CHAPTER 2

Instrumentation and Automation Fuels Customer Experience Data Collection

In Chapter 1, I used a series of case studies to explore practices in Customer Experience Analytics. These scenarios identified a range of capabilities for CEA covering a number of industries. Large automation investments in customer touch points, products, and business processes are rapidly creating enormous volumes of data as well as capabilities to make changes at electronic speeds. This section explores these changes in "instrumentation" and how that provides an environment for CEA.

IVR, kiosks, mobile devices, email, chat, corporate web sites, third-party applications, and social networks have generated a fair amount of event information about the customers. In addition, customer interaction via traditional media, such as call centers, can now be analyzed and organized. The biggest change is in our ability to modify the customer experience using software —policies, procedures, and personalization—making self-service increasingly customer-friendly.

This chapter covers the data and levers for customer experience across functional areas. The availability of raw data about the customers provides us with an unprecedented opportunity not only to analyze and understand the customer but also to adaptively change customer-facing systems and processes to improve customer experience.

Sales and Marketing

Let us start with customer shopping. Analytics related to customers and their experiences has been a widely studied area for over 50 years. Most of the core marketing science and related disciplines developed models of customer behavior, devised ways to measure customer experience, and used analytics to peek into the decision-making process. While academics worked on very impressive customer models and techniques for analysis and prediction, it was often difficult to apply these principles in practice, because of a lack of and high cost of data collection.

For example, when I was working on my Ph.D. thesis, I worked with Professor Robert Meyer to study consumer buyer behavior and help develop a mathematical model.[14] The model used a grocery-store learning game. While it was theoretically possible to create a grocery-store learning model in a game setting, it was impossible to replicate the instrumentation in real life. The good news is that all the work in marketing science can now be applied as the data becomes available. To their definition, I would like to add the tasks associated with data ingestion, categorization, and management to support the analytics.

Sales and marketing got their biggest boost in instrumentation from the Internet-driven automation over the past 10 years. Browsing, shopping, ordering, and customer service on the Web has not only provided tremendous control to end users; it has also created an enormous flood of information to the marketing, product, and sales organization in understanding buyer behavior. Each sequence of web clicks can be collected, collated, and analyzed for customer delight, puzzlement, dysphoria, or outright defection and the sequence leading to this decision.

Self-service has crept in through a variety of means: IVRs, kiosks, handheld devices, and many others. Each of these electronic means of communication act like a gigantic pool of time-and-motion studies. We have data available on how many steps a customer took, how many products she compared, and what she focused on: price, features, brand comparisons, recommendations, defects, and so on. Suppliers have gained enormous amounts of data from self-service, electronic leashes connected to products, and the use of IT. If I use a two-way set-top box to watch television, the supplier has instant access to my channelsurfing behavior. Did I change the channel when the advertisement started? Did I turn the volume up or down when the jingle started to play? If I use the Internet to shop for a product, my click stream can be analyzed and used to study shopping behavior. How many products did I look at? What did I view in each product? Was it the product description or the price? This enriched set of data allows us to analyze customer experience in the minutest detail.

What are the sources of data from such self-service interactions?

- *Product*—As products become increasingly electronic, they provide a lot of valuable data to the supplier regarding product use and product quality. In many cases, suppliers can also collect information about the context in which a product was used. Products can also supply information related to frequency of use, interruptions, usage skipping, and other related aspects.
- *Electronic touch points*—A fair amount of data can be collected from the touch points used for product shopping, purchase, use, or payment. IVR tree traversals can be logged, web click streams can be collected, and so on.
- *Components*—Sometimes, components may provide additional information. This information could include data about component failures, use, or lack thereof. For example, a wireless telecommunications provider can collect data from networks, cell towers, third parties, and handheld devices to understand how all the components together provided a good or bad service to the customer.

As much as we have used instrumentation to collect rich amounts of customer data, CEA can also be used to drive a new set of behaviors. Over the past 30 years, we have seen gradual maturing of our understanding of CEA and how it impacts sales and marketing. The early evolution was in use of CEA for segmentation. The original segmentations were demographic in nature and used hard consumer data—such as geography, age, gender, and ethnic characteristics—to establish market segmentations. Marketers soon realized that behavioral traits were important parameters to segment the customers.

As our understanding grew, we saw more emphasis on micro segments—specific niche markets based on CEA-driven parameters. For example, marketers started to differentiate innovators and early adapters, as compared with late adapters, in their willingness to purchase new electronic gadgets. Customer experience data let us characterize innovators who were eager to share experiences and were more tolerant of product defects.

In the mid-1990s, with automation in customer touch points and use of the Internet for customer self-service, marketing started to get interested in personalization and 1:1 marketing. As Martha Rogers and Don Peppers point out in their book *The One to One Future*, "The basis for 1:1 marketing is share of customer, not just market share. Instead of selling as many products as possible over the next sales period to whomever will buy them, the goal of the 1:1 marketer is to sell one customer at a time as many products as possible over the lifetime of that customer's patronage. Mass marketers develop a product and try to find customers for that product. But 1:1 marketers develop a customer and try to find products for that customer."[15]

Early CEA systems were reporting systems that provided raw segmentation data to the marketing team so that they could use the data to decide on marketing activities, such as campaigns. Automation in marketing and operations gave us the opportunity to close the loop—use CEA to collect effectiveness data to revise and improve campaigns. We are seeing surges in campaign activity. Marketers are interested in micro-campaigns that are designed specifically for a micro-segment or, in some cases, for specific customers. The customer experience information gives us criteria for including a customer in the campaign.

For example, prepaid wireless providers are engaging in micro-campaigns targeted at customers who are about to run out of their prepaid minutes. These customers are the most likely to churn to a competitor and could easily continue with their current wireless provider if they were to be directed to a store that sells prepaid wireless cards.

Another area of interest is Next Best Action (NBA)—in other words, recommending an activity based on the customer's latest experience with the product. This could include an up-sell/cross-sell based on current product ownership, usage level, and behavioral profile. NBA could be offered any time the sales organization has the opportunity to connect with the customer via a touch point. NBA is far more effective in sales conversion compared with canned rules that repeatedly offer the same product over and over across a customer interaction channel. (Imagine your airline offering you a discounted trip to your favorite warm-weather golf vacation spot on a cold day.) NBA can also be revised based on feedback from customer reaction.

Pricing has been a hotly pursued topic for business, as each percent increase in price without a corresponding decrease in demand means an increase in profits. There has been a growing trend to use price optimization models—mathematical programs that calculate how demand varies at different price levels—and then combine that data with information about costs and inventory levels to recommend prices that will improve profits. Given the complexity of pricing and the thousands of items in highly dynamic market conditions, modeling results and insights helps to forecast demand, develop pricing and promotional strategies, control inventory levels, and improve customer satisfaction.[16]

Operations

In a typical operation, automation leads to an opportunity to collect customer data that can be used for analytics. For example, in the health care case study in the preceding chapter, we studied Neonatal Intensive Care Units that collected vital statistics from babies and either alerted the medical staff or took corrective actions based on patient data. In this case, the task of routine monitoring was automated, thereby freeing up the staff time to treatment. The automation provided the opportunity to record all the vitals in an electronic form that can be not only monitored but also collated and analyzed for trends and predictive modeling.

How do we use operational data to improve customer experience? Let us take an insurance example. If we collect enough operational data about the customers, we should be able to measure their health. The obvious impact is in insurance underwriting. Deloitte consulting has developed a predictive model for life insurance[17] that provides a significant reduction in operational cost for life insurance policy evaluation using CEA. The rough sequence is that the insurer receives an application, and then a predictive model score is calculated and a policy is either offered or sent through traditional underwriting. The predictive model is typically used, not to make the underwriting decisions, but rather to triage applications and suggest whether additional requirements are needed before making an offer. To that end, the model takes in information from any source that is available in near real-time for a given applicant. This can include third-party marketing data and more traditional underwriting data. Compared with a traditional underwriting, the predictive model allows an underwriter to skip routine tests for a "healthy customer," leading to a cost saving of $125 per applicant while at the same time improving the customer experience (Table 2.1).

Table 2.1: Illustrative underwriting savings from predictive model requirement cost

Data source	Traditional underwriting	Requirement Utilization	Predictive Model
Paramedical exam	$55	50%	0%
Oral fluids analysis	$25	20%	0%
Blood and urine Analysis	$55	70%	0%
MVR report	$6	70%	75%
Attending physician statement	$100	20%	0%
Medical exam	$120	20%	0%
EKG	$75	10%	0%
Stress test	$450	1%	0%
Third-party data	$0.50	0%	100%
Total cost per applicant		**$130**	**$5**
Savings per applicant		**$125**	

Product Engineering

Products are increasingly run by the electrons, giving us an enormous opportunity to measure customer experience. We take photos digitally and then post them on Facebook, providing an opportunity to do face recognition without requiring laborious cycles in digitization. We listen to songs on Pandora on the Internet, creating an opportunity to measure what we like or dislike, or how often we skip a song after listening to the part of it we like the most. We read books electronically on the Internet or on our favorite handheld devices, giving publishers an opportunity to understand what we read and how many times. We watch television using a two-way set-top box that can record each channel click and correlate it to analyze whether the channel was switched right before, during, or right after the commercial break. Even mechanical products, such as automobiles, are offering an increasing number of ways to interact with them electronically. We make all our ordering transactions electronically, giving third parties opportunities to analyze our spending habits, by month, by season, by ZIP+4 and by tens of thousands of micro-segments. Usage data can be synthesized to study the quality of customer experience and can be mined for component defects, successes, or extensions. This data can also be used by marketing to understand micro-segmentation. In a wireless company, we isolated problems in the use of cell phones to defective device antenna by analyzing call quality and comparing them across devices

Products can be test marketed and changed based on feedback. They can also be customized and personalized for every consumer or micro-segment based on their needs. CEA plays a major role in customizing, personalizing, and changing products based on customer feedback. Product engineering combines a set of independent components into a product in response to a customer need. Component quality impacts overall product performance. Can we use CEA data to isolate badly performing components and replace them with good ones? In addition, can we simplify the overall product by removing components that are rarely used and offer no real value to the customer? A lot of product engineering analytics using customer experience data can lead to building simplified products that best meet customer requirements.

To conduct this analysis and predictive modeling, we need a good understanding of components used and how they participate in the customer experience. Once a good amount of data is collected, the model can be used to isolate badly performing components by isolating the observations from customer experience and tracing them to the badly performing component. Complex products, such as automobiles, telecommunications networks, and engineering goods benefit from this type of analytics around product engineering.

Finance

Chief financial officers (CFOs) are interested in reducing revenue leakage, closely tying revenues to actual product usage and looking for ways to plug pilferage or fraud. Fraud detection is a classic example of CEA's applications to finance.

CEA is used to more accurately compute the overall risk for a customer. The customer may be an individual or a family. Each family member may have one or many accounts with a bank. An account may result in the bank assuming a risk associated with the transactions. By identifying the overall household relationships and all the risks associated with the household, the bank accurately assesses the overall risk. A tremendous amount of public records and credit rating information is available on each member of the household. In addition to the bank records, external data provides data about the relationships the household has with other banks.

How much outside data can we use to compute risks? For example, a life insurance company can purchase location data from a communications service provider, commerce data from the order analytics marketplace (which is in its embryonic stage), and social data from Facebook to compute a health risk index, differentiating junk food addict from fitness crazy person. Can it use this data to offer different risk premiums for life insurance? How about using health insurance transactions to assess life insurance candidacy and risk?

Fraud detection and prevention is another important financial application of CEA data. Predictive models combined with real-time information on location, credit-card transactions, types of calls made, and so on can be used to detect fraudulent use of credit cards, phones, or other products.

Across the Customer Life Cycle

Product managers often study the customer life cycle to explore ways to excel in customer experience. A customer life cycle starts when a customer starts shopping for a product and leans on all available sources for product evaluations. Once the customer decides on the product, he or she proceeds to buy the product and starts using the product. Depending on the use and associated problems, there may be a need for customer service, which results in the customer either becoming an advocate and buying more or becoming dissatisfied. Analytics plays a major role in the customer life cycle in understanding shopping criteria, how customers collect information, how they perceive the ordering experience, what they think of product quality during installation and use, and how they obtain customer service or pay for the product. It provides key insights to improve customer experience across the customer life cycle (see Figure 2.1).

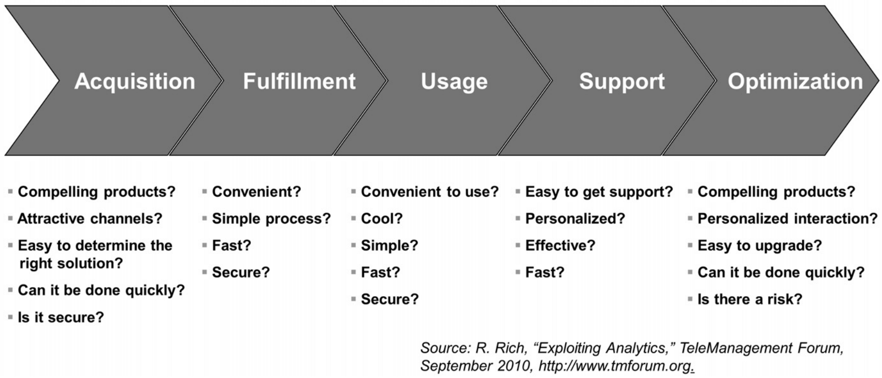

Figure 2:1: Customer life cycle

Conclusions

CEA is based on available customer experience data. This includes customer demographics, psychographics, usage information, customer service experience, payment record, troubleshooting, and sharing of experience. Given the level of automation in customer-facing business processes, a tremendous amount of information is available regarding customer experience. It includes unstructured information, such as blog postings, Twitter feeds, and product reviews, as well as structured information, such as payment, product quality, trouble data, and everything in between.

The Internet has provided worldwide access to every consumer, which is critical when new products are introduced and face customer reviews shared across third-party sites. Sensors provide a lot of data about customer actions, some of which may be duplicated and would require synthesis or harmonization. However, most of this data is fragmented, often duplicated, and full of errors. A critical part of CEA is the collation and synthesis of the data. As we saw in the telecom and healthcare examples in Chapter 1, this may provide us with powerful capabilities for real-time monitoring of customer experience.

A key component of CEA lies in synthesizing historical customer experience data into a set of models. These models represent customer experience and related actions. They predict conditions under which a customer would churn. They provide criteria for further purchase or advocacy to other customers. These models can then be applied during customer experience to score alternatives and provide the "next best action." Depending on the level of sophistication, models could be built by analysts or software and applied via manual changes in processes or automatically inserted into the actions.

The analytics results in certain actions, whether changes to customer policies, business processes, or specific actions inserted during the next customer interaction. The actions may involve changes to the product themselves or to their prices. It may include how many or which channels may be used to sell or serve to the customers. It may include payment platforms. We might use analytics to segment customers and provide different products, prices, promotions, or service depending on customer segment. Models can also be used to understand the location at which a customer is most likely to buy a product, whether physical or virtual. In many cases, policies regarding how we deal with customers play an important role in customer satisfaction, and these policies may be fine-tuned based on profitability and customer satisfaction. For example, providing a refund or discount for poor quality may result in increased customer satisfaction but reduce margins. Analytics can help understand the policy that provides the best balance between the two objectives.

The end result as seen by the customer is a change in product or service. This change must be done while the customer is interacting with the product or a customer touch point. In the past, analytics was used to study customer reactions and make changes in price, product, or promotions with a long lead time between customer reaction and change in product or price. Increasingly, we are seeing adaptive products, prices, or service policies that are changed rapidly in response to customer reaction. For example, a new product introduction may lead to a positive or negative customer sentiment. This sentiment may be captured from third-party blogs and used rapidly to change either the product or associated messaging during the product launch, and this could even be done the same day the blogs were posted!

The inputs include:

- *Customer data*—This includes customer demographics, psychographics, and customer hierarchy/relationships, such as householding. We can segment customers based on where they live, what they like to do, and what they have done historically. Customer data includes third-party information collected, collated, and sold to information consumers.
- *Location data*—Customer location is the most widely debated topic at the time of the writing of this book in the summer of 2011. The presence of smart devices connected to wireless networks have provided a tremendous amount of customer data that can be used (with permission or in a summarized manner) for a variety of applications.
- *Usage/Event data*—Information about product use is typically created through event and alarm generation from the product. We saw a variety of industry-specific data obtained from network (communications service providers), driving behavior (automotive), physiological information (health care), and so on.
- *Payment data*—Information about purchase and payments.
- *Social network data*—Data available from social networking sites, Facebook, Yelp, Twitter, and so on.
- *Other third-party data*—Any other third-party data available for purchase, such as credit rating, location, addresses, and so on.