MAIN ARTICLE

Dell's SupportAssist customer adoption model: enhancing the next generation of data-intensive support services

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Abstract

We developed a decision support system to model, analyze, and improve market adoption of Dell's SupportAssist program. SupportAssist is a proactive and preventive support service capability that can monitor system operations data from all connected Dell devices around the world and predict impending failures in those devices. Performance of such data-intensive services is highly interconnected with market adoption: service performance depends on the richness of the customer database, which is influenced by customer adoption that in turn depends on customer satisfaction and service performance—a reinforcing feedback loop. We developed the SupportAssist adoption model (SAAM). SAAM utilizes various data sources and modeling techniques, particularly system dynamics, to analyze market response under different strategies. Dell anticipates improving market adoption of SupportAssist and revenue from support services, as results of using this analytical tool.

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Introduction

As Moore's law predicts, the speed of computers is rapidly increasing and so too the dependency of individuals and enterprises on computer systems (Moore, 1965). Computer systems now store major customer data and handle various daily routines. Healthcare, banking, transportation, education, electricity, and defense are among the industries that significantly rely on computing devices (Chen and Zhang, 2014; Kambatla *et al.,* 2014). Computer systems failure in these large industries can be disastrous (Patterson, 2002; Scaramella *et al.*, 2016). Hence many enterprise users of computer devices take every step to decrease the likelihood of systems failure and downtime in cases of unexpected events (Sun *et al.,* 2012). As a result, high-quality

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after-sales services and maintenance of computer systems are critical for the success of computer industries.

The concept of proactive and preventive maintenance can be traced back to total productive maintenance, a system that has been used in a range of industries and manufacturing plants for many years (Nakajima, 1988, 1989). In this framework, companies employ proactive and preventive maintenance to maximize the operational efficiency of equipment. Computer industries have also responded to the need for high-quality maintenance by improving their support services. A proactive approach to support in computer industries can decrease the potential costs of system failure by reducing the downtime and derogatory side effects, such as data and productivity loss (Swanson, 2001; Sun *et al.,* 2012).

In this study, our focus is on a specific case study of customer support service at Dell, Inc. The company takes a preventive, proactive, and predictive support approach for after-sales services. Dell's SupportAssist technology is an automated system designed to reduce troubleshooting efforts and maximize uptime of Dell devices including PCs, laptops, tablets, and enterprise devices such as servers, storage, and network devices. In the conventional approach to after-sales service, when a customer experiences a device failure he or she must initiate contact with the correct customer service team associated with the failed component in order to receive support (Garg and Deshmukh, 2006). This process is costly for both the customer and the support service, since it involves multiple rounds of communication between the two parties and potentially several rounds of diagnoses or redirection to the responsible support team. In the new Dell paradigm, SupportAssist detects system failure indicators (e.g., CPU temperature, battery lifetime, hard disk status, and error codes) to automatically diagnose an existing problem or predict a future problem without directly involving the customer in diagnostic or data collection processes (Orozco, 2016). SupportAssist also collects historical system diagnostic data to help Dell perform a root-cause analysis when a device fails. This enables Dell to provide improved, faster support service with less customer effort.

One key difference between Dell's SupportAssist and other forms of proactive maintenance is a high utilization of data and data analytics. SupportAssist continuously gathers consumer-generated data to predict failure in devices. The volume and velocity of such data can be considerable. With more customers using the service, SupportAssist can collect more data and better predict device failure.

Research statement

We pose our main research question: *How can market adoption of SupportAssist be improved?* There is a range of possible reasons for the complexity of

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market adoption in this service. First, the market success of technologically high-performing systems is not necessarily guaranteed (Cooper and Kleinschmidt, 1987; Cooper, 1994). Examples abound of seemingly smart inventions that have failed in the market, as their strengths were not communicated to customers, or they lost the market to strong competitors. Second, there are dynamic complexities for market adoption (Waarts *et al.,* 2002). For example, a future adoption rate often depends on the past adoption rate, which leads to a path-dependent market outcome (see the case of Betamax vs. VHS in Sterman, 2000). Thus strong adoption is critical for long-term market success. Third, Dell needed a method to model the impact of improving design features, marketing, and delivery to maximize the speed of SupportAssist's adoption and usage. This is especially important for data-intensive services such as SupportAssist wherein performance of the service improves with the richness of collected data, which in turn is influenced by market adoption. This creates a feedback loop in which performance depends on the market adoption and vice versa.

The goal of this study was to develop a decision support system, which we call the "SupportAssist adoption model" (SAAM), to explain the dynamics of market adoption of SupportAssist. The system can then be used to help Dell make better design, marketing, and delivery decisions for SupportAssist. The backbone of the decision support system is a system dynamics model (Forrester, 1958; Sterman, 2000) informed by various detailed quantitative and qualitative data. The user interface provides a simple dashboard for decision makers to test decision alternatives.

While SupportAssist has been developed for both individual and professional customers and their different devices (e.g. laptop, tablet, PC, server, network, storage), our focus in this study is on server devices. We also focus on commercial customers—specifically, medium-sized U.S. organizations. This segment has a high stake in terms of profits for Dell, with the largest potential impact in protecting sensitive services, such as healthcare. These customers each have 50–300 servers; a hospital or a university department are good examples. Although in this study we focus on Dell's SupportAssist, our analytical model is applicable to other similar data-intensive services and markets.

SupportAssist: a technologically advanced service

Figure 1 is a simple diagram of information flow through SupportAssist. Many Dell devices from all around the world are connected to the service; SupportAssist operates across all Dell computing product lines. It collects data on device hardware performance—e.g. average temperature, cooling fan speed, error codes and frequency, and hard disk operations. It also collects device hardware failure information (e.g. CPU overheat, hard disk failures, memory

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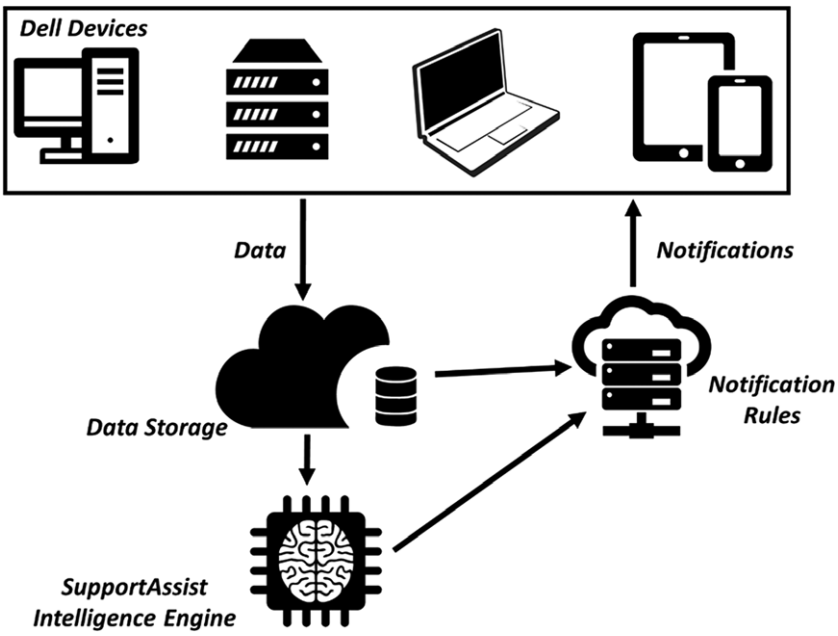

Fig. 1. SupportAssist, a smart support service accelerating failure resolution in Dell devices

failure), and uploads the data to a cloud storage service. SupportAssist has an intelligence engine that uses the data to train a predictive model that correlates measured hardware performance values with the failures. The intelligence engine learns and defines/modifies rules that can predict failures based on the hardware performance values. SupportAssist uses these rules and notifies the user or IT professional regarding possible device hardware failures.

Various versions of SupportAssist software exist for different devices (PCs, tablets, servers, storage, or networking devices) and device operating systems (i.e. Microsoft Windows, Linux/Unix). The software is free but tailors its features based on the service-level entitlement purchased with computing device: Basic, ProSupport, and ProSupport Plus. The Basic entitlement is built into the price of the computer and does not include predictive or preventive features, but does provide such features when the customer runs the software or contacts support. The ProSupport entitlement proactively detects failures and initiates support requests; Dell support staff will contact the customers proactively when a failure is detected. ProSupport Plus expands on service with predictive failure resolution, preventive support, and maintenance reporting. SupportAssist provides other capabilities in addition to the proactive failure prediction feature. Examples include remote monitoring, automated system state information collection, automatic case creation, and proactive contact from Dell technical support on the customer's servers, storage, and networking devices.

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As stated, there is no guarantee of success for a technologically advanced tool in the market. Despite the substantial benefits and positively received features of this industry-leading service, many other factors affect adoption. On the customer side, reimaging of hard drives is an issue that can prohibit built-in installation. In simpler terms, many Dell company customers format and reinstall their new devices based their own needs (reimaging hard devices), which often does not include new software. Lack of trust and understanding of the new technology may also affect customers' use of software. This is despite promises that the only information communicated is hardware related, such as fan speed or temperature.

Theoretical background: a new service paradigm

SupportAssist is an example of an industry-level shift toward data-intensive smart services. As a result of the rapid shift of industries from products to services over the past decades (Oliva and Kallenberg, 2003; Larson, 2016), the importance of technical support services in the information technology (IT) industry has become paramount. The reactive paradigm of *break–analyze–fix*, which has been the cornerstone of technical services in the IT industry since its inception, is no longer desirable in today's commodity-based world. Consumers are increasingly unwilling or unable to devote time to maintaining IT hardware and software functioning at required levels of performance. A new, proactive paradigm of *monitor–predict–fix-before-failure* is emerging that is revolutionizing the way IT services are performed.

The transition of the IT industry to a more service-oriented industry is not straightforward. It has been noted that the transition from product manufacturer to service provider creates major challenges that include changes in management focus, organizational principles, structures, and processes that may be new to the company (Oliva and Kallenberg, 2003). In the IT industry specifically, many service providers try to utilize large volumes of data, which introduces new socio-technical challenges.

Moreover, there has been a major transition in the role of data in service industries (Davenport and Kudyba, 2016). Two decades ago, the focus was on the use of data to make better managerial decisions; however, with today's data-intensive services such as LinkedIn, Google Maps, Yelp, and Facebook, data are the customer's final product. In other words, added value in new service industries comes in the form of informing customers, and customers are paying to receive data products. With this shift, a need exists to reconsider the design and development of data-intensive services as well as distribution strategies for such services. A major challenge is how to make data-intensive services successful in the market.

The Bass model (Bass, 1969) is a classic approach to evaluating market adoption. Developed by Frank Bass in the 1960s, the approach emphasizes

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the reinforcing effect of word of mouth. As more products are installed, more current owners introduce a product to potential adopters, which reinforces the adoption rate. A generic Bass model predicts an S-shaped adoption curve, meaning the exponential growth in adoption is eventually capped by the market size (Bass, 1969; Mahajan *et al.,* 1991). The Bass model and its extensions have been extensively used to model market adoption behaviors in a wide range of products and services. For example, Bass (1980) used the model to study the adoption of durable products; Kobrin (1985) utilized similar models to study the diffusion of oil production nationalization practices across countries; Maier (1998) implemented extensions of Bass models to study the adoption of technological products (microprocessors); and Paich *et al.* (2011) deployed extensions of Bass models to study the adoption of new products in pharmaceutical markets. Other applications include diffusion of investment alternatives, new organization forms, adoption of new maintenance services, pricing strategies, and new information technology (Srivastava *et al.,* 1985; Mahajan *et al.,* 1988; Swanson, 2001; Milling, 2002; Huang and Chen, 2010).

In many cases, however, modelers must adapt the Bass model to their specific cases and include other potential mechanisms that may influence product adoption (Jalali *et al.,* 2016). For example, Bass models have been extended to allow for newer approaches to key parameter estimations (Mahajan *et al.,* 1991), to include successive generations of technology (Norton and Bass, 1992), and to include decision variables, such as prices and advertising (Bass *et al.,* 1994). Other examples of recent extensions include the consideration of rejection dynamics or more detailed categorization of adopter categories (Paich *et al.,* 2011; Ulli-Beer *et al.*, 2010), as well as inclusion of network topology in market adoption (Wunderlich *et al.,* 2014). For a more complete review of the market adoption system dynamics models, see Mahajan *et al.* (1991, 1995), Peres *et al.* (2010), and Grösser (2012, pp. 26–30).

The closest modeling work to our problem is related to the award-winning project of Barabba *et al.* (2002) on market adoption of General Motor's (GM) OnStar. A subsidiary of GM, OnStar provides communication and remote diagnostics systems for the company's products throughout the U.S.-A. It is an important safety service for owners, with the potential for saving lives after major accidents. Barabba *et al.*'s (2002) model helped evaluate strategies that can improve market adoption of OnStar.

Adoption and the quality-market cycle

Recent changes in the nature of service markets require new efforts for modeling market adoption. In fact, market adoption now plays an even more important role in the success of data-intensive services. Figure 2 shows the tight connection between performance of data-intensive services and the richness of the data that feeds to the system; thus, with higher market adoption, more data are available that improve the service quality. Put simply,

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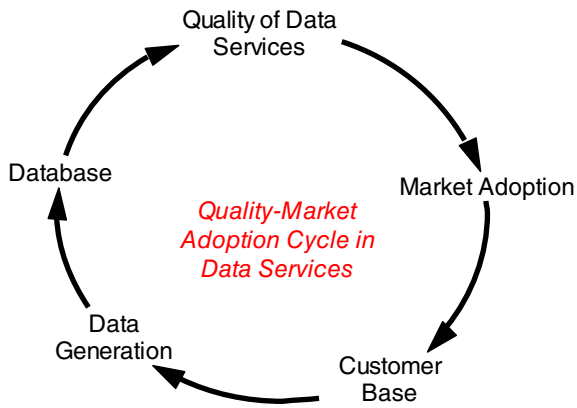

Fig. 2. The interconnection between market adoption and quality of service in data services. [Color figure can be viewed at wileyonlinelibrary.com]

the value and quality of the service depend on its number of adopters, and the adoption rate depends on the service's performance.

The interdependency between market adoption and the value and quality of service is an important mechanism that can hinder the growth and success of data-intensive services. It raises the chicken–egg conundrum: How can we ensure good market adoption and good value and quality from the beginning? Which comes first? Several studies point to the lack of customer trust in automated services, which can further inhibit market adoption (Lee and See, 2004; Merritt *et al.,* 2013). One solution to this interdependency is to increase stakeholder involvement in the design and development of data-intensive services (Davenport and Kudyba, 2016).

Given the evolving nature of service industries and the role of data and data analytics in the new paradigm of value creation, a need exists to develop models and analytical tools for the study of data-intensive services. While our focus is on Dell's SupportAssist, we believe many of our insights could be applied to similar contexts and inform the process of market adoption of data-intensive services.

Research method

Our decision support system is basically a simulation model of SupportAssist market adoption fed by various data. At the core of the system there is a system dynamics model. System dynamics has been previously applied in various industry projects (application examples are reported in Rouwette and Ghaffarzadegan, 2013) and have proven to be an effective method for communication and data elicitation (Black and Andersen, 2012; Black, 2013; Hosseinichimeh *et al.,* 2017) as well as modeling of innovation diffusion (Milling, 1996, 2002). Our model is a framework for policy analysis and testing the effects of different alternatives on market penetration, costs, and

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revenue. Although the basic structure of the model is similar to the Bass model, it is expanded substantially to include more factors relevant to the study, such as several market segments (e.g. geographical, customer type, Dell products). The model is developed to include the evaluation stage of adoption and its corresponding dynamics. The model goes beyond marketing and includes effects of service design and development processes.

We used wide range of data sources for developing and calibrating the model, including customer opinions, SupportAssist performance, expert knowledge, and marketing campaigns on market adoption. On the operation side, we analyzed various data sources on SupportAssist's performance such as issue generation trends, the number of resolved/unresolved issues per month, and the rate of escalated cases regarding SupportAssist's performance. We also analyzed available data on the population of Dell's customers, including different regions and groups (client vs. enterprise) and types of devices. We interviewed about 20 Dell experts, including personnel from the marketing department, SupportAssist programmers, and customer service agents. We conducted a textual analysis of more than 100 team analysis logs on the function of SupportAssist over a 2-year period. The model was calibrated to weekly data (2014–2017) using the partial model calibration method (Homer, 2012). In this method, which has been previously used in various other contexts (e.g. Hosseinichimeh *et al.,* 2015; Ghaffarzadegan *et al.,* 2016), different pieces of the model are calibrated and tested separately to assure the model's validity and avoid overfitting it to the data (Oliva, 2003).

The entire system was built on six main iterations over 2 years and in close collaboration with Dell. After each iteration, the technical details of the model were presented to stakeholders and their feedback was incorporated. The model is validated in different stages based on various tests of behavior and structural validity such as unit consistency, outcome robustness under extreme conditions, and replication of past historical trends (Morecroft, 1985; Barlas, 1996; Sterman, 2000). The validation process was continued until enough confidence among model users was built on the results, and limitations of the model were clarified and communicated (Groesser and Schwaninger, 2012). We also conducted various sensitivity analyses, which proved that the results are robust on changes in parameter values and potential errors in the expert judgments. A summary of the sensitivity analysis is reported in the Appendix. An online dashboard of the model was provided to Dell decision makers in order to analyze potential effects of the company's different business policies.

Modeling

Here we present what is referred to as SAAM-Alpha, a smaller version of SAAM that we developed for outside communication purposes.

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SAAM-Alpha does not use confidential customer data; instead, it is calibrated for synthetic data to keep customer information confidential. Although SAAM has more details, the main insights from the model are qualitatively observable in SAAM-Alpha. Details of the SAAM-Alpha formulation and parameter values are presented in the Appendix, and in the following we discuss the model structure.

Customer flow

Analyzing SupportAssist customer flows, we learned that different levels of adoption exist for different customers and that, at any given time, a large portion of customers are evaluating the product. The marketing literature supports the positive role of evaluation in new product adoption. From the behavioral decision-making perspective, trying a new product for the first time often helps customers overcome the "default bias"—the bias toward maintaining the status quo. Many software packages use free trials as a way to increase market adoption. Further, trials help customers experience the value of a new product, which can lead to permanent adoption. In the case of GM's Onstar, free installation of the service for a short period led potential customers to experience its value. A free or discounted trial period is a common approach in many other service industries; new restaurants, for example, often offer discounted or free services during their opening days.

Figure 3 is a simple representation of the flow of potential customers. For each market segment, we represent the market by *potential adopters*, *evaluators*, and *adopters.* Adopters, in our case, are enterprises that use SupportAssist in the majority of their servers. Before adoption, enterprise customers may begin to evaluate SupportAssist by deploying it for a small portion of their devices (in the figure, evaluators). For example, many mid-size companies with 50–300 servers begin by installing SupportAssist on one to three new servers; and potential adopters are mid-size enterprise customers of Dell who have not tried SupportAssist on their servers.

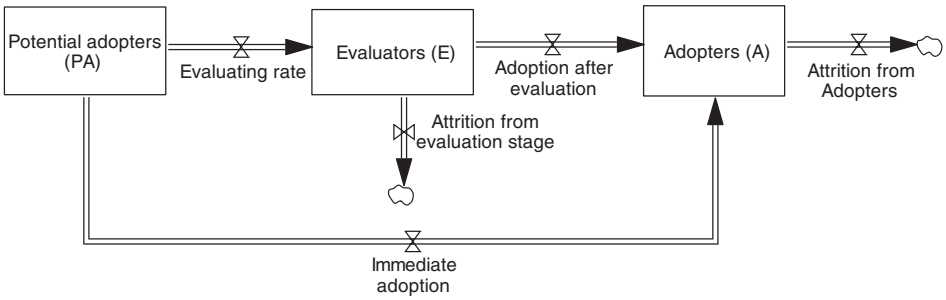

Fig. 3. A simple representation of the flow of adopters

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As Figure 3 shows, there are two inflows to adopters: *adoption after evaluation* and *immediate adoption.* The former represents the flow of customers from evaluators to adopters, and the latter represents direct adoption without evaluation; a chance exists that some potential adopters undertake large-scale adoption of SupportAssist for most of their devices from the beginning.

As the figure shows, there are potential outflows of attrition for both evaluators and adopters. Furthermore, we assume that after attrition we lose the customers. This is reasonable since during our 4–8 years period of analysis it is hard to regain customers' trust.

Basic bass model mechanisms

Figure 4 depicts the major mechanisms in Bass models. Word of mouth is the growth engine of market adoption models (in Figure 4, M1). The basic idea is that with more adopters Dell has more customer advocates, which leads to new adopters. The second mechanism is about market saturation (in Figure 4, M2). There is a natural limit for market adoption that comes from the size of the market. In Bass models, potential adopters represent the limit for adoption.

In our specific case of modeling SupportAssist for company customers, we learned that the word-of-mouth mechanism is weak because it is not common for such company customers to communicate their IT solutions. In other words, based on Figure 4, the parameter *fraction advocating* is a very small number. While word of mouth can play an important role when modeling individual users (such as students using laptops), in the case of company customers we need to rely on other marketing mechanisms.

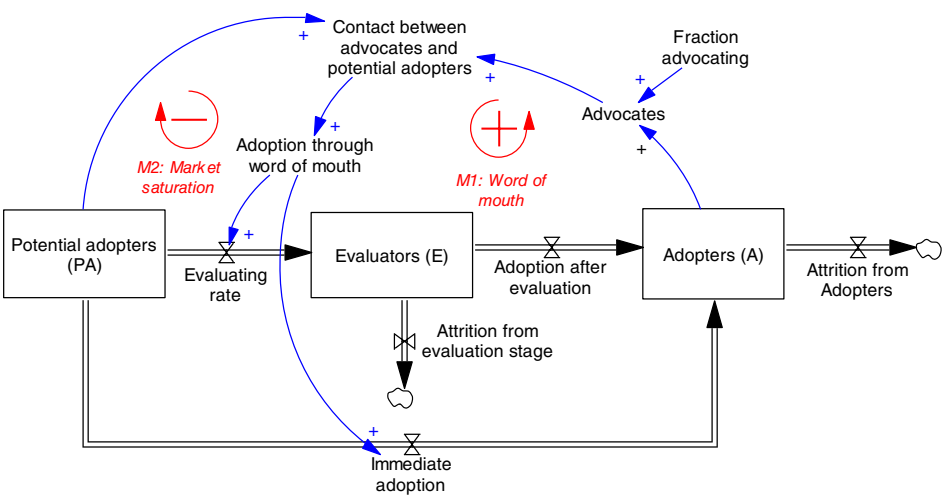

Fig. 4. The generic Bass model mechanisms of word of mouth and market saturation. [Color figure can be viewed at wileyonlinelibrary.com]

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Data-intensive growth mechanism

As stated, performance of data-intensive services depends on the availability of data and analytical capabilities. Larger data sets help the calibration process of predictive models and, as such, provide better prediction and thus higher value for customers. Attrition declines with a better service experience and the adopter population increases. In Figure 5, M3a and M3b represent this mechanism, in which M3a is the effect on evaluators and M3b is the effect on adopters.

Marketing growth mechanisms

Dell relies on marketing activities for improving adoption of SupportAssist. Resources including financial and human increase by seeing indicators of success in market adoption. In SAAM-Alpha, we represent marketing growth at an aggregate level, as shown in mechanism M4 in Figure 6. With more customers and more revenue—a portion of which is allocated to further development of the SupportAssist service—more marketing can be undertaken.

These mechanisms form the structure of SAAM-Alpha. The entire model (and equations) is presented in the Appendix. Here we use synthetic data; the main model is calibrated to Dell's detailed data of potential customers and customer adoption. We also test the sensitivity of SAAM-Alpha to reasonable parameter changes. The results are in the Appendix. In addition, we checked the model's sensitivity to higher orders of delay or reasonable structural changes by expanding the aging chain. The results are qualitatively robust.

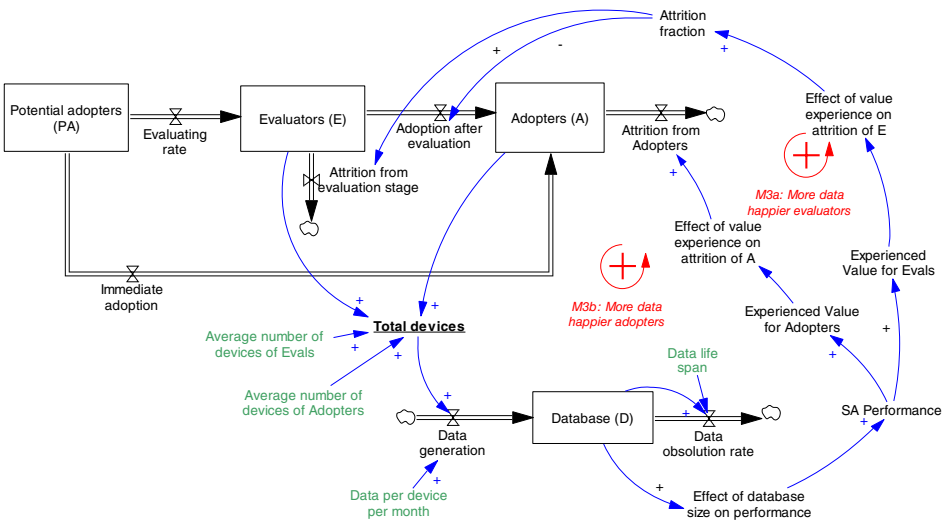

Fig. 5. Market–performance growth cycles in data-intensive services. [Color figure can be viewed at wileyonlinelibrary.com]

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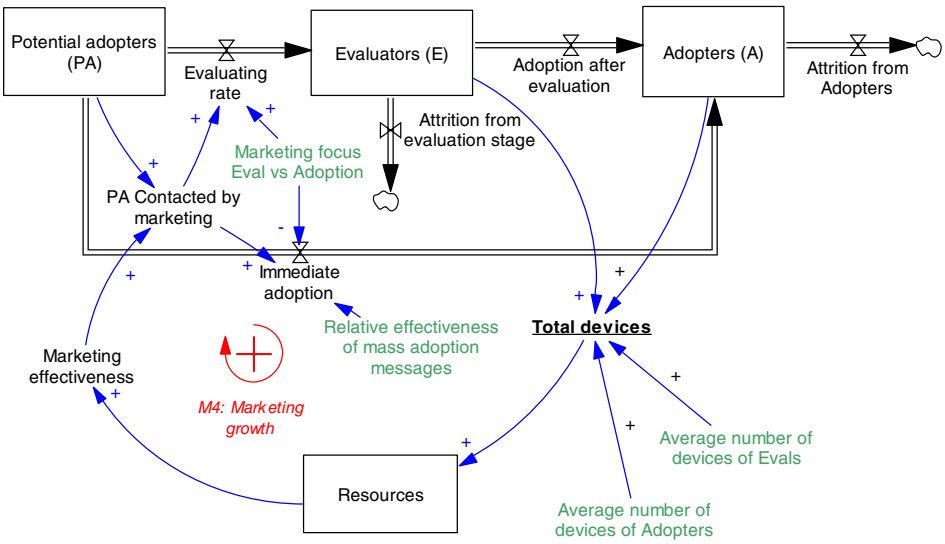

Fig. 6. Growth in marketing initiatives. [Color figure can be viewed at wileyonlinelibrary.com]

Outcomes

A decision support system for SupportAssist

The main outcome of this project is a decision support system that helps Dell decision makers simulate and estimate the effects of different business policies on the future adoption success of SupportAssist. The framework is a password-protected online system that works as a flight simulator for managerial decisions and includes the system dynamics model calibrated based on market adoption of SupportAssist for different devices over the past 3 years. As inputs, the system takes decision variables regarding design (specifically, the characteristics and timing of new releases of SupportAssist), marketing (the focus of marketing staff and marketing resource allocation), and delivery (built-in delivery vs. remote installation vs. customer installation) for different Dell devices. The output of the decision support system is the trajectory of SupportAssist adoption represented by the number of customers and the number of monitored devices for major Dell devices. Outputs are generated under three major scenarios of mean, optimistic, and pessimistic conditions to represent market uncertainties.

Business-as-usual results in gradual market adoption growth

Data show that market adoption of SupportAssist has been organic over the past 2 years. Our simulation model replicates the historical trend and is used to forecast future trends if Dell continues its current design, marketing, and delivery activities.

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Figure 7 shows a sample of model simulation runs. We set the simulation time period from time = −2 until time = 8 (10 years), wherein time = 0 represents the current moment, which is the time for policy implementation. Adoption can be observed by two variables: the percentage of customers using at least one SupportAssist, and the percentage of Dell devices that have SupportAssist. The latter variable is particularly important because although an enterprise customer may adopt SupportAssist for a few devices in order to evaluate it, Dell hopes customers will use the program on most of their devices.

The figure shows that without any change in Dell's strategies regarding SupportAssist a typical gradual growth will take place over the next 2 years. As the figure shows, the percentage of customers adopting SupportAssist reaches around 70 percent after 3 years, but the percentage of Dell devices using SupportAssist (percentage of adoption) never surpasses 30 percent. The percentage of adoption is smaller than the percentage of customers because a company that uses SupportAssist may only do so in a subset of their total devices. Dell wants to increase adoption beyond organic adoption trends.

A sole focus on design or marketing has marginal effects

As Figure 8 shows, a sole focus on design or marketing has marginal effects. New releases of SupportAssist are periodically introduced to the market. Although SupportAssist's design improves in new releases, the model estimates that the effect of design variables on adoption is in the range of 0–10 percent over 8 years. Based on an optimistic scenario of 100 percent improvement in SupportAssist design features that results in doubling accuracy of failure prediction (an extreme case of improvement in design), the adoption growth rate would be only of the order of 10 percent. An increase in marketing activities has also limited impact. The figures also show that with increased marketing adoption does increase in the short run, but there is no significant long-term effect.

A major question is what prevents growth from accelerating beyond gradual adoption. Our model calibration points to the answer: large pipeline leakage in market adoption.

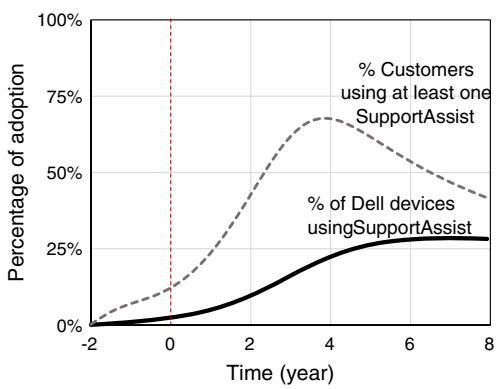

Fig. 7. Market adoption in terms of customers and devices. [Color figure can be viewed at wileyonlinelibrary.com]

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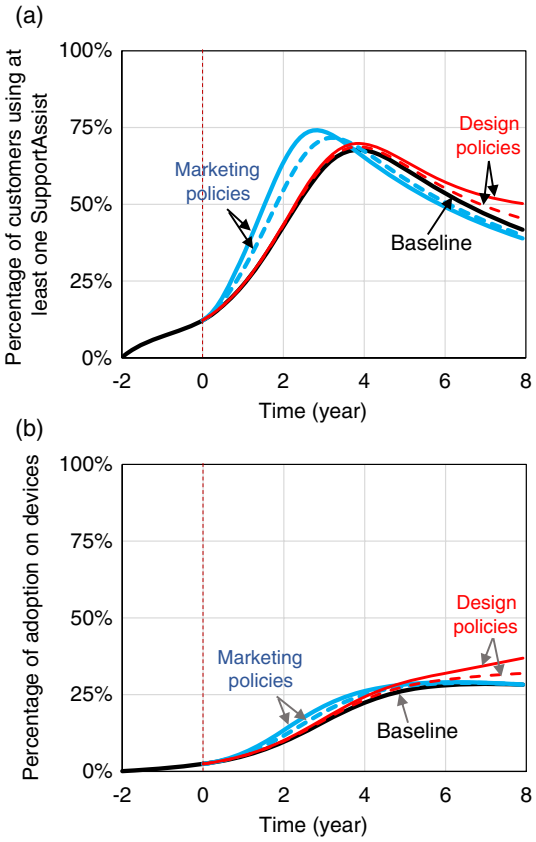

Fig. 8. Market adoption under business as usual (baseline) and under different policies of design or marketing focus (for each policy, dashed lines represent 50 percent improvement and solid lines represent 100 percent improvement). In part (a), the *y*-axis shows the percentage of mid-size enterprise customers who have "at least" one of their 50–300 Dell servers using SupportAssist. In part (b), a better representation of adoption, the *y*-axis shows the percentage of all Dell servers using SupportAssist. [Color figure can be viewed at wileyonlinelibrary.com]

Model calibration uncovers pipeline leakage

Further model analysis reveals that the model fits best if we assume a low flow from evaluators to adopters. This is an unexpected finding, since we intuitively expect that product evaluation should lead to adoption if the product meets customer needs. Customers who have adopted SupportAssist in the majority of their devices are also the most pleased with its value and performance.

After observing this phenomenon in the model, we began further data analysis, which confirmed the model's results. We learned that when customers first begin using SupportAssist, about half evaluate it only on a few devices rather than on most of their devices. Customers that implement a low-unit evaluation stage rarely become adopters; moreover, such customers often become disconnected from Dell's server over the next 12 months. In simple terms, Figure 9 seems to be a better conceptual representation of customer flow than Figure 2: the model loses customers in the evaluation stage at a relatively high rate.

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What is causing this loss in the evaluation stage? Given the relatively high performance of SupportAssist, our main hypothesis is that customers in the evaluation stage are not experiencing SupportAssist value.

SupportAssist experiential learning for evaluators is ineffective

Periodic contact with customers who are evaluating SupportAssist reveals that many are unaware that SupportAssist is installed on their devices, and others are unaware that they are disconnected from the Dell server. With this lack of awareness, experiential learning is apparently ineffective. Thinking about the nature of SupportAssist reveals a major challenge: For any customer to experience SupportAssist's value, at least one of their devices with SupportAssist should fail. As the chance of any single new Dell device failing during the evaluation period is very small, customers with a lower number of SupportAssist devices have a corresponding lower likelihood of experiencing its value.

Let us look at an illustrative example. Table 1 compares the chance of having at least one device fail for four typical customers with 1, 2, 50, and 100 devices. The first two customers are not likely to experience any value even if the devices fail at the rate of 10 percent. However, even with very small rates of failures, adopters with high utilization of SupportAssist are likely to experience benefits; there is a good chance that at least one of their devices fails, and they experience the service. It is important to mention that we are talking about mid-size customers, many of whom are sensitive to IT performance (such as hospitals) and for which failure of even one device is unacceptable.

Furthermore, we learned that the customer point of contacts (IT personnel in mid-size companies) "float"; that is, they change their jobs and positions rapidly and thus no organizational memory exists that SupportAssist has been adopted for a few devices unless value is experienced. In sum, the likelihood of benefiting from SupportAssist for a customer with SupportAssist installed on only a few new devices is low. This is what makes the evaluation stage less effective and attrition from the evaluation stage more likely.

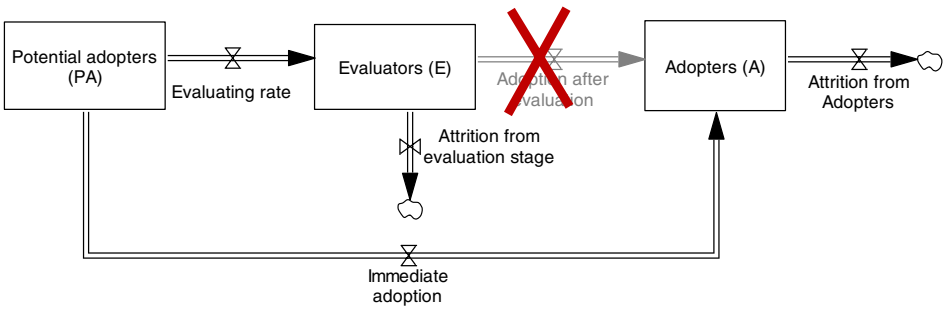

Fig. 9. The disconnect between evaluators and adopters. [Color figure can be viewed at wileyonlinelibrary.com]

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Table 1. The chance of experiencing the value of a support service depends on the number of devices that receive the support service

	The chance of experiencing SupportAssist value for different customers			
Scenario: The chance of failure of 1 device	Customer with 1 device on SupportAssist (evaluator)	Customer with 2 devices on SupportAssist (evaluator)	Customer with 50 devices on SupportAssist (adopter)	Customer with 100 devices on SupportAssist (adopter)
0.01	0.01	0.02	0.39	0.63
0.02	0.02	0.04	0.64	0.87
0.05	0.05	0.10	0.92	0.99
0.1	0.10	0.19	0.99	1.00

Experiencing value = Having at least one device fail = 1 − (1 − chance of failure in one device)$^{\text{number of devices}}$.

Change in marketing focus

The customer adoption decision depends on several factors, including marketing activities. Until now, the focus on marketing has been on persuading customers to evaluate the device. Our analysis shows that evaluation is not an effective tool for adoption. Considering that marketing for high adoption has higher costs, we simulate a condition wherein the marketing staff takes further steps to persuade high utilization for the customer. We expect that although this action will, in the short term, inhibit adoption (since more resources are needed) it could possibly result in more adoption in the long term. Figure 10 shows the results from SAAM-Alpha (run P3, compared with runs baseline, P1 (100 percent improvement in design), and P2 (100 percent improvement in marketing)). The shift in marketing focus does work better in the long term; however, it still takes a long time to have a reasonable level of adoption.

We also combine all strategies, shown as the run "P1 + P2 + P3," which results in a much better outcome. The reason is that the model is able to quickly pass the tipping point and activate the reinforcing loops that result in faster growth. Simulation results depict the nonlinearity in the system, whereby combining all three policies lead to more adoption than the sum of the effects of each policy. Additional analysis on the nonlinearity is offered in the Appendix.

Discussion and conclusion

A global transition of manufacturing toward service is observable in the IT industry. The competitive advantage of many computer production companies depends upon their support service offerings. Furthermore, the paradigm shift of service industries toward utilizing large volumes of data offers a unique opportunity for this industry to employ system data and offer preventive and proactive support service. As discussed, Dell's SupportAssist is an example of this new generation of services, in which huge volumes of real-

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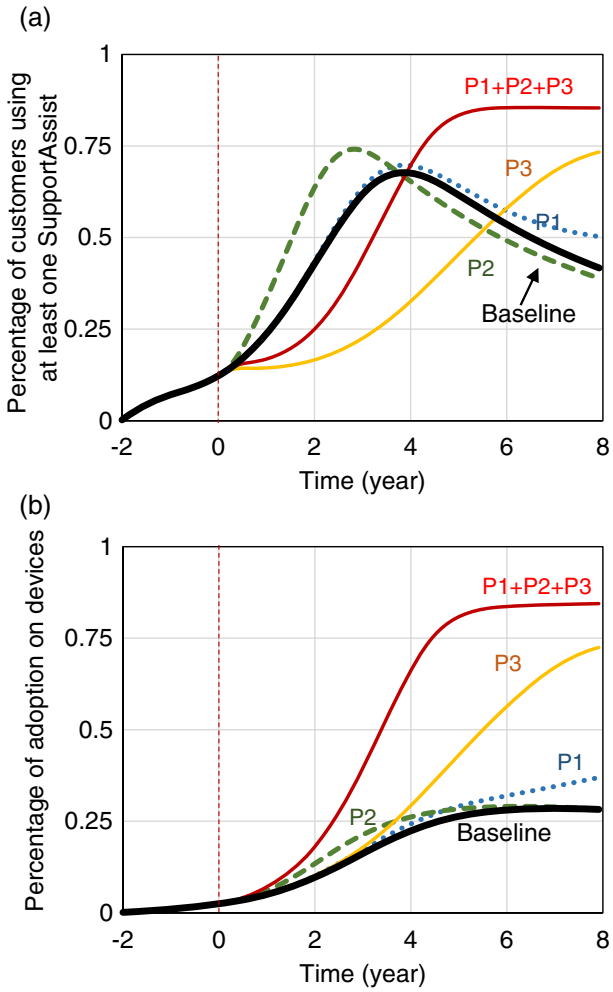

Fig. 10. A shift in marketing focus (P3) is more effective than a sole focus on design (P1) and marketing (P2). An integration of the three is the most effective policy. [Color figure can be viewed at wileyonlinelibrary.com]

world system data are stored in cloud servers and analyzed using a variety of analytical techniques. The added value for customers is the prediction of product failures, which compels preventive support. However, a major challenge is market adoption of these services and the interdependency of adoption and performance. This paradigm shift in the IT industry requires further investigation of the cyclic effects of market adoption and performance of the new generation of support services. Our study moves in this direction, reporting a real-world case of SupportAssist, Dell's after-sales support service.

In this paper, we reflected on a 2-year project at Dell and reported on the development and utilization of a decision support system known as SAAM. Informed by various analytical techniques—a system dynamics model in particular—SAAM forecasts the market adoption of SupportAssist under different scenarios

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and helps Dell managers make decisions that lead to faster and higher market adoption. The model offers several policy insights into how market adoption of SupportAssist can be accelerated, and demonstrates that a sole focus on design or marketing will have only limited effects on market adoption.

Decision support systems such as SAAM help decision makers examine various policies and see the potential effect of the strategies on the market and the adoption of such services. Such models can also help decision makers plan for different cycles of the product. For instance, such models can help them plan promotions (e.g. free trials) through which to collect sufficient data for the system to function at an acceptable level of performance. Planning for new releases and examining the effect of new features or improvements is another example.

The project has various impacts at different levels. First, improving performance and adoption of SupportAssist has major social significance. Currently, many sensitive services in healthcare, defense, and energy infrastructures depend largely on IT systems. In the healthcare sector, for example, large volumes of databases need to be accessible at any time, and many of these services also require live computing processing (e.g. defense satellite communication systems, algo-trading systems, and online/virtual care systems, among others). Downtime in such sensitive IT-based services could have serious social effects beyond any financial losses. Decreasing downtime in such services by developing proactive and predictive support is a significant step toward organizational resilience.

Second, developing SAAM helped Dell to better analyze and make decisions regarding its support services. Dell expects to improve adoption by using SAAM. The process of model building also helped communication across different organizational levels and departments, which is essential for the success of any new product or service.

Academic contributions and implications

In this paper, our intention was to offer an example of system dynamics application to a major industry problem. We assume that the main audience for this paper is composed of scholars and practitioners looking for system dynamics application examples and cases. As Rouwette and Ghaffarzadegan (2013) point out, about half of the System Dynamics Society members have self-reported their primary work as non-academics, and about one-quarter of the members are in consulting sectors. This paper is primarily framed for this audience. However, we would also like to state that the paper has several academic contributions that could lead to future research and theoretical developments. We outline a few such contributions.

First, we introduced and modeled the quality/market adoption cycle, specific to data-intensive services. The mechanism is different from other feedback loops discussed in social networks such as network externalities (Peres *et al.,* 2010). In this case, customers do not necessarily care if their friends and

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colleagues have joined the network/service; they care about service performance. However, the performance of the service they are receiving depends on the volume and velocity of the data affected by other users of the system. This creates a major challenge for market adoption of data-intensive services. Our research also contributes to the smart service paradigm (Larson, 2016), and builds on Davenport and Kudyba's (2016) framework to offer a dynamic perspective on challenges for the success of data-intensive services. Future research should address specific strategies that can make data-intensive services more successful from the time of their first release.

Second, the modeling practice in this project uncovers several challenges in using evaluation as a stage in market adoption of proactive and preventive services. It shows why many common organizational strategies such as focusing on short-term, low-scale evaluation to customers must be reworked if they hope to accelerate adoption. Complexity of experiential learning in these services, since one can only learn the benefits of a support service if the device fails, is a major impediment for effectiveness of evaluation-focused strategies. This becomes especially challenging in cases where customers do not communicate with each other and thus word of mouth is weak. A future avenue of research is to find ways to communicate the service value to customers of preventive maintenance services.

Third, our model can be used as a general framework for adoption of data-intensive services. Although we focus on the specific case of SupportAssist, it is likely that many other data-intensive services would encounter similar challenges. SAAM can be adapted to market adoption and performance of other data-intensive services. In particular, for data-intensive services in which the performance of the system is more tied to the adoption and the amount of collected data, using market adoption decision support systems can significantly boost the chances of success. We invite more studies on design, performance, market adoption, and competition of data-intensive services.

Finally, the iterative process of model building in this project was helpful in improving communications with technical experts at Dell. This point resonates with Black and colleagues' arguments on the effectiveness of systems maps and system dynamics models as boundary objects and communication tools (Black and Andersen, 2012; Black, 2013). Our paper also provides more evidence that model building is an iterative process in which insights are generated in different stages, and each insight can lead to the next (deeper) question. The process of iterative modeling is more effective when stakeholders are involved throughout building and testing the model.

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References

Barabba V, Huber C, Cooke F, Pudar N, Smith J, Paich M. 2002. A multimethod approach for creating new business models: The general motors OnStar project. *Interfaces* **32**(1): 20–34.

Barlas Y. 1996. Formal aspects of model validity and validation in system dynamics. *System Dynamics Review* **12**(3): 183–210.

Bass FM. 1969. A new product growth for model consumer durables. *Management Science* **15**(5): 215–227.

Bass FM. 1980. The relationship between diffusion rates, experience curves, and demand elasticities for consumer durable technological innovations. *Journal of Business* **53**: S51–S67.

Bass FM, Krishnan TV, Jain DC. 1994. Why the bass model fits without decision variables. *Marketing Science* **13**(3): 203–223.

Black LJ. 2013. When visuals are boundary objects in system dynamics work. *System Dynamics Review* **29**(2): 70–86.

Black LJ, Andersen DF. 2012. Using visual representations as boundary objects to resolve conflict in collaborative model-building approaches. *Systems Research and Behavioral Science* **29**(2): 194–208.

Chen CP, Zhang CY. 2014. Data-intensive applications, challenges, techniques and technologies: A survey on big data. *Information Sciences* **275**: 314–347.

Cooper RG. 1994. New products: The factors that drive success. *International Marketing Review* **11**(1): 60–76.

Cooper RG, Kleinschmidt EJ. 1987. New products: What separates winners from losers? *Journal of Product Innovation Management* **4**(3): 169–184.

Davenport TH, Kudyba S. 2016. Designing and developing analytics-based data products. *MIT Sloan Management Review* **58**(1): 83–89.

Forrester JW. 1958. Industrial dynamics: A major breakthrough for decision makers. *Harvard Business Review* **36**(4): 37–66.

Garg A, Deshmukh SG. 2006. Maintenance management: Literature review and directions. *Journal of Quality in Maintenance Engineering* **12**(3): 205–238.

Ghaffarzadegan N, Ebrahimvandi A, Jalali M. 2016. A dynamic model of posttraumatic stress disorder for military personnel and veterans. *PLoS One* **11**(10): e0161405.

DOI: 10.1002/sdr

Groesser SN, Schwaninger M. 2012. Contributions to model validation: Hierarchy, process, and cessation. *System Dynamics Review* **28**(2): 157–181.

Grösser SN. 2012. *Co-Evolution of Standards in Innovation Systems: The Dynamics of Voluntary and Legal Building Codes*. Springer Science & Business Media: Berlin.

Homer JB. 2012. Partial-model testing as a validation tool for system dynamics (1983). *System Dynamics Review* **28**(3): 281–294.

Hosseinichimeh N, Rahmandad H, Wittenborn AK. 2015. Modeling the hypothalamus–pituitary–adrenal axis: A review and extension. *Mathematical Biosciences* **268**: 52–65.

Hosseinichimeh N, MacDonald R, Hyder A, Ebrahimvandi A, Porter L, Reno R, Maurer J, Andersen DL, Richardson G, Hawley J, Andersen DF. 2017. Group model building techniques for rapid elicitation of parameter values, effect sizes, and data sources. *System Dynamics Review* **33**(1): 71–84.

Huang CY, Chen HN. 2010. Global digital divide: A dynamic analysis based on the bass model. *Journal of Public Policy and Marketing* **29**(2): 248–264.

Jalali MS, Ashouri A, Herrera-Restrepo O, Zhang H. 2016. Information diffusion through social networks: The case of an online petition. *Expert Systems with Applications* **44**: 187–197.

Kambatla K, Kollias G, Kumar V, Grama A. 2014. Trends in big data analytics. *Journal of Parallel and Distributed Computing* **74**(7): 2561–2573.

Kobrin SJ. 1985. Diffusion as an explanation of oil nationalization: Or the domino effect rides again. *Journal of Conflict Resolution* **29**(1): 3–32.

Larson RC. 2016. Commentary—Smart service systems: Bridging the silos. *Service Science* **8**(4): 359–367.

Lee JD, See KA. 2004. Trust in automation: Designing for appropriate reliance. *Human Factors* **46**(1): 50–80.

Mahajan V, Sharma S, Bettis RA. 1988. The adoption of the M-form organizational structure: A test of imitation hypothesis. *Management Science* **34**(10): 1188–1201.

Mahajan V, Muller E, Bass FM. 1991. New product diffusion models in marketing: A review and directions for research. In *Diffusion of Technologies and Social Behavior*. Springer: Berlin; 125–177.

Mahajan V, Muller E, Bass FM. 1995. Diffusion of new products: Empirical generalizations and managerial uses. *Marketing Science* **14**(Suppl. 3): G79–G88.

Maier FH. 1998. New product diffusion models in innovation management: A system dynamics perspective. *System Dynamics Review* **14**(4): 285–308.

Merritt SM, Heimbaugh H, LaChapell J, Lee D. 2013. I trust it, but I don't know why: Effects of implicit attitudes toward automation on trust in an automated system. *Human Factors* **55**(3): 520–534.

Milling PM. 1996. Modeling innovation processes for decision support and management simulation. *System Dynamics Review* **12**(3): 211–234.

Milling PM. 2002. Understanding and managing innovation processes. *System Dynamics Review* **18**(1): 73–86.

Moore GE. 1965. Cramming more components onto integrated circuits. *Electronics* **38**(8): 114–117.

Morecroft JD. 1985. Rationality in the analysis of behavioral simulation models. *Management Science* **31**(7): 900–916.

Nakajima S. 1988. *Introduction to TPM: Total Productive Maintenance*. Productivity Press: Boca Raton, FL.

DOI: 10.1002/sdr

Nakajima S. 1989. *TPM Development Program: Implementing Total Productive Maintenance*. Productivity Press: Boca Raton, FL.

Norton JA, Bass FM. 1992. Evolution of technological generations: The law of capture. *MIT Sloan Management Review* **33**(2): 66–77.

Oliva R. 2003. Model calibration as a testing strategy for system dynamics models. *European Journal of Operational Research* **151**(3): 552–568.

Oliva R, Kallenberg R. 2003. Managing the transition from products to services. *International Journal of Service Industry Management* **14**(2): 160–172.

Orozco GM. 2016. Artificial Intelligence Opportunities and an End-Do-End Data-Driven Solution for Predicting Hardware Failures. Doctoral dissertation, Massachusetts Institute of Technology.

Paich M, Peck C, Valant J. 2011. Pharmaceutical market dynamics and strategic planning: A system dynamics perspective. *System Dynamics Review* **27**(1): 47–63.

Patterson DA. 2002. A simple way to estimate the cost of downtime. *LISA* **2**: 185–188.

Peres R, Muller E, Mahajan V. 2010. Innovation diffusion and new product growth models: A critical review and research directions. *International Journal of Research in Marketing* **27**(2): 91–106.

Rouwette EA, Ghaffarzadegan N. 2013. The system dynamics case repository project. *System Dynamics Review* **29**(1): 56–60.

Scaramella J, Brothers R, Perry R. 2016. *Why Upgrade your Server Infrastructure Now?* IDC White Paper: Framingham, MA.

Srivastava RK, Mahajan V, Ramaswami SN, Cherian J. 1985. A multi-attribute diffusion model for forecasting the adoption of investment alternatives for consumers. *Technological Forecasting and Social Change* **28**(4): 325–333.

Sterman JD. 2000. *Business Dynamics: Systems Thinking and Modeling for a Complex World*. Irwin/McGraw-Hill: Boston, MA.

Sun B, Zeng S, Kang R, Pecht MG. 2012. Benefits and challenges of system prognostics. *IEEE Transactions on Reliability* **61**(2): 323–335.

Swanson L. 2001. Linking maintenance strategies to performance. *International Journal of Production Economics* **70**(3): 237–244.

Ulli-Beer S, Gassmann F, Bosshardt M, Wokaun A. 2010. Generic structure to simulate acceptance dynamics. *System Dynamics Review* **26**(2): 89–116.

Waarts E, Everdingen YM, Hillegersberg J. 2002. The dynamics of factors affecting the adoption of innovations. *Journal of Product Innovation Management* **19**(6): 412–423.

Wunderlich P, Größler A, Zimmermann N, Vennix JA. 2014. Managerial influence on the diffusion of innovations within intra-organizational networks. *System Dynamics Review* **30**(3): 161–185.

Appendix

Model formulation

Fig. A1 is a stock–flow representation of the SAAM-Alpha model, which is a smaller version of the main model with no confidential data. Table A1 shows the model formulation

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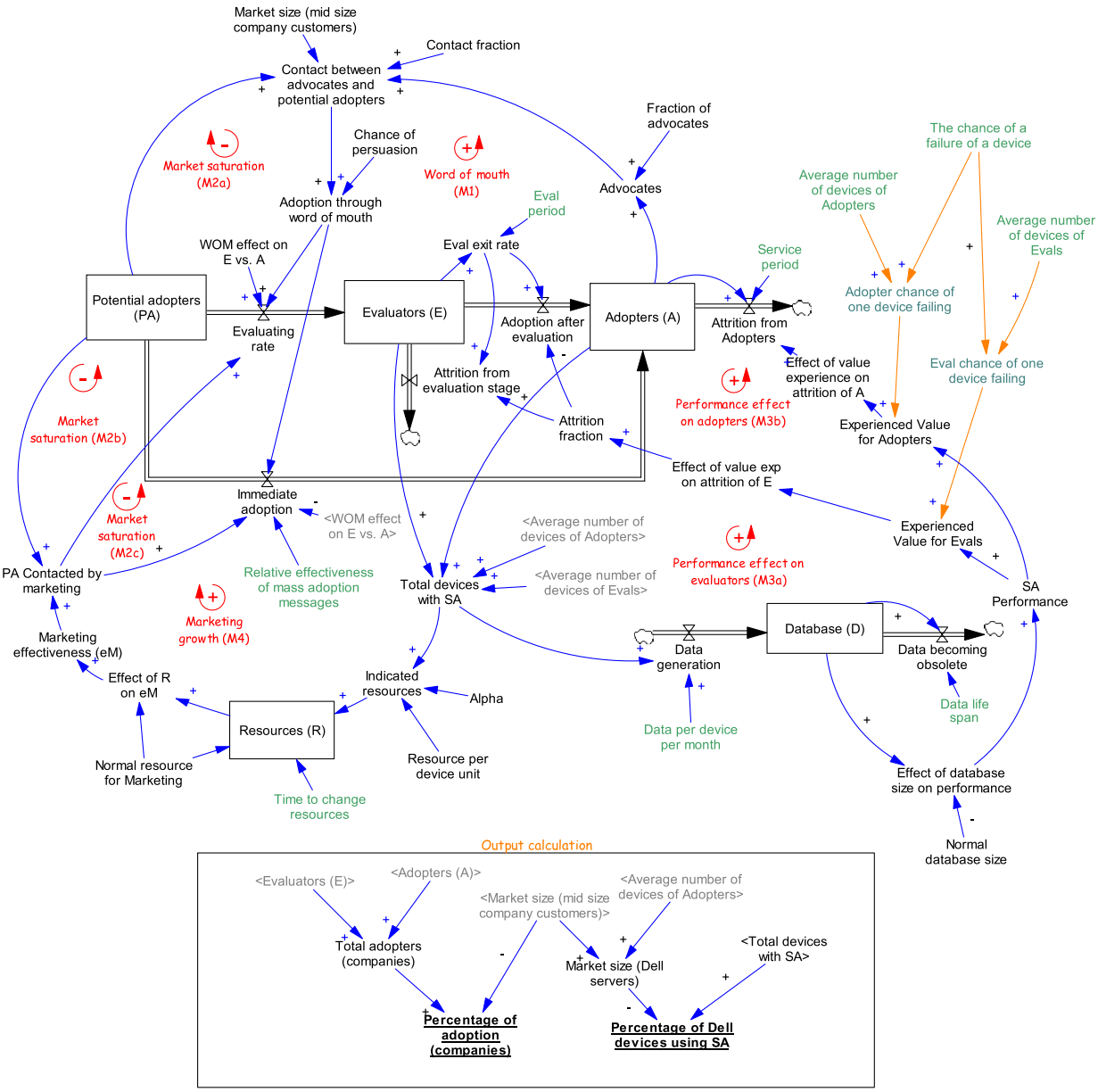

Fig. A1 The SAAM-Alpha stock flow representation. [Color figure can be viewed at wileyonlinelibrary.com]

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Table A1 SAAM-Alpha formulation

Variable/parameter	Equation (units inside "[]")
1. Potential adopters	$\mathrm{PA} = \int_{t=0}^{T} (-r_{\mathrm{E}} - r_{\mathrm{AI}})\mathrm{d}t + \mathrm{PA}_0$ PA: potential adopters [customer] r_{E}: evaluating rate [customer/month] r_{AI}: immediate adoption [customer/month] PA_0: initial value for PA = 1000 [customer] Potential adopters are those who could either become adopters of SupportAssist immediately (r_{AI}) or start evaluating it (r_{E}).
2. Evaluators	$E = \int_{t=0}^{T} (r_{\mathrm{E}} - r_{\mathrm{AE}} - a_{\mathrm{E}})\mathrm{d}t + E_0$ E: evaluators [customer] r_{E}: evaluating rate [customer/month] r_{AE}: adoption after evaluation [customer/month] a_{E}: attrition from evaluation stage [customer/month] E_0: initial value for E = 1 [customer] SupportAssist evaluators are those who are evaluating the product on few of their servers. It increases with rate of r_{E} and could either adopt SupportAssist (r_{AE}) or eventually stop evaluating it (a_{E}).
3. Adopters	$A = \int_{t=0}^{T} (r_{\mathrm{AE}} + r_{\mathrm{AI}} - a_{\mathrm{A}})\mathrm{d}t + A_0$ A: adopters [customer] r_{AE}: adoption after evaluation [customer/month] r_{AI}: immediate adoption [customer/month] a_{A}: attrition from adopters [customer/month] A_0: initial value for A = 1 [customer] SupportAssist adopters are those who adopted the product either after evaluation (r_{AE}) or without going through evaluation (r_{AI}).
4. Total adopters	TA = A + E TA: adopters [customer] A: adopters [customer] E: evaluators [customer] Total customers using SupportAssist at least in one of their devices, which includes evaluators as well.

(Continues)

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Table A1. Continued

Variable/parameter	Equation (units inside "[]")
5. PA contacted by marketing	$PA_C = PA \times e_M$ PA_C: PA contacted by marketing [customer/month] PA: potential adopters [customer] e_M: marketing effectiveness [1/month] This variable represents the number of potential adopters (PA) contacted by SupportAssist marketing.
6. Contact between advocates and potential adopters	$C = PA \times e_W \times (qA/n)$ C: contact between advocates and potential adopters [customer/month] PA: potential adopters [customer] e_W: contact rate [1/month] n: market size [customer] q: proportion of adopters who are advocates [Dmnl] A: adopters [customer] Contact between advocates and potential adopters is the number of potential adopters (PA) contacted by advocates (qA; $q = 0.1$) with a contact rate of $e_W = 1$ customer/customer/month. Total market size (n) is set at $PA_0 + E_0 + A_0 = 1002$ customers.
7. Adoption through word of mouth	$PA_w = f \cdot C$ PA_w: adoption through word of mouth [customer/month] f: chance of persuasion [Dmnl] C: contact between advocates and potential adopters [customer/month] f Portion of people contacted by other adopters will adopt the product. We assume $f = 0.1$.
8. Evaluating rate	$r_E = PA_C \times I_{AE} + PA_W \times W_{AE}$ r_E: evaluating rate [customer/month] PA_C: PA contacted by marketing [customer/month] I_{AE}: marketing focus eval vs. adoption [Dmnl] PA_w: adoption through word of mouth [customer/month] W_{AE}: WOM effect on E vs. A [Dmnl] The evaluation rate comes from marketing and adoption from word of mouth. The first term is equal to the ratio of potential adopters in contact with SupportAssist marketing (PA_C) who decide to evaluate the service ($I_{AE} = 0.75$). The second term is equal to the ratio of potential adopters that are contacted by other customers (PA_W) and convinced to evaluate SupportAssist ($W_{AE} = 0.9$).

(Continues)

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Table A1. Continued

Variable/parameter	Equation (units inside "[]")
9. Immediate adoption	$r_{AI} = PA_C \times (1 - I_{AE}) \times F_{AE} + PA_W \times (1 - W_{AE})$ r_{AI}: immediate adoption [customer/month] PA_C: PA contacted by marketing [customer/month] I_{AE}: marketing focus eval vs. adoption PA_w: adoption through word of mouth [customer/month] W_{AE}: WOM effect on E vs. A F_{AE}: relative effectiveness of mass adoption messages. Rate of immediate adoption equals that due to marketing plus that due to word of mouth. The first term is the ratio of potential adopters in contact with SupportAssist marketing (PA_C) who decide to adopt the product ($(1 - I_{AE}) \times F_{AE}$, $F_{AE} = 0.1$). F_{AE} represents marketing teams' difficulty of persuading high-utilization adoption in comparison to evaluation. The second term is the ratio of potential adopters that are contacted by other customers (PA_W) and convinced to adopt SupportAssist ($1 - W_{AE} = 0.1$).
10. Eval exit rate	$Ex_E = E/T_E$ Ex_E: eval exit rate [customer/month] E: evaluators [customer] T_E: eval period [month] Evaluators are assumed to make their decision with an average delay of T_E, which is based on case information, and set to 36 months.
11. Attrition from evaluation stage	$a_E = Ex_E \times \gamma$ a_E: attrition from evaluation stage [customer/month] Ex_E: eval exit rate [customer/month] γ: attrition fraction [Dmnl] Rate of attrition from evaluation stage is the ratio of evaluators who discontinue the service after the evaluation period.
12. Adoption after evaluation	$r_{AE} = Ex_E \times (1 - \gamma)$ r_{AE}: adoption after evaluation [customer/month] Ex_E: eval exit rate [customer/month] γ: attrition fraction [Dmnl] Rate of adoption after evaluation is the fraction of evaluators (E) who adopt SupportAssist ($1 - \gamma$) after a period of evaluating the service.
13. Marketing effectiveness	$e_M = e_{M,N} \times \frac{R}{R_N} \times MM$ e_M: marketing effectiveness [1/month] $e_{M,N}$: normal marketing effectiveness [1/month]

(Continues)

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Table A1. Continued

Variable/parameter	Equation (units inside "[]")
	R: resources [\$/month] R_N: normal resource [\$/month] MM: marketing multiplier [Dmnl] Marketing activities are represented as normal marketing effectiveness ($e_{M,\ N}$ = 0.01) multiplied by normalized resources ($\frac{R}{R_N}$) . (R_N = \$100). In the base run, MM = 1, and as explained in the experimental setup section, for tests of effects of more focus on marketing, different values for MM were entered.
14. Total devices with SA	$S = M_A \times A + M_E \times E$ S: total devices with SA [device] M_A: average number of devices of adopters [device/customer] A: adopters [customer] M_E: average number of devices of evals [device/customer] E: evaluators [customer] Total devices with SupportAssist is the average number of devices with SupportAssist for each customer who adopted (M_A = 100) or is evaluating it (M_E = 2) multiplied by the number of customers (A or E).
15. Resources	$R = f(S)$ R: resources [\$/month] S: total devices with SA [device] $f(S)$ is a function and should be set in a way that $\dot{f}(.) > 0$. For the range of value, from expert judgment we know $\ddot{f}(.) > 0$. We use the simple function of $R = smooth3i\ (r \times S^{\alpha},\ T,\ R_N)$. In this equation r = 0.05 [\$/month] and represents the level of resources when S = 1. Also, α = 1.1 [Dmnl]. T is the time delay to adjust resources, assumed to be 12 months. Initial resource is assumed to be R_N = \$100. By changing α we can test the model for various functions.
16. Database	$D = \int_{t=0}^{T} (d_g - d_o)\,dt + D_0$ D: database [data unit] D_0: initial database [data unit] d_g: data generation [data unit/month] d_o: data becoming obsolete [data unit/month] Amount of collected data (initially equal to D_0 = 100) increases by data generation (d_g) and decreases by data becoming obsolete (d_o).

(Continues)

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Table A1. Continued

Variable/parameter	Equation (units inside "[]")
17. Data generation	$d_g = S \times F_{DG}$ d_g: data generation [data unit/month] S: total devices with SA [device] F_{DG}: data generated per device per unit of time [data unit/(month × device)] Rate of data generation is the rate of data generated (F_{DG} = 1) by all devices with SupportAssist (S).
18. Data becoming obsolete	$d_o = D/T_{DA}$ d_o: data becoming obsolete [data unit/month] D: database [data unit] T_{DA}: data life span [month] We assume data degenerates after a period of time (T_{DA} = 24 months).
19. SA performance	$P_C = P_N \times g(D) \times \mathrm{DM}$ P_C: SA performance [value unit] P_N: SA normal performance [value unit] $g(.)$: effect of data on performance [Dmnl] DM: design multiplier [Dmnl] SupportAssist performance is a function of data available that is represented by $g(D)$. SupportAssist normal performance is set P_N = 1. In base run, DM = 1, and as explained in the experimental setup section, for tests of effects of new releases of SA, different values for DM are entered. An S-shaped look-up function is used for g using these points: (0, 0.2), (0.5e6, 0.25), (0.7e6, 0.5), (1e6, 1), (1.4e6, 1.6), (1.8e6, 2.5), (2.4e6, 2.8), and (3e6, 3).
20. Experienced value for evals	$V_E = P_C \times C_{FE}$ V_E: experienced value for evals [value unit] P_C: SA performance [value unit] C_{FE}: evals chance of one device failing [Dmnl] To experience the value of SupportAssist while evaluating, we assume that at least one device with SupportAssist should fail (C_{FE}) and SupportAssist A has to have the performance capacity to predict or capture the failure (P_C).

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Table A1. Continued

Variable/parameter	Equation (units inside "[]")
21. Experienced value for adopters	$V_A = P_C \times C_{FA}$ V_A: experienced value for adopters [value unit] P_C: SA performance [value unit] C_{FA}: adopter chance of one device failing [Dmnl] To experience the value of SupportAssist after adoption, we assume that at least one device with SupportAssist should fail (C_{FA}) and SupportAssist has to have the performance capacity to predict or capture the failure (P_C).
22. Eval chance of at least one device failing	$C_{FE} = 1-(1-p)^{\tilde{M}_E}$ C_{FE}: eval chance of at least one device failing [Dmnl] p: the chance of a failure of a device [Dmnl] $\tilde{M}_E$: the power of average number of devices of evals [Dmnl] (the same value as M_E) We calculate the probability of at least one device failing for evaluators. The chance of at least one device failing while evaluating is one minus the chance of none of the devices failing $(1-p)^{M_E}, p = 0.05$.
23. Adopter chance of one device failing	$C_{FA} = 1-(1-p)^{\widetilde{M}_A}$ C_{FA}: adopter chance of at least one device failing [Dmnl] p: the chance of a failure of a device [Dmnl] $\tilde{M}_A$: The power of average number of devices of adopters [Dmnl] (the same value as M_A) We calculate the probability of at least one device failing for adopters. The chance of failing at least one device after adoption is one minus the chance of none of the devices failing $(1-p)^{M_A}$, ,p = 0.05.
24. Attrition fraction	$\gamma = h(V_E)$ γ: attrition fraction [Dmnl] V_E: experienced value for evals [value unit] $h(.)$: effect of experienced value on attrition [Dmnl] This variable represents the fraction of evaluators that drop out at the end of their evaluation period. The function h should be defined in such a way that as V_E increases γ declines. In the interest of parsimony, we used a simple linear function of $h(x) = 1 - x$, so $h(x) = 1$ and $h(0) = 0.5$.

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Table A1. Continued

Variable/parameter	Equation (units inside "[]")
25. Attrition from adopters	$a_A = (A/\tau) \cdot h(V_A)$ a_A: attrition from adopters [customer/month] A: adopters [customer] τ: service period [month] V_A: experienced value for adopters [value unit] $h(.)$: effect of experienced value on attrition [Dmnl] Attrition from adopters is assumed to be affected by value experience and the normal duration of the service, which is assumed to be 36 months. The function h should be defined in such a way that as V_A increases γ declines. In the interest of parsimony, we used a simple linear function of $h(x) = 1 - x$, so $h(x) = 1$ and $h(0) = 0.5$.
26. Percentage of adoption (companies)	$O_1 = \frac{TA}{n}$ O_1: output 1: percentage of adoption by companies [Dmnl] TA: total adopters [customer] n: market size [customer] This measure is used to calculate the percentage of companies that have at least one SupportAssist in their servers.
27. Percentage of Dell devices using SA	$O_2 = \frac{S}{m} = \frac{S}{M_A \times n}$ O_2: output 2: percentage of Dell devices using SA [Dmnl] S: total devices with SA [device] m: market size in terms of number of servers [device] This measure is used to calculate the percentage of servers with SupportAssist.

Experimental setups

Table A2 describes how the simulation runs in the paper (Tests 1–7) can be replicated.

Nonlinearity of the effect of change in marketing focus

We argued that a shift in the marketing paradigm toward mass adoption is needed to see any major effect in adoption. Here we provide more evidence for the nonlinear effect of the change in marketing focus, showing that after a tipping point (around 0.2) the effect becomes more observable. To that end, we run a more general condition of Test 6 by ranging *marketing focus eval vs. adoption* variable from 0 to 1, with 0.025 interval, which produces 41 simulation runs in total.

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Table A2 Experimental setups

Test name	Operationalization	Output
1. Base run	Run the Vensim model with the provided parameter values in Table A1	Figure 7
2. Effects of 50percent design improvement	If you are using the provided Vensim file: simply change *new release effectiveness* from 1 to 1.5. Or: if you are using the reported equations in Table A1 and rebuilding the model in other software, change DM from 1 to DM = 1 + RAMP(0.5/6, 0, 6), or other ramp functions that your software package uses. The ramp function is supposed to add 0.5 to DM in the period of 6 months starting from $t = 0$.	Figure 8, graphs for design policies
3. Effects of 100 percent design improvement	If you are using the provided Vensim file: simply change *new release effectiveness* from 1 to 2 Or: if you are using the reported equations in Table A1 and rebuilding the model in other software, change DM from 1 to DM = 1 + RAMP(1/6, 0, 6), or other ramp functions that your software package uses. The ramp function is supposed to add 1 to DM in the period of 6 months starting from $t = 0$.	Figure 8, graphs for design policies
4. Effects of 50 percent marketing improvement	If you are using the provided Vensim file: simply change *New marketing campaign effectiveness* from 1 to 1.5 Or: if you are using the reported equations in Table A1 and rebuilding the model in other software, change MM from 1 to MM = 1 + RAMP(0.5/6, 0, 6), or other ramp functions that your software package uses. The ramp function is supposed to add 0.5 to MM in the period of 6 months starting from $t = 0$.	Figure 8, graphs for marketing policies

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Table A2. Continued

Test name	Operationalization	Output
5. Effects of 100 percent marketing improvement	If you are using the provided Vensim file: simply change *New marketing campaign effectiveness* from 1 to 2. Or if you are using the reported equations in Table A1 and rebuilding the model in other software, change MM from 1 to MM = 1 + RAMP(1/6, 0, 6), or other ramp functions that your software package uses. The ramp function is supposed to add 1 to MM in the period of 6 months starting from $t = 0$.	Figure 8, graphs for marketing policies
6. A shift in marketing focus	Change *Marketing focus eval vs. Adoption* from 0.75 to 0.	Figure 10, graph P3
7. Combination of all policies	Execute tests 3, 5, and 6 in the same time.	Figure 10, graph "P1 + P2 + P3"

Fig. A2a depicts the final value of percentage of devices with SupportAssist in these simulations. The results further support our argument that a major shift in marketing focus is needed. Figure A2b shows the marginal

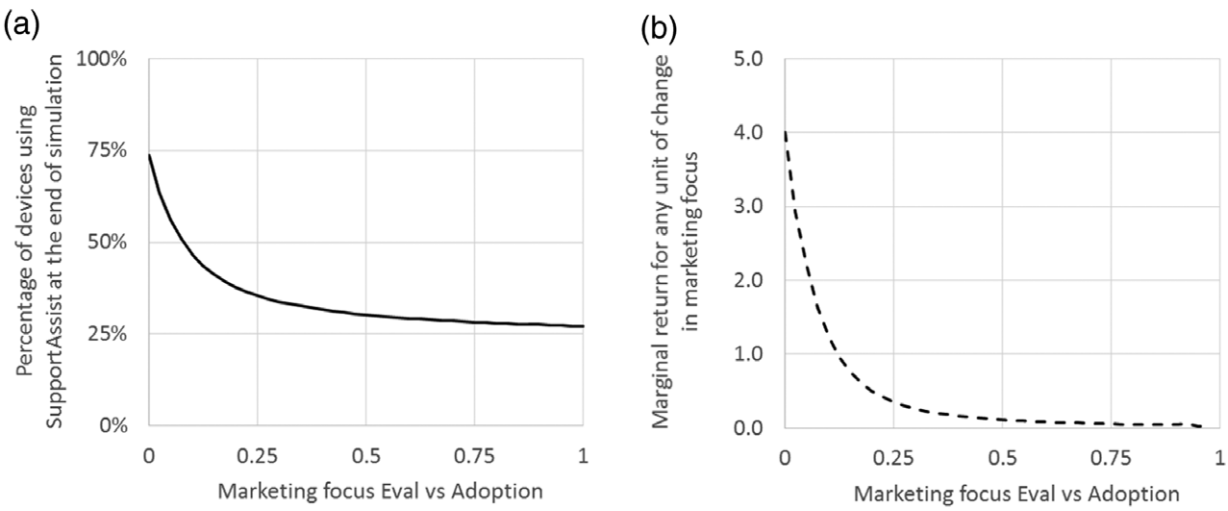

Fig. A2 The nonlinear effect of change in marketing focus

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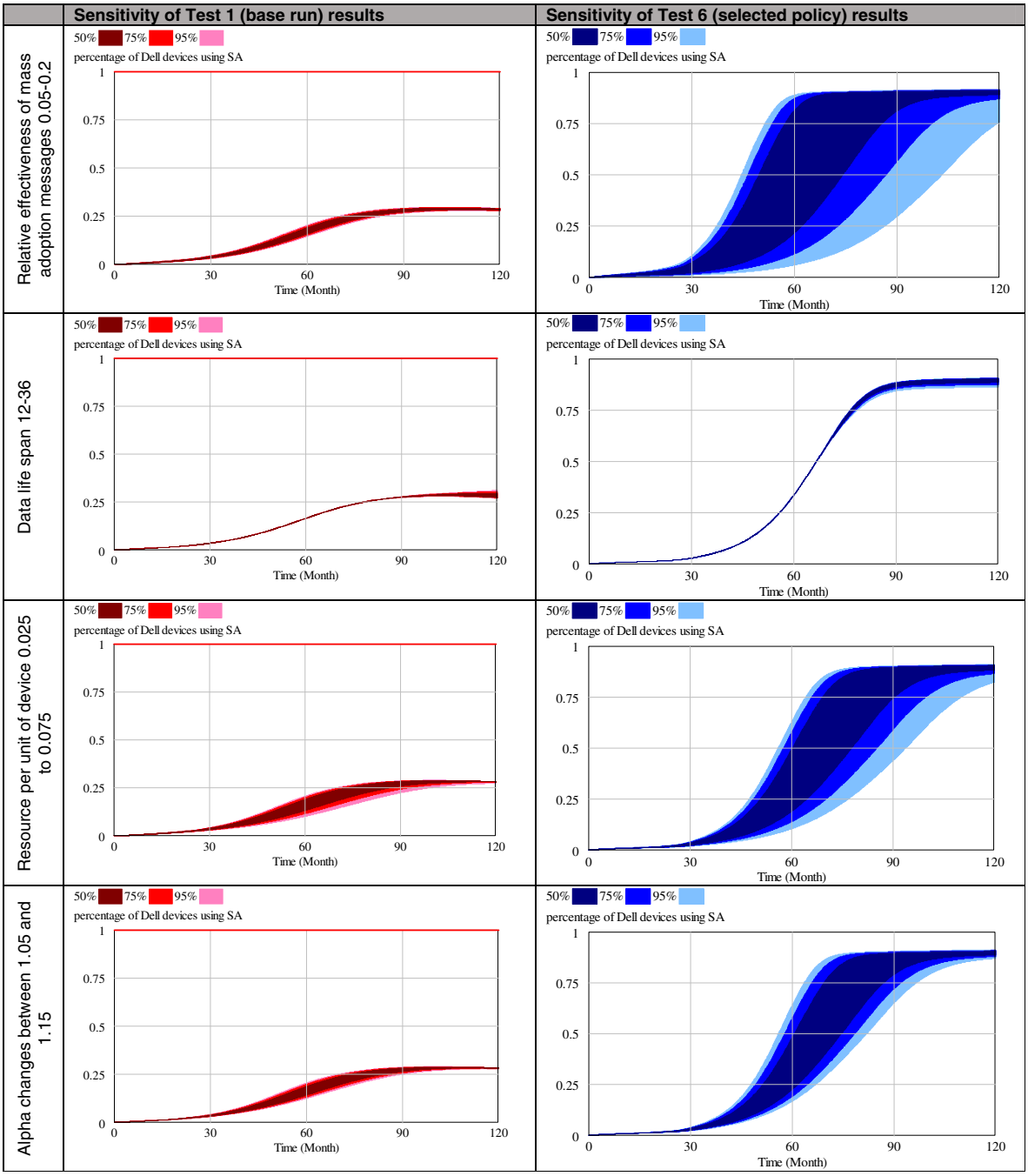

Fig. A3 A sensitivity analysis for change in one parameter. [Color figure can be viewed at wileyonlinelibrary.com]

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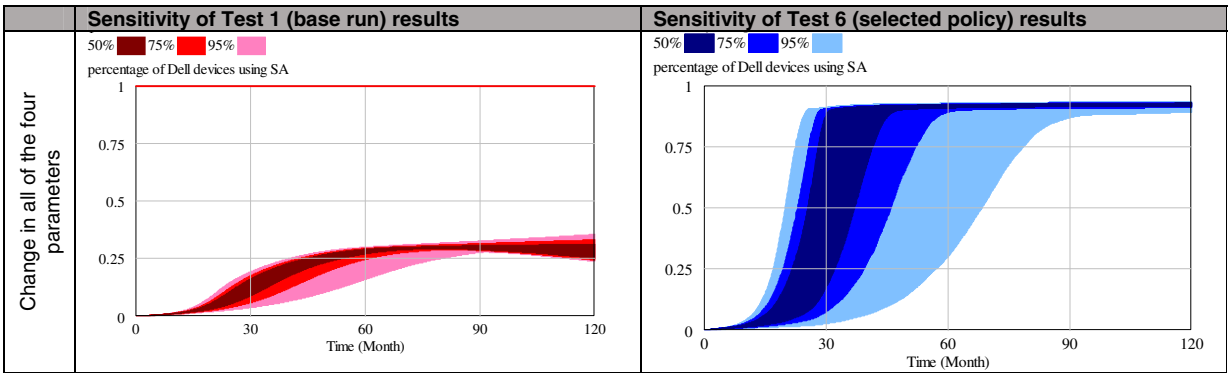

Fig. A4 A sensitivity analysis for change in all four parameters. [Color figure can be viewed at wileyonlinelibrary.com]

effect of the change in focus, which mathematically is the derivative of the graph shown in Figure in respect to its *x*-axis. This figure better demonstrates the importance of moving toward the left end of the spectrum and focusing on mass adoption. The current state of *marketing focus eval vs. adoption* is assumed to be around 0.75. The implication of this analysis is that Dell should not expect to see any major return by marginally changing its current marketing focus; instead, a major shift in marketing focus is needed

Sensitivity analysis

We conduct a Monte Carlo analysis to examine the robustness of the model. Our focus is on effects of change in parameters that may take significantly different values from what is assumed in our illustrative model. These parameters are *relative effectiveness of mass adoption messages*, *data life span*, *resource per device unit*, and *Alpha*. For other parameters, values are either known to the modelers or are policy parameters to operationalize policy tests.

We check the sensitivity of two major simulation outcomes: the base run (Test 1) and the combined policy test (Test 6) to reasonable changes in each of the mentioned parameters (Figure A3). In addition, we also test the sensitivity of our results to changing all four parameters combined (Figure A4). Each sensitivity test is the result of 1000 simulation runs based on randomly (uniform distribution) selected values for the parameters in the intervals specified below. The results are qualitatively robust and, considering that the model is illustrative with the purpose of examining general behaviors, the variability of the results are in acceptable ranges, showing the same behavior patterns reported in the main body of this paper.

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