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Access and Use: Improving Digital Multimedia Consumer Health Information

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Abstract. This project enabled novel organisational insight into the comparative utility of a portfolio of consumer health information content, by measuring patterns of attrition (abandonment) in content use. The project used as a case study the event activity log of a fully automated digital information kiosk, located in a community health facility. Direct measurements of the duration of content use were derived from the user interface activity recorded in the kiosk log, thus avoiding issues in using other approaches to collecting this type of data, such as sampling and observer bias. The distribution patterns of 1,383 durations of observed abandonments of use for twenty-eight discrete modules of health information content were visualised using Kaplan-Meir survival plots. Clear patterns of abandonment of content use were exhibited. The method of analysis is cost-effective, scalable and provides deep insight into the utility of health promotion content. The impact on the content producers, platform operators and service users is to improve organisational learning and thus increase the confidence in stakeholders that the service is continuously delivering high quality health and wellbeing benefits.

Keywords. Public health, quality, improvement, event stream, survival analysis, attrition, kiosk

Introduction

Measurement of the actual use of consumer health information (CHI) content is important because it forms the basis of evidence for systematic improvement, and systematic improvement is an attribute of high quality health service providers.

Where CHI service providers operate a digital content delivery platform, the routine data collected from instrumentation of the system's presentation layer can be used to compute quantitative usage data. This quantitative usage data is amenable to statistical methods that enable an exploration of observed use, and provides new information and knowledge to CHI content producers. This knowledge is employable in ways that can create positive feedback loops of learning, driving improvements with high organisational impact.

Direct measures of CHI use are explored in this paper. The paper uses as a specific case study a dataset supplied by an Australian social enterprise that operates a nationwide network of public health and wellbeing information kiosks.

1. Background

CHI services can positively affect behavior [1, 2], and are central to efforts to promote health. That said they also often fail [3], with dropout rates of internet e-health trials of 65-99.5% across a selection of studies [8].

CHI services designed for mainstream consumers are often not culturally appropriate or adjusted to accommodate low literacy levels, and may even have negative outcomes in complex areas of human behavior [4]. Physical communications media such as pamphlets often cannot be read due to low literacy levels, and in remote areas can be difficult to distribute and update [5].

CHI services can be evaluated for impact using two distinct measures - access and use [6]. Previous studies on digitally-delivered health information for health promotion have tended to focus on measures of access rather than use [7], yet measurement of the actual use of consumer health information content is important because it forms the basis of evidence for systematic improvement of health promotion efforts.

There are a number of frameworks that can be used to improve quality. Improvement is most effective when feedback is used to identify the focus of effort and determine whether changes actually lead to improvement. The Model for Improvement employs a PDSA (Plan, Do, Study, Act) cycle of activities for a trial-and-learning approach to learning and improvement. When a cyclical improvement model is employed organisational performance in health systems is more likely to occur compared to alternatives such as "trial-and-error" or exhaustive problem studies [8-10]. These ideas are also known as lean thinking [11], which is a favored approach in startup enterprises [12-14] and recommended for e-health technologies [3, 15] and health communication programs [16].

The usage of CHI content is considered to be a function of its quality, with high quality content actively engaged with for longer periods compared to lower quality content that gets relatively quickly abandoned. The type of CHI content is also an influence, with multimedia such as YouTube health videos gaining in appeal [17] as distinct from static content such as PDF information sheets. These contributory elements of "stickiness" are identified as a critical success factor in public e-health innovations [18].

Mining log files for user access pattern discovery from internet devices [19] is an established data science practice [20]. The duration time of an observed use of multimedia content that is deliberately, purposefully and meaningfully started, and then later actively abandoned, is a form of event-time or time-to data that can be mined from internet device log files. The duration of use can be considered a measure of 'surviving' abandonment by the user, or conversely a 'failure' to engage the user, for which there are at least fourteen affective factors [21].

Survival analysis can be used for exploring event-time or duration data and driving improvement using planned experimentation. Survival analysis has been used to examine the phenomenon of people dropping out of e-health application trials [21]. In survival analysis the probability distribution of duration times are step plotted, from which various measures of "half-life" could be used as a metric for their efficacy.

Interpreting the meaning behind the shape of the survival plots is the challenge. An almost perfectly used bit of content would be one in which there is virtually no user abandonment during its use. In this case the survival plot would exhibit a uniform distribution, as illustrated by the plot labeled D in Figure 1.

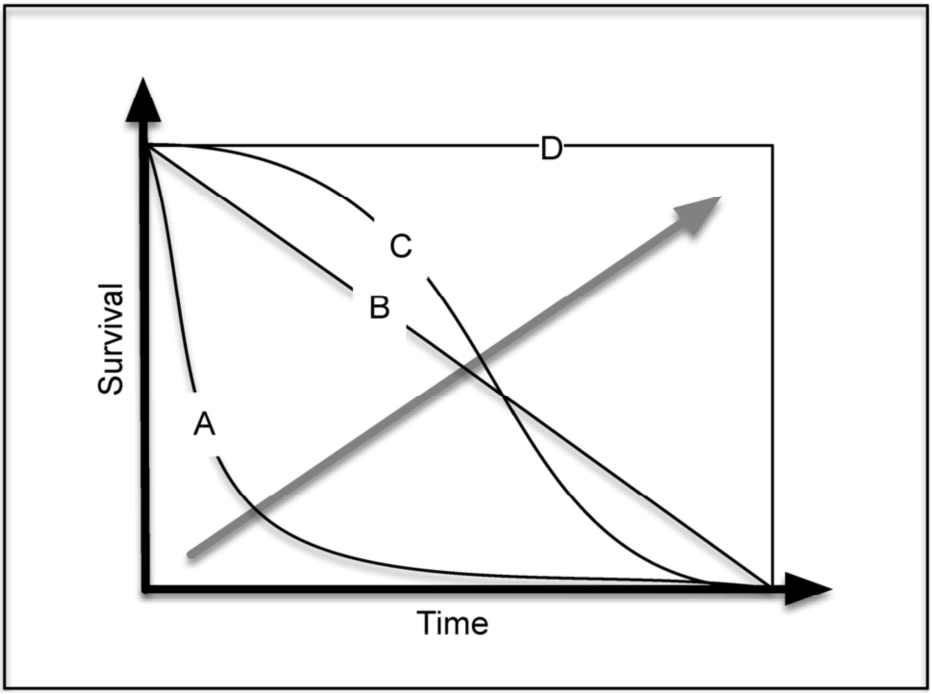

Figure 1. Illustrative survival plots for three patterns of content use. The shape of a plot can vary along the grey vector, with (A) an L-shaped plot indicating low curiosity and poor survival, (B) a straight line plot indicating constant attrition, (C) a sigmoidal S-shaped plot indicating a curiosity plateau and a cohort of hardy users through to (D) a uniform plot indicating near perfect survival.

Eysenbach [21] proposes some interpretations of the curves, including a logarithmic curve indicating a steady rate of attrition, a sigmoidal curve that suggests a 3-phase usage model where an early curiosity plateau gives way to high attrition until a set of hardy users remain and an L-shaped curve reflecting rapid dropout with only hardy users remaining and - crucially - no curiosity plateau.

Sharp variations from smooth and regularly shaped probability distribution curves are suggestive of some ‘special cause’ of variation. Reading the X axes of the plot from where the variation occurs can pinpoint the time within the content’s presentation that the special cause of variation occurs, but the analysis gives no indication of what the cause is.

2. Methods

A case study research methodology was adopted, within which a data science method [20] was used, to generate knowledge about content quality based on patterns of observed use. These patterns were derived from analysis of the event clickstream of a digital content delivery platform hosting multimedia content. The content was presented to users in the form of twenty-eight discrete multimedia modules, which could be randomly selected from a menu screen.

The digital content delivery platform consisted of multiple kiosks, with only one used in this case study. The kiosk was located in a remotely located community center.

The kiosk log file was provided by the data owning organisation, with Human Research Ethics approval, and mined for transaction sequences to produce a dataset of observed durations of content use and active abandonment of content. All user activity on the kiosk for an entire year was analysed, without any sampling, randomised allocation or blinding. Individual users were not identifiable in the log file data.

Active abandonment of a content module by a kiosk user is where a user deliberately closed a content module before it played to completion, and was the phenomena of prime interest in this analysis.

The analysis consisted of two steps. Firstly the normalisation of duration of use times against the maximum observed duration of use time for each module, then combining the frequency probability plots of normalised duration of use times for all modules. Where content modules played to completion they were excluded because without external observation it would not be possible to know whether the user deliberately stopped the content (active abandonment), or rather that they had walked away and the content continued to play in their absence (passive abandonment).

3. Results

There were 1,568 accesses of the twenty eight modules, of which eighty-three percent (n=1,297) were actively abandoned. Only one module achieved notably more than 50% of its potential use. The normalised frequency distributions of the active abandonments are plotted in Figure 2.

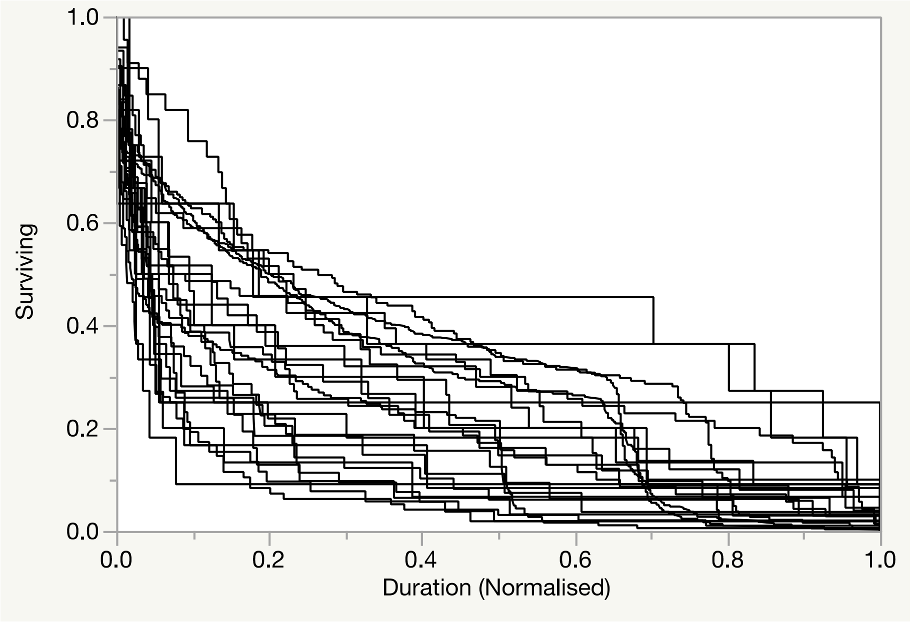

Figure 2. Attrition in observed use shows a variety of survival distributions. Each module's survival distribution has been normalised by the maximum observed duration of abandoned use.

Plot curves include sigmoidal shaped curves, diagonally shaped curves, and L-shaped ones with very high rates of attrition early in the content use. The distribution curves displayed sharp drop-offs at specific durations, suggestive of a special cause for the abandonment.

4. Discussion

The analytics approach proved successful in being able to quantitatively measure and identify patterns of abandonment of use. The use of normalisation of multiple survival plots enabled comparison across a portfolio of content.

The study method is generalisable to other CHI digital delivery platforms for multimedia content. For health service providers delivering CHI, using the methods employed in this project to deliver continuous improvement could help address industry standards. For CHI content producers this method could inform editing of content and enable experimentation with multiple content versions. This methodology applies specifically to digital multimedia CHI content as distinct from static content such as printed information sheets.

5. Conclusions

This study should be of interest to CHI platform service providers, health promotion program/project managers and CHI content producers. It illustrates a novel use of transforming routinely or simply collected system use data typically generated through event logging mechanisms into knowledge and insight, from which organisational learning and improvement can occur.

This method would be relatively straightforward to operationalise and scale for digital multimedia content delivery platforms with a growing diversity and abundance of widely distributed devices.

A key learning from this study is that service providers should ensure that active abandonment events are logged and use a data driven process for content improvement through observed use. Doing so is foundational for improving practice amongst both CHI platform service providers and digital content producers.

6. Disclaimer and Acknowledgements

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References

[1] Finkelstein, J., et al., Enabling patient-centered care through health information technology, in Evidence Report/Technology Assessment No. 206. 2012, Agency for Healthcare Research and Quality: Rockville, MD.
[2] Gibbons, M.C., et al., Impact of consumer health informatics applications, in Evidence Report/Technology Assessment No 188. 2009, Agency for Healthcare Research and Quality: Rockville, MD.
[3] van Gemert-Pijnen, J.E., et al., A holistic framework to improve the uptake and impact of eHealth technologies. J Med Internet Res, 2011. **13**(4): p. e111.
[4] Cho, H. and C.T. Salmon, Unintended effects of health communication campaigns. Journal of Communication, 2007. **57**: p. 293-317.
[5] Alper, J., Health literacy and consumer-facing technology: Workshop summary. 2015, The National Academies Press: Washington, DC.
[6] State of Victoria, Measuring health promotion impacts: A guide to impact evaluation in integrated health promotion. 2003, Department of Human Services: Melbourne.
[7] Nicholas, D., P. Huntington, and J. Homewood, Assessing used content across five digital health information services using transaction log files. Journal of Information Science, 2003. **29**(6): p. 499-515.
[8] Blumenthal, D. and J.M. McGinnis, Measuring Vital Signs: an IOM report on core metrics for health and health care progress. JAMA, 2015. **313**(19): p. 1901-2.
[9] Institute of Medicine (U.S.). Committee on Quality of Health Care in America., Crossing the quality chasm : a new health system for the 21st century. 2001, Washington, D.C.: National Academy Press. xx, 337 p.
[10] Rubin, J.C. and C.P. Friedman, Weaving together a healthcare improvement tapestry. Learning health system brings together health data stakeholders to share knowledge and improve health. J AHIMA, 2014. **85**(5): p. 38-43.
[11] Ries, E., The lean startup : how today's entrepreneurs use continuous innovation to create radically successful businesses. 1st ed. 2011, New York: Crown Business. 320 p.
[12] Blank, S.G. and B. Dorf, The startup owner's manual. Vol. 1 : the step-by-step guide for building a great company. 2012, Pescadero, Calif.: K&S Ranch, Inc. xxix, 571 p.
[13] Osterwalder, A., et al., Value Proposition Design. 2014: Wiley. 290.
[14] Osterwalder, A., Y. Pigneur, and T. Clark, Business model generation : a handbook for visionaries, game changers, and challengers. 2010, Hoboken, New Jersey: John Wiley & Sons. [281] p.
[15] van Limburg, M., et al., Why business modeling is crucial in the development of eHealth technologies. J Med Internet Res, 2011. **13**(4): p. e124.
[16] Neuhauser, L. and G.L. Kreps, Integrating design science theory and methods to improve the development and evaluation of health communication programs. J Health Commun, 2014. **19**(12): p. 1460-71.
[17] Madathil, K.C., et al., Healthcare information on YouTube: A systematic review. Health Informatics J, 2015. **21**(3): p. 173-94.
[18] Lorenzi, N.M. and K.M. Unertl, Effective strategies for implementation and evaluation of public ehealth innovations. Studies in health technology and informatics, 2011. **172**: p. 45-53.
[19] Cooley, R., B. Mobasher, and J. Srivastava, Web mining: information and pattern discovery on the World Wide Web, in Tools with Artificial Intelligence. 1997, IEEE: Newport Beach, CA. p. 558-567.
[20] Donoho, D. 50 years of data science. 2015 10-Feb-2016]; Available from: http://courses.csail.mit.edu/18.337/2015/docs/50YearsDataScience.pdf.
[21] Eysenbach, G., The law of attrition. J Med Internet Res, 2005. **7**(1): p. e11.