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What We Can Learn from Amazon for Clinical Decision Support Systems

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Abstract. Health care continue to lag behind other industries, such as retail and financial services, in the use of decision-support-like tools. Amazon is particularly prolific in the use of advanced predictive and prescriptive analytics to assist its customers to purchase more, while increasing satisfaction, retention, repeat-purchases and loyalty. How can we do the same in health care? In this paper, we explore various elements of the Amazon website and Amazon's data science and big data practices to gather inspiration for re-designing clinical decision support in the health care sector. For each Amazon element we identified, we present one or more clinical applications to help us better understand where Amazon's

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Introduction

There is good evidence that computerized clinical decision support systems (CCDSS) have a modest impact on improving processes of care [1]. However, the evidence they have an impact on patient care is somewhat spotty [2]. Most CCDSS systems are relatively static, using expert systems or machine-learning for their inference engines. Evidence-based criteria or predictive algorithms are used to assess patient states and if a state is assessed as abnormal, an evidence-based recommendation is made to the user of the system. Effectiveness of CCDSS is measured using effect size calculations [1, 3]. There are several efforts underway to identify new models for implementing and delivering CCDSS to the point of care [3, 4, 5]

Most CCDSS have enjoyed little success outside of the institution where they were created and tested [3]. Simultaneously in recent years, e-commerce sites like Amazon have revolutionized online retail by using conversion rate optimization (CRO) to influence customer behavior and encourage increased sales of products. The site has achieved intuitive usability and is very effective at supporting purchasing decisions with a variety of aids [6]. Can these lessons be translated to health care? If so, how?

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1. Learning from Amazon

We asked ourselves several "What if" questions, using Amazon as the source for our inspiration. "What if EMRs | EHRs worked like the World Wide Web?" "What if we could improve user experience rapidly because we could see how users were using their EMR | EHR?" "What if we could make actionable information available at the point of care instantly by using Big Data techniques?" "What if we could quickly test whether those new ideas actually worked and make them available in all EMRs immediately?"

Unfortunately, our healthcare has not evolved in the same manner as the Internet. EMRs and EHRs in hospitals and clinics all work independently of each other and maintain data in silos. More importantly, they also maintain data entry screens and templates in off-line silos, preventing use of A/B testing and other conversion rate optimization tools. Previously, we proposed an architecture that would allow data entry forms and clinical decision support to be provided in multiple EMRs | EHRs [7]. In this paper, we extend the concept to include ways of improving computerized clinical decision support across multiple-EMRs | EHRs.

2. Types of Decision-Aids

Amazon provides visitors to their site with purchasing decision aids to assist them in making their purchase. This has the salutary effect of improving Amazon's sales while simultaneously assisting the customer to get the best product for their needs. Helping customers in this way increases trust and loyalty and ensures return visits to the site. In the following text, we identify Amazon purchasing decision support best practices and point out the possible clinical applications. These potential clinical applications are intended to be new hypotheses that can be tested in CCDSS systems.

2.1 Product Information at a Glance

Amazon® provides visitors with key product information at a glance. Author, publisher, price, number of pages, etc. are all available without asking for it. This makes it easy for visitors to make purchasing decisions quickly.

Clinical application: Providing diagnostic testing and medication information tailored to the patient's symptoms and diagnoses is much easier today than it has been in the past. Machine learning technologies can easily curate this type of information on the fly and display it to a physician, when an EMR template is web-based. Providing the prior-probabilities, costs or leaving out a particular diagnostic test from a diagnostic plan can have a large impact on diagnostic testing [8]. Although the evidence for medication information is weaker [9], providing patient-specific medication information with shared decision-making information (see below), may help strengthen this type of intervention.

2.2 Reviews

Amazon encourages its customers to rate and write reviews about the products they purchase. This helps other customers with their product purchases, as it is easier for visitors to make selections based on honest reviews. Reviews provide an on-line version of word of mouth marketing, a very powerful tool to disseminate knowledge and experience to others.

Clinical application: Personal health records (PHRs) could allow patients to provide feedback on the medications that they take for sharing with other patients. This information could be of great benefit in supporting shared decision making (SDM), an important and proven modality for improving patient choice and adherence to medications [10].

2.3 See What Others Purchased or Viewed

Amazon makes clever recommendations that are based on choices of customers with similar interests. By using Market basket analysis (a data mining technique), it aggregates the vast information from its databases of purchases to make recommendations for visitors. On viewing other's purchases, visitors to the site are able to make better choices for themselves.

Clinical application: Allow physicians to see the diagnostic or treatment plan used by other physicians for similar patients. This could help not only standardize care, but also help make rapid shifts to better forms of care, when they become available. Physicians tend to be conservative. But if they could see the impact of a new medication being used by their peers, they might switch faster or remain on the older one with greater confidence, if they don't perceive a large enough benefit from the new.

2.4 Recommendations for you Based on Your Previous Choices

Amazon has developed a smart recommendation system. It stores and keeps track of all previous purchases, wish lists and searches of customers. Every search on Amazon is carefully recorded to maximize customer satisfaction by providing the best possible recommendations.

Table 1. Impact of ACE Inhibitor on Systolic Blood Pressure in the Elderly by Sex

ACE Inhibitor	Female	Male
CAPTOPRIL	21.6	14.2
ENALAPRIL	10.4	11.0
FOSINOPRIL	3.2	2.0
PERINDOPRIL	3.1	3.1
QUINAPRIL	4.9	4.0
RAMIPRIL	0.4	0.4

Clinical application: We recently analyzed data from CPCSSN (www.cpcssn.ca) and identified some opportunities for advanced decision support based on historical data in the EMR. In this case, we analyzed the impact of different blood pressure lowering drugs on blood pressure. Table 1 shows how different drugs from the same class of blood pressure lowering medications (ACE Inhibitors) have very different effects on elderly patients of different sexes. This table could be used by a clinician to help them make a better prescribing decision when faced with a difficult therapeutic decision. For example, when prescribing an antihypertensive to seniors, Captopril seems to be the most effective ACE inhibitor for seniors (65-90), especially women. If a physician was planning on using an ACE inhibitor for kidney protection in a diabetic with microalbuminuria (an early sign of kidney disease), but the patient had low blood pressure, they might want to use Ramipril instead. This type of table may be able to help a physician see the impact a medication has had previously in their clinic and use it prospectively to decide upon a treatment plan. Data from other clinics could also be added to the list, making it even more powerful and generalizable.

2.5 Optimal

2.6 Action Affordances and Placement of Affordances

The art and science of designing products, system or websites to take into account the interaction between customers and the system. Amazon is constantly coming up with new affordances like "Buy now", "1-click buy", "Add to cart" and “Wish List”. These affordances are constantly updated to increase usability, conversion rates and return on investment (ROI).

Clinical application: A web-based EMR template can allow for new affordances to be added to the form on an on-going basis, as new ideas are generated and new interventions are considered. Current EMRs are not architected for on-going evolution and incremental improvements over time.

2.7 Conversion Rate Optimization and A/B Testing

A/B testing is a method to compare two versions of a webpage to find out which one works better. Using an experimental design, different variants of the webpage are randomly shown to visitors and statistical analysis is used to determine the best one. It helps Amazon generate hypotheses, create variations of webpages for testing, run experiments and eventually improve conversion rates.

Clinical application: Current EMR | EHR forms are not intuitively usable. This is because they are constructed in silos. Use of A/B testing could allow large scale, real-time testing of new data entry features, new affordances and different ways of providing clinical decision support at the point of care. A/B testing could allow us to speed up data entry and improve clinical decision support to optimize patient care.

3. Discussion and Conclusion

Computerized clinical decision support systems have a long history in health informatics. However, they have had limited success in improving physician practice or patient outcomes. This paper draws inspiration from the success enjoyed by Amazon® to provide guidance and provocation for a new generation of CCDSS. It is unlikely that the new CCDSS we envisage can be provided by technology vendors. The medical knowledge, the ability to extract new knowledge from the literature and the ability to develop new insights from data science on an on-going basis is likely to be a major barrier for most vendors. Health informaticists will need to forge partnerships with clinicians, guideline implementers and researchers to develop the skills and capabilities to deliver this new type of CCDSS.

There are several barriers to use of the new approach to CCDSS, including lack of any existing web-based forms integration with multiple EMRs | EHRs, lack of access to standardized product databases, lack of a singular organization in the health care system that can integrate patient and clinician reviews of diagnostic tools and interventions and lack of centralized databases that allow for Big Data approaches. On the positive side, there are many tools now available for improving the usability of sites using advanced statistical approaches [11]. Integrating an open-source EMR | EHR with a web-based form is relatively easy to do and can open up new possibilities for testing the intuitive usability of clinical forms [12].

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