers. Also, X_j^P indicates the service product p consists of the j-th product or service component out of a large set of available component choices with a total number of n. Figure 3 illustrates the indicated 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 tipping behavior. It essentially entails a cascading two-stage mapping process to fulfill the service value that finally results in tips. The first stage takes place on the supply side: the service provider commits certain manpower and resources to create the requested 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 such mapping mechanism of tipping behaviors sheds light on developing insights into the design of tip nudging with better user experience.

3. Technical Approach and Method: Data-Driven Smart Tip Nudging 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). For example, using an iPad to suggest tip amounts with default options can be regarded as a means of digital nudging. Thus, tip nudging refers to indirectly persuading consumers to tip.

Service providers can alter certain features to nudge customers to tip more or more often. Because tipping accounts for a large value in the economy, small changes in tipping behavior can have largescale revenue impacts. How we present choices impacts what people will decide to do. By taking advantage of the aspect of choice architecture to alter behavior in a predictable way, a smart tip nudging design can be created to indirectly alter a consumer's tipping behaviors.

In practice, in order to establish various parameters of the service quality and prospect value functions, tremendous effort is necessary to set up user experiments and conduct comprehensive data collection and analysis. For a digital tip nudging case, this research proposes a pragmatic approach using advanced data-driven analysis techniques to avoid a costly experiment and parameter tuning process by using the large data of sales transactions available due to the adoption of electric payment systems widely used in the fast-causal service sector. For this purpose, machine learning techniques are particularly useful for achieving a smart tip nudging 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 of 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 consumer finally paid a tip amount T_i (e.g., $T_i = 14\%$) to Mr. David.

To identify the tipping patterns from a large dataset of past transaction records, machine learning techniques can be applied to classify different categories of services $\{S_1, \dots S_k, \dots, S_K\}$ that typically tend to yield high or low tip amounts. For example, star waiters and waitresses or ordering the best sellers on a menu will result in higher-than-average tips. Likewise, inexperienced waiters and waitresses or ordering basic items on a menu will result in below average tips.

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, deciding which tip options should be suggested becomes a classification problem. Since the inputs involve both the service worker and service product factors, the mapping of $\boldsymbol{F}(\boldsymbol{X}) \to T$ is not guaranteed to be linear and is therefore learned through a multilayer neural network. A neural network is a non-parametric model with a more 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 smart tip 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, outside factors also affect the tip amount. For example, during the peak hours, the waiting time for the service may be expected to take longer than usual. During this situation, the default tip options can be compromised a bit, e.g., displaying {0%, 4%, 9%, 14%,19%, Other}, instead of {0%, 5%, 10%, 15%, 20%, Other}.

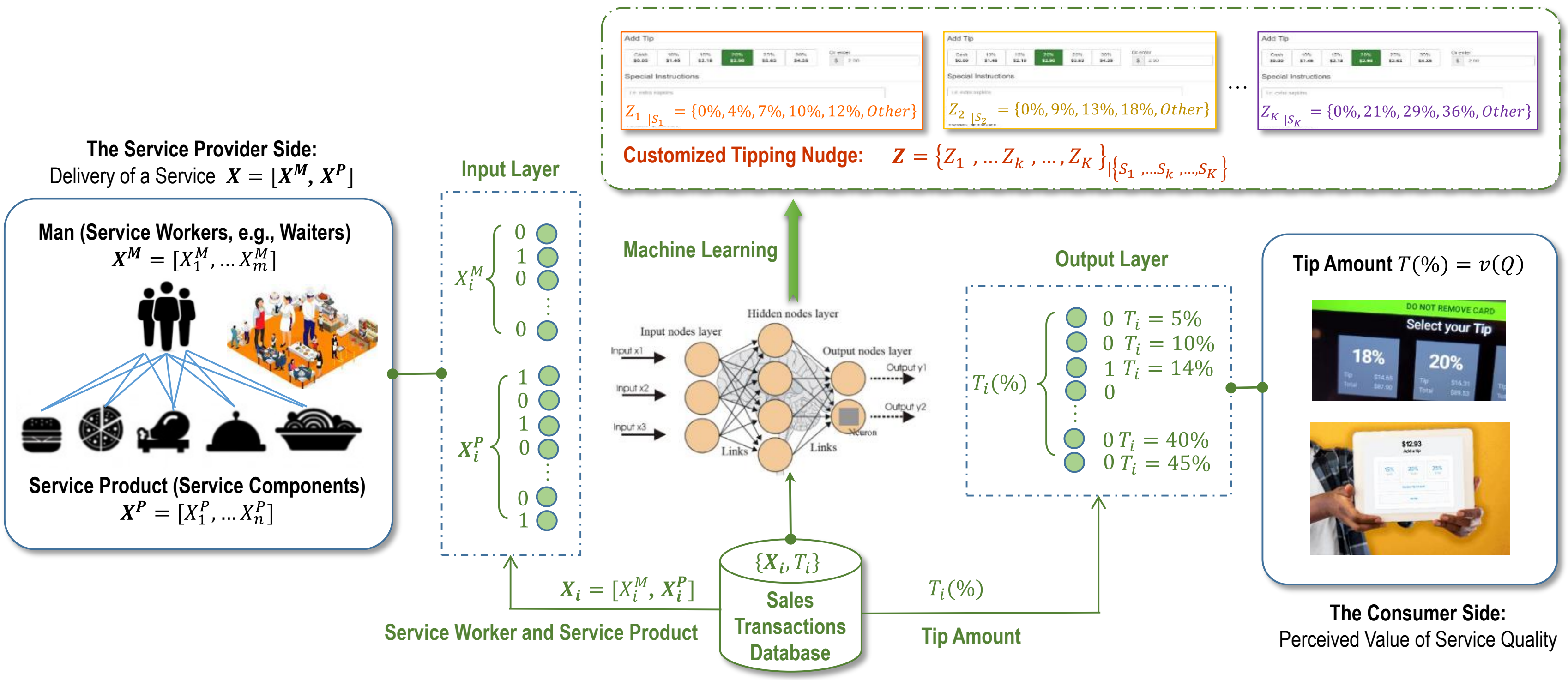
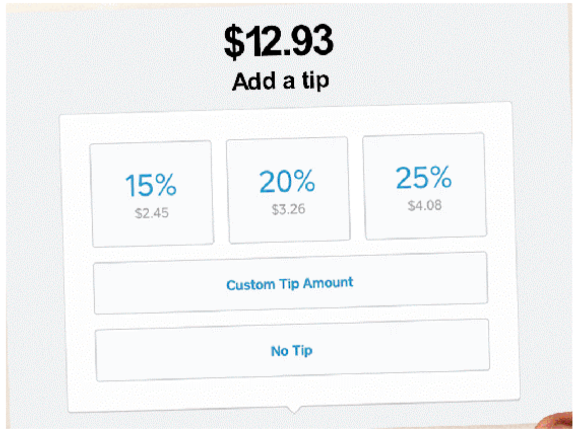


Figure 4. Data-driven smart tip nudging through analysis and learning of historical tip transactions

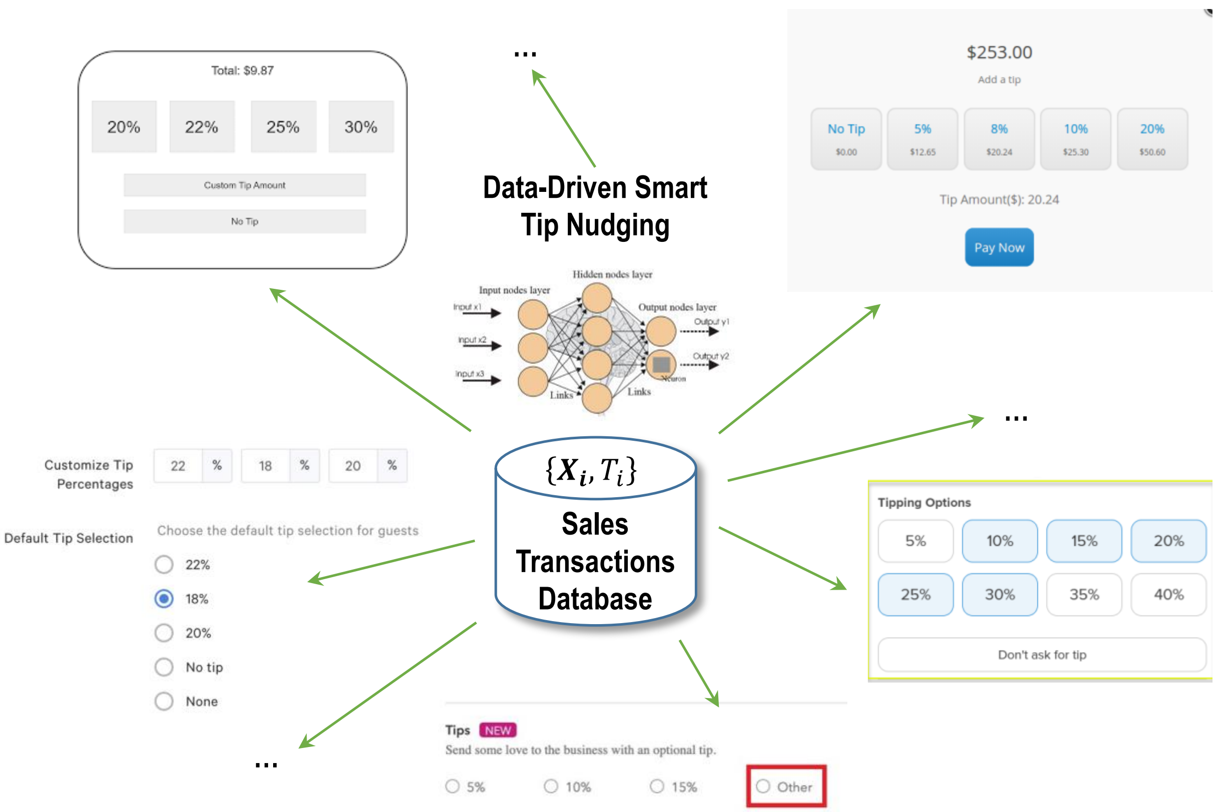
For instance, Mr. David is one of the star waiters in the restaurant who always delivers 5-star service and have received large tips in the past. Similarly, a house steak is one of the best sellers on the menu and usually leads to higher tips as well. If a customer happens to be served by Mr. David and happens to order the house steak, then the payment terminal will display higher tip options, e.g., $Z_{K\ |S_K} = \{0\%,\ 21\%, 29\%, 36\%, Other\}$, that are tailored to this high-end service. Similarly, if a low-end service if provided, implying a smaller chance in receiving a large tip, the system should smartly display more conservative tip options, e.g., $Z_{1\ |S_1} = \{0\%,\ 4\%,\ 7\%, 10\%, 12\%, Other\}$.

The end result of smart tip nudging is shown in Figure 5. Figure 5(a) shows the as-is model of the current practice in the market, where only one set of standard default tip options, e.g., {No, 10%, 15%, 20%, Other} are displayed regardless of whatever kind of service to be delivered. This completely ignores the fact that different service workers exhibit varying competency in receiving a higher tip amount. Likewise, a basic service like handing a muffin versus a more complex job like handmaking a complicated coffee order inherently implies different values of services; the tip amount indicating how the consumer perceives the value.

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 tip nudging enables customized tip options that are tailored to the varying tendency of different services for potentially high or low tip amounts. The adaptability of a smart system conforms to the consumers' perception on paying tips revealed by the prospect-theoretic model. Therefore, smart tip nudging leads to better user experience on the consumer side and results in a better chance of higher tips on the supply side.



(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

4. Experiment and Pilot Results

4.1 Field Experiment and Data

A field experiment was conducted at a local bubble tea shop located in Sandy Springs, Georgia in the USA. It is a typical food business offering fast-causal service where the required quick turnaround time makes default tip options using an electronic payment system 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, likely due to decreased sensitivity of the consumers towards a relatively small bill size. Due to extensive variety of drinks and the large variations in adding many different toppings and specifying different sweetness and ice levels, almost every bubble tea order is custom-made by the tender and results in a lot of tips.

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

4.2 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, and 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 approximately 88.74% accuracy on the testing dataset, suggesting the proposed neural network 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’s 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.

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		

To test the significance of the designed smart tip nudge, I set up a virtual experiment using discrete event simulation to simulate the ordering preference of 20 pseudo customers. Variation of customer orders were randomly generated in accordance with common probabilistic distributions of customer preferences widely recognized in the fields of marketing and service sectors. The design of the experiment simulated transaction data and product choices, as shown in Table 3. Each pseudo customer responded to each scenario (standard/smart nudge) by ordering one type of drinks each time. Overall, each customer 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 6 random runs of the experiment, the average tip amount for the standard and smart nudge cases are 12.34% and 17.86% respectively. The experiment indicated that the smart nudge outperforms 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}	

5. Discussions and Conclusions

There are varying perspectives on the correlation between tipping and service quality in 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 some arguing if it is because of a weak relationship or just weak measurement (Lynn, 2003). The proposed prospect-theoretic modeling finds that the process of delivering a service result 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 tipping behavior. Further research in real-life application case studies across different service sectors will help understand the broader impact of the digital economy.

The prevailing behavioral economics and experimental psychology studies on the behavior of tipping are mainly empirical-based 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. This research approaches this issue from an engineering design perspective through smart tip nudging. Designing a smart tip nudging system 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 tip options tailored to varying tendency of different services for potentially high or low tip amounts. This conducts 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 validate the findings. The proposed data-driven approach indicates the potential to embrace data analytics, machine learning, and AI technologies, given pervasive connectivity, massive data, and smart sensor technologies widely available in business operations. For example, data-driven parameter tuning is a promising means to enhance the prospect-theoretic value function formulation to model irrational decision-making underlying several social-economic phenomena.

Bibliography

Abdukadirov, S., Nudge Theory in Action, behavioral design in policy and markets, 1st edition, *Springer International Publishing*, Cham, 2016.

Azar, O., The implications of tipping for economics and management, *International Journal of Social Economics*, vol. 30, no. 10, pp. 1084-1094, 2003.

Azar, O., The social norm of tipping: A review, *Journal of Applied Social Psychology*, vol. 37, no. 2, pp. 380-402, 2007.

Azar, O., Tipping motivations and behavior in the U.S. and Israel, *Journal of Applied Social Psychology*, vol. 42, no. 2, pp. 421-457, 2010.

Azar, O., Business strategy and the social norm of tipping, *Journal of Economic Psychology*, vol. 32, no. 3, pp. 515-525, 2011.

Bodvarsson, Ö. And Gibson, W., An economic approach to tips and service quality: Results of a survey, *The Social Science Journal*, vol. 36, no. 1, pp. 137-148, 1999.

Brod, A., Mechanism Design and Behavioral Economics: Incentivizing Optimal Pre-Trial Discovery, *Yale Law School*, 2021.

Chandar, B., Gneezy, U., List, J., and Muir, I., The drivers of Social Preferences: Evidence from a nationwide tipping field experiment, *National Bureau of Economic Research*, no. w26380, 2019.

Dupond, S., A thorough review on the current advance of neural network structures, *Annual Reviews in Control*, vol. 14, pp. 200-230, 2019.

Green, L., Myerson, J. and Schneider, R., Is there a magnitude effect in tipping?, *Psychonomic Bulletin & Review*, vol. 10, no. 2, pp. 381-386, 2003.

Hassenzahl, M. and Tractinsky, N., User experience – a research agenda, *Behavior & Information Technology*, vol. 25, no. 2, pp. 91-97, 2006.

Hummel, D. and Maedche, A., How effective is nudging? A quantitative review on the effect sizes and limits of empirical nudging studies, *Journal of Behavioral and Experimental Economics*, vol. 80, pp. 47-58, 2019.

Kahneman, D. and Tversky, A., Prospect theory: an analysis of decision making under risk, *Econometrica*, vol. 47, no. 2, pp. 263-291, 1979.

Lynn, M., Restaurant tips and service quality: A weak relationship or just weak measurement, *International Journal of Hospitality Management*, vol. 22, no. 3, pp. 321-325, 2003.

Lynn, M., Tipping in restaurants and around the globe: An interdisciplinary review, *Handbook of Contemporary Behavioral Economics*, pp. 648-666, 2015.

Meske, C. and Amojo, I., Status quo, critical reflection, and the road ahead of digital nudging in Information Systems Research: A discussion with Markus Weinmann and Alexey Voinov, *Communications of the Association for Information Systems*, pp. 402-420, 2020.

Miller, B., Compensation practices in restaurants and the impact on service quality, *Journal of Foodservice Business Research*, vol. 13, no. 1, pp. 24-35, 2010.

Nelson, M., A case study in tipping: An economic anomaly, *Crossing Borders: A Multidisciplinary Journal of Undergraduate Scholarship*, vol. 2, no. 1, 2017.

Pesendorfer, W., Behavioral economics comes of age: A review essay on advances in behavioral economics, *Journal of Economic Literature*, vol. 44, no. 3, pp. 712-721, 2006.

Rabin, M., Psychology and economics, *Journal of Economic Literature*, vol, 36, no. 1, 1998.

Saayman, M. and Saayman, A., Understanding tipping behavior – an economic perspective, *Tourism Economics*, vol. 21, no. 2, pp. 247-265, 2015.

Samson, An introduction to behavioral economics, Available: https://www.behavioraleconomics.com/resources/introduction-behavioral-economics/, April 29, 2022.

Shamir, B., A note on tipping and employee perceptions and attitudes, *Journal of Occupational Psychology*, vol. 56, no. 3, pp. 255-259, 1983.

Tung, I., Wait staff and bartenders depend on tips for more than half of their earnings, Available: https://www.nelp.org/publication/wait-staff-and-bartenders-depend-on-tips-for-more-than-half-of-their-earnings/, May 17, 2022.

Tversky, A. and Kahneman, D., Advances in prospect theory: Cumulative representation of uncertainty, *Journal of Risk and Uncertainty*, vol. 5, no. 4, pp. 297-323, 1992.

Warren, N., Hanson, S., and Yuan, H., Who's in Control? How Default Tip Levels Influence Customer Response, *Marketing Science Institute Working Paper Series*, vol. 21, no. 126, 2021.

Zarrabian, D., Tip Nudging: A 3-Part Experimental Analysis of Influencing Tips Through Technological Default Menus, *Harvard College*, Cambridge, MA., 2019.