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# Addressing Emergency Department Overcrowding Through a Systems Approach Using Big Data Research

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## Abstract

The emergency department (ED) is the canary in the coalmine for the healthcare system. The issues that EDs are facing are having adverse effects, and their causes can be better understood by viewing the ED as part of the entire health and social system. Policy decisions can be supported by sharing data across various health service areas, ministries and census data. Big Data research can support the integration and correlation of variables in large volumes of diverse datasets. Furthermore, the science of Visual Analytics can provide interactive visualization of the data to support evidence-based healthcare policy.

**Keywords:** Emergency departments; Overcrowding; Healthcare systems; Big data; Visual analytics

## Introduction

The Emergency Department (ED) has been labeled the "canary in the coalmine" of the healthcare system [1,2], and the struggles of the ED continue to dominate headlines [3]. Faced by rising patient volumes and profound numbers of admitted patients waiting for transfer to an inpatient bed, overcrowding in the ED is having detrimental effects. Recent literature reports treatment delays for patients with serious illness [4,5], patient and staff dissatisfaction [6-8], rising "left without being seen" rates [9], inadequate management of severe pain [10], and increased patient mortality [11,12]. But if emergency departments are failing, this failure is largely due to system issues beyond the walls of the ED, including patients in hospital beds when care would be better provided elsewhere, shortfalls in the community primary care system, and failure in other parts of the system to provide psychosocial and socioeconomic supports. These root causes cannot be addressed by individuals, or at the departmental or hospital level. Rather, they require changes at the system level driven by changes in health policy, which requires analysis of data and information across multiple health delivery areas and ministries, and use of Canadian census data. We propose that decision support of evidence-based policy development can be provided through Big Data research that can be augmented by the science of Visual Analytics. By Big Data, we are referring to large datasets from a variety of sources that cannot be managed or process using standard software tools within a reasonable time [13]. By Visual Analytics, we are referring to "the science of analytical reasoning facilitated by interactive visual interfaces" [14].

## The Emergency Department as Part of the Health System

Looking at the ED as a component of the healthcare system is not new. The *Input-Throughput-Output* conceptual model has been widely accepted for ED congestion [15]. The *input* component from the model refers to the demand on emergency services, and it is influenced by timely access to primary and community services, and by prevalence of conditions such as acute illnesses, chronic illnesses, trauma, and mental illnesses. The proportion of people that are vulnerable based on socioeconomic factors also influences the *input* component. ED *throughput* refers to internal ED efficiencies and patient processing capacity. Factors that affect *throughput* include having efficient processes, physical space, and staff resource availability. The *output* component reflects the movement of patients out of the ED and is influenced by many factors including the availability of inpatient beds and indirectly of long-term care, and access to community services such as home care.

The *Input-Throughput-Output model* can be expanded to conceptualize the ED within the entire health and social system through the use of *system dynamic modeling*. Figure 1 illustrates the ED within the health care system by considering the complexities of services and types of illnesses based on dynamic modeling [16]. The health system involves the flow of patients between service delivery areas. Within the health system, only walk-in clinics and EDs offer services without prior scheduled appointment or referral and after regular business hours; therefore EDs have become a central hub for patient access. Self-care through use of Internet searches and government-funded initiatives can reduce the demand for ED care. The demand for any health services comes from a variety of reasons: chronic illness, trauma/injury, mental illness, and acute illness. Prevention initiatives, psychosocial risks, and population and age mix affect the prevalence of these illnesses, which drives the need for care.

Changes occurring in society and throughout the health care system often manifest in the ED, and policy decisions made in one part of the

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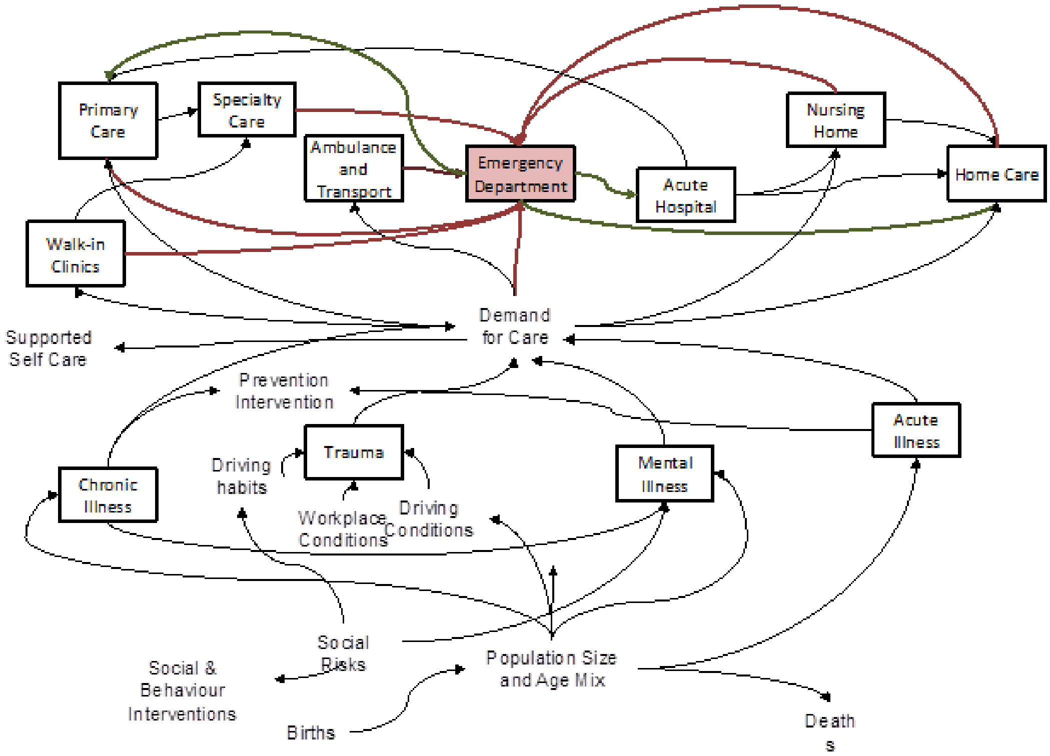


**Figure 1:** Model of health care delivery system.

system can ripple across geographic and ministerial boundaries. Long-time intervals between cause and effect result in failure to appreciate the full consequences of policy decisions. System interactions and complexities make it difficult to learn from evidence, data and other information that is available. Furthermore, human behaviour change is often required for an intervention to work.

A systems approach that crosses ministerial boundaries can assist the development of high-level public policies that will provide solutions to problems where the causes of ED overcrowding are elsewhere in the system. For example, policies of the Ministry of Social Developmentcan affect ED demand, and studies have shown that the need for ED service increases as impoverished population grows [17]. One study shows evidence of a significant increase in mortality and morbidity immediately following “Welfare Wednesday” when social assistance is administered [18]. Furthermore, the policies of the Ministry of Transportation and Infrastructure can also have an effect on the safety of highways, which change the demand for ambulance and ED services. The Ministry of Justice affects how ED staff needs to handle assaults, sexual assaults and suspected abuse, which then can interface with the Ministry of Children and Family Development. The Ministry of Education and the Ministry for Advanced Education can influence the number of graduates and training programs required for resourcing EDs and other areas of the health system.

As shown above, the sharing of data between health service delivery areas, ministries and census data have the potential to provide policy-makers with an understanding of the entire system in order to make evidence-based policies. However, there are several barriers to simply linking these data sources to support evidence-based policy development. Existing data linking, analysis and visualization tools are not sufficient to manage the volume and complexity of the data, and to make sense of it in a meaningful manner. We propose a research agenda that is based on Big Data [13], and we look beyond the hype to explicitly understand how it can support evidence-based policies, Big Data Research Agenda.

The integration of all the data sources within the health system, across multiple ministries, and census offers profound intelligence into the healthcare system and the effects on the ED; however, accessing and interpreting the information is not trivial. The datasets are large and disparate, and easily falls into the emerging domain of Big Data [13]. Not surprising, the Obama administration recently announced commitment to research and development in Big Data. However, before we jump on the bandwagon of Big Data, we need to better understand this term, how (or if) it can assist us in making evidence-based policies for healthcare, and the implications.

The use of the term Big Data is growing as corporations and governments heavily invest into it. The volumes of data ballooning exponentially drive this investment. Increasing data storage capacity, processing capability and diversity in the data types is driving much of this new discipline. However, there has been debate about whether Big Data is truly a new discipline or whether its research and work can be covered by existing disciplines such as computer science and statistics. However, Big Data has been found to be taking us to new places that were unimaginable in the past through the ability to test millions of hypotheses using methods to control for false-discoveries and other calculations that are made possible by massively-parallel algorithms. Big Data is indeed an exciting and “emerging major interdisciplinary triumph” [13]. Health care has been said to be behind the private sector in the leveraging the data that is available [19]; however, the opportunities for improving health services and reducing costs are significant through the use of the multiplicity of data. By putting a Big Data lens on the multiple data sources that can inform healthcare policy, we can look at ways to manage the variability in the data sources; automate ways to discover and handle invalid data; and find correlations across data sources, geographic boundaries and time, and control for privacy and security. Furthermore, we are beginning to us of Big Data in healthcare to support personalized healthcare [20] and medical research [21].

How can Big Dataoffer support for evidence-based policies in healthcare? One of the most important discoveries about data is that as more data becomes available to computer algorithms, predictions can be made with greater precision [22]. Research into the field of machine learning for natural language has found that statistical machine translation and statistical speech recognition have become much more accurate as more and more data have become available. This data has become available through the operation of human translation services such as the European Union for machine translation and human transcription services such as closed-caption broadcasts for speech recognition, which have formed large training datasets, and allowed for much greater accuracy in computerized translation and speech recognition [22]. From this experience, we can take health system modeling to the next level. By feeding existing datasets into new statistical models and analysis, more accurate simulations and predictions can be made about how specific policy decision can affect outcomes in health service quality, efficiency and cost.

We want to further the call of Big Data research by adding the benefits of Visual Analytics, which is the "science of analytical reasoning facilitated by interactive visual interfaces" [14]. Visual Analytics couples with Big Data by allowing development of interactive computer generated visualizations of the data from multiple sources, which is designed in a manner that accounts for the policy-makers' cognitive abilities and organizational contexts. It also allows for collaboration with others in the exploration of the data. Simply, Visual Analytics is the integrated approach of combining visualization, human factors, and data analysis [23].

The science of Visual Analyticsincludes: 1) analytical reasoning techniques to support policy-makers in the assessment of evidence and ability to reach a decision; 2) visual representation and interaction techniques that exploit the human eye's broad bandwidth pathway into the mind to allow analysts to explore and understand large amounts of data; 3) data representation and transformation to convert all types of conflicting and dynamic data in ways that support visualization and analysis; and 4) methods to be able to *produce* (and re-produce) information summaries, *present* the produced information in meaningful and reusable formats, and *disseminate* the presented information to others in a manner that encourages engagement in the information [14]. An example of Visual Analytics research is to conduct user studies with representative users in their work environment using prototypes of software that represent interactive visualization of multiple data sources; furthermore, various modalities such as large touch screen monitors or table top displays can also be evaluated.

Visual Analytics can be used to better understand the effects on the ED of various aspects of the healthcare system, social programs, and public infrastructure. Historical data from multiple sources can be pulled into an interactive interface, which flags data that is potentially invalid explicit to allow the analyst to decide whether to disregard or to include this data. The effects on ED use by exploring patient volumes and wait times for an inpatient bed can be predicted based on changes in various healthcare policies such as increased investment in specific social programs, harm reduction programs for drug users, and investment in education programs to increase family physicians in both urban and/or rural communities. These calculated correlations could be displayed showing the potential time delays and geographic variation of the effects on the ED for any policy decision. The user interactions on the display can include changing the amount of investment made to any of the above areas to better understand how much investment is required before effects are seen in the ED.

## Conclusions

The systems surrounding the ED–health, social, economic, and justice-drive the causes of ED overcrowding and congestion. These effects can be better understood by drawing information from various data. By using the methods from the emerging interdisciplinary field of Big Data, calculations can be made to find correlations in the data across various data types, and invalid data can be teased out. By further employing the science of Visual Analytics, healthcare policy-makers can explore the calculated data to make sense of the correlations through interactive information visualizations that has taken cognition and context of the policy-maker into account. These emerging research domains can provide for the creation of reusable interactive visualization and data exploration tools to facilitate evidence-based healthcare policy development.

### References

1. Ross J (2010) The Patient Journey Through Emergency Care in Nova Scotia: A Prescription for New Medicine. Government of Nova Scotia.
2. Mulligan C (2012) Canary in Coal Mine. Sudbury Star.
3. Weichel A (2013) BC Doctors Expose Emergency Room Horror Stories. CTV News.
4. McCarthy ML, Zeger SL, Ding R, Levin SR, Desmond JS, et al. (2009) Crowding delays treatment and lengthens emergency department length of stay, even among high-acuity patients. Ann Emerg Med 54: 492-503.
5. Schull MJ, Vermeulen M, Slaughter G, Morrison L, Daly P (2004) Emergency department crowding and thrombolysis delays in acute myocardial infarction. Ann Emerg Med 44: 577-585.
6. Rowe BH, Bond K, Ospina MB, Blitz S, Schull M, et al. (2006) Emergency department overcrowding in Canada: what are the issues and what can be done? Technology overview 21, Ottawa: Canadian Agency for Drugs and Technologies in Health.
7. Pines JM, Iyer S, Disbot M, Hollander J, Shofer F, et al. (2008) The effect of emergency department crowding on patient satisfaction for admitted patients. Acad Emerg Med 15: 825-831.
8. Abu-Laban R (2006) The Junkyard Dogs Find Their Teeth: Addressing the Crisis of Admitted Patients in Canadian Emergency Departments. Can J Emerg Med 8: 388-391.
9. Bullard MJ, Villa-Roel C, Bond K, Vester M, Holroyd BR,et al. (2009) Tracking Emergency Department Overcrowding in a Tertiary Care Academic Institution. Healthcare Quarterly 12: 99-106.
10. Pines JM, Hollander JE (2008) Emergency department crowding is associated with poor care for patients with severe pain. Ann Emerg Med 51: 1-5.
11. Sprivulis PC, DaSilva JA, Jacobs IG, Frazer ARL, Jelinek GA (2006)The association between hospital overcrowding and mortality among patients admitted via Western Australian emergency departments. Med J Aust 184: 208-212.
12. Guttmann A, Schull MJ, Vermeulen MJ, Stukel TA (2011) Association between waiting times and short-term mortality and hospital admission after departure from emergency department: population based cohort study from Ontario, Canada. BMJ 342: d2983.
13. Diebold FX (2012) A Personal Perspective on the Origin(s) and Development of 'Big Data': The Phenomenon, the Term, and the Discipline, Second Version. PIER Working Paper 13-003.
14. Thomas JJ, Cook KA (2006) A Visual Analytics Agenda. IEEE Computer Graphics and Applications 10-13.

15. Asplin BR, Magid DJ, Rhodes KV, Solberg LI, Lurie N, et al. (2003) A conceptual model of emergency department crowding. Ann Emerg Med 43: 173-180.

16. Homer JB, Hirch GB (2006) System dynamic modeling for public health: background and opportunities. Am J Public Health 96: 452-458.

17. Gallagher EJ, Lynn SG (1990) The Etiology of Medical Gridlock: Causes of Emergency Department Overcrowding in New York City. J Emerg Med 8: 785-790.

18. Verheul G, Singer SM, Christenson JM (1997) Mortality and morbidity associated with the distribution of monthly welfare payments. Acad Emerg Med 4: 118-123.

19. Safran C, Bloomrosen M, Hammond WE, Labkoff S, Markel-Fox S, et al. (2007) Toward a national framework for the secondary use of health data: an American Medical Informatics Association White Paper. JAMIA 14: 1-9.

20. Chawla NV, Davis DA (2013) Bringing big data to personalized healthcare: A patient-centered framework. J Gen Intern Med 28: 660-665.

21. Larson EB (2013) Building trust in the power of 'big data' research to serve the public good. JAMA 309: 2443-2444.

22. Halevy A, Norvig P, Periera F (2009) The Unreasonable Effectiveness of Data. IEEE Intelligent Systems 8-12.

23. Keim DA, Mansmann F, Schneidewind J, Zieler H (2006) Challenges in Visual Data Analysis. 10th International Conference on Information Visualization 9-16.