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Assessing Technology Success and Failure Using Information Value Chain Theory

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Abstract. Information value chain theory provides a straightforward approach to information system evaluation and design. It first separates the different benefits and costs that might be associated with the use of a given information technology at different stages along a value chain stretching from user interaction to real world outcome. Next, using classical decision theoretic measures such as probabilities and utilities, the resulting value chain can be used to create a profile for a particular technology or technology bundle. Value chain analysis helps focus on the reasons for system implementation success or failure. It also assists in making comparative assessments amongst different solutions, to understand which might be best suited for different clinical contexts.

Keywords. Evaluation, Value of information, Utility, Information technology

Learning objectives

After reading this chapter the reader will:

1. Describe the typical steps in an information value chain for information technology use in healthcare.
2. Understand and demonstrate proficiency with value of information calculations.
3. Appreciate that different technologies will generate different value chain profiles.
4. Use value profiles to explain where in the chain a specific technology is most and least effective.
5. Use value chains to diagnose problems in the implementation of a specific technology bundle.

1. Introduction to Information Value Chain Theory

The closely linked processes of design and evaluation are crucial to ensuring informatics interventions work. There are two basic goals when evaluating any information or communication system. Firstly the evaluation must help determine if a system is fit for purpose, or its *efficacy* (i.e. does it do what it is meant to do?). Secondly we may want to decide if a system is the best choice amongst alternatives when used in to solve a problem in the real world (its relative *effectiveness*) (i.e. which solution should we pick?).

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Neither of these goals is easy to achieve in health informatics, for a number of reasons. Firstly there are many ways to measure success and not every success measure tells us the same thing. Should we pay more attention to surveys of user satisfaction, rates of adoption, or should we only focus on improvements in clinical outcomes? Further, given the complex organizational space within which any informatics intervention must co-exist, it is not surprising the same system, when tested in different clinical settings, usually achieves different outcomes[1]. The effects of the way a technology is implemented, the specific context in which it is used, and how it is used, all shape the outcomes of system use. With so many confounding factors, getting design right or demonstrating system success is non-trivial.

Information value chain theory provides a straightforward approach to both system design and evaluation[1 2]. With its foundations in classical decision science, it provides a mechanism to tease apart the different benefits that might be associated with the use of a given information technology, and also helps identify why expected benefits may not be detectable. Using classical decision theoretic measures such as utilities, and by sequencing the different types of information system functions and their associated outcome measures, value chain analysis helps focus on the reasons for system implementation success or failure. It also assists in making comparative assessments amongst different solutions, to understand which might be best suited for different clinical contexts.

1.1. A value chain extends from system use to health outcome

To undertake a value chain analysis, we begin by describing a value chain that connects use of an information system to final outcomes (Figure 1).

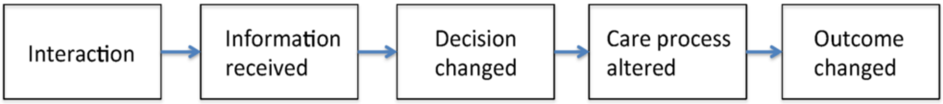

Figure 1. *The information value chain starts with a user interacting with an information system, but must go through many steps before changing clinical outcomes* (from Coiera, 2015).

The chain typically begins with a user interacting with a system (interaction). Some but not all of these interactions potentially providing information that is then received by a user (information received). Some of this information may lead to a decision being changed (decision changed), sometimes leading to a change in the process of care (care process altered). Finally, some of these process changes may then impact the outcome for a patient (outcome changed).

For example, a clinician may interact with an electronic health record, and examine a patient's laboratory test results. Amongst all the information in the available results, one specific test provides important new information. All the other information received adds nothing new and has no impact on the clinician's thinking. Based on that specific new information, the clinician ceases a medication and prescribes a new one (a change in care process). In some circumstances this change is beneficial or harmful to the patient – both leading to a change in outcome for the patient. It is also quite possible that this clinical process change, one amongst many that happen daily, leads to no change in the patient's outcome.

Evaluation can take place at each of these steps in the value chain, but it is not correct to assume that a good result at one step necessarily translates into a good result at the next. Nor should we even desire that improvements at one step in the chain flow downstream. For example, a new telecommunication system between a primary care physician and patients at home may allow a doctor to talk to their patients without the need for a physical visit. We might be able to demonstrate high system utilization and user satisfaction with this telehealth system, but also be surprised to find that there is no significant change to the survival or quality of life for patients. Why might this be so, and should we consider such a system a 'failure'?

There are many reasons why benefits at one step in the value chain do not manifest in later steps. Sometimes a technology intervention behaves as a *substitute* for an existing service process, but does not to improve it. So, when the quality of normal care is already of a high standard, any telehealth substitute for face-to-face interaction should aim to be non-inferior i.e. be no worse. All that we are doing is replacing face-to-face interactions with online ones. If the goal of this telehealth system were only to reduce the need for a patient to travel to the office, then demonstrating a cost-effective reduction in such visits (once we add in the costs of the telehealth system) would be considered a success. There should be no expectation that benefits at the initial interaction stage of the chain translate to clinical outcomes. We should just be mindful to not see any deterioration in outcomes.

1.2. Different evaluation measures may be used at different steps in the value chain

Which stages of the value chain are formally evaluated will depend on the type of system in question, and the purpose of the evaluation. Unsurprisingly, the processes that are studied, and their related measures, can vary with both the step in the chain, and the type of system being developed (Table 1). For example, we might evaluate the quality of interaction with an information retrieval search engine using metrics for the ease with which a query can be formulated to retrieve relevant information, whilst measuring the quality of a telehealth interaction would perhaps focus on the quality of the video call, the rate of technical disruptions to the call, or a user's perceived satisfaction with the call.

1.3. The value of information can be quantified

Value chain analysis makes clear that creating and accessing information alone does not always lead to a change in process or clinical outcome. We know from Shannon's Information Theory that not every additional piece of data is as informative as another [3]. The amount of Shannon information is a measure of how "surprising" new data are compared to our expectation. If data do not tell us anything new, they bring little or no new information. Another way of thinking about this is to ask how many times information must be read before there is a measureable impact on clinical outcomes. Metrics such as the *number needed to read* [4] and *the number needed to benefit from information* [5] are related attempts to correlate access to information such as clinical guidelines with their impact on process or outcome.

Table 1. *Examples of measures that can be used to evaluate systems at different stages of the interaction value chain for information retrieval systems which search for documents, and telehealth systems which support the communication of patient information (n = number of).*

	Interaction	Information	Decision	Care process	Outcome
Information retrieval system	*n* queries made, *n* query reformulations	*n* documents retrieved, precision and recall, document relevance	*n* correct or incorrect decisions, decision velocity	*n* and type of tests ordered, medications prescribed, cost of care	Morbidity and mortality, Quality Adjusted Life Year (QALY)
Telehealth system	*n* conversations, call quality and time, user satisfaction	Quality and quantity of patient level data shared	*n* additional correct or incorrect decisions	Health service utilization rates, travel costs	Blood pressure, HbA1c, blood glucose etc., Morbidity and mortality, QALY

Decision theory provides us with a powerful and theoretically robust way of estimating the *value* we place on receiving new information. For example, if a new diagnostic test result changes a patient's treatment and saves their life, then instinctively the value of that information is high. If a diagnostic test allows a patient to avoid a risky treatment and to follow a less risky but equally beneficial option, then the information's value is based on those avoided risks. If a new diagnostic test result only confirms what is already most likely, and it triggers no change to treatment, then it might have a relatively low value.

This *Value Of Information* (VOI) can be defined as the value we place on receiving particular data prior to making a decision [6]. We could calculate such a value in financial terms such as money saved or earned, or as patient expressed preferences. In other words, VOI is the *difference* between the value of persisting with the present state of affairs and the value to us of being able to embark on a new decision, influenced by new information. VOI is zero whenever obtaining new data does not change decisions or outcomes.

VOI also has a decision-theoretic interpretation. Imagine for example that a patient undertakes a test, and will be given different treatments depending on the blood test result. Each of these two treatments will result in a different outcome for the patient. How do we determine the value of each outcome to the patient? A preference for one outcome over another can be represented with a quantitative value called a *utility*. A utility is a number between zero and one and the outcome with the highest utility is the preferred one.

A utility value is thus a model of an individual's preference for an outcome, expressed in numerical form, and can be derived by a number of different means. Common methods to estimate utilities include *rating scales, standard gambles* and estimating quality-adjusted life expectancy e.g. using a *time trade-off* [7] [8].

Next we need to consider that each of the two potential treatment outcomes is uncertain. A given treatment will not always have the same effect on different patients. So even if one outcome might have higher utility for a patient, we need also to consider how likely that utility will ever be realized. To do that we now calculate the *expected utility* e of making one choice over another, which is simply the product of its probability p and its utility u:

$$e(x) = p(x) \times u(x) \qquad (1)$$

Expected utility is thus a measure of the actual benefit that can be expected from an event over multiple trials, given uncertainty about the event occurring.

The expected VOI that helps us choose between two different courses of action can now considered to be the difference in the expected utility of the different decision options [9 10] i.e.:

$$VOI = expected\ utility\ (Option\ 1) - expected\ utility\ (Option\ 2) \qquad (2)$$

For example, assume that the probability of a clinician finding a new pharmacogenomic test result when interacting with a patient's electronic record is 0.4 because the clinician usually must check the EHR several times before seeing a result. The utility of this result is high at 0.9, because it allows the clinician to choose between two different drug treatments. The Expected utility of this outcome is 0.36 i.e.:

$$0.36 = 0.4 \times 0.9$$

In comparison, the probability of not finding the test result is 0.6. We might assign a utility to proceed without the test result of 0.1 (because there is a good chance that the drug is ineffective for most patients who do not have the gene). The expected utility of proceeding without a gene test is thus 0.06 i.e.:

$$0.06 = 0.6 \times 0.1$$

We can now calculate the VOI for a clinician accessing a gene test result:

$$VOI = 0.36 - 0.6 = 0.3$$

A key idea here is that for new information to have value, the information must be *actionable* in some way. It is not enough that data provide us with a new diagnosis, that diagnosis must then trigger some new action in the world [11]. The action needs to result for example, in a change in morbidity, mortality, or in some other way increase a patient's quality of life. VOI could be negative if the proposed method to gather new information does not lead to an actionable decision with potential benefits, and gathering the data has costs for the patient such as risks of complications that lead to harm, from pain through to injury and even death.

1.4. The value of events along the information value chain can be quantified

Now that we have a way of calculating the value of information for any step in the information value chain, we can turn to look at the way information value changes down the chain. We first look at the frequency with which events occur at each stage in a chain. For example, over a 24-hour period, the EHR in a hospital may be accessed thousands of times, but decision support systems may be accessed only hundreds of times. One interesting property of the information value chain is that there is typically an asymmetry both in the *number of events* at each step, as well as in the *value* of the events (Figure 2).

Firstly, we note that there is a probability for moving from one step in the chain to another. Thus there is a probability (but not a certainty) that interacting with an information system will yield information, or that the information will lead to a decision change. For example, the number of times a clinician reads a patient record is always going to be greater than the number of times that reading leads to a change in decision. Similarly, not every computer generated alert will result in a change in decision. The number of times a decision is changed is also going to be greater than the number of times any such change leads to a measureable improvement in patient care.

Additionally the value of events early on in the value chain will often be lower than for events later on. For example, optimizing user interaction with medication alerts is likely to be of much lesser value than reducing the number of unsafe medication prescriptions, which in turn is of lesser value than reducing the number of adverse outcomes from medication errors. Similarly, the time saved in optimizing a user interaction with an EHR is likely to be of lesser value than improvements to the way tests are ordered, and these are often of lesser value than patient outcome changes such as improved survival or QALYs based on more appropriate investigation of patients.

This typical increase in value of events as we move down the chain is driven by increased value associated with real world health outcome changes compared to the value of improvements in process alone. It is however quite possible that in some settings that it is the early stages in the chain that are of higher value. For example, if human resources are scarce and expensive, then using information tools to optimize human efficiency and effectiveness might have very great value.

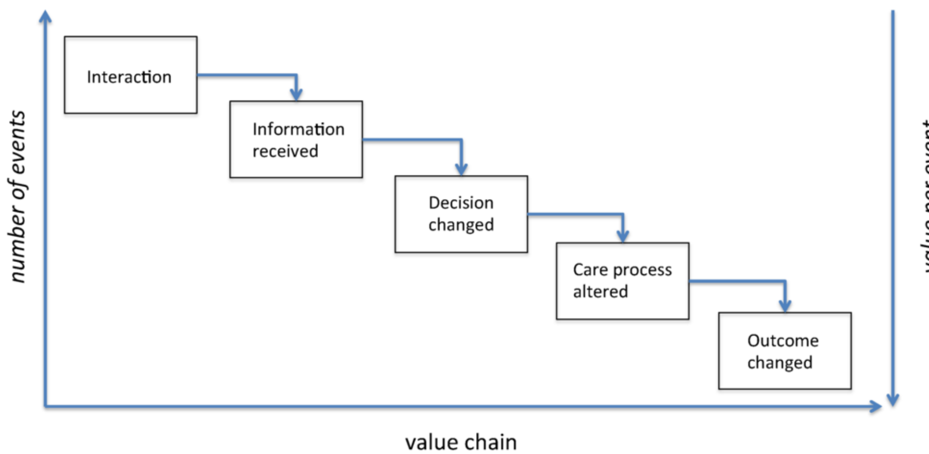

Figure 2: *The number of events is typically higher earlier in the value chain, whilst the value of individual events tends to be higher further down the chain. Combining event frequency (or probability) with event value (or utility) provides the expected utility at each point in the chain* (from Coiera, 2015).

Recall that by combining event frequency (or probability) with event utility, we arrive at an *expected utility*. We can thus calculate the expected utility of using a given system along the different steps in the value chain. The resulting *value profile* of expected utility will not necessarily be constant across the different steps. For example, a telecare system may be designed to maximize expected utility at the interaction stage by reducing face-to-face interactions, but with no expectation of changing clinical outcomes.

A decision support system would be designed specifically to improve decision-making and outcomes, while an EHR is typically designed to improve record keeping, and process improvement goals are reserved for other functions such as CPOE.

We can thus imagine different systems having quite different profiles for their expected utility at different stages of the information value chain. In Figure 3 hypothetical utility profiles are presented for four different classes of informatics intervention. They illustrate that an intervention:

1. May be designed to provide value by improving the quality of interactions in a health service but may provide little additional information compared to current practice (teleconsultation);
2. May optimize the quality of information capture (EHR);
3. May be designed to improve the quality and efficiency of clinical processes (care pathways) or
4. May be intended to intervene in the decision-making process to improve clinical outcomes. Some downstream benefits may even incur an upstream cost (e.g. interacting with some EHRs requires more time than normal practice).

The actual benefits for these intervention classes may be very different, depending on the specific bundle of services offered. For example, it is likely a system that bundles together EHR and decision support will have higher utility than each system alone.

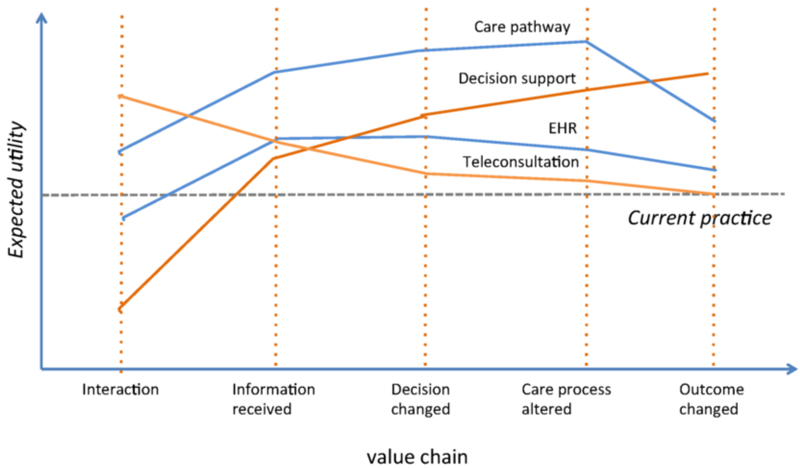

Figure 3: The profile of expected utility for an intervention will vary across the steps of the information value chain, depending on the primary purpose of the system (from Coiera, 2015).

2. Use of information value chain theory in health informatics

Given its relative simplicity, and its foundation in standard decision theoretic concepts such as utility and value of information, value chain analysis has broad application in healthcare. In particular, it can be used to assess the specific benefits of a given technology, or make comparative assessments between competing technologies. Such evaluations might happen post-hoc, for example trying to explain why outcomes for a particular technology implementation did not meet expectations. They can also be used much earlier on, in system design, when the likely impact of different technology bundles is compared and decisions made about system design.

2.1. Case Study 1: The value of using national summary electronic health records

For any formal evaluation of an electronic record system (EHR), whether at a single institution or at nation scale, measurements need to be taken at multiple points along the value chain (Figure 4). The outcome at any stage can only be understood by modeling earlier upstream events. Thus, failure to demonstrate clinical outcome changes following the implementation of an EHR might arise because of problems with events early in the chain e.g. record quality. Alternately, a lack of impact on outcomes may be unrelated to the EHR (for example organizational challenges may prevent important information from the EHR being translated into process changes).[12]

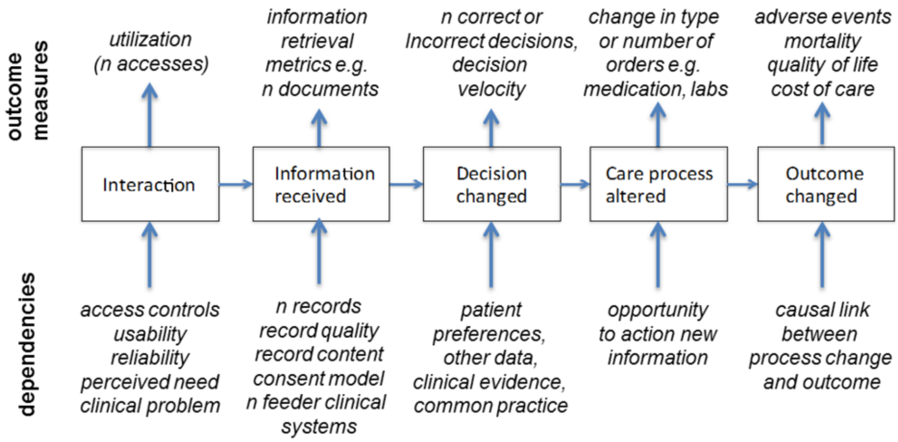

Figure 4*: The information value chain provides a simple causal model connecting EHR use and clinical outcomes. Each step is characterized by different measures, and is dependent on different elements of shared record system design and use (adapted from Bowden and Coiera, 2017).*

For example, imagine that a government has built a national summary health record for every citizen. The system is classed as a success because a large number of citizens have records created for them, and there is a regular stream of record updates every month. What if we however look not at how much data are uploaded into the system, but how often clinicians queried the data? If the system was not often used to support clinical care, perhaps the evaluation might be very different.

Evaluation might reveal that the system was not easy to use by clinicians (who therefore were abandoning it), or that the information within the records was not useful, or even that the systems in place to access the records were not mature compared to the data upload arm of the system. Finally one might look at the downstream impact of system use on the cost and quality of care delivered. What changes to care result from accessing the record? Do these changes translate into better decisions that improve patient outcomes or create service efficiencies? It might prove very difficult for a government to answer these final questions, and very easy to provide data about record or usage numbers. There is however no logical reason to assume that usage of a system translates into changes in end outcomes.

2.2. Case Study 2: Clinical Audit and Feedback

Audit and feedback (A&F) interventions have had mixed success in ensuring patients receive improved care [13 14]. Unlike clinical decision support tools, which provide clinicians with patient-specific advice at the point of care, A&F tools provide data about quality indicators at a population level over a period of time. Reasons for their variable effectiveness are unclear because the mechanisms behind intervention success or failure are poorly understood [15].

Value chain analysis can assist in identifying where potential barriers to effective use of A&F reside[2]. For example, in a situation in which A&F is focussed on improving prescribing, does the type and number of feedback alerts a clinician receives influence the probability that clinicians actually notice them, or subsequently influence their decision making, or which medications are dispensed by pharmacists or finally how many unscheduled hospital admissions are prevented?

In a study by Gude et al., the number of events at each stage of the A&F value chain for medication prescription were measured [16]. System designers were faced with a situation in which A&F was not having any perceptible impact on clinical outcomes, and wanted to understand why this was the case. Analysis of the A&F value chain (Figure 5) reveals a major disconnect between events. Firstly there is a steep reduction between the number of indictors demonstrating poor performance, and the number of indicators flagged for action. An even more dramatic reduction occurs between the problems identified by these indicators, and any action to change clinical process. Of 379 indicators targeted for an action, only 31 were addressed. The study noted "feedback did not lead to teams focusing their quality improvement decisions on low performance areas, and that planned improvement actions were often not completed".

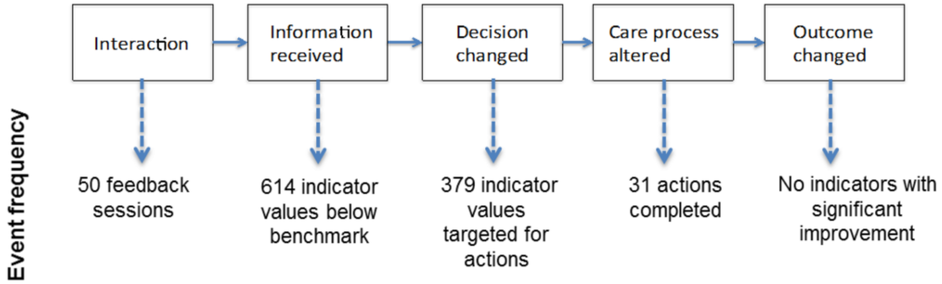

Figure 5. *The information value chain for a computerized Audit and Feedback (A&F) intervention in cardiac rehabilitation. Clinical teams received feedback multiple times on a set of eighteen quality indicators (adapted from Gude et al. 2016 [16]).*

Focusing just on the probabilities of events in the value chain, as shown in Figure 5, can tell us *where* a problem is occurring. The next stage of analysis requires measuring the utility of events at each step, to provide more focused information on *why* events do or do not occur. In this case study, measuring utility can help identify the source of the problem more precisely. Was the lack of outcome change because the alerts about abnormal indicators (information received), were of low perceived value (perhaps

[2] See Chapter 14 "Control Theory to design and evaluate audit and feedback interventions" for an analysis of the same case using Control Theory.

because there were too many of them, or the alerts had low sensitivity or specificity). Was it instead that the cost of changing a clinical process (care process altered) was too high, perhaps because clinical staff were resource constrained, and had little capacity to make the changes needed?

Table 2 provides an example of the calculations that can be made for expected utility, based on measurements of the probability and utility of each step in a value chain. It demonstrates that in this particular scenario, the problem lies in the implementability of decisions to improve practice. There is clear benefit in what the Feedback and Audit tool tells clinicians, and it is also clear that there is benefit in undertaking the recommended changes. There however is no ability to translate this feedback into effective real world actions. The main problem in this example is not with the technology, or the information it generates, but with the socio-technical context in which it is used. Consequently creating a better tool would still not change the outcome. Instead, more resources and leadership might be needed to action the information generated by the analytics tool.

Table 2. *Worked example of a value chain analysis for a computerized Audit and Feedback report. Probabilities are obtained by measuring real world event frequencies, Local utilities are obtained by measuring clinician value assessments at each step in the value chain, using a standardized measurement instrument. The expected utility for any path fragment is calculated from the utility of the node at the end of the path and the probabilities of every node in the path.*

	Step 1: Interaction	**Step 2: Information received**	**Step 3: Decision changed**	**Step 4: Care process altered**	**Step 5: Outcome changed**
Event probability	1.0 (1000/1000)	0.61 (614/1000)	0.62 (379/614)	0.08 (31/379)	0 (0/31)
Utility	0.8	0.9	0.9	0.92	0.95
Local expected utility	0.8 (0.8 x 1.0)	0.55 (0.9 x 0.61)	0.56 (0.9 x 0.62)	0.074 (0.92 x 0.08)	0 (0 x 0.95)
Path expected utility	0.8 (0.8 x 1.0)	0.55 (0.9 x 1.0 x 0.61)	0.34 (0.9 x 1.0 x 0.61 x 0.62)	0.028 (0.92 x 1.0 x 0.61 x 0.62 x 0.08)	0 (0.95 x 1.0 x 0.61 x 0.62 x 0.08 x 0)
Analysis	Utility of a accessing 1000 indicators is high because the there is a high expectation they will contain actionable information. Report length may reduce utility.	Utility of receiving specific information from a report about abnormal indicators is high, but expected utility is lower as probability that any indicator is abnormal is moderate.	Utility of decision to deal with an abnormal indicator is high, given likely benefit. Expected utility is lower as only some indicators are chosen.	A collapse in expected utility at this stage occurs because most decisions in Step 3 do not translate into process changes in Step 4.	The potentially high utility of process changes is entirely negated by the very limited process changes arising from Step 4.

3. How value chain analysis can assist in explaining health IT success or failure

Value chain analysis has a role both in explaining what has already occurred, through retrospective evaluation, as well as in shaping the design of technology and the way it is embedded in the larger socio-technical system. It can be applied in a number of different circumstances, including:

1. *Qualitative retrospective analyses*. The overall evidence for the benefit of a specific technology is often patchy, and the choice of outcome measures for evaluations may not always be ideal. As we saw in Case Study 1, it is easy to pick intermediate process measures which give a false sense of success, just as it is easy to over-emphasize clinical outcomes when the real benefit of a technology is to optimize events earlier in the chain. Value chain analysis can provide a template to consider the real-world costs and benefits of a technology at different points in the chain, identifying gaps in knowledge about performance, as well as guiding the interpretation of success and failure [17].
2. *Quantitative retrospective analyses*. When performance data are available for a specific system, as in Case Study 2, then value chain analysis can reveal specific problems in the design, implementation or use of a system. Event frequency data is ideally recorded automatically as part of system operation, and utility data can be obtained from system users, potentially even retrospectively.
3. *Prospective quantitative studies*: If a value chain can be provided with estimates of expected usage and benefit of an implemented technology, it can be used to provide predictions about overall system utilization and benefit. Such hypotheses can then be tested in prospective trials.
4. *Technology design*: Typically a digital service is built up of a bundle of separate elements. A decision support system bundle will actually require components that access the electronic health record, a user interface, and alerting strategy, and so on [18]. The overall performance of the bundle is thus dependent on the performance of individual components, and the dependencies between components. For example, if the electronic record component is suboptimal, then it does not matter how good the decision support engine might be, as the quality of recommendations will still be poor quality. System designers can estimate the necessary value profile for each element of a bundle, so that together the bundle performs as expected.

4. Discussion

Value chain theory makes very few assumptions about the nature or purpose of technology, and so has broad applicability. The strongest assumption is that the purpose of technology is to improve specific decisions, and that there is a prospect that those decisions have a detectable outcome in the real world. By relying on standard tools such as probabilities and utilities, value chain analysis is strongly grounded upon well-accepted and proven analytic concepts and methods.

One can consider a value chain to be the equivalent of a single path down a decision tree, but with some key differences. Most critically, in a decision tree we only calculate the utility of the final or terminal node. What is interesting about value chains compared to decision trees is that each node in a chain *could be* the terminal node, each with its own intrinsic and different utility in the world. One could stop a chain at reading an electronic record, and calculate the expected utility *to this point only*. Alternatively, one could add decision support to the electronic record, which would change the utility and disutility associated with system use. Since some electronic records have decision support, and some do not, these separate calculations of utilities allow us to make comparisons using the value chain. For a decision tree, we calculate expected utility by multiplying the utility of a terminal node by the probabilities of each step in the path to that node. We calculate a similar path expected utility in a value chain, but can do so for each node in the chain (see Table 2). This path expected utility for a node in a value chain represents the *expected utility of ending the chain at a given node*.

A related question is whether the utility of one node directly determines the value of the subsequent nodes. The answer is that earlier nodes in a chain do influence the utility of later ones, but not in an easily definable way. A value chain is typically an open world. Each node has a separate utility because different populations of patients and users, technologies and external factors all might contribute to each node's utility. So whilst each earlier stage does shape downstream utility, we do not know the specific mathematical function that describes how it contributes, and there is no easy way to infer one directly from the other. For this reason we re-measure utilities at every node.

Although value chain theory is essentially quantitative – it asks us to calculate the value of information at different steps – it is important to remember that in many cases we will be making qualitative comparisons between different stages in the chain. This means that in some cases where great precision in value calculation is difficult, approximating the value of information still allows meaningful qualitative comparisons to be made – usually where there is substantial difference in the VOI at different stages in the chain. As with any theory that relies on quantitative measurements, it is important to ensure that data used in any analysis actually measures what it is meant to. Standard epidemiological challenges such as dealing with confounding factors and noise, as well as temporal variations such as seasonality in disease and service patterns, all need to be addressed.

It is important to recognize that value chain theory does not attempt to provide detailed mechanistic explanations for the impact of information technology beyond the causality implied in the structure of the chain itself. From this perspective it provides a lens to focus on areas of concern or benefit, and other approaches to analysis that assist in untangling the reasons for a particular outcome are then needed.

Value chain theory can also help answer questions about the need for automation, and thus help decide which tasks should or should not be automated [19]. Recognizing that there will likely be different expected utility profiles for completing a task by machine or by human, we can calculate both profiles and plot the resulting curve to generate a summary profile (Figure 6). Undertaking this type of analytic exercise allows us to identify whether tasks are better automated, left to humans, or performed jointly [2]. Understanding the answer has fundamental implications for the strategy taken and its likelihood of success.

Whilst the generic value chain in Figure 1 is applicable to a broad class of information and communication systems, there appears to be no theoretical restriction to imagining different chains of events, or adapting this chain to meet the needs of a specific setting, technology or purpose. One alternate formulation by Parasuraman et al. uses a simplified four step information processing model to create a similar pipeline [20], in contrast to the model used here, which is instead based on human decision making.

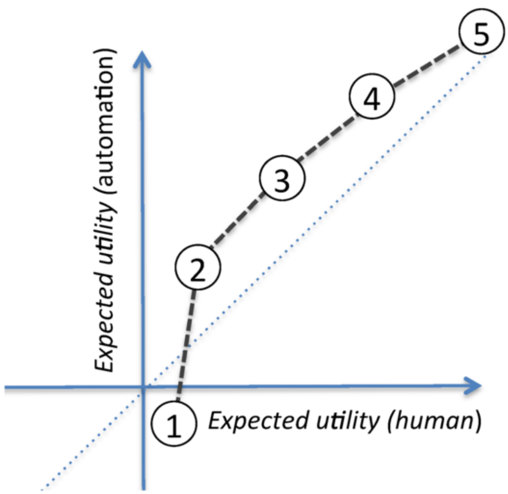

Figure 6: The expected utility (EU) of completing a given task by human or computer can be plotted over a task space. The information value chain (represented as 5 separate tasks) can be plotted into this human-computer task space. The resulting value profile is a function of the given task, the specific technology implementation, the human user, and the context of use. The shape of the plot will likely vary by changing any of these four variables (from Coiera, 2016).

Teaching questions for reflection

1. Describe the typical steps in an information value chain and explain how you would measure the effectiveness at each step for a conversational agent that assists patient's check their symptoms and decide whether to seek professional help.
2. What is the value of information for a new radiological test that has an accuracy of 95%, and which is 20% more accurate in identifying early stage cancer than the current standard test, knowing that undetected cancers will otherwise result in death? Patients report that on a scale of 1 to 10 for discomfort, the new test rates 6, whilst the old test rated 2.
3. Figure 3 shows possible value profiles for several different classes of health information system. Which bundle of two technologies is most likely to improve patient outcomes, using three example profiles?
4. Looking at the value profile for telemedicine, how reasonable is it to expect that widespread use of telemedicine will improve patient outcomes? Contrast the scenario where patients all have full and easy access to face to face consultations with the circumstance where patients are in remote settings.
5. What advice would you give to a hospital proposing to implement a new Audit and Feedback tool to improve the quality of their oncology service, referring to the experience in Case Study 2?

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