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Toward an Agent-Based Patient–Physician Model for the Adoption of Continuous Glucose Monitoring Technology

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Abstract

Health care is a major component of the U.S. economy, and tremendous research and development efforts are directed toward new technologies in this arena. Unfortunately few tools exist for predicting outcomes associated with new medical products, including whether new technologies will find widespread use within the target population. Questions of technology adoption are rife within the diabetes technology community, and we particularly consider the long-term prognosis for continuous glucose monitoring (CGM) technology.

We present an approach to the design and analysis of an agent model that describes the process of CGM adoption among patients with type 1 diabetes mellitus (T1DM), their physicians, and related stakeholders. We particularly focus on patient–physician interactions, with patients discovering CGM technology through word-of-mouth communication and through advertising, applying pressure to their physicians in the context of CGM device adoption, and physicians, concerned about liability, looking to peers for a general level of acceptance of the technology before recommending CGM to their patients.

Repeated simulation trials of the agent-based model show that the adoption process reflects the heterogeneity of the adopting community. We also find that the effect of the interaction between patients and physicians is colored by the nature of the environment as defined by the model parameters.

We find that, by being able to represent the diverse perspectives of different types of stakeholders, agent-based models can offer useful insights into the adoption process. Models of this sort may eventually prove to be useful in helping physicians, other health care providers, patient advocacy groups, third party payers, and device manufacturers understand the impact of their decisions about new technologies.

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Abbreviations: (ABS) agent-based simulation, (CGM) continuous glucose monitoring, (T1DM) type 1 diabetes mellitus

Keywords: agent-based models, continuous glucose monitoring, innovation diffusion, technology adoption, word-of-mouth learning

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Introduction

Continuous glucose monitoring (CGM) devices have not found widespread use among the type 1 diabetes mellitus (T1DM) population. The fate of innovative products in the area of diabetes care is dependent on a number of factors attributable to different stakeholders, the majority of which fall outside the control of the device manufacturer. In particular, manufacturers have an uncertain grasp of market needs, and the medical merits of an innovation alone do not guarantee its commercial success. As a case in point, consider efforts to develop an inhalator for insulin, where both Pfizer and Eli Lilly put an end to their efforts to develop such a device,[1,2] both companies citing, among other things, poor commercial potential. In the case of Pfizer, the decision was taken nearly two years after it had obtained regulatory approval,[3] incurring a $2.8 billion charge, according to Reuters.[1] Inhalators were reported to be unpopular (1) among the patients because of design flaws and (2) among doctors because of the risk they posed to lung functions. The case of inhaled insulin, although an ongoing saga, provides a window into the complexity of the system of stakeholders of various types that comprise the potential adopting community for an innovative diabetes care device. The system within which the device or pharmaceutical product is introduced is decentralized, and although regulatory institutions provide some guidelines, the bulk of the adoption process is not governed, but comes about as a result of the interactions between the stakeholders, e.g., physicians, patients, regulatory institutions, medical journals, insurance companies, and device manufacturers.

Typically a device manufacturer will turn to the traditional tools of discrete choice analysis to characterize the commercial appeal of their products. Discrete choice analysis is a kind of statistical inference within which the dependent variables are binary. In marketing research discrete choice analysis involves scrutinizing and evaluating product attributes against demographic variables of interest, e.g., age group, sex, ethnicity, and income bracket, usually focusing on end user product selection (i.e., picking a specific product out of a line of products with comparable features) and issues affecting desirability. The results of the analysis could be misleading if not all the relevant features are included in the analysis. It is clear that certain aspects of the failure of inhaled insulin were due in part to incomplete applications of discrete choice analysis; however, components of this failure were also due the complex interaction between doctors and patients and would not have been detected within the rubric of discrete choice analysis.

Objective

We propose a modeling approach that is robust to the incentive structures within the diverse community of stakeholders. Our objective is to investigate the use of agent-based simulation (ABS) to gain insight into the complex process of CGM adoption. In this paper we introduce this methodology by looking specifically at the effects of the interactions between patient and physician on the adoption model outcome.

Related Literature

While technology adoption has long been a topic of study within economics, the application of these ideas in health care offers unique challenges.[4] The health care sector is unique in its complexity. Accurate quantitative models for health care require an understanding of all the interactions that continuously and simultaneously occur between the different stakeholders as well as the interactions of these stakeholders with technology.[5] Thus the benefits of new health care technology cannot be determined exclusively from technical/functional improvements; impacts have to be assessed from a system-wide perspective.[6] In addition, the impact that social and political issues have on health care is seen in few other markets. Insurance companies play a major role in the sector and are sure to have tremendous influence on health care issues such as universal coverage. Regulation and liability also have a strong effect on what new technologies are adopted, affecting the development decision along with the profits that vendors may receive.

Within the microeconomic field of industrial organization, there are already mature literature on the dynamics of a market considering technology innovation. Economists have considered the effects of network externalities, standardization, and compatibility in the strategic adoption of new technologies.[7] Seminal contributions to the field are due to Farrell and Saloner[8] on the demand side and Katz and Shapiro on the supply side.[9,10] The adoption of technology innovations has been modeled as a diffusion process.[11] Diffusion processes have been explained as the consequence of network externalities associated with the innovation under consideration.[12,13] This innovation diffusion is motivated by the good's

network externalities, that is, the benefits that a consumer extracts from the good are dependent on the user base of the good. Fax machines are an example of a good with network externalities. Diffusion can also be modeled as the result of a social learning process, as in word-of-mouth communication.[14,15] However, the assumptions made in canonical models in the literature, namely, that (1) competing products are perfect substitutes and (2) the owners of the innovations are not monopolists, are often not well suited for analyzing health care markets. As an alternative approach, Ratna and colleagues[16] tracked the diffusion process obtained as a result of an ABS model built using SmallTalk from the data of Coleman and associates.[17] The latter performed a detailed sociological study of the diffusion of a medical innovation, a new antibiotic dubbed gammanyn, 16 months after its introduction in a medical community spanning four cities. The diffusion was tracked among the physicians, and extensive data about their "environment" were collected via lengthy interviews. Using the computational approach allowed by the ABS along with certain tools from network analysis, Ratna and colleagues[16] were able to arrive at an understanding of the diffusion process beyond the limitations of the pairs analysis of Coleman and associates,[17] using the data in the study to generate an heterogeneous community around the physicians.

In modeling the system of stakeholders responsible for the adoption of an innovative technology, it is important to keep track of the incentive structures at play. One such structure is the relationship between physicians and patients. The diffusion of new technology in the field of health care may be very unpredictable due to the differences in the willingness to adopt by certain stakeholders. Hall and Kahn[18] showed that those differences affect the economic value of the innovation. For example, physicians may be more concerned about saving lives than learning how to use new systems[19] and taking on the risk of recommending new systems. Patients, on the other hand, want a new technology if it means a possible improvement in their quality of life. Indeed the interests of doctors and patients may not be completely aligned, and their interactions are consequently difficult to model. Patients are in need of care but lack the expertise to make the optimal choice. They rely on the physicians and count on them to supply the expert advice needed to proceed. Physicians are certainly motivated to provide expert advice, but they do so within the constraints of their skill level and ability to tolerate risk. If the patients were able to observe the skill level of the physicians, they would choose one capable of providing them with the optimal level of care consistent with their budget and medical needs. This is a central asymmetry of information in health care and can be considered as a motivation for medical malpractice liability. Medical malpractice can be seen as a mechanism that attempts to resolve the information asymmetry between patient (principal) and physician (agent).[20] In order to mitigate this risk, physicians rely on the establishment of medial norms to which they adhere. In this sense a physician might be resistant to adopt a novel medical technology if it is not widely used within his/her peer groups. Our underlying thesis is that, while medical norms are established by the entire health care community, physicians play a key role through (i) their interactions with patients and (ii) their interactions with each other in disseminating medical knowledge.[21] Consequently the standard assumption of a homogenous adopting community in developing diffusion models of technology adoption is unlikely to be fruitful in the context of health care. Only since 2007 have models of heterogeneous adopting populations appeared in the literature,[16,22] and the agent-based model presented here is in this vein.

Because our model focuses primarily on patient–physician interactions, we do not attempt to relate our work to current directions within the broader framework of evidence-based medicine. We plan to engage this aspect of innovation diffusion in health care with a future model that will feature a more representative set of the stakeholders at play in evidence-based medicine, e.g., patient, physician, third party payers, device manufacturers, advocacy groups, and regulatory agencies.

Methodology

To gain insight into the complex process of CGM adoption within the insulin-pumping T1DM community, we built an agent-based model representing the key stakeholders and then used basic tools of statistical analysis to parse the output of an ABS derived from the model. The model itself was constructed to represent the interests, in the context of CGM technology adoption, of patients, physicians, and the CGM device manufacturing community (as an aggregate) and sought to predict the percentage of patients and physicians adopting CGM technology as a function of time, relative to (hypothesized) regulatory approval of CGM for medical decision making. (We said that a physician has "adopted" CGM if he/she has accepted that CGM is both beneficial and worth the liability risk of recommending the technology to patients.) The effects of the regulator, of favorable publication in a major medical journal, and of

the extent of insurance coverage in the patient population were captured via state variables.

Here we provide details of the agent model, focusing on each stakeholder in turn and then describing their dynamic interactions.

Agent Models

Patient Model

Each patient agent, say patient i, is described by a vector of state variables, $X_i = (I_i, Y_i, S_i)$ where I_i is a Boolean variable that describes whether the patient is interested in CGM (prior to adoption), Y_i is a Boolean variable that describes whether the patient has already adopted CGM, and S_i describes whether the patient is satisfied with CGM technology (after having already adopted), taking on the value of 1 if satisfied and -1 otherwise. The state of each patient is updated in discrete stages so that $X_i(t)$ refers to the state vector of patient i at stage t.

Patient interest I_i is updated via a word-of-mouth learning process.[14,15] Within this framework each patient formulates an interest in the device by polling a small subset of the patients who have already adopted the device. Specifically, at time period t, we let $q_{i,t}$ be the set of n patients that patient i uniformly (randomly) selects to ask about their device, and we compute

$$I_i(t) = \begin{cases} \text{TRUE if } DA_i = \text{TRUE and } \sum_{k \in q_{i,t}} S_k(t) > 0 \\ \text{FALSE otherwise} \end{cases}, \quad (1)$$

where DA_i is a Boolean parameter randomly attributed to patient i at stage $t = 0$ that describes whether CGM is affordable for patient i. According to **Equation (1)**, patient i is interested in CGM at stage t if the technology is affordable and if a majority of the sampled patients using CGM is satisfied. (The intuition of this is that if a patient finds that the average experience with CGM is positive, he/she will be inclined to inquire about CGM the next time he/she visits his/her physician.) The parameter DA_i is derived from another randomly assigned Boolean parameter, DC_i, which describes whether CGM is covered by the insurance policy of patient i. First DC_i is assigned the value TRUE at stage $t = 0$ with probability IC independent of all other patients, where IC is a model parameter describing the fraction of patients whose insurance policy covers CGM. (If CGM is not covered for patient i, then DC_i = FALSE.) Next, if regulatory approval for use of CGM in medical decision making has been granted, we set $DA_i = DC_i$. If regulatory approval for medical decision making has not been granted, then, as long as CGM is covered for patient i, the affordability parameter DA_i is set to TRUE with probability $\frac{NTA}{IC}$, where NTA is another model parameter describing the fraction of the patient population that can afford CGM. The number of patients (who have already adopted CGM) sampled in **Equation (1)**, n, is a model parameter.

All patients start out having not adopted CGM. Thus the initial adoption state for patient i is $Y_i(0)$ = FALSE. Patient i transitions from Y_i = FALSE to TRUE to in stage t if

1. the patient is interested in CGM at stage t, i.e., $I_i(t)$ = TRUE,
2. the patient's doctor has adopted CGM, which we denote as $Z_{D(i)}$ = TRUE, where $D(i)$ is the label associated with the physician of patient i, and Z_D refers to the adoption state of physician d (to be discussed in the physician model), and
3. CGM technology is affordable for patient i, i.e., DA_i = TRUE.

Patient satisfaction with CGM is randomly assigned upon adoption. Specifically the value of the satisfaction variable for patient i is initialized as $S_i(0) = 0$. Then, if patient i adopts CGM in stage t, $S_i(t)$ is set to +1 with probability $\frac{1+NTE}{2}$, where NTE is a model parameter that describes the average "effectiveness" of CGM technology, otherwise $S_i(t)$ is set to -1.

Physician Model

Physicians are also modeled as agents. Each physician, say physician j, is described by a vector of state variables, $\tilde{X}_j = (P_j, Z_j)$, where P_j describes the interest level about CGM among the patients of physician j, and Z_j is a Boolean variable that describes whether physician j has already adopted CGM. As with the patient model, the state of each physician is updated in discrete stages so that $\tilde{X}_j(t)$ refers to a state vector of physician at j stage t.

The patient interest variable $P_j(t)$ is computed as the fraction of the physician's patients that are currently interested in CGM:

$$P_j(t) = \frac{1}{C_j} \sum_{i \in \{\text{patients of } j\}} 1_{I_i(t) = \text{TRUE}}, \quad (2)$$

where

- C_j is the number of patients in the clinic of physician j, which in this paper is taken to be an integer value

uniformly randomly chosen between 1 and a maximum number of patients (a model parameter) and

- $1_{I_i(t)=\text{TRUE}}$ takes on the value of 1 if $I_i(t) = \text{TRUE}$ and takes on the value of 0 otherwise.

All physicians start out having not adopted CGM. Thus the initial adoption state for physician j is $Z_j(0) = \text{FALSE}$. Physician j transitions from $Z_j = \text{FALSE}$ to TRUE in stage t if the net utility $U_j(t)$ of adopting in stage t exceeds a specific threshold. Drawing upon insights from Cabral[12] regarding diffusion with network externalities, we model net utility as follows:

$$U_j(t) = v_j + \left(\rho \cdot P_j(t) + (1-\rho)\cdot D(t)\right)^{\alpha} - \beta, \quad (3)$$

where

- v_j is the "native" utility that physician j perceives about CGM technology, which in this paper is modeled as an exponentially distributed random variable with given mean value. We use $\bar{v}$ to denote the mean value of the random variable v_j in situations where unfavorable articles about the clinical effectiveness of CGM have been published in a major journal. The mean value of v_j in situations where favorable publications have appeared is $2\bar{v}$.
- ρ is a model parameter that describes the relative importance of patient interest versus peer interest in CGM technology.
- $D(t)$ is the fraction of physicians in the model that have already adopted CGM:

$$D(t) = \frac{1}{\text{number of physicians}}, \quad (4)$$

  where $1_{Z_j(t)=\text{TRUE}}$ takes on the value of 1 if $Z_j(t) = \text{TRUE}$ and the value of 0 otherwise.
- The parameters α and β are model parameters that influence the outcome of external effects, i.e., patient interest and peer adoption.

Finally in our model physician j transitions from $Z_j = \text{FALSE}$ to TRUE in stage t if $U_j(t) > 0$.

Note that $U_j(t)$ is an increasing function of both the physician's native interest in the technology and the percentage of the physician's patients and peers that have already adopted CGM. The dependence $D(t)$ on captures the physician's consideration of liability risk; there is less risk associated with larger percentages of peers that have already accepted the technology. Suppose a doctor is planning a recommendation for a patient. When it comes to selecting a treatment option that deviates from status quo, the more standard the option, as measured by the percentage of the community that has already adopted the treatment option, the less liability risk the doctor assumes, since the doctor should be able to show in court the he/she acted according to standard practices and was therefore not reckless.

Device Manufacturer Model

The collection of device manufacturers (as an aggregate) control the upfront cost of CGM technology prior to regulatory approval, the inherent effectiveness of CGM, and the frequency with which patients who can afford the innovative device ask their physicians about it. Affordability is modeled as a number in (0,1), representing the fraction of the patient population that, on average, would be able to afford the innovation given the price set by the device manufacturer; this is a parameter of the model that is fixed at the start of a simulation run for the duration of a run. The inherent effectiveness of CGM is modeled as a number in (0,1), indicating the fraction of users who, on average, would see an improvement in their control of insulin level upon switching to the innovation. The frequency of patient queries about CGM technology is modeled as the relative weight, ρ, in the physician utility model **Equation (2)**, with which the physicians weight their colleagues' actions versus their patients' inquiries. We assume here that physicians are informed about their peers' decision, at least in an average sense.

Agent Dynamics

A run in a simulation consists of repeatedly asking doctors and then patients to make a decision until all adoption decisions have resolved. At each stage of the run (corresponding to 8 weeks), doctors are asked to make a decision, and is A_j updated. Once doctors have moved, patients check whether or not they can afford the new technology (either out of pocket or that, because of regulatory approval, it is now covered by insurance). If they can afford it, they start using it if it is approved by their doctor, updating A_i, and they immediately form a once and for all opinion of the product, updating S_i. If not they ask other users about their satisfaction with the new technology; if it is positive on average, the patient becomes interested, updating $I_{i,t}$.

Experimental Design

We have implemented the agent model as a NetLogo ABS,[23] where it is possible to capture the simple mathematical behaviors of the agents as simulation code and then watch their interactions as a sample trajectory of the

dynamic model. NetLogo allows us to create agents with a sets of attributes.

Using this simulation we investigate relationships between adoption among patients and physicians as a function of the following model parameters:

- Patient Pressure, ρ: measure of relative importance of patient and peer externalities for each physician (patient concerns versus liability).
- Affordability of CGM, *NTA*: number between 0 and 1 indicating the percentage of the population that would have access to the technology prior to it being covered by their insurance.
- Effectiveness of CGM, *NTE*: number between 0 and 1 indicating the average percentage improvement in blood glucose controllability the device delivers on status quo treatment options.
- Regulatory Approval: Boolean indicating whether or not the technology has been approved for medical decision making.
- Favorable Publication: Boolean indicating whether or not there has been publication of favorable clinical trial results in a major medical journal.
- Insurance Coverage, *IC*: number between 0 and 1 indicating the percentage of the population whose use of the technology would be covered upon regulatory approval.

We ran a total of 9720 simulations with the following:

- Each simulation instantiated 100 physicians and on average 1299 patients (SD = 71.7), C_j~Uniform;[15,22]
- v_j~Exponential($\bar{v} = 1$);
- *NTA* taking values 5, 10, and 25% of patients;
- *NTE* taking values 10, 20, and 50 % better than status quo;
- *IC* being 50, 70, and 90% of the patient community;
- ρ being 0.5, 0.7 and 0.9;
- Regulatory approval and favorable publication being for different experiments TRUE or FALSE.

Preliminary Results

Influence of Regulatory Approval for Medical Decision Making

Figures 1 and **2** present box plots of adoption rate (percentage of the population to adopt CGM) among physicians and patients, respectively, across all 9720 simulation runs. As expected, a major factor influencing adoption was whether CGM had obtained regulatory approval for medical decision making. We note that regulatory approval has a larger influence on the adoption among patients than on adoption among physicians. When the data were split according to regulatory approval status, a Welch two-sample *t* test

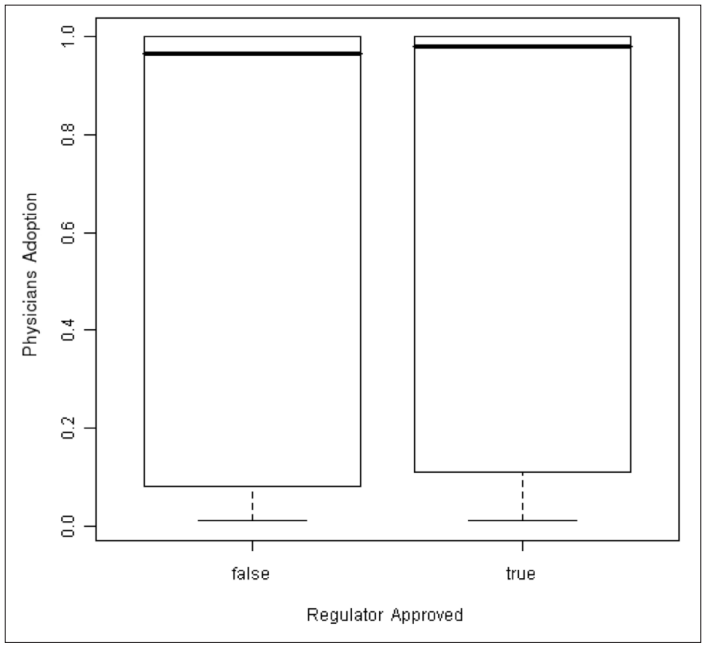

Figure 1. Physician adoption barely depends on the regulatory approval for medical decision making.

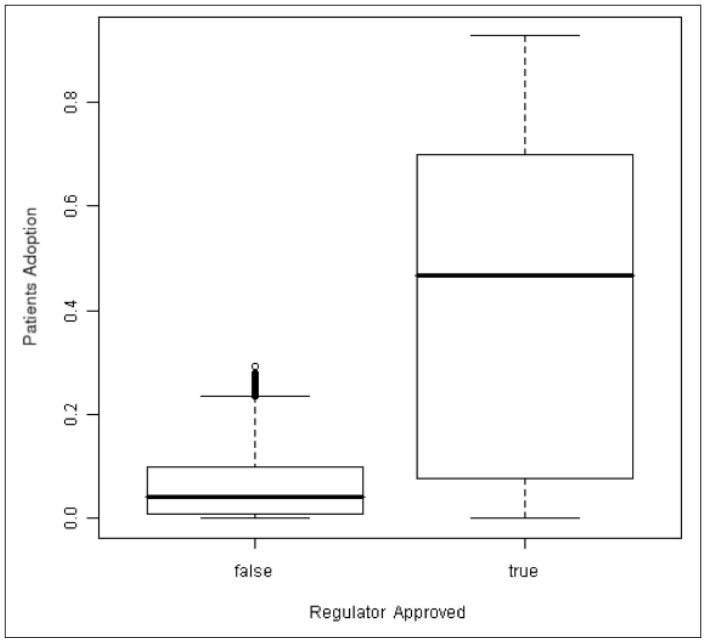

Figure 2. Patient adoption clearly depends on the regulatory approval for medical decision making.

could not reject the null hypothesis that there is a difference in the mean adoption rate in the two data sets for physicians. (At the 5% level, the t statistic was 1.7958 and the p value was 0.07255.) The strong influence of regulatory approval is perhaps not surprising, given that insurance companies would have a strong incentive to cover the cost of CGM if continuous monitoring was deemed to be the standard of care for T1DM patients. We point out that the heterogeneity of the adopting community (physicians and patients) is reflected in their actions, as the two groups respond differently to the same environmental parameter within the model, i.e., regulatory approval.

Influence of Favorable Publication

As shown in **Figures 3** and **4**, adoption among patients and physicians was strongly influenced by the publication of favorable clinical trial results in a medical journal. Physician adoption correlated much more strongly. In fact, favorable publication correlated to almost certain adoption among physicians. This may in fact constitute a weakness of the model, which could be addressed by introducing yet another global parameter, which would dictate the extent to which physicians are affected by the favorable publication.

Influence of Physician Adoption on Patient Adoption

Given the structure of the agent model in the Methodology section, especially the assumption that patients can only adopt CGM after their physicians have adopted, it is reasonable to expect that there is a strong correlation between physician adoption and patient adoption in the experimental study. The Pearson's product-moment correlation test yielded a 0.641641 correlation coefficient between physician adoption and patient adoption with $p < .0001$.

Interestingly, as shown in **Figure 5**, which plots patient adoption versus physician adoption, we observe categories of the adoption rate; those classes of adoption rates are not completely explained by the regulatory approval or favorable publication status. However, taking the color coding into account, where we color coded the data points dependent on whether or not there was regulatory approval and whether or not there had been a favorable publication, the plot starts to put in evidence the effect of regulatory approval and publication of favorable results of clinical trials in a major journal. It also reflects the fact that the relationship between physician adoption and patient adoption was dependent on the nature of the environment as defined by those parameters.

Influence of Affordability, Insurance Coverage, and Effectiveness

In conducting linear regression analysis adoption rate as a function of the experimental parameters, we determined the combinations of parameters that best explain the data for both patients and physicians. We found that insurance coverage, affordability, regulatory

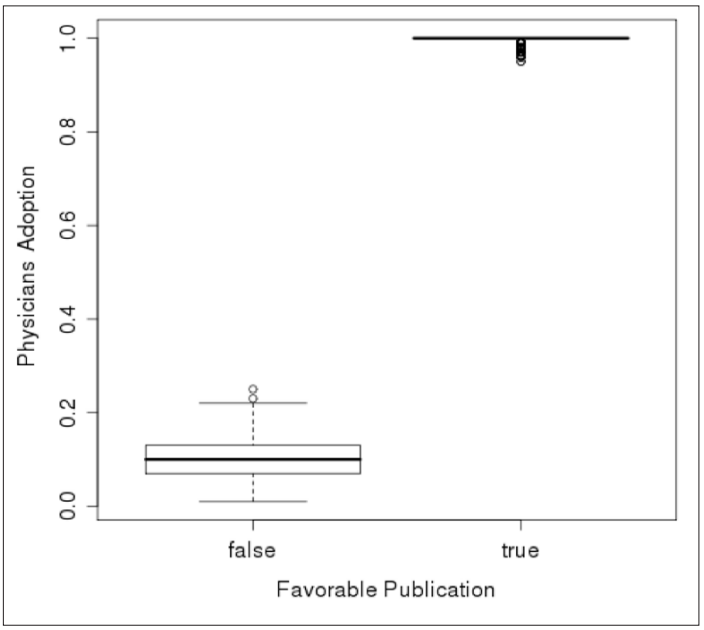

Figure 3. Physician adoption depends on the existence of publications reporting favorable results in clinical trials.

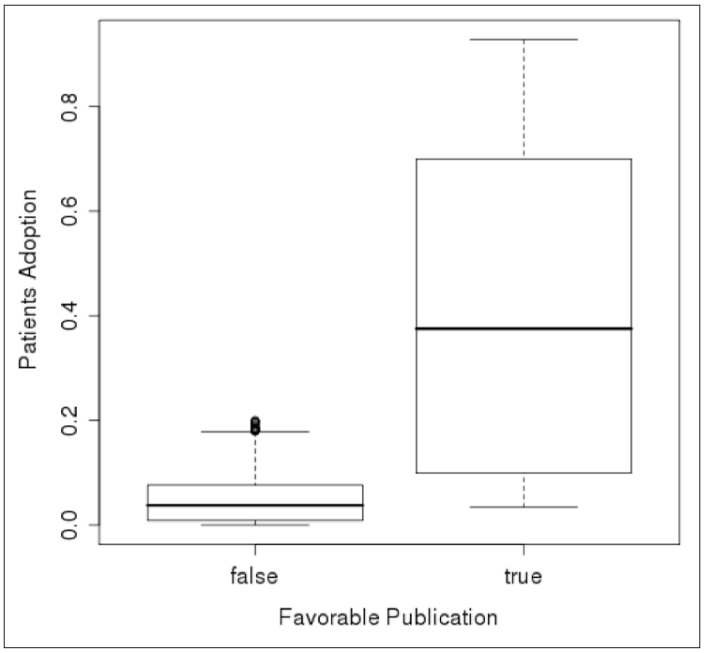

Figure 4. Patient adoption depends on the existence of publications reporting favorable results in clinical trials.

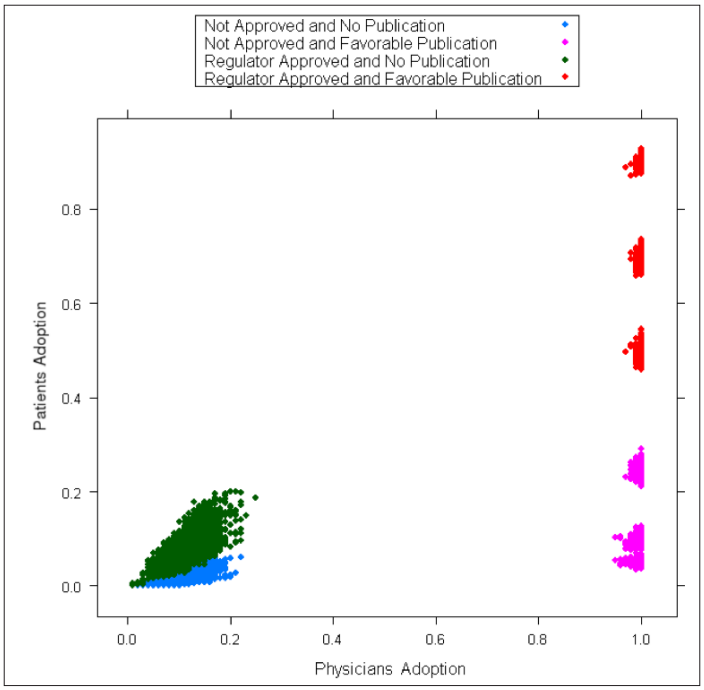

Figure 5. Patient versus physician adoption, with color coded points.

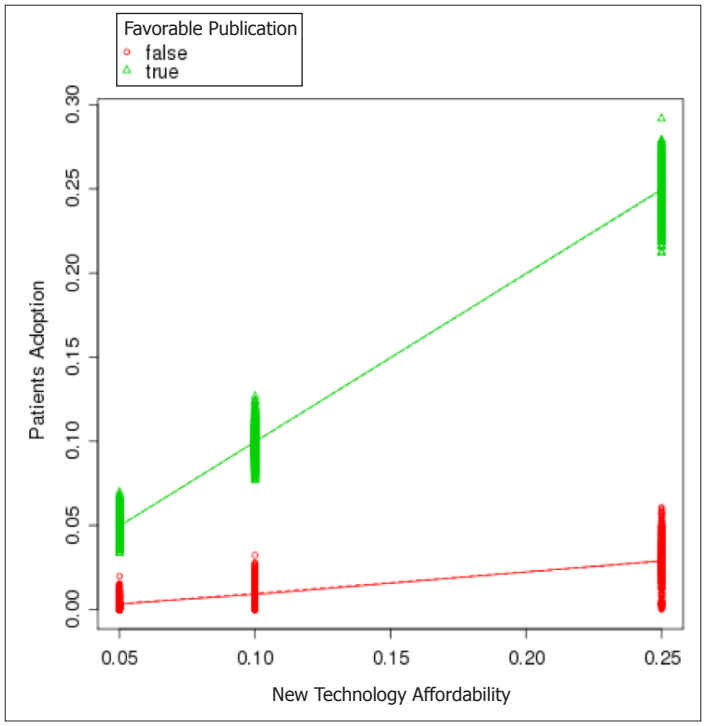

Figure 6. Patient adoption as a function of affordability prior to regulatory approval.

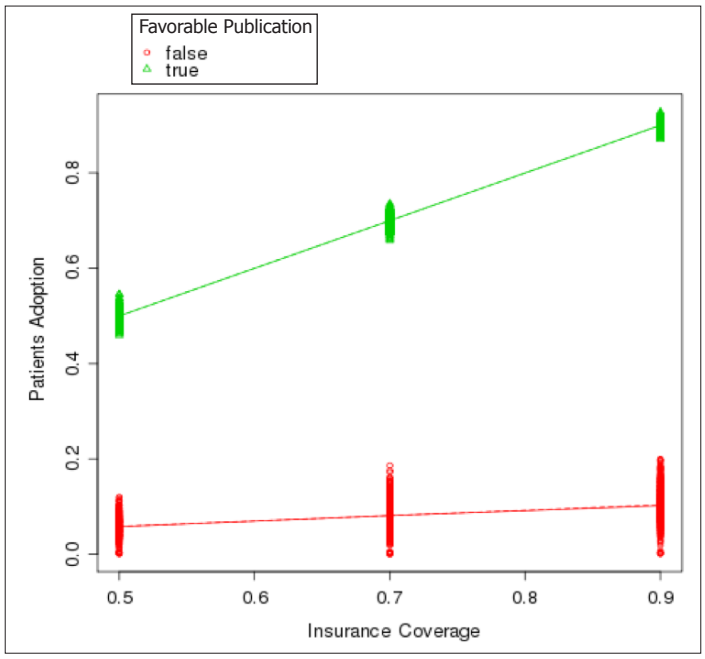

Figure 7. Patient adoption as a function of insurance coverage after regulatory approval.

approval, and favorable publication jointly formed a good predictor of patient adoption (adjusted $R^2 = 0.7391$). Recall that affordability, much like insurance coverage, regulatory approval, and favorable publication, is a model parameter; we did not fix affordability, but we allowed it to change across simulation runs in order to understand its effects on the model. For physicians we found that a different subset of parameters led to the best prediction of adoption, namely, patient pressure, affordability, regulatory approval, and favorable publication (adjusted $R^2 = 0.9961$). The overlap in these predictor sets is significant, suggesting that the adoption process among patients and physicians was strongly linked, though perhaps not in a linear fashion. We found that the parameters that predicted the patient adoption rate were dependent on the nature of the environment within which the process was taking place. Prior to favorable publication and regulatory approval, affordability and patient pressure best explain adoption. After regulatory approval, adoption was, in this patient–physician model, explained chiefly by patient pressure and insurance coverage. After a favorable publication, see **Figures 6** and **7**, adoption prior to regulatory approval was due to affordability; whereas postregulatory approval was due to insurance coverage. In **Figure 6** the difference in the linear dependence, between affordability and adoption as a function of the favorable publication, is reflected in the relative inclination of the red (no favorable publication) and green lines.

Interestingly CGM effectiveness did not factor strongly in the adoption rate for both patients and physicians. Under the Pearson's product-moment correlation test, the null hypothesis that the correlation was zero could not be rejected (p value was 0.7795 and 0.8156 for physicians

and patients, respectively). This points to a possible but understandable limit of the current model; as only patients and physicians were modeled as interacting agents, the potential effects of other stakeholders—third party payers and device manufacturers for whom other aspects of the devices, like cost effectiveness and commercial success, are important—were minimally taken into account. However, we found that CGM effectiveness was instrumental in predicting the time it took for the adoption process to stabilize; the correlation coefficient was -0.286 with $p < .0001$.

Discussion

Agent-based models can shed light on the complex process of technology adoption within the health care sector, including CGM adoption within the T1DM community. By providing insight into how new technologies may be received by the intended marketplace, agent-based models may encourage the development of new products that ultimately reduce cost and improve overall quality of care. The model developed in this paper suggests that, although regulatory approval and favorable publication of clinical trials are crucial for adoption, factors like affordability and patient pressure play a nontrivial role. This role is enhanced when considering actions by the manufacturer prior to and after regulatory approval. Our model further suggests that the need for decomposition of the system along the timing of environmental variables like regulatory approval or publication of clinical trials is strongly dependent on which adoption process is being investigated. Our model also suggests that, in order to understand adoption within any particular group, it is necessary characterize and model interactions across diverse groups of potential adopters. We find that models that take into account the disparate interests of different population groups (e.g., patients and physicians) can yield insights into the interactions between these groups in reality. Indeed it is perhaps best, as we have done, to model physicians as being coupled with patients as an irreducible substructure of the adoption process, an entity that cannot be broken apart if one hopes to understand the behavior of the entire system.

Agent-based models may provide a promising avenue for the investigation of the structure of complex technology adoption processes in health care, precisely because they allow for the exploration of technology diffusion in a heterogeneous community of stakeholders. Agent-based simulation tools, like NetLogo[24] (as well as others, including Repast[25] and MASON[23]), can provide a convenient means of testing hypotheses about the interactions of different stakeholders. Of course there are many ways to refine the model that we have presented here, including changes to the structure of the agent model and the dynamic interactions between agents of different types. Ultimately, in order to make predictions about a specific population of patients and physicians, it would be necessary, at a minimum, to collect demographic information about the population, to translate this information into appropriate parameter values that govern the instantiation of agents and their behaviors, and to conduct experiments that validate the model and allow for meaningful conclusions.

References:

1. Beasley D. Inhaled insulin flops, but field may hold promise. Reuters. http://www.reuters.com/article/healthNewsidUSN1344143820080413. 2008. Accessed November 28, 2008.
2. Pierson R. Eli Lilly drops inhaled insulin program. Reuters. http://www.reuters.com/article/healthNews/idUSN0732561420080307. 2008. Accessed November 28, 2008.
3. U.S. Food and Drug Administration. FDA approves first ever inhaled insulin combination product for treatment of diabetes. http://www.fda.gov/bbs/topics/news/2006/NEW01304.html. 2006. Accessed November 28, 2008.
4. Laupacis A, Feeny D, Detsky AS, Tugwell PX. How attractive does a new technology have to be to warrant adoption and utilization? CMAJ. 1992;146(4):473–81.
5. Lyons SS, Tripp-Reimer T, Sorofman BA, DeWitt JE, Boots-Miller BJ, Vaughn TE, Doebbeling BN. Information technology for clinical guideline implementation: perceptions of multidisciplinary stakeholders. J Am Med Inform Assoc. 2005;12:64-71.
6. Wears RL, Berg M. Computer technology and clinical work: still waiting for Godot. JAMA. 2005;293(10):1261–3.
7. Tirole J. The theory of industrial organization. Cambridge: MIT Press; 1988.
8. Farrell J, Saloner G. Installed base and compatibility: innovation, product preannouncements, and predation. Am Econ Rev. 1986;76(5):940–55.
9. Katz ML, Shapiro C. Network externalities, competition, and compatibility. Am Econ Rev. 1985;75(3):424–40.
10. Katz ML, Shapiro C. Technology adoption in the presence of network externalities. J Political Econ. 1986;94(4):822–41.
11. David PA. A contribution to the theory of diffusion. Research Center in Economic Growth Memorandum No. 71. Stanford University; 1969.
12. Cabral LMB. On the adoption of innovations with "network" externalities. Math Social Sci. 1990;19(3):299–308.
13. Cabral LMB. Equilibrium, epidemic and catastrophe: diffusion of innovations with network effects. In: Antonelli C, Foray D, Hall B, Steinmueller WE, eds. New frontiers in the economics of innovation and technology: essays in honor of Paul David. London: Edward Elgar; 2006, pp. 427–37.
14. Ellison G, Fudenberg D. Word-of-mouth communication and social learning. QJE. 1995;110(1):93–125.

15. Banerjee A, Fudenberg D. Word-of-mouth learning. Games Econom Behav. 2004;46(1):1–22.

16. Ratna NN, Dray A, Perez P, Grafton RQ, Newth D, Kompas T. Diffusion and social networks: revisiting medical innovation with agents. In: Qudrat-Ullah H, Spector JM, Davidsen PI. Complex decision making: theory and practice. Berlin: Springer-Verlag; 2007.

17. Coleman JS, Katz E, Menzel H. Medical innovation: a diffusion study. New York: Bobbs-Merril; 1966.

18. Hall BH, Kahn B. Adoption of new technology. In: Jones D, ed. New economy handbook. New York: Elsevier; 2003.

19. Kanellos M. Intel's medical ambitions. CNET News. *http://news.cnet.com/Intels-medical-ambitions/2008-1082_3-5867843.html*. 2005. Accessed November 28, 2008.

20. Danzon PM. Liability for medical malpractice. J Econ Perspect. 1991;5(3):51–69.

21. Phelps CE. Diffusion of information in medical care. J Econ Perspect. 1992;6(3):23–42.

22. Young HP. Innovation diffusion in heterogeneous populations: contagion, social influence, and social learning. Center on Social and Economic Dynamics at Brookings. Working Paper No. 51. 2007.

23. MASON. *http://cs.gmu.edu/~eclab/projects/mason/.* Accessed November 28, 2008.

24. NetLogo. *http://ccl.northwestern.edu/netlogo/*. Accessed November 28, 2008.

25. Repast. *http://repast.sourceforge.net/.* Accessed November 28, 2008.