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Aug 10th, 12:00 AM

Structural and Temporal Topic Models of Feedbacks on Service Quality – A Path to Theory Development?

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Completed Research

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Abstract

There is growing interest in applying computational methods in analysing large amount of data without sacrificing rigour in Information Systems research. In this paper, we demonstrate how the use of structural and temporal topic modelling can be employed to produce insights of both theoretical and practical importance from the analysis of textual comments on the quality of services in hospitals. As a first step, we revealed the thematic structures in the comments as topics which were aligned with the SERVQUAL dimensions. Following this, we established the temporal precedence among SERVQUAL factors based on the evolution of the topics over time. Theoretically, our findings are consistent with the emerging consensus on the nature of SERVQUAL dimensions from extant quantitative research and offer new propositions on the relationships among these dimensions. From the practice perspective, we produced quantified measures of factors associated with healthcare service experience.

Keywords

Structural topic model, SERVQUAL, theory building, health service quality

Introduction

One of the main levers for improving the quality of services is an understanding of the customers' expectations and perception of service quality. Perceived service quality according to Parasuraman et al. (1988) is "*consumer's judgment about the entity's overall excellence or superiority*". It is also a "*form of attitude, related but not equivalent to satisfaction, and results from a comparison of expectation with perceptions of performance*" (Parasuraman et al. 1988). Hospital service quality could be defined as the "*discrepancy between patient's or patient's attendants' perceptions of services offered by a particular hospital and their expectations about hospitals offering such services*"(Aagja and Garg 2010). Significant research has been devoted to the study of healthcare service quality (HSQ) largely addressing (i) services quality dimensions (Parasuraman et al. 1988) and (ii) main factors affecting services quality level (Otalora et al. 2018). Most of these research are quantitative and based on data collected through questionnaires. Online reviews are complementary and proven high-quality sources of data for analysing service quality. As a resource in the healthcare domain, online reviews allow patients to share their care experience and access the opinions of other patients with minimal restrictions on the contents and length of comments. It also provide healthcare providers with relevant information on the perceived quality of their services and suggestions for improvement. However, such online sources of free-text data (or big data) are rarely exploited for novel insights. One reason for this is that traditional data analysis approaches are not suitable for processing large amount of unstructured data. Recently, disciplines including Information Systems have started exploiting computational techniques like topic modelling to process vast amounts of textual data (Müller et al. 2016). Topic modelling is an effective instrument for extracting knowledge from unstructured textual data (Blei et al. 2010; Roberts et al. 2014). While the use of computational techniques such as topic modelling does not automatically yield insights nor automatically contribute to theory (Müller et al. 2016), systematic application of computational techniques like topic modelling can yield rigourous analysis and enable inductive theory generation (Berente and Seidel 2014). Structural topic modelling is particularly very promising for building substantive theory as it enables relating known covariates or metadata of documents with the latent topics uncovered from the content (Schmiedel et al. 2019). In this paper, our goal is to demonstrate how structural topic modelling could be employed to determine: (*1) latent topics contained in free-text comments about the perceived quality of healthcare and the service quality dimensions associated with positive and negative experience (2) theoretical relationship among the SERVQUAL constructs based on the temporal evolution of the identified topics.*

Theoretical Framework

The most popular model for evaluating service quality and gap is the SERVQUAL model (Parasuraman et al. 1988; Zeithaml et al. 1990). The model is used for evaluating both the service user's expectations and perceptions of the provider's performance. The model comprises five dimensions namely Tangibles, Reliability, Responsiveness, Assurance and Empathy. Several studies have employed the SERVQUAL model for measuring the quality of healthcare services (Valencia-Arias et al. 2018). Also, the authors of (Butt and Run 2010) confirmed the validity of using SERVQUAL scale for measuring the quality of the Malaysian private healthcare services. Also, the five SERVQUAL dimensions were found to be a consistent and reliable scale for measuring the quality of healthcare services in the United Arab Emirates context (Al-Neyadi et al. 2018). Furthermore, SERVQUAL was successfully employed for evaluating the impact of healthcare service quality on overall patient satisfaction (Al-Damen 2017). Moreover, the authors of (Lee et al. 2018) described a topic modelling algorithm for assigning tweets to SERVQUAL dimensions to track perceived service quality for policymakers. At the same time, there are studies casting doubt on the adequacy of the five SERVQUAL dimensions and offering additional factors to extend the model. These categories of studies employ different types of statistical analyses including correlation, regression, exploratory factor analysis, principal component analysis on survey results to identify the most significant factors affecting healthcare service quality (Abuosi and Atinga 2013; Turan and Bozaykut-Bük 2016).

While healthcare service quality evaluation may appear to be well studied, there are knowledge gaps to be filled including: (1) the predominant data source in extant healthcare service research are questionnaires underpinned by known constructs making the discovering of new or emergent knowledge less probable; (2) the few studies that have employed computational or analytic models for generating latent topics from free-text comments do not consider the context (e.g. the metadata) associated with the content; and (3) consequently, none of the existing studies employing analytic techniques such as topic modelling have attempted to produce insights that could advance theoretical knowledge of the SERVQUAL factors. This paper contributes to bridging these gaps by showing how structural topic modelling helps in answering the following research questions (R): (*R1) what are the latent topics in the feedback texts and how they are associated with service experience? (R2) how do the SERVQUAL constructs relate based on the temporal evolution of the identified topics?*

Methodology

The methodology adopted comprises three major stages: 1) Topic generation – generation of the latent topics in the free-text using the Latent Dirichlet allocation (LDA) algorithm and the Structural Topic Model (STM) implementation, 2) Lifting latent topics – mapping of the generated topics to the five SERVQUAL constructs, 3) Time covariate analysis – analysis of how the generated topics vary with time the associated comments were made and 4) Temporal precedence relations – establishing the span and evolution of topics and the related SERVQUAL factors over time. In the first step, Structural Topic Model variant of the LDA (Roberts et al. 2014) was adopted. LDA is an unsupervised learning-based text analysis method that provides both a predictive and latent topic representation of a corpus (Blei et al. 2010). This modeling technique is widely adopted in recent healthcare service quality studies and used for exploring the topics in free-text comments on online platforms (Bahja 2018). STM which is a generalization of LDA and correlated topic models, offers the opportunities for predicting the topics distribution and in addition: i) estimating the impacts of metadata on topic prevalence and (ii) revealing trends in topic proportions over time and (iii) estimating the relationships between covariates and topic prevalence or word-use within a topic. STM has been used for textual analysis in the domains of political science, aviation, and hospitality (Kuhn 2018).

Data Collection and Preparation

The source of our data is the free-text comments provided on the hospital review platform "*ratemyhospital.ie*"[1]. We extracted comments made from October 1, 2010, to November 1, 2019, using a Python library. As a result, 5,220 English-language comments on 70 hospitals were collected. Each comment in our dataset contains (1) Comment ratings and (2) Comment date as its metadata. As part of the pre-processing step, we calculated the sentiments of each comment. Sentiments of comments were estimated through an ensemble of techniques: (1) converting the rating values assigned to comments by their authors to categorical values – "positive" for comments with a rating greater than 4 points and "negative" otherwise; (2) using the VADER Sentiment Analysis library in Python[2]; (3) using the Bing Tidy Sentiment Analysis library in R[3]; (4) two independent expert assessments of the sentiment. The degree of discrepancy between the results of sentiment analysis (methods 2, 3) and the proposed patient rating interpretation (method 1) was around 5.2%. The summary of the dataset after pre-processing showing the distribution of comments (CN) across years; the average length of comment in words (ACL) and the total number of positive and negative comments are given in Table 1.

	Year										Sentiment	
	2019	2018	2017	2016	2015	2014	2013	2012	2011	2010	Pos	Neg
CN	272	337	361	509	619	622	811	724	810	155	2055	3165
ACL	434	386	435	386	435	444	403	363	386	383	263	499

Table 1. Sample Summary

The last stage of the data *preparation* consists of (i) text preprocessing (including word normalization, stemming, removal of stop words, punctuations, and numbers) and (ii) converting data set into STM text *Corpus* format *(C),* composed of three elements namely *the document term matrix, vocabulary character vector* and the *metadata matrix* containing document covariates.

Structural Topic Model Setup

Based on the research questions, we employed STM for determining (1) the latent topics in the feedback comments about hospital services and their proportions, (2) the effect of time prevalence of the identified topics and (3) possible relationship among the topics based on their temporal precedence. STM implements these tasks by building a generalized linear model of influence of document-level covariates on the topical prevalence parameter μ, which in turn determines the θ document-topic proportions (DTP). To determine the optimal number of topics, 15-, 20-, 25- and 30-topics models were built as part of a model selection procedure. The 30-topic model (*N=30*) was selected based on semantic coherence and exclusivity outcomes. Thus, the following *STM models* were built: (1) at the stage of main topics identification, STM_1 model was built with *Source*: *C (i.e. Corpus)*; N (number of topics); *Outcome*: topic-words distribution β; document-topic proportions θ; list of highest probability-, FREX-, lift- and score-keywords; (2) to evaluate the effect of comment's sentiment on the topical prevalence, STM_2 model was built with *Source*: *C*; N; *Outcome*: sentiment-influenced topic-words distribution β^{sent} and DTP θ^{sent}; *Covariate*: Sentiment; lastly (3) we evaluated the effect of time (2010-2019) on the topical prevalence (μ) distribution by building STM_3 model with *Source*: *C*; N; *Outcome*: time-influenced topic-words distribution β^{time} and DTP θ^{time}; *Covariate*: Year.

Topic Labeling

The process of topics labeling was implemented in several stages: (1) two *experts* independently labelled the topics to produce the first version of labels; (2) *experts discussed the labels* and resolved discrepancies in labelling; (3) the experts independently refined topic labels based on the analyses of 10 of the most representative (or exemplar) comments of the topics; (4) experts discussed to align and consolidate the refinements done in step 3 by jointly reading and analyzing most representative comments; and

[1] http://www.ratemyhospital.ie

[2] https://github.com/cjhutto/vaderSentiment

[3] https://www.tidytextmining.com/index.html

(5) experts agreed on final topic labels and jointly developed the topic descriptions.

Lifting Latent Topics to SERVQUAL Dimensions

For a richer interpretation of latent topics, we mapped the identified topics to the five SERVQUAL dimensions through the following steps: (i) *review the definitions and various scales associated with* each of the five SERVQUAL dimensions in extant literature related to healthcare services, (ii) two experts first *independently mapped each of the topics to exactly one SERVQUAL dimension and subsequently met to integrate and agree on the mappings*; (iii) *checking* the internal consistency of the SERVQUAL dimensions with respect to their composite topics using the *Cronbach's alpha* coefficient (α) using the topic-words distribution β. Considering the bottom-up and inductive nature of our analysis, we considered a value α=0.5 as acceptable; lastly, (iv) *experts iteratively reviewed and refined the mappings for dimensions* α<0.5 by reclassification and exclusion; (v) the refinement process was halted when no further improvement was obtained concerning Cronbach's alpha value of the dimensions. Topics that did not fit into any of the existing SERVQUAL dimensions were assigned into a new group.

Analysing Topic Importance and Sentiments in Service Experience

To determine the relative importance of identified topics and how they relate to service experience we proceed in two stages using the results obtained through the STM_1 and STM_2 models. At the *first* stage, STM_1 model yields the following information: (1) topic labels; (2) topic's description; (3) a set of keywords most associated with topics; (4) the total topics proportion (TP), calculated as a sum of DTP (θ) of each topic in all documents; (5) examples of the comments most associated with the topic. *The total topic proportion provides a measure of the importance of the topics for service users.* In the *second* stage, we assess the prevailing sentiment for each topic from the results of the STM_2 model. The *average expected "Sentiment Topic Proportion"* ETP^{sent} indicator reveals the overall valence of the topic. To interpret ETP^{sent}, *we assume that if the average proportion of a topic within negative comments is significantly larger than within positive comments, such a topic can be identified as a negative topic.* Otherwise, the topic is considered positive. The values of this indicator vary in the range from -1 to 1. A negative values indicating that the *corresponding topic is associated relatively with negative experience* while a positive value of the indicator implies that the *topic is associated with a positive experience*.

Analysing Topic Evolution and Temporal Precedence Relations

To determine the evolution of the topic over time consequently the temporal precedence relationship among topics we proceed as follows using model STM_3: (1) First we determine the theme spans TS_s^t for each topic, $s(2010{,}2019)$. *By "theme span" we understand the periods (years) for which a topic is most associated*. To measure the strength of topics associated with a particular year we compute the average expected *"Topic Proportion Over Time"* ETP^t produced in our STM_3 model. As a threshold to demarcate the theme spans for each topic we propose to use ξ_t as the minimum of all maximum ETP^t values for each topic. (2) Second, we identify the "*Evolutionary Transitions*" between theme spans TS_s^t . *There is an evolutionary transition between these two topics if: (a) the span of topic 1 (the years with which this topic is most associated) precedes the span of topic 2 (i.e.* $TS_{2s}^t > TS_{1s}^t$*), and (b) the similarity between topics 1 and 2 is above a threshold value* ξ_s. To measure the similarity between time-influenced topic-words distribution β^{time} of two topics, we used the Kullback-Leibler divergence (KLD) function – an approach for computing the asymmetric divergence between two probability distributions. The choice of this indicator is due to its asymmetry property, which allows determining the strength of topics similarity *considering the direction of their evolution* (Mølgaard et al. 2009). (3) Using the results from step 2, we create a topic span map and indicate "*Temporal Thematic Streams" – the set of the topics connected by evolutionary transitions in their theme spans*. To depict the evolutionary transitions between theme (or topic) spans we use the graphical representation shown in Figure 4. (4) Finally, we induce probable "*Temporal Precedence*" relations among the topics based on the evolutionary transitions of topics. *Temporal precedence is one of the conditions for a causal relationship*. It expresses if a change in a construct precedes, accompanies, or follows a change in the measure (Edwards and Bagozzi 2000).

Results Validation

Results related to the first research question (R1) were validated by *triangulation of generated topics and associated sentiments* with information published in other sources about healthcare experience in Ireland within the same time-span. Results for the second research question (R2) were validated with findings from *extant empirical studies* on SERVQUAL factors in healthcare and other sectors. Secondary reports consulted for validation results for the first research question include (1) information in published news stories about hospital services in specific periods [4], (2) coding framework [5], (3) manual of inspection of raw comments.

Findings

We summarize our findings based on our research questions. **Research Question 1:** *Major topics and effect on service experience*. Answer to this question identifies and improves our understanding of (i) how the emergent latent *topics* are associated with the perception of *service quality* and (ii) *how these emergent topics align with the SERVQUAL constructs*. A total of 30 topics were identified and labelled. The top five (5) most important topics account for 34.2% of the analyzed comments and include *Hospital environment experience; Nursing care and attention; Organization of care processes; Waiting time; and Communication from doctors* (additional information is provided in the repositories [6,7]). The sentiment *associated with the topics determined through model* STM_2 model are as follows: (i) 66.67% of topics are negative (left side of figure 1) and comprise 58.9% of the comments in our dataset; 33.33% of topics are positive (right side of figure 1) and account for 41.1% of the comments dataset; (ii) relative *sentiment strength* (ST) of the topics (from -0.0560 to 0.0847).

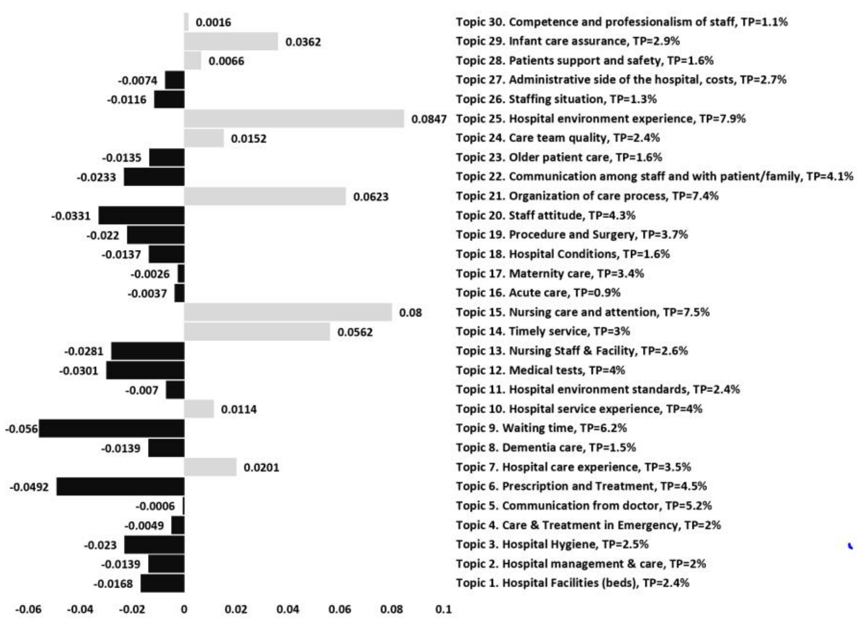

Figure 1. Sentiments and Prevalence of Topics

We summarise our findings from the above as follows: (1) overall the feedback on hospital service quality are more about negative than positive; (2) when writing positive comments, patients are more likely express general impressions about their experience, e.g. good *Attitude* or *Organization of the Care Process*; (3) when writing negative comments, patients are more likely to describe specific problems, e.g.

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[4] http://www.ratemyhospital.ie

[5] Findings of the 2017 National Inpatient Survey

[6] Topics Keywords

[7] Comments Examples

the Waiting Time at the hospital reception, *inaccuracies in Medical Prescriptions* (see supplementary material in the repositories [8]).

The mapping of the topics to the SERVQUAL dimensions allowed us to measure the SERVQUAL construct as shown below in (Figure 2).

SERVQUAL Dimension		**SERVQUAL Dimension**	
# Tangible	*Cronbach's alpha=0.67; Total Topic Proportion (TTP) =12.9%*	**Reliability**	*Cronbach's alpha=0.69; TTP=25.2%*
Topic 13	Nursing staff and facility	Topic 19	Procedure and surgery
Topic 18	Hospital conditions	Topic 11	Hospital environment standards
Topic 1	Hospital facilities (beds)	Topic 4	Care and Treatment in Emergency
Topic 3	Hospital hygiene	Topic 2	Hospital management and care
Topic 27	Administrative side of the hospital, costs	Topic 8	Dementia care
Topic 30	Competence and professionalism of staff	Topic 12	Medical tests
# Responsiveness	*Cronbach's alpha=0.20; TTP=16.6%*	Topic 16	Acute care
Topic 9	Waiting time	Topic 26	Staffing situation
Topic 21	Organization of care process	Topic 23	Older patient care
Topic 14	Timely service	Topic 24	Care team quality
# General Experience	*Cronbach's alpha=0.46; TTP=15.4%*	Topic 17	Maternity care
Topic 25	Hospital environment experience	**Assurance**	*Cronbach's alpha=0.51; TTP=18.3%*
Topic 7	Hospital care experience	Topic 22	Communication among staff and with patient/family
Topic 10	Hospital service experience	Topic 6	Prescription and treatment
# Empathy	*Cronbach's alpha=0.57; TTP=11.8%*	Topic 5	Communication from doctor
Topic 20	Staff attitude	Topic 29	Infant care assurance
Topic 15	Nursing care and attention	Topic 28	Patients support and safety

Figure 2. Mapping of Topics to SERVQUAL Dimensions Construct

In addition, we identified a dimension (General Experience) not covered by the SERVQUAL model. Our experience here is consistent with the findings from existing studies such as (Lai et al. 2007) which revealed the need for additional dimensions to those of the SERVQUAL model to measure service quality in their respective domains. The Cronbach's alpha indicators show fairly good internal consistency for factors measured through latent topics. Responsiveness and General Experience dimensions will require further investigation. We summarise our findings from the mapping in Figure 2 follows: (1) that patients are most concerned the reliability of services (*Reliability*, TTP=25.2%); the capacity of healthcare service to transfer trust, reliance and support to patients through confidential and courteous services (*Assurance*, TTP=18.3%); readiness and willingness of hospital staff to offer timeliness and properly organized services (*Responsiveness*, TTP=16.6%). (2) Based on the topics sentiment (Figure 1), we determined the sentiments for each of the SERVQUAL dimensions (mean of ST for the topics within dimension, MST) as follows: *Tangible* (MST=-0.015), *Reliability* (MST=-0.010) and *Assurance* (MST=-0.006) dimensions are associated with negative experience while the dimensions of Empathy (MST=0.023), Responsiveness (MST=0.021), as well as general experience (MST=0.039), are associated with positive experience. The results are consistent with findings from quantitative studies, in which, expectations exceeded perceptions of service quality in dimensions of Tangibles (Parasuraman et al. 1988), Reliability (Purcărea et al. 2013), and Assurance (Lai et al. 2007) dimensions.

Research Question 2: *Relationship among SERVQUAL constructs based on the temporal evolution of the identified topics?* To answer this question, we first determined the *topic spans* over time (see Figure 3). Second, we compute the Evolutionary transitions between themes. Third, we identified ten *temporal thematic streams* (TTS) as shown in Figure 4. The strength of the transitions in the streams is the normalized values indicated as labels on the lines while the dotted lines denote continuity of span. Positive topics are marked with (+) sign.

[8] Most Negative and Most Positive Topics Examples

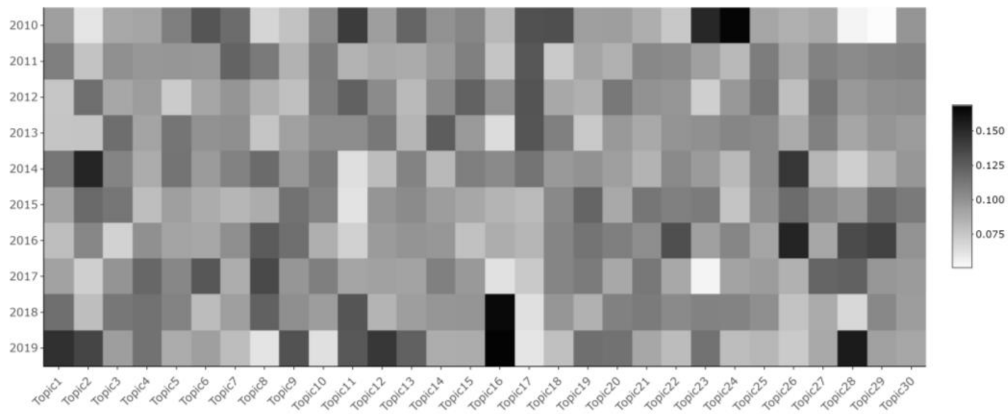

Figure 3. Topic Changes Over Time

Thus, the main *findings* for this part of the study are as follows. The ten temporal thematic streams shown in Figure 4 comprising groups of evolutionary transitions were discovered from the dataset: (1) TTS "A" can be called *General Hospital Care & Service experience* and is comprised exclusively of positive topics. (2) TTS "B" is closely related to the *Infants' Healthcare* and is characterized by the stable theme of Maternity care for 5 years, as well as the occurrence of problems related to *Communication from doctors*. (3) TTS "C" signals the stable recurrence during the entire period under analysis of *Older patient care* problems closely interconnected with Dementia. (4) The TTS "D" is on a wide range of problems with *Hospital Conditions*, transforming into a more specific manifestation of such problems as *Hospital Hygiene*. (5) TTS "E" mainly concerns the *Hospital Environment and Administrative Standards* transitioning to issues Administrative and cost issues including comparing conditions in public and private hospitals. (6) TTS "F" is characterised by problems of the *Hospitals Staff*, and the closely interconnecting issues of teamwork quality, staff professionalism, and problems with the nursing staff. (7) TTS "G" allows tracking the evolution of issues about prescription and *Treatment Quality* to issues about medical tests and subsequently procedures and surgery, revealing increasing deeper issues over time. (8) TTS "H" is associated with the positive theme of *Patients* Care *& Support*, evolving into general issues of care organization, and patient safety issues. (9) TTS "I" reflects the complexity of the problem regarding the *Organization of the hospital care process*, which evolved to issues about the attitude and communication of medical personnel among themselves, patients, and their families, as well as the conditions of patients in the wards. (10) TTS "J" reflects the main weaknesses in healthcare service regarding *Waiting time* which evolved into issues like Acute and Emergency Care.

When we express the evolutionary transitions of topics above in terms of their subsuming SERVQUAL dimensions, we obtain the following propositions on the temporal precedence among the dimensions: (P1) *Empathy issues precede Assurance issues*; (P2) *Assurance issues precedes Reliability issues*, (P3) *Responsiveness issues precedes Reliability issues*; (P4) *Reliability issues precedes Tangibility-related issues*; (P5) *Empathy precedes Responsiveness issues*. We interpret the above propositions to mean that issues in one service quality dimension may lead to another as indicated in the propositions. These precedence relations implicitly indicate a high degree of relatedness of these dimensions. This result is consistent with findings from several studies including in (Neupane and Devkota 2017) which reported high correlations among the five SEVQUAL factors to be in a range between 0.71 and 0.92.

Discussion and Conclusion

Firstly, a major *methodological contribution* of our work is in demonstrating how computational and analytics-driven methods could be successfully used in information system research to build explanatory models in addition to the exploratory and predictive models that these methods are traditionally associated with. From the practice perspective, our results confirm that deep insights can be extracted from freely available patient feedbacks on online platforms to complement data obtained from carefully designed surveys. Specifically, 27 out of the 30 STM-extracted topics have appeared in the literature,

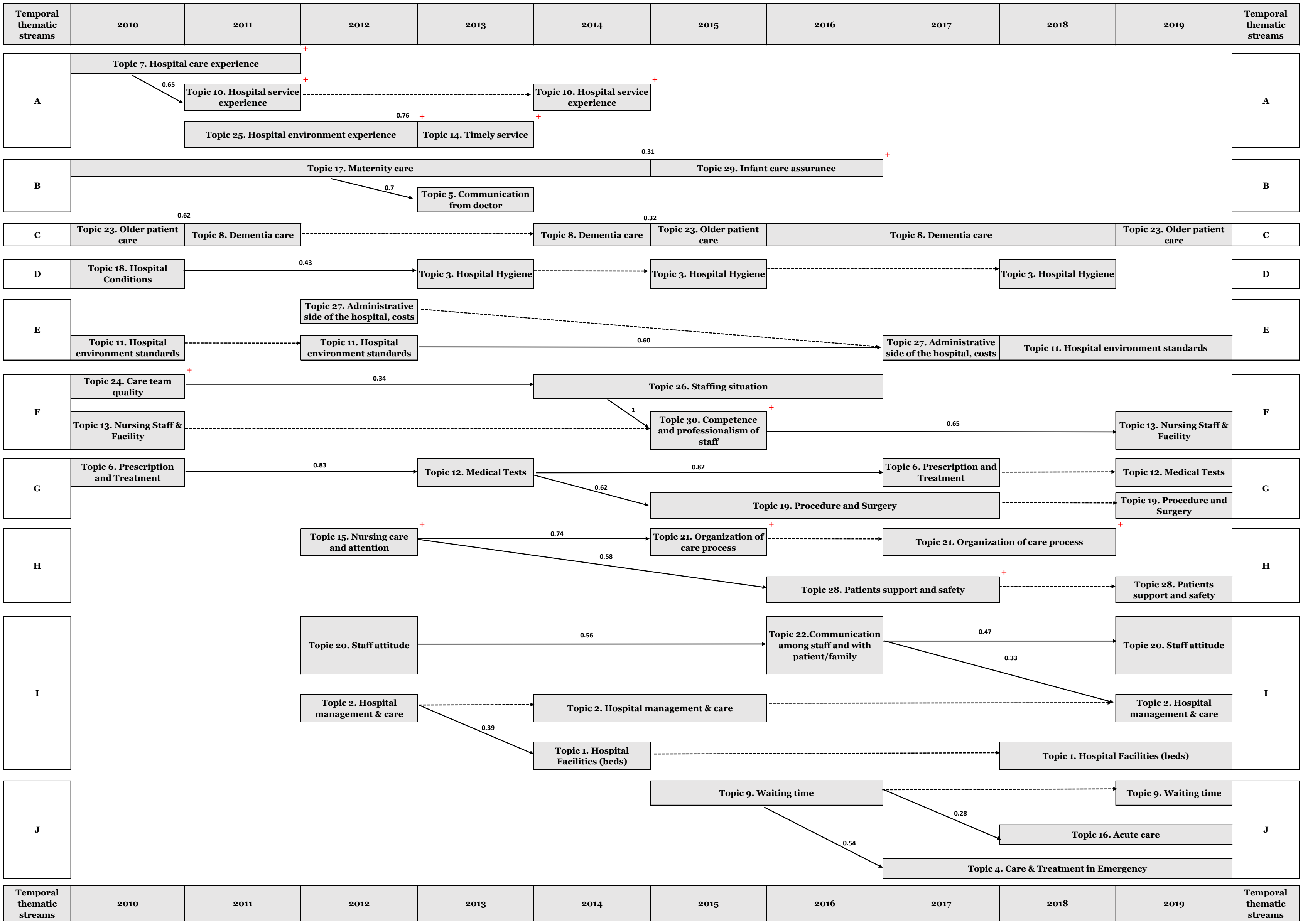

Figure 4. Temporal Evolution of Topics

which involved (i) quantitative studies based on questionnaires (Turan and Bozaykut-Bük 2016), (ii) manual coding underpinned by extant constructs [9,10,11] (Wiseman et al. 2015; Cunningham and Wells 2017) and automated topic modelling (James et al. 2017) of free-text comments. The discovery of emergent themes such as Dementia care, Maternity Care, and Infant care; attest to the utility of analytical methods and techniques such as STM in generating new insights of theoretical importance from unstructured data. Also, *the ability to quantify the topics (in terms of proportions and prevalence) and the corresponding SERVQUAL dimensions have significant theoretical value. This implies that our approach could be employed to measure theoretical constructs based on latent topics discovered automatically from big textual data*. Secondly, our work contributes a better understanding of the issues and factors associated with *healthcare service quality*. In this respect, some of the negative topics highlighted in our study (e.g. Waiting time, Prescription and Treatment, Staff attitude, Medical tests, Nursing Staff & Facility), are part of the identified perceived service gaps in the extant literature and official reports. For instance, gaps like Poor care; Poor communication; *Waiting times*; *Information*; were identified in (Wiseman et al. 2015). Similarly, issues including Physician interactions, Doctor interested, Doctor available/emergency, *Professionalism*, Reasonable fees, *Professional competence*, *Latest technologies*, *Diagnostics*, *Staff interactions* were presented as services gaps in (Brown and Swartz 1989). Furthermore, *Staff and timeliness*, Quality Experience, *Diagnosis* were identified in (James et al. 2017). Moreover, the National Experience Survey Report published by the government of Ireland has identified *Emergency Department waiting times and improving communication and engagement with patients*; Communication and engagement with patients; Food and nutrition; *Staff attitude*; Patient advocacy; Communications skills of healthcare teams; Health information for patients; Information and communication during the discharge process; Work for nursing staff within acute hospitals; as areas that could be improved [9, 10, 11]. Thirdly, revealing the *Temporal Evolution* of topics allows for tracking the presence of issues that could over time transform into significantly more complex problems. This has significant practical value in the area of early intervention and major theoretical value in establishing temporal precedence relations (a condition for causal inference) among constructs. Our results in this aspect have been validated by triangulating some of our findings on the theme span of specific issues like *Acute care* and evolutionary transitions from *Waiting time to Acute* Care *and Treatment in Emergency* with findings in the series of official reports [9, 10, 11]. Fourthly, our work contributes to advancing *theoretical knowledge of the SERVQUAL framework* by confirming findings from extant quantitative studies, identifying emergent themes in service quality measurement, and providing theoretical propositions about SERVQUAL dimensions. In conclusion, we believe that the question is no longer about the feasibility of using computational and analytical methods for methodologically sound information systems research to generate substantive theories from big textual data. In our opinion, the main question is how to improve existing techniques and develop new ones to leverage new data sources beyond text towards refining existing and generating new information systems theories.

Acknowledgements

This work was supported, in part, by Science Foundation Ireland grant 13/RC/2094.

References

Aagja, J., and Garg, R. 2010. "Measuring perceived service quality for public hospitals (PubHosQual) in the Indian context," *International Journal of Pharmaceutical and Healthcare Marketing* (4:1), pp. 60–83.

Abuosi, A. A., and Atinga, R. A. 2013. "Service quality in healthcare institutions: establishing the gaps for policy action," *International Journal of Health Care Quality Assurance* (26:5), pp. 481–492 (doi: 10.1108/IJHCQA-12-2011-0077).

Adams, J. L. T. R., Iii, J. L. T., and Adams, S. R. 2009. "Incorporating patients ' assessments of satisfaction and quality : an integrative model of patients ' evaluations of their care," (11:4), pp. 272–286.

Al-Damen, R. 2017. "Health Care Service Quality and Its Impact on Patient Satisfaction 'Case of Al-Bashir Hospital,'" *International Journal of Business and Management* (12:9), p. 136 (doi: 10.5539/ijbm.v12n9p136).

Al-Neyadi, H. S., Abdallah, S., and Mohsin, M. 2018. "Measuring patient's satisfaction of healthcare services in the

[9] National Patient Experience Survey, 2017

[10] National Patient Experience Survey, 2018

[11] National Patient Experience Survey, 2019

UAE hospitals: Using SERVQUAL," *International Journal of Healthcare Management* (11:2).

Bahja, M. 2018. "Automated Analysis of Patient Experience Text Mining using a Design Science Research (DSR) Approach," in *BUSTECH 2018 : The Eighth International Conference on Business Intelligence and Technology regarding*, pp. 21–24.

Berente, N., and Seidel, S. 2014. "Big data & inductive theory development: Towards computational Grounded Theory?," in *20th Americas Conference on Information Systems, AMCIS 2014*, pp. 1–11.

Blei, D., Carin, L., and Dunson, D. 2010. "Probabilistic topic models," *IEEE Signal Processing Magazine* (27:6), pp. 55–65 (doi: 10.1109/MSP.2010.938079).

Brown, S. W., and Swartz, T. A. 1989. "A Gap Analysis of Professional Service Quality," *Journal of Marketing* (53:2), p. 92 (doi: 10.2307/1251416).

Butt, M. M., and Run, E. C. 2010. "Private healthcare quality: applying a SERVQUAL model," *International journal of health care quality assurance* (23:7).

Cunningham, M., and Wells, M. 2017. "Qualitative analysis of 6961 free-text comments from the first National Cancer Patient Experience Survey in Scotland," *BMJ Open* (7:6), pp. 1–16 (doi: 10.1136/bmjopen-2016-015726).

Edwards, J. R., and Bagozzi, R. P. 2000. "On the Nature and Direction of Relationships Between Constructs and Measures," *Psychological Methods* (5:2), pp. 155–174 (doi: 10.1093/annonc/mdx426.009).

James, T. L., Villacis Calderon, E. D., and Cook, D. F. 2017. "Exploring patient perceptions of healthcare service quality through analysis of unstructured feedback," *Expert Systems with Applications* (71), Elsevier Ltd, pp. 479–492 (doi: 10.1016/j.eswa.2016.11.004).

Kuhn, K. D. 2018. "Using structural topic modeling to identify latent topics and trends in aviation incident reports," *Transportation Research Part C: Emerging Technologies* (87:December 2017), Elsevier, pp. 105–122 (doi: 10.1016/j.trc.2017.12.018).

Lai, F., Hutchinson, J., Li, D., and Bai, C. 2007. "An empirical assessment and application of SERVQUAL in mainland China's mobile communications industry," *International Journal of Quality and Reliability Management* (24:3), pp. 244–262 (doi: 10.1108/02656710710730852).

Lee, H. J., Lee, M., and Lee, H. 2018. *Understanding Public Healthcare Service Quality from Social Media* (Vol. 1), Springer International Publishing (doi: 10.1007/978-3-319-98690-6).

Mølgaard, L. L., Larsen, J., and Goutte, C. 2009. "Temporal analysis of text data using latent variable models," *Machine Learning for Signal Processing XIX - Proceedings of the 2009 IEEE Signal Processing Society Workshop, MLSP 2009* (doi: 10.1109/MLSP.2009.5306265).

Müller, O., Junglas, I., vom Brocke, J., and Debortoli, S. 2016. "Utilizing Big Data Analytics for Information Systems Research: Challenges, Promises and Guidelines," *European Journal of Information Systems* (forthcomin:November 2014), Nature Publishing Group, pp. 1–14 (doi: 10.1057/ejis.2016.2).

Neupane, R., and Devkota, M. 2017. "Evaluation of the Impacts of Service Quality Dimensions on Patient/Customer Satisfaction: A Study of Private Hospitals in Nepal," *International Journal of Social Sciences and Management* (4:3), Nepal Journals Online (JOL), pp. 165–176 (doi: 10.3126/ijssm.v4i3.17520).

Otalora, M. L., Rosenbaum, M. S., and Orejula, A. R. 2018. "Understanding health care service quality in developing Latin America," *Health Marketing Quarterly* (35:3), Routledge, pp. 167–185 (doi: 10.1080/07359683.2018.1514733).

Parasuraman, A., Zeithaml, V., and Berry, L. L. 1988. "SERVQUAL: A Multiple-Item Scale for Measuring Customer Perceptions of Service Quality," *Journal of Retailing* (64), pp. 12–40 (doi: 10.1002/9781118785317.weom090654).

Purcărea, V. L., Gheorghe, I. R., and Petrescu, C. M. 2013. "The Assessment of Perceived Service Quality of Public Health Care Services in Romania Using the SERVQUAL Scale," *Procedia Economics and Finance* (6:13), pp. 573–585 (doi: 10.1016/s2212-5671(13)00175-5).

Roberts, M. E., Stewart, B. M., Tingley, D., Lucas, C., Leder-Luis, J., Gadarian, S. K., Albertson, B., and Rand, D. G. 2014. "Structural topic models for open-ended survey responses," *American Journal of Political Science* (58:4), pp. 1064–1082 (doi: 10.1111/ajps.12103).

Schmiedel, T., Müller, O., and vom Brocke, J. 2019. "Topic Modeling as a Strategy of Inquiry in Organizational Research: A Tutorial With an Application Example on Organizational Culture," *Organizational Research Methods* (22:4), pp. 941–968 (doi: 10.1177/1094428118773858).

Turan, A., and Bozaykut-Bük, T. 2016. "Analyzing perceived healthcare service quality on patient related outcomes," *International Journal of Quality and Service Sciences* (8:4), pp. 478–497 (doi: 10.1108/IJQSS-04-2015-0042).

Valencia-Arias, A., Piedrahita, L. B., Zapata, A. B., Benjumea, M., and Moya, L. P. 2018. "Mapping the healthcare service quality domain: A bibliometric analysis," *Journal of Clinical and Diagnostic Research* (12:8), pp. IC01–IC05 (doi: 10.7860/JCDR/2018/30361.11863).

Wiseman, T., Lucas, G., Sangha, A., Randolph, A., Stapleton, S., Pattison, N., O'Gara, G., Harris, K., Pritchard-Jones, K., and Dolan, S. 2015. "Insights into the experiences of patients with cancer in London: Framework analysis of free-text data from the National Cancer Patient Experience Survey 2012/2013 from the two London Integrated Cancer Systems," *BMJ Open* (5:10), pp. 1–10 (doi: 10.1136/bmjopen-2015-007792).

Zeithaml, V. A., Parasuraman, A., and Berry, L. L. 1990. *Delivering quality service: balancing customer perceptions and expectations*, New York : London: Free Press.