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The Past, Present and Future of Measuring Customer Satisfaction with Artificial Intelligence and Machine Learning

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ABSTRACT

This article briefly sketches the evolution of Customer Satisfaction (C-Sat) measurements from a historical point of view and contributes to the future discussion from both academic and practitioner point of views. Firstly, this article argues that traditional methods of measuring C-Sat do not adequately meet current business needs. Secondly, this article suggests that Artificial Intelligence (AI) and Machine Learning (ML) tools and algorithms are capable of complementing or even replacing traditional C-Sat measurements and are even able to help predicting C-Sat before customers themselves enter a transaction. A global managerial survey confirms these propositions.

Keywords: Customer satisfaction; CES; NPS; Artificial Intelligence; Machine Learning

INTRODUCTION

In the last few decades, organizations have been relying heavily on survey-based traditional customer satisfaction (C-Sat) measurements such as service quality, customer effort score (CES) or net promoter score (NPS). These are inadequate for current business needs for several reasons. First, they are mostly descriptive and cross-sectional and are based on small and often biased sample groups. Secondly, these measurements don't truly reflect the volatility in customer experience in a multi-channel and multi-platform environment in which customers interact with firms. These interactions occur across multiple channels and reflect customer impressions in many varied social media and review sites. Finally, there is often a significant time lag between measurements and improvement actions which makes it challenging to recover customer dissatisfaction or adjust the problematic processes in a timely fashion. Therefore, marketing scholars and practitioners are in search of new methodologies that make use of Artificial Intelligence (AI) and Machine Learning (ML) tools to understand customer insights across different channels and online platforms. AI & ML tools can provide relevant insights and predictions based on firms' internal data from Customer relationship Management (CRM) and Enterprise Resource Planning (ERP) systems as well as on external data from customers' online activities such as searching, browsing, and contributing to social media and review platforms. Analyzing this type of internal and external data thus offers new opportunities for diagnosing potential issues, predicting likely outcomes, and prescribing actionable insights which can help firms observe and predict likely C-Sat before customers even experience a (dis)satisfactory event.

Historical developments in customer satisfaction research and measurement

Customer satisfaction has been the object of academic interest for several decades. In early academic research, Flanagan (1954) introduced the critical incident technique to determine C-Sat items and customer requirements. Word-of-mouth (WoM) is defined as an important factor in C-Sat and purchase decisions (Whyte, 1954; Arndt, 1967). Katona (1975) suggested that C-Sat not only depends on the quality of the product, but also the expectations of the customers. Churchill and Surprenant (1982) advocated the idea of C-Sat needs being the center of marketing practice and consumer research, since satisfying the customers has some obvious benefits, such as saving money and increasing revenue, as well as bringing new and repeat business. Parasuraman et al. (1988) in their SERVQUAL model established the link between service quality and C-Sat with five dimensions: tangibles, reliability, responsiveness, assurance, and empathy. Based on this model, Cronin and Taylor (1992) proposed the SERVPERF model which abandoned the difference analysis method and directly measured the customer's perceived service performance.

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Following ongoing service satisfaction research, Bolfing (1989) investigated the way customers express dissatisfaction and what service marketers can do about it. Hart at al. (1990) suggested that service recovery is fundamental to service excellence and should, therefore, be regarded as an integral part of company strategies. Rust and Zahorik (1993) and Anderson et al. (1994) researched the relationship between C-Sat, customer retention, market share and customer loyalty. Service quality is traditionally defined as the difference between expected and perceived service performance and is assessed by how customers perceive service offerings (Parasuraman et al., 1994; Cronin & Taylor, 1994). Heskett et al. (1997) introduced the service profit chain which linked profit and growth to loyalty, satisfaction, and value.

Oliver (1997) stated that the most frequent customer response to both satisfying and dissatisfying transactions was for the customer "to do nothing, absolutely nothing." As similarly argued by Birgelen et al. (2000) "in the modern context of tremendous information availability through advances in information technology and research practice, use of customer satisfaction-related information does not always appear to be optimal." Referring to Mulder (1999), they noted that "decision-makers get frustrated when it turns out that, despite repeated measurement and attention for quality-related issues, no changes in customer satisfaction levels are evident."

In order to quickly measure C-Sat, sales growth and loyalty intentions, Reicheld (2003) introduced The Net Promoter Score (NPS) as "the one number you need to grow", seemingly as a derivative concept based on WoM with a single question: "How likely are you to recommend us to others?" Scores between 0 and 6 are considered detractors, 7 and 8 as passively satisfied, and 9 and 10 as promoters. NPS is the percentage of promoters minus detractors. Morgan and Rego (2006) examined commonly used and widely advocated customer feedback metrics and found that average satisfaction scores have the greatest value due to their ability to predict future business performance. Their research also indicated that prescriptions to focus customer feedback systems and metrics solely on customers' recommendation intentions, such as NPS, are misguided. Furthermore, longitudinal research conducted by Keiningham et al. (2007) did not find evidence that monitoring NPS leads to customer loyalty or increased financial performance.

While debate continued about which metric is most helpful for measuring C-Sat, Güngör (2007) found empirical evidence suggesting that frontline employees can observe C-Sat with a very high degree of accuracy, especially when customer interactions are remarkably negative or positive. The average frontline customer service agent e.g., in a call center, can easily interact with 8-10 customer per hour, more than 60 per day, more than 300 per week and up to 15.000 customers per year (Güngör, 2010). And this number is much more than an average business intelligence unit collects as feedback with traditional C-Sat surveys. Hence, collecting C-Sat information from frontline employees could potentially be more efficient and more effective than traditional customer surveys.

Güngör (2009) analyzed 850 retail banking customers in the United Kingdom and revealed that when determining NPS calculations, passively satisfied customers (7-8) are erroneously separated from promoters (9-10) since no significant differences exist in the loyalty intentions of these two groups (analysis of variance, $p > .80$). Furthermore, although recommendation and loyalty intentions are positively correlated ($r = 0.41$, $p < 0.01$), low recommendation scores do not necessarily indicate customer defection since only less than 25% of so-called detractors were intending to leave their bank. Consequently, this research suggests that the likelihood of recommendation might be one indicator of C-Sat or loyalty intentions but the relationship between customer loyalty and NPS might be a "false alarm".

It is interesting to observe that while criticism of NPS was growing among scholars, more than two thirds of Fortune 1000 firms across numerous industries were applying NPS to their business (Kaplan, 2016). This is possibly because NPS is easy to understand and its methodology is easy to implement with only "one" question. The popularity of this single-item metric to shed light on the customer experience has led to another easily explainable model with a single question: Dixon et al. (2010) introduced the Customer Effort Score (CES) and argued that it is a better predictor of satisfaction or loyalty than C-Sat questions. CES measures the amount of effort a customer has to exert to get an issue resolved, a request fulfilled, a product purchased/returned, or a question answered. Wiesel et al. (2012 and 2015) compared different customer metrics – namely C-Sat, NPS, and CES – to test their ability to predict retention across a wide range of industries and concluded that the different customer metrics differ depending on the industry and the unit of analysis; and combining different metrics improves predictions about customer retention.

Güngör (2017) analyzed C-Sat and loyalty intentions with a large SERVQUAL dataset obtained from 3.581 customers from 66 Cambodian companies in six different industries. Five popular C-Sat and loyalty metrics were used as dependent variables: overall satisfaction, customer effort, recommendation, loyalty and repurchase intentions. Correlations (Table 1) among these variables varied between 0.722 and 0.798 ($p < 0.01$) with a very high internal consistency (Cronbach alpha, 0.94). Linear regression analysis showed that recommendation was the strongest predictor of overall C-Sat with ($r = 0.795$, $p <0.01$) and explained 63% of the variance. These results indicated that measuring recommendation might show similar results as overall satisfaction, especially when scores are collected and analyzed without manipulation e.g., without creating so-called 'promoter' or 'detractor' subgroups.

Table 1: Correlations among popular C-Sat and customer loyalty related questions

		OverallSatisfaction	CustomerEffortScore	Recommedation	LoyaltyIntention	RepurchaseIntention
OverallSatisfaction	Pearson Correlation Sig. (2-tailed) N	1 3581	.787** .000 3581	.795** .000 3581	.723** .000 3581	.751** .000 3581
CustomerEffortScore	Pearson Correlation Sig. (2-tailed) N	.787** .000 3581	1 3581	.775** .000 3581	.722** .000 3581	.727** .000 3581
Recommedation	Pearson Correlation Sig. (2-tailed) N	.795** .000 3581	.775** .000 3581	1 3581	.768** .000 3581	.798** .000 3581
LoyaltyIntention	Pearson Correlation Sig. (2-tailed) N	.723** .000 3581	.722** .000 3581	.768** .000 3581	1 3581	.778** .000 3581
RepurchaseIntention	Pearson Correlation Sig. (2-tailed) N	.751** .000 3581	.727** .000 3581	.798** .000 3581	.778** .000 3581	1 3581

**. Correclation is significant at the 0.01 level (2-tailed)

Weber and Chatzopoulos (2019) research, looked at the differences between digital and non-digital customer experiences, and showed that while C-Sat scores remain flat in one channel, recommendations could decline in another, indicating potential discrepancies in different metrics between online and offline channels. Bjorn (2020) measured five different customer journeys in the automotive industry in the Netherlands and found that C-Sat, Recommendation (NPS), and CES are interrelated; namely, customer satisfaction leads to customer recommendation and this relationship is mediated by customer efforts.

In sum, there are inconsistent findings and recommendations about C-Sat measurements and about NPS in particular (Klie, 2020; Baehre et al., 2021). Even the creator of the NPS (Reichheld et al., 2021) admitted that "NPS started to be gamed and misused in ways that hurt its credibility." Consequently, and unsurprisingly, one-third of customer service and support leaders are either unsure or disagree that NPS is valuable to customer service. It's predicted that more than 75% of organizations will abandon NPS as a measure of success for customer service by 2025 (Gartner, 2021).

Artificial Intelligence (AI) And Machine Learning (ML) in Marketing and Service Research

There is a growing interest in AI & ML in marketing and service research in order to understand, design and deliver personalized service and offerings as well as understanding customer satisfaction (Syam & Sharma, 2018; Chaffey, 2019; Grewal et al., 2020; Stone et al., 2020; Mustak et al. 2021; Verhoef et al., 2021). Huang and Rust (2018, 2021, 2022) defined a strategic framework for AI in marketing, incorporating multiple AI benefits: mechanical AI for automating repetitive marketing activities, thinking AI for processing data to arrive at decisions, and feeling AI for analyzing customer interactions and emotions. Mariani et al. (2021) provided an integrated view on AI in marketing, consumer research, and psychology literature, identifying major clusters such as big data, AI, ML, data mining, and neural networks.

Artificial Intelligence is an umbrella term for various methodologies designed to provide computers with human-like abilities of hearing, seeing, reasoning and learning to support the replication of human analytical and/or decision-making capabilities (Güngör, 2020). Kaplan and Haenlein (2019) defined AI as a system's ability to correctly interpret external data, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation. The mega trends leading to the rise of AI, according to Burgess (2018), are the role of big data, the availability of cheap storage, faster processors, Internet connectivity and connected devices, developments in machine learning and the prevalence of cloud AI from tech giants like Google and Amazon.

Machine Learning is the use of mathematical procedures (algorithms) to analyze data and identify useful patterns (relationships or correlations) between different items and learn from them. Once the relationships are identified, they can be used to make inferences about the behavior of new cases when they are present (Finlay, 2018). There are three major types of ML widely used in business: *Supervised learning* algorithms train systems using examples classified (labelled) by humans, *unsupervised learning* algorithms explore input data without being given an explicit output variable and to discover patterns in unlabeled data, and *reinforcement learning* algorithms learn to perform tasks simply by trying to maximize rewards they receive for their actions.

Deep learning is a type of ML that trains a computer to perform human-like tasks, such as recognizing speech, identifying images or making predictions (SAS, 2018). Artificial **Neural Networks**, as part of deep learning (Nevala, 2017; Nvidia, 2017), try to learn tasks mimicking the behavior of brain; and are increasingly used to measure and predict C-Sat and loyalty drivers (Ansari & Riasi, 2016; Kalinic et al., 2021).

AI & ML can indeed support companies offering important customer benefits, such as advice with recommender systems, peace of mind with smart household products, and convenience with voice-activated virtual assistants (Puntini et al., 2021; Pitardi & Marriott, 2020). Sales and service employees are also increasingly augmented with AI-based tools and software (Davenport et al., 2020; Henkel et al., 2020).

AI & ML tools are leading to new avenues in understanding and predicting C-Sat and loyalty intentions – by utilizing internal and external data source

Aksoy et al. (2020) suggested that managers working with advanced enterprise feedback management (EFM) software are still primarily tracking relatively simple customer metrics such as overall satisfaction, complaints, recommend intention, etc. In fact, such information is relatively easy to capture with today's massive internal and external data availability and relatively easy to interpret and analyze, thanks to new developments in AI & ML tools.

Analyzing firms' internal information, Bauman et al. (2012) compared customer survey data with the available information about the same customers. Their data mining model explained almost 60 percent of the variation in loyalty intentions, whereas their survey data additionally explained only 8.4 percent. Baier et al. (2020) applied supervised machine learning to identify dissatisfied customers when they initiate a service request in company incident management systems. They demonstrated that text-based incident descriptions can be used to identify and flag dissatisfied customers for a potential service recovery. Similarly, Sidaoui et al. (2020) demonstrated that chatbot data is suitable for analyzing sentiment to extract customer experience and feelings. AI even has the ability to identify dissatisfied customers that do not share their experiences explicitly during service interactions by recognizing emotions in facial expressions (González-Rodríguez et al., 2020) and sentiment in live speech and recordings (Henkel et al., 2020; Schuller & Schuller, 2021).

Analyzing external information, data outside company boundaries, Kang and Park (2014) suggested that customer reviews contain valuable information for monitoring C-Sat. Research by Fan et al. (2015) found that analyzing social media content offers more value than the more traditional approaches such as customer surveys or focus groups. Similarly, Xiang et al. (2015) found a strong correlation between experiences shared in online reviews and satisfaction ratings given by those customers. Klostermann et al. (2018) analyzed image and textual data from social media, such as Facebook, Instagram, and Twitter, and concluded that aggregating and mapping textual information into image clusters enabled marketers to derive meaningful insights about what consumers think and feel about their brands. Korfiatis et al. (2019) further suggested that online reviews with unstructured information can be of value to increase competitive performance. Liang et al. (2020) evaluated online reviews in takeaway platforms and concluded that such reviews give restaurants untapped opportunities to better understand their customers and find ways to improve their services.

AI & ML tools are also revolutionizing the way customers interact and engage with brands (Guha et al. 2021; Lim et al., 2022), e.g., by **AI-enabled service encounters** (Ameen, et al., 2020). Indeed, modern service encounters are technology dominant and characterized by complex service systems, including AI assistants (Dawar & Bendle, 2018; Kaplan & Haenlein, 2019), computers and AI as customers (Huang & Rust, 2022) and service robots (Dirican, 2015; van Doorn et al., 2017; Wirtz et al., 2018; Morita et al., 2019; Prentice et al., 2020; Lu et al., 2021). With the increasing number of connected devices such as autonomous vehicles and smart home appliances, even **Machine-to-Machine interactions** (Güngör, 2018) can provide relevant information to predict the likelihood of product or service events and failures, and consequently, predict C-Sat and behavior.

The use of AI & ML tools in alignment with a well-defined digital strategy can indeed generate competitive advantage (Borges et al., 2021). However, AI & ML tools do not automatically bring these advantages since there are many organizational requirements and pitfalls, privacy concerns and growing regulations around using AI & ML responsibly (e.g., GDPR, 2016; European Commission 2019; European Parliament, 2021; OECD, 2020; Zhu et al., 2021; Jöhnk et al., 2021).

Managerial Reflections from a Global Survey

In order to verify the assumptions emerging above, a short survey has been shared with several customer experience management groups on LinkedIn, an online professional networking platform. More than 3000 views resulted in 111 survey participations with 101 completed surveys. Participants with different tenures from various organizations were from Europe (75%), North America (16%) and Asia (9%).

Results showed that around 75% of the firms are using simple C-Sat metrics in combination with other metrics, especially the NPS, but also with CES and frontline input. 27% of the firms were involving less than 1% of their customers with their C-Sat measurements; and 22% of the firms were measuring C-Sat only once a year. Firms using only simple C-Sat metrics were 29% whereas firms only using the NPS were 13%. CES and frontline input were rarely used as a standalone metric and AI & ML tools were used only in less than 5% of the firms that participated in the survey.

One of the interesting outcomes of the survey was about the relationship between participant tenures and how C-Sat measurements as well as AI & ML were perceived. When the tenure is increased from entry-level towards c-level, perceptions about the adequacy of traditional metrics gradually decreased and confidence about the capability of AI & ML gradually increased. Participants across all tenures similarly disagreed that *"their organizations had a sound strategy in customer satisfaction measurements and how AI & ML can improve it."*

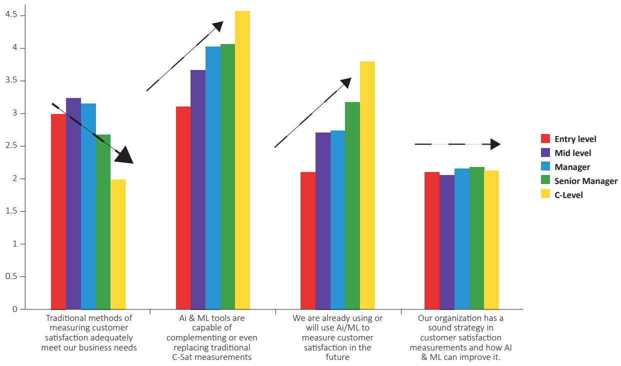

Figure 1: Perceptions about C-Sat and AI & ML across tenures

Managerial Implications

With the help of currently available Ai & ML tools, firms are already improving their learning and decision making capabilities; and able to (1) predict using supervised algorithms (e.g. linear regression) to estimate customer lifetime value (CLV); (2) classify using supervised algorithms (e.g. decision trees) to identify customers likely to churn or buy a new product; (3) cluster using unsupervised algorithms (e.g. k-means) to identify specific segments e.g. highly (dis)satisfied customers; and (4) optimize using deep learning (e.g. neural networks) algorithms to adjust service levels for customers, for instance, by dynamic routing to a virtual chatbot or to a specific customer service representative.

While CRM and ERP providers (e.g. Oracle, SAP) have the potential to utilize the predictive power of their data platforms, enterprise feedback management (EFM) providers (e.g., Medallia, Satmetrix, Qualtrics) have the potential to incorporate multiple data sources to augment customer feedback data and offer insight with, for example, text and sentiment analysis, prescribe actions such as connecting specific service employees or virtual assistants (e.g., Amelia, Watson) to customers based on their predicted service needs and emotional states (e.g., Afiniti, Affectiva) and even coach employees in real time (e.g., Cogito).

Consequently, a broader picture of C-Sat can be compiled around the customer rather than relying on frequent customer feedback requests that have a low and even negatively biased response rates (Güngör, 2009), and which eventually may demotivate service departments and employees as observed by recent research (Gartner, 2021).

CONCLUSIONS

Based on relevant literature review and empirical data, and as confirmed by a global survey, it appears that traditional methods of measuring C-Sat do not adequately meet current business needs. Frontline employee observations that are captured in the customer information systems can partly compensate these shortcomings and can elucidate even subtle customer experience fluctuations. However, there are much more to gain when ML & AI tools and methodologies are applied.

AI & ML tools and methodologies are capable of listening, understanding and diagnosing C-Sat issues, analyzing and generating insights from both internal and external data sources, predicting potential outcomes, and finally recommending personalized actions for customers such as a service recovery activity or a new product recommendation. Consequently, AI & ML tools and algorithms are also capable of complementing or even replacing traditional C-Sat measurement tools and methodologies to the point where they can even predict customer experience before a transaction occurs.

Nevertheless, while AI & ML methodologies have become quite useful, tools alone are insufficient for improving processes and cannot solve complex customer problems. Leveraging these tools for competitive advantage requires a sound strategy in both C-Sat measurements and AI & ML analytics, which seems to be the missing link at the moment.

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