Optimal Online Health Information Market: An Empirically-Based Market Design Approach

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List of Abbreviations

eHealth: Electronic Health

HONCode: Health On Net Foundation Code of Conduct

MSP: Multi-Sided Platform

NHS: National Health System

Q&A Platforms: Questions and Answer platforms

Web 2.0: Web version 2.0

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Abstract

Advances in information technology have made a significant influence on healthcare. Among technological breakthroughs, Internet has revolutionized the way people have access to health information. People increasingly use the Internet to search for, exchange and post health information on various types of websites. Internet offers invaluable benefits to its users; nevertheless, this very freedom to post information and the resulting enormous body of information is also one of the major sources of concerns. There have been misgivings about the quality of online health information since the Internet has been introduced. The 'top-down' approaches to control the quality of online health information proved to be neither practical nor desirable. The advent of web 2.0 (read and write version of web) enables user-driven approaches to improve the quality of information through 'bottom-up' approaches. The critical question is what type of bottom-up approach is suitable to provide online users with high quality health information.

Drawing on the market design literature, this research proposes a framework to understand and address (improve) the problem of quality of online health information. The research aims to identify the conditions under which a market for exchange of online health information works efficiently and then study the mechanisms to achieve the efficiency conditions and maximise quality. It also highlights the literature gaps for designing an online market that ensure the quality of exchanged health information.

The research collected data from question and answer platforms to carry the empirical analysis. One hundred actual question and answers from nine platforms (900 in total) were collected. The quality of health information was determined by medical expert assessors and related design features were collected form Internet. Statistical algorithmic modelling was adopted for data analysis. Supervised learning methods and mainly regression tree method was used to investigate the relationship between design and quality of health information.

The study uncovers the mechanisms and design features that are associated with the quality of health information. It reveals the interaction between design features that lead to high quality health information. The results particularly highlight the importance of experts' participation in the platform for increasing health information quality. It also shed light on the importance of financial incentives in enhancing health information quality. Building on the empirical findings, the research proposes four design scenarios of an online health information market and their respective outcome in terms of quality.

The research opens a new perspective for researchers on how to tackle the problem of quality of online health information by framing this problem as a 'market design' issue. It provides important design lessons for managers and designers on how to enhance the quality of online health information in their platforms. It gives policy makers empirically supported guidance for recognising and promoting online procedures that lead to production of high quality online health information.

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To My parents, Tahereh & Hassan

&

My best friend, Fatemeh

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1 Introduction

1.1 Introduction

Advances in information technology have made a significant contribution to healthcare. Examples of these breakthroughs are numerous, in the form of availability of various sources of health information on the Internet; social media; smartphone applications; electronic and personal health records; to more complex and emerging medical diagnostic systems such as IBM Watson and genome sequencing technologies, etc. What these have in common is that they are sources of information that should enable users to make more informed decisions related to health. Access to health information is thought to give patients more autonomy and empower them to play a more active role in managing their own health.

Among technological breakthroughs, the Internet has arguably had the biggest and broadest impact on healthcare. It has become the main source of health information for users (Tang & Ng 2006; Bessell et al. 2002; Bennett & Glasgow 2009) and has forever changed the way health information is accessed (Deshpande & Jadad, 2009). People have increasingly used the Internet to search for, exchange and post health related information on various types of websites, including those run by government organisations, charities, patient group websites, social networks, wikis, Q&As and individuals' own sites and blogs.

Nevertheless, this very freedom to post information and the resulting amount of that information is also one of the major sources of concerns. There have been misgivings about the quality of online health information since the Internet was introduced (Eysenbach & Powell 2002; Eysenbach & Diepgen 1998; Meric et al. 2002). Several initiatives were developed to address the quality issue. These initiatives can be classified into five broad categories: (1) codes of conduct (e.g., American Medical Association); (2) quality logos (e.g., Health on the Net Foundation); (3) third party certification (e.g., Utilization Review Accreditation Commission); (4) filters (e.g., intute.ca.uk); and (5) user guides (e.g., DISCERN) (Deshpande & Jadad, 2009). However, there is no clear evidence that these instruments have been effective (Seale 2005; Burkell 2004).

Moreover, different aspects of quality initiatives have been seriously criticised. The usability and technical aspects of these initiatives are questionable because users either do not notice these instruments (e.g., quality logos) or if they notice, they are not able to understand them (Adams & de Bont, 2007). Furthermore, the process of acquiring them lacks transparency (Adams & de Bont, 2007). There are also questions about the underlying assumption of these instruments that ignores the complexity and dynamism of the Internet and certifies offline and online health information in the same way (Deshpande & Jadad, 2009). The transition of the Internet from web 1.0 (read-only version) to web 2.0 (read and write version) intensified the complexity of online health information and further weakened the capability of these quality control initiatives (Adams, 2010). The third aspect of criticism of quality control initiatives is related to the lack of incentives for information providers to comply with them and follow the best practices (Nuffield Council on Bioethics, 2010).

Moreover, there is actually very little *demonstrable* evidence confirming the assumption of a relationship between serious physical harms and online health information (Eysenbach 2008). For example, a single case of fatality was reported to a database established in Europe for reporting harms as a result of using health information available on the Internet (Stone & Ferguson 2007). Together, the decentralised and complex nature of the Internet and lack of evidence proving harms has resulted in policy makers being reluctant to formulate ‘top-down’ interventions, rather, encouraging information providers to voluntarily adopt best practices (Nuffield Council on Bioethics, 2010). However, the net result is that the problem remains unsolved because, in the opinion of bodies such as the Nuffield Council on Bioethics, it is still problematic for users to differentiate relevant and quality health information on the Internet (Pletneva et al. 2011; Nuffield Council on Bioethics 2010). Although the harm associated with health information may not be directly measureable, it may still be there. More importantly, the prospects of fully exploiting the opportunities and benefits of online health information are limited if users cannot distinguish and thus act on high quality information. Therefore, there is a need for finding a way to enable users to recognise the quality of online health information to fully exploit the opportunity of the Internet as a channel of information to look after their own health.

The advent of web 2.0 provides just such a possibility, as it enables user-driven approaches through which users determine the quality of content through collective ‘bottom-up’ rather than ‘top-down’ approaches. E-health literature highlights the emergence of bottom-up approaches to guide users to relevant and accurate health information. For example, Eysenbach (2008) conceptualises the role of new forms of intermediaries on the Internet called apomediaries. He argues that, traditionally, people had access to health information only through health professionals such as physicians and pharmacists. The Internet challenges the role of health professionals as intermediaries or gate keepers of health information and provides people with direct access to unfiltered information. The main problem of bypassing the health intermediaries is that users get lost in the vast amount of information and arrive at wrong or irrelevant information. Apomediation theory argues that the users of the Internet are finding new 'bottom-up' (i.e., apomediary) ways to find credible information. This can be by recognising human beings such as peers, a patient or caregiver dealing with a similar disease who has developed a credible amount of knowledge, or through collective filtering tools, such as customer rating. These new intermediaries enable and facilitate 'down-stream filtering' and steer users to relevant and high quality information.

Nevertheless, having established the capacity of bottom-up approaches to address the quality issue, there is still an open question regarding what type of bottom-up approach is suitable for addressing quality or what form this bottom-up approach should take. Therefore, the overall aim of this research is to fill this gap and investigate and design an optimal bottom-up approach or set of approaches that should steer uses to high quality health information.

In order to achieve the research aim, this research argues that 'market design' and 'multi-sided platform' frameworks are the suitable theoretical lenses. One unique contribution of this research is to translate the research problem into a market design problem and suggest solution(s) to address the quality of online health information based on this approach.

Market design is considered as an engineering side of economics. It goes beyond just understanding and analysing economic structures to looking at designing and building them. It begins with identifying the desired outcome and speculates what form of mechanism is useful to reach the desired outcome. Defining the outcome and the desirability of the outcome depends on the context.

In the context of this research, the ultimate outcome is to maximise the quality of exchanged online health information. The approach taken in this research is that exchange of health information generally on the Internet and specifically in Q&A platforms is a form of transaction and can be studied through the concept of market design. A market can be described as a set of institutions, rules of the game, which facilitate exchange. A well-functioning market depends on how well these rules are designed. Different market designs lead to different outcomes in terms of efficiency and participation (Roth 2007; 2002). Online users face difficulty in finding relevant, reliable, trustworthy online health information (Nuffield Council on Bioethics, 2010) which means that this market does not work efficiently. This research argues that the present markets for exchange of online health information do not work properly as the design of the market is inefficient. This research aims at suggesting an optimal market design for exchange of online health information.

This study further specifies the online health information market as a multi-sided market or platform. The market for exchange of online health information is a multi-sided platform because it has two distinct players or sides, namely information seekers and information providers. Furthermore, the participation of each player depends on the contribution of the other side. Therefore, there is a need for designing an efficient market or platform that brings health information providers and seekers together and establishes rules that guarantee the high quality of exchanged health information.

Inspired by the research framework of market design and multi-sided platforms, the literature review chapter extracts conditions under which a market for exchange of online health information works efficiently and focuses on conditions that maximise the quality of health information. In the next step, mechanisms to achieve the efficiency conditions and maximise quality are differentiated and discussed. In order to speculate on the mechanisms that can be deployed to maximise quality, this study critically assess and analyse knowledge sharing and online mechanism design literature, identify the knowledge gaps in the literature for design of a health information market, and propose empirical research questions to fill the gaps.

Data for tackling the empirical research questions were collected from question and answer platforms because they are obvious examples of the proposed theoretical framework. Forty Q&A platforms were carefully examined and those that represent instances of the mechanisms identified and extracted in the theoretical chapter were purposefully selected. One hundred actual questions and answers from nine platforms (900 in total) were collected. The quality of health information (collected questions and answers) was determined by expert assessors and mechanisms (i.e. sets of design features) related to the platforms were extracted.

The data analysis was conducted using statistical algorithmic modelling, using supervised learning methods and regression tree methods to investigate the relationship between the dependent variable (i.e., the quality of health information) and independent variables (i.e., design features of the platforms) in order to understand the interplay between independent variables and dependent variable. The use of follow-up analyses such as random forest procedures ensures that the results of the initial regression tree analyses are robust.

1.2 Research Aims and Objectives

The overall aim of this research is to investigate what type of bottom-up approach is suitable for addressing the problem of online health information quality and to study the design of an optimal bottom-up approach that provides users with high quality health information. In particular, the research objectives are:

1. Proposing a theoretical framework to study the design of the market for exchange of online health information
    - Identifying the conditions under which a market for exchange of h health information works efficiency and as a result the quality of exchanged health information improves
    - Suggesting mechanisms to achieve the identified market efficiency conditions
2. Investigating and proposing the mechanism(i.e. design features) that maximise quality of information in an online health information market

- Investigating the motivations that work best in maximising quality of health information
- Identifying the design features that contribute to generation of high quality health information in an online health information market
- Investigating the interplay and interactions between design features in online health information markets.
- Proposing scenarios for designing online health information markets that maximise quality of information based on interaction between design features

1.3 Structure of Study

The background chapter (Chapter 2) defines online health information clearly and clarifies the focus of the study. It presents the background of the research problem and critically analyses the approaches (top-down and bottom-up) to tackle the concerns relating to quality of online health information. It argues that a bottom-up approach is suitable to address the research problem. At the end, the research gap is highlighted.

The theoretical chapter (Chapter 3) translates the research problem into a market design problem and argues that market design and multi-sided platform are proper research frameworks to address the research problem. It critically reviews the knowledge sharing and online mechanism design literature and identifies the knowledge gaps related to designing a market for exchange of online health information. At the end the empirical research questions based on the identified research gaps are proposed.

The methodology chapter (Chapter 4) explains the philosophical approach of the thesis and positions the research approach within the pragmatism school of thought. It outlines the conduct of the research and explains the data collection process. It also presents the measurements of both quality of information (i.e., dependent variable) and design features (i.e., independent). It describes the characteristics of the collected data for answering the research questions. Finally, it elaborates the analytical approach and methods of data analysis.

The findings chapter (Chapter 5) presents the results of data analysis for both sides of the health market. It discusses the results of exploratory analysis, regression trees models and evaluates the performances of the proposed models. It also outlines the robustness analysis mainly based on the random forests method. At the end, the main findings of the empirical work are highlighted.

The discussion chapter (Chapter 6) comprehensively discusses the results of the research. It clarifies how the results of the findings chapter answer the research questions proposed in the literature review.

The conclusion chapter (Chapter 7) presents the concluding remarks and highlights the contributions of the study. It also highlights the managerial implications of the study for theory and practice. Finally, the limitations of the study are discussed and future research needs and directions suggested. Figure 1 indicates the road map of this research.

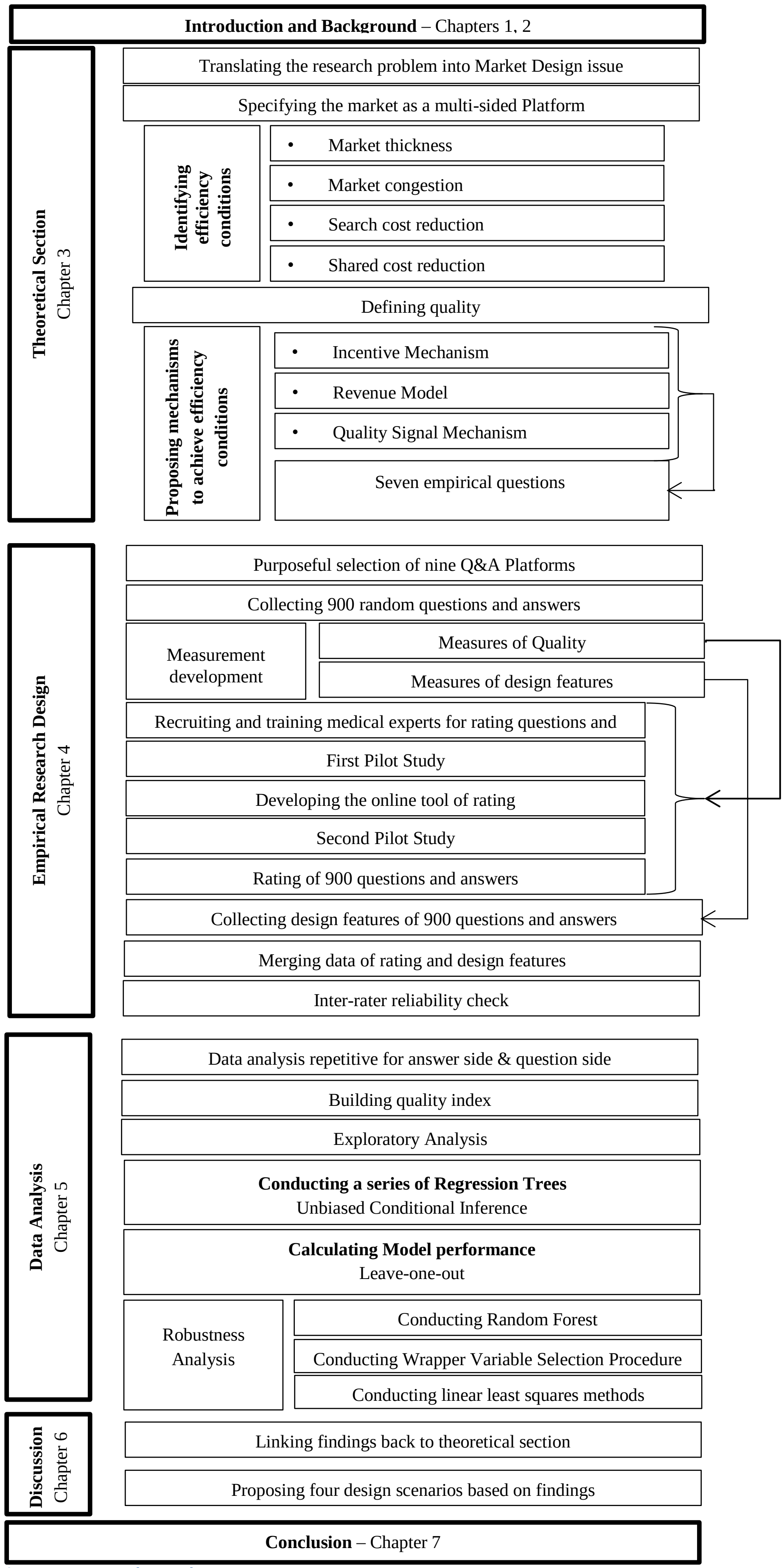

Figure 1 Research Road Map

2 Background

2.1 Introduction

Advances in information technology and data science have created novel opportunities in the health sector. The underlying technical advances are not specific to the health sector but their impact in healthcare can be really profound. Examples of these advances are numerous, from the availability of various source of health information on the Internet such as social networks, wikis, health Q&As; different smartphone applications such as MyFitnessPal, Apple HealthKit; personal health records services such as HealthVault; to more complex and emerging medical diagnostic systems such as IBM Watson and genome sequencing technologies.

People are able to keep track of their health information and data over their lifetime by using 'personal health records' (P. Tang & Ash, 2006). HealthVault is an example of a free personal health records service provided by Microsoft that allows people to gather, store, use, and share health information online. Dossia by AT&T and World Medical Card provided by World Medical Centre are providing a similar service (Sunyaev & Chornyi, 2010). This is in contrast with 'electronic medical records', electronic health information systems about patients, which are managed and maintained by health organisations such as the NHS.

A number of applications have emerged for tracking daily life ('life logging') that enables individuals to self-monitor their daily life and improve their health. Often these applications have the option of uploading data to the Internet (mostly social media) to inform those with similar interests. For example, MyFitnessPal is a mobile app that helps users track their calorie intake and exercise. It claims over 65 million registered users and it is one of the most popular digital health apps (Ziobro, 2013). Screening devices such as continuous blood pressure recorders are widely used (in the UK) and help patients to screen their status besides the blood pressure screening provided by the National Health Service (Nuffield Council on Bioethics, 2015). Another dominant example is Apple HealthKit, a new app designed to help users keep better track of their personal health and fitness data. HealthKit allows all the health and fitness apps in the users' iPhones to work together and provides an integrated and easy-to-access dashboard where users can monitor important health metrics on a daily basis. It also examines and reports users' fitness trends over a longer period of time (Munro, 2014).

Gene sequences have been used for decades to inform diagnosis, disease prediction and clinical management. Recent advances in technologies are reducing the cost of sequencing dramatically. Although estimates vary, a whole human genome (i.e. the full sequence of more than three billion base pairs comprising the DNA molecules contained in a human cell nucleus) can currently be sequenced for approximately $5,000 while it used to be $2.7 billion (Nuffield Council on Bioethics, 2015). As a result, it is now affordable for individuals to have their genes sequenced. It has also become commercially attractive for companies to create gene sequencing platforms. Such developments have created new possibilities for individuals and help them to identify means of prevention or lifestyle changes that can reduce the likelihood or severity of disease. For example, Google Baseline is a medical and genomics project which uses Google's computational power to analyse gene data and detect tendencies in our bodies that can be addressed before they become life-threatening. Project Baseline's information could suggest people change their behaviour before their first heart attack, or enable scientists to develop something to help at-risk people break down fatty foods.

Watson is an artificially intelligent computer system built by IBM and is capable of answering questions posed in natural language. The capabilities of Watson, including hypothesis generation, evidence-based learning and natural language processing, can be utilised in medical diagnosis. Watson can get a query describing symptoms and other related factors, and then mine patient data to find facts relevant to the patient's medical history; it then examines available data sources to form and test hypotheses, and finally provides a list of individualised, confidence-scored recommendations. The sources of data that Watson uses for analysis can include treatment guidelines, electronic medical record data, notes from physicians and nurses, research materials, clinical studies, journal articles, and patient information. It should be noted that although Watson has been marketed as a diagnosis and treatment advisor, it has never been actually used in the medical diagnosis process. It has only been involved in assisting professionals with identifying treatment options for patients who have already been diagnosed (Mathews 2011; Leske 2013).

All these technological advances empower both professionals and non-professionals to make more informed decisions and actions affecting health. It also gives the patients more autonomy and puts them in control of their own health. One of the more widely accessible technological means for patient empowerment is the Internet. People have increasingly used the Internet to search for, exchange and post health information on various types of websites, including those run by governments and charities, patient group websites and individuals' own sites and blogs. This raises the issue of how users can ensure they are receiving good quality and reliable information. Several attempts in the form of quality initiatives have been made to address this issue. However, it is still problematic for users to assess the quality of online health information and information providers have not been given a strong incentive to provide high quality information. This chapter aims at putting the research problem in a wider context and clarifies the underlying approach to tackling the research problem.

The chapter first defines health information and clarifies the focus of this study. It explains the extent of use and the format of online health information. It outlines why and how online health information is produced and clarifies the reasons people use the Internet to access health information. Next, it explains the concerns about quality of online health information and reviews the top-down approaches to addressing quality of online health information. It argues that a top-down approach is not an appropriate way of addressing the dynamism and complexity associated with quality of online health information and suggests using a bottom-up approach instead.

2.2 Online Health Information

Health information can be defined as information for staying well, preventing and managing disease, and making other decisions related to health and health care. It includes information for making decisions about health products and health services. It may be in the form of data, text, audio, and/or video (Rippen & Risk, 2000). This study focuses on information about conditions, treatments, and medicines and not on information about health services. Health information on the Internet is available for both medical professionals and non-professional users, but the study focuses on its use by the non-professional user.

2.2.1 The Rise of Online Health Information

Before the development of the Internet, people found health information by consulting with their doctor or other health professional; from books, newspapers and magazines; or from family and friends. The Internet has quickly become a major source of information for Internet users, and it has been argued that the demand for online health information is overwhelming (Shaw, 2009). The Pew Research Centre (2012) reports that 72% of American Internet users say they looked online for health information. The 2013 Oxford Internet Survey shows that in Britain 69% of Internet users searched for health information online and this figure remained almost constant from 2007 (Dutton, Blank, & Groselj, 2013). In addition to simply seeking information, substantial numbers of people are reported to participate in patient groups and other online communities associated with health information. For example, 34% of American Internet users share their health tracking records or notes with another person or group; and 26% of Internet users have read or watched someone else's experience about health or medical issues in the last 12 months (S Fox & Duggan, 2013). Online health information is conceptualised by the current NHS framework as a primary care resource for patients, because the responsible, educated healthcare consumer should be expected to research their health before attending their physician for a confirmatory diagnosis (Tang & Ng 2006; D'Auria 2012).

2.2.2 Different sources of information

Health information has long been available in books, magazines and other print media. The underlying concept of acquiring information applies to both print material and the Internet, but there are some important differences. It is often easier to determine the author/publisher of printed material and hence establish responsibility and liability. Furthermore, information provided in print media or through radio/television has a 'static' nature, as opposed to the potential of websites to be continuously updated. Vast quantities of searchable information are rapidly becoming available, much but not all of that information being free. Online information may appear to be more personalised when it is returned in response to information submitted by the user. The key difference between offline and online information is the speed at which an enormous variety of information can be accessed (Nuffield Council on Bioethics, 2010).

2.2.3 Why and how online health information is provided

Online health information is provided by online platforms (i.e. platform owner) for various reasons, including for commercial purposes and for non-profit reasons such as public policy (for example policy aimed at improving the health of the population) and altruistic reasons, such as a desire to help and learn from those with similar health problems. Health information on the Internet comes in many formats including data, text, audio and video (Rippen & Risk, 2000). The background of those who provide the content varies; Patients UK identifies medical writers and editors, physicians and health educators amongst its editorial staff. Other sites take a more user-orientated, ‘Web 2.0’ approach whereby content is user generated, and collaboration, information-sharing and interactivity is paramount, for example blogs which are often developed and run by people with a particular condition. Other online health information resources, such as some health-related wikis, involve a collaborative Web 2.0-style approach. For example, AskDrWiki is a site upon which anyone with a proven medical background can provide information, or PatientsLikeMe connects people with similar conditions and helps them to support and learn from each other. Table 1 indicates these variations in source and type of online health information by providing some examples.

Table 1: Different sources of online health information

Name	URL	Type	Purpose	Information generation	Source of revenue
Patient UK	http://patient.info	General Health	Provide non-medical people in the UK with good-quality information about health and disease	Employed board of professional editors	Completely funded by Egton Medical Information System company Generate revenue through advertisement which goes to EMIS No user charge No funding from external sources, e.g. Drug companies
NHS Direct[1]	http://www.nhsdirect.nhs.uk/	General Health	A self-help service which provides expert health advice, information and reassurance/ reduces face-to-face service demand	Trained professionals who are supervised under Clinical Supervision Policy of the NHS	National Health system (NHS)
Alzheimer's Society	www.alzheimers.org.uk	Disease-specific	Support and inform people with dementia and their family, friends and carers	Board of editors	Charity
Health unlocked	https://healthunlocked.com	Online community	Enabling people to share online their health experiences and information that helps decision-making, improves health and well-being, and provides support	User generated content with moderation from community and occasional monitoring from HealthUnlocked	Selling data to research partners; including charities, healthcare commissioners, hospitals, academic institutions, and private researchers e.g. medical device companies and pharmaceutical companies

[1] It is no longer active website

Name	URL	Type	Purpose	Information generation	Source of revenue
AskDrWiki	www.askdrwiki.com/	Wiki	Providing health information for physicians, nurses, and medical students	Credentialed authors	Non-profit website funded by the Open Access Medical Informatics Group
PatientsLikeMe	https://www.patientslikeme.com/	Social Network	Connecting patients with similar conditions and providing support	User generated content with tools to connect users plus moderation based on users' feedback	Describing itself a 'not just for profit' company, the main source of revenue is selling data to business partners
Keeping healthy	http://www.gettheglos s.com/article/blogger-	Blog	Personal aim defined by the blogger owner	Owner posts and visitors comment	Advertisement

2.2.4 Why people use online health information

The Internet offers a unique opportunity to empower patients and increase health literacy. It combines enormous amounts of information with powerful mechanisms for rapid search and retrieval. It enables people to have convenient access to health information in the privacy of their own homes, at the time they wish and for as long and as many times as they wish. Online health information can be accessed without embarrassment and without needing to talk face-to-face with a doctor or health professional. It also saves money if the patients would otherwise need to pay for a consultation with a doctor or miss work to do so. Given the shortness of the patient-physician encounter, e.g. 11.7 minutes in the UK in 2007 (The Information Centre for Health & Social Care Information Centre, 2008), patients are greedy to know more about their conditions, possible treatments and preventive actions. Furthermore, given the prevalence of medical errors and misdiagnoses, online information can help people to identify such errors more easily (Nuffield Council on Bioethics 2010). Table 2 summarises the benefits and harms associated with online health information.

For consumers facing barriers to healthcare access, the Internet can be a particularly appealing source of health information. Individuals with financial barriers to healthcare access, difficulty getting timely appointments with doctors, and conflicts in scheduling during clinic hours are more likely to search for health information online than those without these access barriers. The Internet may offer a low-cost source of health information and could help meet the heightened demand for health-related information among those facing access barriers to healthcare (Bhandari, Shi, & Jung, 2014).

Additionally, a European study (the countries covered by the survey were Denmark, Germany, Greece, Latvia, Norway, Poland and Portugal) found that 30% of Internet users across seven countries felt reassurance or relief when accessing health-related information on the Internet, while 15% stated that they had feelings of anxiety (Andreassen, 2007). The relative perceived importance of the Internet as a source of health information has also been studied. One survey, again of the same seven European countries as the study mentioned above, found that, in 2007, approximately 47% of survey respondents considered the Internet as an "important" source of health information (Kummervold & Chronaki, 2008).

The quality of online health information is variable: from strictly evidence-based to misleading and even malicious (Bovi, 2003). Many publications warn about the potential harm online health information may cause for patients (Corcoran & Haigh 2009; Fitzsimmons & Michael 2010). Potential risks originate from irrelevant or inaccurate information or from misunderstanding of relevant and valid information, either of which can lead to misuse of health information that may cause physical harm. Inappropriate treatment or adverse effects of untreated disease can be named as examples of physical harm. Furthermore, it may cause emotional side effects such as giving false hope or anxiety about diagnostic, prognostic, or therapeutic consequences. Financial risk such as expenses associated with unnecessary second opinions and purchase of inappropriate services or products is another harm this information may cause (Crocco et al. 2002). However, information does not necessarily have to be inaccurate in order to have the potential to harm. Accurate information that is taken out of context can also be harmful (Eysenbach 2008a). Table 2 summarises the benefits and harms associated with online health information.

Numerous studies highlighted the problems associated with Internet-based health information. For example, a systematic review in 2002 found that most authors found significant problems related to online health information including: criticising lack of completeness, difficulty in finding high-quality sites, and lack of accuracy. However, the review also noted that, while online health information quality may be variable "due to differences in study methods and rigor, quality criteria, study population, and topic chosen, study results and conclusions on health-related Web sites vary widely" (Eysenbach & Powell, 2002). Another showed that approximately one in four patients who used the Internet to research found the information worrying or confusing (Tamhankar & Mazari, 2009).

Table 2: Benefits and harms associated with online health information

Benefits	Harms
• Convenience • Patients' empowerment relative to doctors • Provides protection from medical malpractice or incompetence • Facilitates mutual support among patients	• Physical harm e.g. inappropriate treatment or adverse effects of untreated disease • Financial expenses, e.g. purchase of inappropriate services or products • Emotional side effects e.g. false hope or anxiety

2.3 Quality of online health information

The quality of online information can be handled in two ways: Top- down approach and bottom-up approach. Top-down approach refers to managing information at upstream level and by centralized authority. For example, child pornography content is blocked and considered as illegal content in UK. Filtering and legal intervention are methods of handling information using Top-down approach. On the other hand, bottom-up approach in quality assurance means handling information in downstream level and in decentralized way. Mechanisms that are devised within websites to manage the quality such as reputation system are considered as bottom- up approach.

2.3.1 Quality initiative (Top-down approach)

The quality of information on the Internet has been a matter of concern since the technology was first introduced (Lupiáñez-Villanueva, 2012). The growth of health information on the Internet on the one hand and concern over the potential harm of this kind of information on the other hand made policy makers develop initiatives to address this issue, including several initiatives designed to manage health information.

In England, the Department of Health launched a health information accreditation system called 'Information Standard' in 2009 which aimed to ensure that people could identify high-quality health information through a Kitemarking scheme. The Information Standard is "a quality filter which helps people to identify reliable information". Organisations that meet the quality criteria specified by the Information Standard are entitled to place a quality mark on their materials, including websites and print media. In the USA, an independent, not-for-profit organisation, the Utilization Review Accreditation Commission (URAC), aims to promote healthcare quality through accreditation and certification programmes. URAC accredits many types of healthcare organisations, including health websites. It reviews a company's operations to ensure that the company is conducting business consistent with national standards. The Health on the Net Foundation Code of Conduct (HONcode) was developed in the mid-1990s by the HON Foundation, a Swiss-based international organisation. The stated aim is to encourage the dissemination of quality health information for patients and professionals, and to facilitate access to the latest and most relevant medical data. The HONcode specifies eight principles for the presentation of medical and health information on the Internet (https://www.hon.ch/HONcode/Conduct.html). Where a website conforms to the HONcode, and has applied for certification from the HON Foundation, the website is entitled to display the HONcode logo.

A comprehensive review of the key initiatives addressing the quality of online health information compared and analysed the approaches of thirteen different programmes to clarify the issues around the development and enforcement of standards for health information on the Internet. The study categorised the mechanism into three classes of: (1) codes of conduct, (2) third-party certification and (3) tool-based evaluation. Codes of conduct are based on principles of ethical behaviour. Third-party certification is involved with recurrent validation of compliance with a set of standards. These standards may or may not be based on the codes of conduct and require payment of fees to the certifying company. Tool-based evaluation is mostly based on a predefined questionnaire that would produce a certain "quality score" for the content under evaluation for example, questionnaires that are filled by hand or embedded software that automatically gives access to the quality attributes of the site (Risk & Dzenowagis, 2001).

Khoja et al. (2012) conducted a structured review of both peer-reviewed and 'grey' literature from 1998–2008 to extract policy issues and solutions related to e-Health as a tool for improving health care delivery and access to health information at different levels. They categorised policy issues under three levels – international, national, and institutional – and insisted that global policy making is required in order to manage health information on the Internet (Khoja, Durrani, Nayani, & Fahim, 2012).

2.3.2 Criticism of Top-down approach

Quality initiatives have received several serious criticisms from different aspects. The first aspect of criticism was related to the usefulness of these initiatives for users and the technical problems with them. The second aspect was related to the underlying assumption of these approaches that ignores the complexity of the Internet and exaggerates the harms associated with using online health information. The third aspect is about the lack of incentive for health information providers to follow these initiatives.

Adams et al. (2007) proposed a series of criticisms of quality initiatives. First, whether online health information seekers are aware of a quality control initiative or not is under question. Second, even if they are aware of these initiatives, whether they can understand the information provided to indicate the quality of health information for example as quality logo is not guaranteed. Third, it is easy to acquire such instruments without the confirmation of the developers. Fourth, the process of acquiring such instruments has been criticised for lack of transparency and for the interests of those involved (Adams & de Bont, 2007).

The quality control projects assume that techniques used to evaluate paper-based information can be applied to online resources, ignoring the added complexity created by the multiple media formats, players, and channels that are brought together by the Internet (Deshpande and Jadad, 2009). For example, in the 'Information Standard' scheme, the certification procedure remains the same for all delivery channels which the organisation uses to distribute information; user generated information is out of the scope of certification and the scheme is more focused on textual information.

Furthermore, the assumption of potential harm of online health information has been challenged by two comprehensive efforts performed to evaluate the number and characteristics of harms that happened as a result of online health information. The first was an extensive review of the worldwide medical literature, looking for reported cases of patients who had died because of poor online information or advice. The researchers found that for the first decade of the Internet's existence, only a single case had been reported, which is by no means conclusive. In the second, as a part of Medcertain project, Eysenbach and his colleagues established the Database of Adverse Events Related to Internet Use (DAERI) to gather data of cases of harm to patients resulting from poor online information. After four years of the project, only a single case of a possible fatality was reported. The project has since been discontinued (Stone & Ferguson, 2007).

In the meantime, the Internet has undergone a major technological transition from Web 1.0 (read-only version) to Web 2.0 (read-write version) (Hardey, 2008) which intensified both the risks and opportunities of online health information. Web 2.0 allows users to generate information, share their experiences and help each other, yet the potential risks of inaccurate content produced by non-professional participators also increases. This advent further complicated the situation and weakened the top-down approach of addressing the problem.

Nuffield Council on Bioethics (2010) reports that in spite of existing interventions by the state or third parties, it is still problematic for individuals to assess the quality or accuracy of online health information with regard to their particular circumstances for several reasons. The often unrestricted character of information provision on the Internet means that individuals cannot easily ascertain the legal jurisdiction within which any given website is operating. Also, there are no strong incentives for information providers to follow ‘best practice’ (Nuffield Council on Bioethics, 2010).

In summary, the decentralised nature of the Internet on the one hand and the lack of evidence proving the harmful events resulting from harms of online health information on the other hand made policy makers sceptical about formulating formal intervention to control online health information. Voluntary adoption of good practices is a common approach followed by states, despite thoughtful criticisms regarding the efficiency of it (Adams & De Bont, 2007; Lupiáñez-Villanueva, 2012). Although there is not enough evidence to show the harmfulness of online health information, the opportunity of the Internet as a source of health information cannot be fully exploited as users face difficulty in finding relevant, reliable, trustworthy online health information (Nuffield Council on Bioethics, 2010). Therefore, there is a need for finding a way of recognising the quality of online health information in order to enable users to fully exploit the opportunity of the Internet as a channel of information to look after their own health.

2.3.3 Bottom-up Approach

One of the premises of Web 2.0 relates to the ability of a large number of users to manage huge volumes of online information. Web 2.0 enables a user-driven process through which users determine the quality of the content through a collective “bottom-up” approach rather than “top-down” that reflects their needs, knowledge, and real-life experiences. For example, Internet users could provide ratings or recommendations based on their own experiences to judge the quality and relevance of health information. Aggregation of ratings from many individuals can be considered as a form of crowdsourcing that highlights “good” information, while “not so good” information gets pushed to the bottom (Eysenbach, 2008; Deshpande & Jadad, 2009).

There is an emerging trend in the e-Health literature that highlights the possibility of using bottom-up approaches to address quality of health information. For example, the apomediation theory conceptualises the role of “apomediaries” which refers to Web 2.0 approaches that can “push” or “guide” users to relevant and accurate information. Apomediation is a new socio-technological term that was coined to avoid the term Web 2.0 in the scholarly debate (Eysenbach, 2007). It characterises the “third way” for users to identify trustworthy and credible information and services. The first possible approach is to use intermediaries (i.e. middlemen or “gatekeepers”), for example health professionals giving “relevant” information to a patient. Trusted Web portals containing only information vetted by experts can also be seen as an intermediary. The second possibility is to bypass “middlemen” completely, which is commonly referred to as disintermediation. Examples are patients searching for information on the web, or travellers booking their flights directly on the booking system of an airline, bypassing travel agents. The third way, prevalent in the age of Web 2.0, is a special form of disintermediation: an information seeking strategy where people rely less on traditional experts and authorities as gatekeepers, but instead receive “guidance” from apomediaries, i.e. networked collaborative filtering processes. The difference between an intermediary and an apomediary is that an intermediary stands between the consumer and information, meaning that he is a necessary mediating agent to receive the information in the first place. As a result, the credibility and quality of the intermediary heavily determines the credibility and quality of the information a consumer receives. In contrast, apomediation means that there are agents (people, tools) who stand by to guide a consumer to high quality information and services without being a prerequisite to obtain that information or service in the first place, and with limited individual power to alter or select the information that is being brokered (Eysenbach 2007; Eysenbach 2008). It should be emphasized that this approach to manage quality of information is under researched area and there is not much knowledge available on the shortcomings related to it. For example, whether the ratings that are provided by users without medical background are indicator of quality or not, etc.

In the health context, disintermediation means more direct access by consumers to health information on the web. The traditional role of the middleman is to guide consumers to relevant and credible information. Thus, the main problem of bypassing the middleman is that consumers may “get lost” in the vast amount of information and arrive at wrong or irrelevant information. The apomediation theory argues that apomediaries, such as users and friends in the case of Digg or technologies like PICS or MedPICS (i.e. metadata that clarifies the quality of information), can help users navigate through the onslaught of information afforded by networked digital media (Eysenbach, 2007). Therefore, the question is what type of Web 2.0 mechanisms (or apomediary) can lead users to high quality health information. Figure 2 summarizes the history of managing the quality of online health information since the advent of internet.

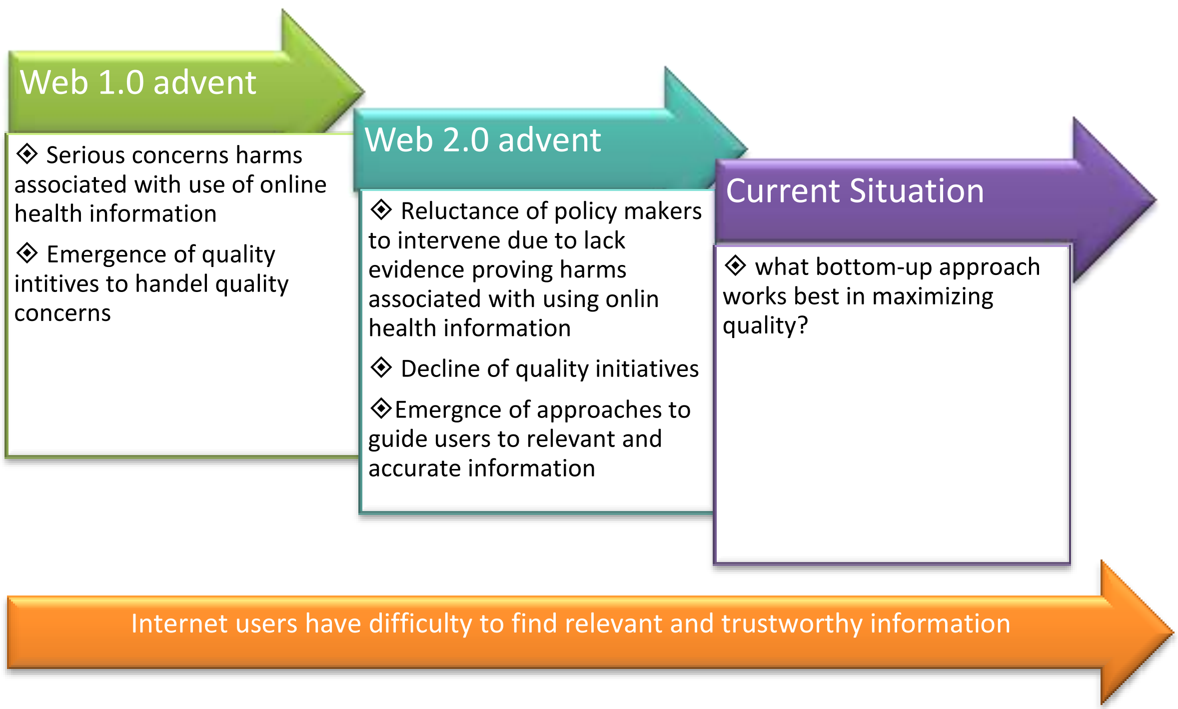

Figure 2: Quality of health information over time

The "market design" notion can be thought of as an engineering side of economics. Market design begins with identifying the desired outcome and asks what form of mechanism can help us to reach the desired outcome. There is a new and fairly rich strand of literature in economics and management which theoretically and empirically looks at designing online mechanisms (e.g. reputation systems, recommendation systems, etc.) that help users to find relevant online information and distinguish its quality. Thus, the aim of this study is to design a platform that enables information providers and seekers to interact effectively under a set of rules and tools which guarantees the high quality of exchanged health information. The next chapter further elaborates the market design framework and explains why and how it is relevant to the research problem.

3 Literature Review

3.1 Introduction

Searching for health information online is among the most common activities on the Internet (Susannah Fox, Duggan, & Purcell, 2013). Health information is being published on the Internet from countless information sources. In particular, the recent transition from Web 1.0 (read-only version) to Web 2.0 (read-write version) (Hardey, 2008) enabled individuals, as well as companies, to generate online information more easily than ever and tremendously boosted the quantity of online health information.

In spite of different types of interventions initiated by the state or third parties, it is still problematic for individuals to find and assess the quality or accuracy of information being provided to them online (Pletneva, Vargas, & Boyerr 2011). Furthermore, due to the amount of available health information and the diversity of sources, finding relevant information is very difficult. Health information providers are not motivated to generate good quality information.

Web 2.0 enables a user-driven process through which users determine the quality of content through a collective “bottom-up” rather than “top-down” approach that reflects their needs, knowledge, and real-life experiences. The question is what type of web 2.0 mechanisms can lead users to high quality health information. This study argues that by applying the notion of “market design”, a market for exchange of online health information can be designed that brings health information providers and seekers together and establishes rules that facilitate efficient exchange of online health information.

This chapter begins by translating our research problem as a market design problem in section 2; then it further specifies our market and conceptualises it as a multi-sided platform; section 4 proposes the optimal conditions for a health information platform to work efficiently; section 5 outlines an appropriate platform design that maximises the quality of health information; finally, section 6 summarises the finding and highlights the research questions.

3.2 Market Design

Market can be described as a set of institutions, rules of the game, which facilitate exchange. “Market design” recognises that well-functioning markets depend on how well these rules or institutions are designed (Roth, 2002). Different market mechanisms can lead to very different outcomes in terms of participation and efficiency. In other words, choosing the most effective market design is essential, as there is a significant opportunity to enhance efficiency through the design of the market mechanism. The notion of ‘market design’ focuses on design of the rules of the game by which different forms of exchange can occur efficiently (Gans & Stern, 2010).

This notion has been applied to traditional markets in which money plays a critical role such as a market for labour or radio spectrum; and also to market-like procedures that involve neither prices nor an exchange of money such as assigning children to schools or facilitation of kidney exchange (Roth, 2007). The “market design” notion can be thought of as an engineering side of economics. It begins with identifying the optimal or desirable outcome and what form of mechanism could be designed to attain that outcome. The definition of the outcome and the desirability or optimality of the outcome is context dependent (Roth, 2002).

The inefficient exchange of health information on the Internet can be studied using this notion. In other words, there is a need for an efficient market that brings health information providers and seekers together and establishes rules that facilitate efficient exchange of online health information. Market design is particularly relevant to the research problem as it is particularly concerned with situations where markets do not emerge spontaneously or work efficiently and a business is needed to create the market or fix it to function efficiently (Roth, 2007).

The aim of this study is to design an efficient market for exchange of online health information. In order to reach this aim, first, the conditions under which such a market works efficiently will be identified and, in the next step, the mechanisms through which these efficiency conditions can be achieved will be evaluated.

3.2.1 Design Conditions of an Efficient Market

Roth (2007) proposes a framework and conditions upon which market designers can evaluate the effectiveness of their designed market. Specifically, Roth highlights three outcomes that are associated with efficient market operation: market thickness, lack of congestion, and market safety. Market thickness refers to bringing together a large number of potential buyers and sellers within a market to provide opportunity for both sides to engage in a satisfactory transaction. Congestion can be a result of market thickness and should be overcome by giving market participants enough time to make a proper choice when they are faced with a variety of choices. Market safety is ensuring conditions in a way that market participants are willing to reveal their preferences and disclosure of their confidential information does not undermine their bargaining power (Roth, 2007). Roth et al. (2006) also highlight the importance of dealing with “repugnance”. Some markets are constrained by social norms or legal restrictions that limit the price system as an allocation mechanism, such as a market for sex or kidneys. Effective market design should address these constraints (Roth, 2006).

Dealing with these issues is of various importance in different markets. One market might suffer from lack of thickness while the other lacks enough congestion. Based on the lessons from market design for effective functioning of the market, the condition under which the market for online health information works efficiently, and also which conditions are more important to fulfil, will be discussed.

3.3 Multi-sided Platform

Two-sided platforms or more a generally multi-sided platform (MSP) is defined as a market which facilitates interactions or transactions among two or more customer groups, such that one group's benefit from joining a platform depends on the participation of the other group that joins the platform. It is important to make a distinction between firms that compete to have one or more customer segments on board and the case of MSPs. Obviously, firms are likely to earn more profit if their products attract both men and women; however, in MSPs (e.g. a dating club) the benefit enjoyed by a member of one customer group (e.g. men) depends upon how well the platform does in attracting customers from the other customer groups (e.g. women) (Armstrong, 2006).

In the traditional value chain, value moves from left (supplier) to right (customers). The left side of the company generates cost and the right side creates revenue; however, in two-sided markets cost and revenue are generated at both left and right side because the platform has a distinct group of customers on each side. In other words, the platform incurs costs in serving both groups and can collect revenue from each, although one side is often subsidised (Eisenmann, Parker, & Alstyne, 2006).

Examples of two-sided markets readily come to mind: videogame platforms such as Sony PlayStation and Microsoft Xbox that need to attract both gamers and game developers to their videogame console; dating clubs that need to get both men and women on board in order for the platform to have a service to offer to either one. MSPs have existed for a long time but have risen to prominence only recently, mostly due to the advancement of information technology which has tremendously increased the opportunities for building larger, more valuable and powerful platforms such as eBay, Facebook, iTunes, etc. (Hagiu, 2009).

In a platform's business model, involvement of each customer group makes the platform less or more attractive for others; this phenomenon is called the 'network effect' by economists. Exhibition of positive network effect is a vital element of MSPs to distinguish between a multi-sided platform and a single-sided market (Hagiu, 2009). MSPs exhibit two types of network effects, which may be either positive or negative: In same-side effect, also called direct network effect, increasing the number of users on one side of the platform makes it either more or less valuable to users on the same side. Same-side network effects are often negative, for example sellers preferring fewer rivals in a B2B exchange platform; however there are some cases of positive effect, for example, Microsoft Xbox owners valuing the fact that they can play games with friends. In a cross-side effect, also called indirect network effect, increasing the number of users on one side of the platform makes it either more or less valuable to the users on the other side. Cross-side network effects are typically positive; for example, players prefer more game developers to program for their game console, but they can be negative, for example TV viewers preferring fewer ads (Eisenmann et al., 2006). Positive network effect and direct interaction between sides of the market helps distinguish MSPs from related but distinct business models. Figure 3 depicts the multi-sided platforms versus single-sided platforms (Hagiu & Wright, 2015).

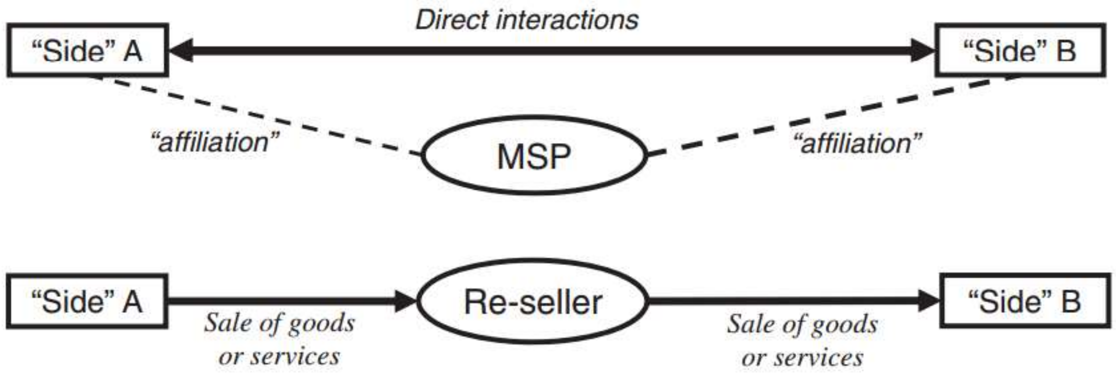

Figure 3: Multi-sided vs. Single-sided platforms
Source: (Hagiu & Wright 2015)

The online market for exchange of health information has two distinct types of contributors, i.e., health information seekers and providers, and the contribution of each side depends on the participation of the other side. That is, the market is only attractive for information seekers when a sufficient number of information providers are available to generate high quality information; and information providers are attracted to a market in which a sufficient number of information seekers are in need of their participation. Furthermore, in this market, both sides are incurring cost; revenue is mostly generated from information seekers who are in need of health information and information providers are subsidised to participate (other forms of revenue model are probable and will be discussed in section 3.5.5).

By adopting the framework of a multi-sided platform, the online market for exchange of health information is further specified as a 'platform' for exchange of health information on the Internet. Next, the key functions of multi-sided platforms will be presented.

3.3.1 Key Functions of MSPs

Hagiu (2009) argues that regardless of industry, there are two types of basic functions that MSPs can perform at the most fundamental level: (1) reducing search costs induced by the MSP's sides before transacting, and (2) reducing shared costs, incurred during the transactions themselves. Any feature or functionality of an MSP falls into either of these two fundamental types.

3.3.1.1 *Reduce Search Cost*

Search costs refer to the costs incurred by the multiple sides before they actually interact, in order to determine the best "trading partners". MSPs can be further divided into two types - match making and audience making platforms, according to whether each of the two sides is searching for each other or only the one is. In two-sided matchmaking platforms like eBay, both sides are searching for each other and the platform reduces search costs for both buyers and sellers. On the contrary, some platforms reduce search costs just for one side, for example, advertising platforms have a non-searching side (audience). As a result, the platform reduces search cost for advertisers and provides standalone service to attract audiences (Hagiu, 2009).

The main function of two-sided platforms in a matchmaking setting is selecting a sample of candidates for transaction. The platform tries to establish a large database of both sides to perform better matchmaking. However, in two-sided audience making platforms like TVs, one side is searching for the other side and the platform reduces the search cost for the advertisers and helps them to reach their audiences. In this kind of platform, the higher the audience a platform has the more attractive it is for advertisers to use the platform; however, audiences do not care about the number of advert or even prefer fewer.

The different nature of matchmaking and audience-making platforms dictate different design guidelines (Hagiu, 2009). Our platform can be categorised as a matchmaking two-sided platform which tries to attract both a large number of information seekers and providers on the platform. The platform needs to have a large number of information providers on board to be able to provide information for seekers who are in need of information and vice versa.

3.3.1.2 *Reducing Shared Costs*

The second fundamental function of MSPs is reducing costs during transition. MSPs try to reduce shared cost through facilitating transactions after the point the search is over and transacting parties have found each other and want to perform a transaction. Since, a portion of these costs are common to all transactions, not just those in MSPs, they are called shared or duplicate costs. For example, by introducing PayPal accounts, eBay provided an infrastructure which significantly eases transactions between buyers and sellers by eliminating the need for barter. Another example of reducing shared cost is a game console which reduces cost for both gamers and game developer through the elimination of duplication. Without a game console platform, the game developers had to build a console for each game, which imposes a high cost to both sides. It is worth noting that it was the case until the end of the 1970s and each videogame was hardwired into a game machine (Hagiu, 2009). Based on what kind of shared cost should be reduced, different design is needed. It will be discussed later what type of shared cost is incurred in our platform in Section 3.4.4, and how the platform can reduce shared cost to make our market for online health information more efficient, see Section 3.5.6.

3.4 Optimal Efficiency Conditions for Online Health Information Markets

Inspired by the theory of 'market design' and 'multi-sided platforms', this theoretical framework speculates on which conditions must be met for the platform of online health information to work properly. There are three primary players involved in our platform: 1) health information providers, 2) health information seekers, and 3) platform owners. The behaviour of these players has an effect on how well our platform operates efficiently and as a result should be considered in identifying efficient conditions. Furthermore, the nature of online health information itself imposes some constraints on the effectiveness of our platform (See Sections 3.5.1, 3.5.2 and 3.5.3).

3.4.1 Market Thickness

Efficient market design, as highlighted by Roth (2007), must ensure market thickness. Market thickness refers to bringing together a large enough number of potential buyers and sellers within a market to provide opportunities for both sides to engage in a satisfactory transaction. Sufficient thickness means that there are enough participants in the market to make it thrive (Roth, 2007).

Our market has two distinct groups of participants: information seekers and information providers. Each side has its own motivations and barriers to engage in the platform. Fundamental to the design of our platform is the ability to attract sufficient contributions from both sides.

The viability of knowledge markets e.g. Google Answers, like other forms of market, as Chen et al. (2010) argued depends on their ability to encourage sufficient high-quality contributions. Regardless of the structure, knowledge markets derive their value from both the quantity and quality of contributions from their participants. Fundamental to the design of a knowledge market is the ability to encourage sufficient high-quality contributions. If the majority of questions in a knowledge market are left unanswered (i.e., question starvation), this may discourage continued participation of information seekers and ultimately affect the viability of the market. On the other hand, if the overall volume of questions is small, it may not provide enough value to become a preferred destination for information providers (Chen et al., 2010).

It should be noted that people's time, energy and knowledge are personal assets and are limited. Their contribution neither is formed spontaneously nor can be forced, but it rather should be encouraged and facilitated. As virtual platforms for exchanging information proliferate, they must compete for users' participation. People assess the value of their contribution against the costs and contribute only if it is rewarding (Chang & Chuang, 2011; Hung, Durcikova, Lai, & Lin, 2011). It is essential for the platform to understand the factors that generate interest and attract attention for both sides and design mechanisms accordingly to have sufficient participants on board. The important lesson that should be highlighted is that making a thick market not only depends on the quantity of contributions but also is contingent to the quality of contributions. Therefore, design mechanism should address both quantity and quality of contributions.

The health information market, as two-sided platform that attempts to bring together both information providers and information seekers without getting involved in production of health information exchanged in this market, faces a chicken-and-egg problem. This problem is observable in MSPs, for example when the platform needs to attract buyers to be a valuable platform from the seller point of view; however, sellers do not register without handsome registered buyers. Both sides are needed to get on board for success (Caillaud & Jullien, 2003). In our platform the information seeker does not ask questions on the platform if there are not enough information providers to answer their questions and information providers are not willing to participate if there is not enough numbers of questions on the platform. One way of avoiding this problem is starting from a single-sided platform and establishing of a large installed base on one side and then expanding to a two-sided platform, eventually building a multi-sided platform (Hagiu, 2009). Yahoo Answers is a successful example of an information market which utilised this strategy. It overcame the chicken-and-egg problem by leveraging its existing customer base. The online health information market needs to incentivise an adequate number of participants and have a strategy to handle the chicken and egg problem.

3.4.2 Market Congestion

Efficient markets needs to overcome the congestion that thickness can bring. It means that markets should give market participants enough opportunities to make satisfactory choices when faced with a variety of alternatives (Roth, 2007). Congestion arises when the timing or circumstances of potential transactions requires that transaction are completed without assessing the alternative options in the marketplace. The degree of congestion depends on how well the market mechanisms are designed (Gans & Stern, 2010).

For example, in online dating websites, a member who is rated as very attractive (in absence of any cost) will receive too many offers. In this circumstances, the market suffers from congestion problems because the high numbers of dating requests that an attractive member receives makes it harder for him/her to evaluate all the requests and make a satisfactory choice (Lee & Niederle, 2014). A similar congestion phenomenon happens in labour markets. When the cost of application is too low, the number of applications received by each employer increases. Consequently, many employers face the near impossible task of reviewing and evaluating hundreds of applications (Coles et al., 2010). The increase in applications leads to the situation where many applications that are sent are never even screened and as a result, suitable choices will not be made.

In order to overcome this issue, markets make it costly to send dating requests or applications. For example in online dating market such as OkCupid.com, the number of requests users can send is limited. This makes partner seekers more selective when they want to send a dating request (Lee & Niederle, 2014)..

The online health information market faces the congestion problem similar to the problem occurring in online dating markets. Participants often ask many questions as there is a low cost for asking and a high value for being answered. Consequently, many respondents face the problem of reviewing and evaluating too many questions to find those questions which really need an answer. This wastes the valuable time and attention of respondents in the market that could be otherwise being spent on answering questions. A platform designer must ensure low levels of congestion in the platform for example by imposing some asking cost to increase efficiency. It should be noted that cost can be either financial or social. Losing some virtual points or limiting the number of questions a user can ask are examples of social cost that can reduce market congestion.

3.4.3 Search Cost Reduction

As the amount of available information and the number of sources on the internet increases, efficient retrieval becomes more difficult. Although most information on the internet is available for free, locating information requires substantial effort, sometimes more than a single information seeker is willing to invest (Ge et al,. 2005). It is observed that lay users and medical professionals equally are overwhelmed by the quantity of information available online and the associated time consumption (Pletneva, Vargas, & Boyer, 2011). Furthermore, the design of effective consumer health information systems requires an understanding of the context of consumer health information searching. It is argued that users without medical training have difficulties in formulating their requests at three levels, including: (1) mental model levels: lay people describing disease and conditions in simple terms, (2) Semantic level: lay vocabulary does not match with medical terminology, (3) lexical level: misspellings, partial words, and use of abbreviations are common, which often cause search failures (Zhang, 2010). Designing an MSP for the exchange of online health information and bringing together the information seekers and providers reduces the search cost for both sides of the platform. If the platform facilitates the interaction between information seekers and providers in a natural language, the problem of using simple terms or using medical terminology may relieve because they have the opportunity of clarifying their points. The platform owner may decide to further reduce the search through embedding mechanisms such as search tools, recommendation systems, etc.

3.4.4 Shared Cost Reduction

Shared cost through facilitating transactions after the point of search is over and both are ready to interact and perform a transaction. The main source of shared cost in both sides of our platform is related to quality of the opposite side's contribution.

It is difficult for an information seeker without medical background to assess the credibility and true value of the accessed information. In an ideal world, everyone would post and share information in an ethical and comprehensive way. Reality however is different. The information provided is often incomplete and in some cases, misleading (Pletneva & Vargas, 2011). Dushnitsky et al. (2011) argue that online knowledge market facilitates more efficient transactions through reducing search cost; but also gives rise to substantial problems. Online marketplaces are a particularly attractive setting for malfeasant individuals who pose as owners of valuable knowledge assets (Dushnitsky & Klueter, 2011). This has particular importance for health information to be accurate, complete and verifiable (Fichman, 2011) as it could literally be a matter of life and death. The health information market needs to address particular quality concerns associated with the exchange of online health information.

In many markets, quality can be difficult to predict prior to consumption, but is observed upon consumption. In healthcare markets, quality can also be difficult for consumers to assess even after consumption. This is so because health outcomes can have large stochastic components, can be very dependent on specific, unobservable patient conditions and can be very poor even for patients receiving the best available care (Katz, 2013). In our platform, it is particularly difficult for information seekers without a medical background to assess the true ability of the information providers to contribute the high quality health information or to assess the quality of information. This issue can lead to a market for lemons where poor quality is crowding out the higher quality (Akerlof, 2013). It means that contributing high-quality information imposes cost to information providers that is not compensated. Without a mechanism signalling quality, information providers do not have any incentive to contribute high quality information, and as a result the platform will be a flood of low quality contributions. This type of information asymmetry can be addressed using reputation systems. Reputation systems keep the track of users' contributions to the platform and publicize it within the platform. This works as an incentive for information providers to contribute high quality information (See Section 3.5.2 and 3.5.6.1).

The quality of information seekers' contributions also matters. For example, one source of inefficiency in question and answer platforms is the existence of spam and unserious questions on the platform that waste the valuable time and attention of the potential answerers that otherwise could be spent on real question that truly need answers (Mamykina et al., 2011). An efficient platform design must reduce shared cost through ensuring quality contribution on both sides of the platform.

3.5 Platform Design for Maximising Quality

The design of the platform refers to the set of rules and mechanisms established by the platform owner in the market. The platform design, along with overall industry regulations, will shape the behaviour of information seekers and information providers and ultimately determine the extent to which the platform for exchange of online health information, like any other market, operates efficiently or yields to platform failures (Agrawal et al., 2013).

Efficiency has a lot of aspects and four of them have been discussed, including market thickness, market congestion, search cost reduction and shared cost reduction. But the main focus of this research is on the quality of health information as an important deriver of platform efficiency. Specifically, how the generation of high quality information is ensured on the platform. This section describes the platform design mechanisms that can be deployed to maximise quality of information. It begins by defining quality and will discuss how the nature of the online health information impacts on the design of the platform. Then, it focuses on how various market mechanisms (the incentive model, revenue model and quality signal mechanisms) affect the quality of health information. It further highlights the question which should be addressed in the empirical part.

3.5.1 Quality Definition

Information quality can generally be defined as information's "fitness for use" (Wang & Strong, 1996). To be more specific, the information quality should be defined within its context as the same information may be valued differently in a different context. Furthermore, the quality of information is evaluated by the value or cost of decisions made based on the information (Stvilia & Gasser, 2008). Since, health decisions and actions are matters of human life and death, the value of health information is very high (Stvilia et al., 2009). It is often very difficult for users to evaluate the quality of health information even after information consumption because the users lack the necessary skill for its evaluation.

There are three kinds of goods in terms of quality evaluation: search, experience, and credence. The quality of search goods can be determined before consumption. Commodities such as paper are search goods. The quality of experience goods can only be determined after consumption (Nelson, 1974). For example, a user requires actually eating at a restaurant to be able to evaluate its quality. Finally, the quality of credence goods is difficult to evaluate for consumers even after consumption because they lack the necessary skills (Darby & Karni, 1973). Typical examples of credence goods include medical procedures, automobile repairs, dietary supplements, and education. In these cases the recipient has to trust either the provider, a certification, or a third party (Muller, 2005).

It is argued that consumers of healthcare are not good evaluators of objective quality measures of healthcare. Patients are able to recognise whether a physician is respectful, attentive, and clear in explaining clinical issues and operating a clean and efficient office; however they were found to be inaccurate in evaluating the technical quality of care. It means that patients are not accurate in judging whether a physician supplied appropriate evidence-based treatment (Frank, 2004). Similarly, (Chang et al., 2006) through interviewing 245 patients, showed that the technical quality of care is not significantly associated with the quality of care from a patient’s perspective. That is, patients are reporting quality based on the quality of their interaction with the health provider rather than the technical aspect of quality. In this sense, health information can be categorised as credence good and evaluating its quality needs medical skills, though, there is nascent literature that suggests a meaningful relationship between the technical quality of healthcare and patients’ feedback. For example, Bardach et al. (2013) showed that better scores of hospitals on Yelp (a commercial review website) are correlated with lower mortality rates. This findings reinforce the early observations from the UK, which imply that consumers posting ratings on commercial websites are reflecting meaningful aspects of hospital quality of care (Greaves et al., 2003). Whether or not patients are able to report on the quality of health information or not has a specific effect on the design of the platform which will be discussed later in Section 3.5.6.1.

Many empirical studies developed a set of criteria to assess the quality of online health information that are suitable for our research. For example, after reviewing 79 empirical studies of consumer health information on the internet , Eysenbach et al. (2002) found Accuracy (i.e. the degree of concordance of the information provided with the best evidence or with generally accepted medical practice.), Completeness, Readability, Design, Disclosures, and References as the most frequently cited quality criteria (Eysenbach et al., 2002). Similarly, many initiatives tried to propose a set of criteria for evaluating online health information. For example, under the UK health information accreditation system (2009), online health information needs to be Clear, Accurate, Impartial, Balanced, Evidence-Based, Accessible and Up to Date. The context of information of this research and initiatives are websites, webpages, or documents. As Stvilia et al. (2008) argue evaluating information quality is context dependent. These measures will be refined later to define specific quality measures for the context of this study. Please see Section 4.4.2 for measures of quality.

3.5.2 Information Asymmetry

The consumers' inability to assess the quality of health information directly is a source of information asymmetry. Information asymmetry refers to the situations in which one side of a transaction has more or better information that the other side. The health information exchanged in our platform belongs to a category of experience good or credence good. This kind of asymmetric quality information can lead to a "market for lemons" (Akerlof, 2013). The effect would be that poor quality is crowding out the higher quality information and the market would be dominated by poor quality information. The common approach to handling information asymmetry is using mechanisms such as reputation systems which signal the quality in the market. See Section 3.5.6.1 for an explanation of reputation systems.

3.5.3 Returns to Scale

One of the important peculiarities of health information, like other types of information is that it is expensive to produce but cheap to reproduce (Bates, 1989; Shapiro and Varian, 1999). It can easily cost over a hundred million US dollars to produce the first DVD of a Hollywood film, whilst the second DVD can cost well under a dollar. This cost structure - high fixed costs and low marginal costs - cause great difficulties for markets (Varian, 1998).

In the context of this study for producing customised information targeted to the information seeker's requirements; an information provider may spend a considerable amount of time searching, acquiring, and customising the information, but once the information has been produced, the cost of selling another piece of it is close to zero (Ge et al,. 2005). When users can reproduce information at very low cost, there is often no control on how the information user exploits or distributes the information. The unique cost structure of information makes it very hard to generate revenue from trading information itself and should be considered in designing the revenue model for our platform (see Section 3.5.5).

3.5.4 Incentive Mechanism

The platform must ensure sufficient thickness, which means it should attract a satisfactory number of information providers and seekers. It also needs to overcome the congestion that thickness can bring to the market. Incentive mechanism refers to set of design features that ensure market thickness and overcome congestion in this research. In order to design an appropriate incentive mechanism, it is needed to understand the motivation and barriers behind participation of both sides of the platform. This section summarises these motivations and barriers and discusses an appropriate design to achieve sufficient market thickness and manage the level of congestion. It should be noted that further empirical study is needed to determine the most efficient incentive mechanism. Research questions that should be answered empirically are highlighted.

3.5.4.1 *Incentives for Information Providers*

The viability of the health information platform depends on the ability of encouraging sufficient high-quality information providers. If the majority of questions in a information market are left unanswered (i.e., question starvation), this may discourage the continued participation of information seekers and ultimately affect the viability of the market (Chen et al., 2010). People's contribution to online platform is voluntary and therefore it cannot be forced. Rather it should be encouraged and facilitated. People assess the value of their contribution against its costs and contribute only if it is rewarding for them (Chang & Chuang, 2011; Hung, Durcikova, Lai, & Lin, 2011). The cost of providing information includes loss of exclusivity of information and investment of time and effort to device piece of information. On the other hand, the sense of satisfaction for having helped someone or recognition of contribution by offering points or financial rewards are examples of benefits for sharing information.

Different theories have been used in information management literature to identify and understand the influential factors on sharing information. The most relevant theories are brought together to build a complete picture of the reason behind information providers' decisions to participate in the online health information platform.

Social Cognitive Theory

Social Cognitive Theory (SCT), which explains how people acquire and maintain certain behavioural patterns, has been widely applied in information management literature (e.g. Chen & Hung, 2010; Chiu et al., 2006). SCT argues that human behaviour is shaped in terms of a triadic, dynamic, and reciprocal model in which behaviour, personal factors, and environmental influences all interact (Bandura, 1989). According to SCT the question of "why do information providers share their information?" should be tackled from the perspective of both individuals and contextual factors (See Figure 4). Bandura believes that 'self-efficacy' and 'outcome expectation' are the personal factor influencing behaviour. In the context of this research, self-efficacy means that individuals share their information if they feel confident about their ability of providing information. Outcome expectation means that individuals contribute their information if they expect benefits out of their contribution. In other words, individuals choose to share their information if they evaluate it as an advantageous activity.

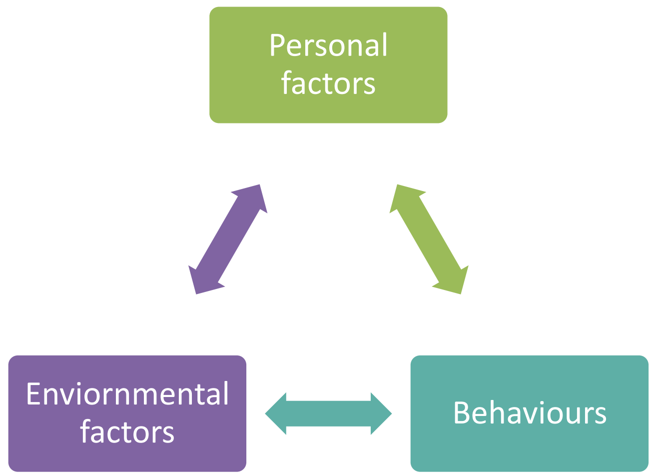

Figure 4: Social cognitive theory

Although SCT considered contextual factors as an important pillar of explaining human behaviour, it is limited in addressing what components are within a social network and how they influence an individual's behaviour. People who choose to share their information in the health information platform engage in a social interaction and form a kind of social network. This network influences the behaviour of information sharing. For example, the norm of reciprocity could provide important environmental conditions for knowledge exchange (Chang & Chuang, 2011). Social Capital Theory can supplement the Social Cognitive Theory (Chiu et al., 2006) to explain how the nature of social interactions and benefits embedded in network affect information sharing.

Social Capital Theory

Social capital refers to the assets or resources embedded within, available through, and derived from the networks of relationships between individuals and their communities (Nahapiet & Ghoshal, 1998). The main argument of Social Capital Theory (SCT) is that social relationships amongst people can be fruitful resources. In the context of this study, social capital theory can explain how social capital can influence the extent of information sharing. Nahapiet and Ghoshal classify social capital with three distinct dimensions: structural (the overall pattern of connections between actors), relational (the kind of personal relationships people have developed with each other through a history of interactions), and cognitive (those resources providing shared representation, interpretations, and systems of meaning among parties) (Nahapiet & Ghoshal, 1998). In the information sharing context, the structural dimension of social capital is manifested as social interaction ties, the relational dimension is manifested as trust, the norm of reciprocity and identification, and the cognitive dimension is manifested as shared vision and shared language (Chiu et al., 2006) (See Figure 5). Social Capital Theory can be helpful in explaining the social benefits enjoyed from sharing information in the online health information market. For example, according to SCT, members are motivated to contribute more when they expect that their invested time and effort is reciprocated by other members (Chang & Chuang, 2011).

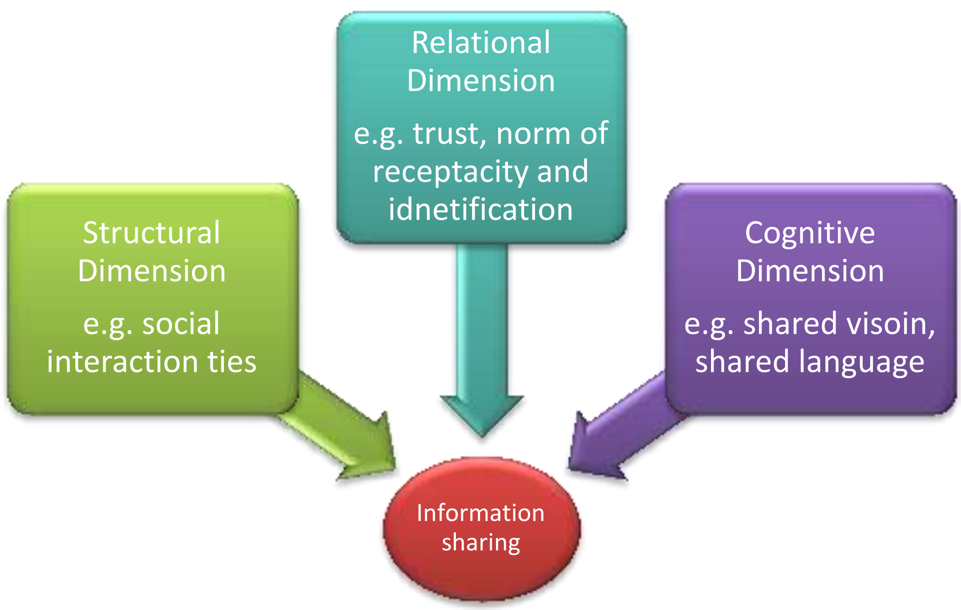

Figure 5: Social factors affecting information sharing based on social capital theory

Obviously SCT focuses on the social influences of information sharing and ignores the individual motivation affecting information providers to participate in the Health Information Market. On the other hand, Social Cognitive Theory generally argues that people are more likely to share their information if they feel confident about their ability and if they expect beneficial outcomes out of their contribution. However, it remains silent about what sort of benefits are associated with information sharing. Economic Exchange Theory and Social Exchange Theory can be used to elaborate these benefits.

Economic exchange theory

In the economic exchange theory (EET) perspective, each person's behaviour is influenced by rational self-interest. When a person feels that the obtained rewards are more than the cost, they will share their knowledge (Constant et al., 1994). It implies that information providers are more likely to participate if their cost of contribution will be compensated by extrinsic benefits such as monetary rewards or reputational feedback (See Figure 6). EET is focused on the extrinsic benefits of behaviour and ignores the intrinsic benefits of information sharing.

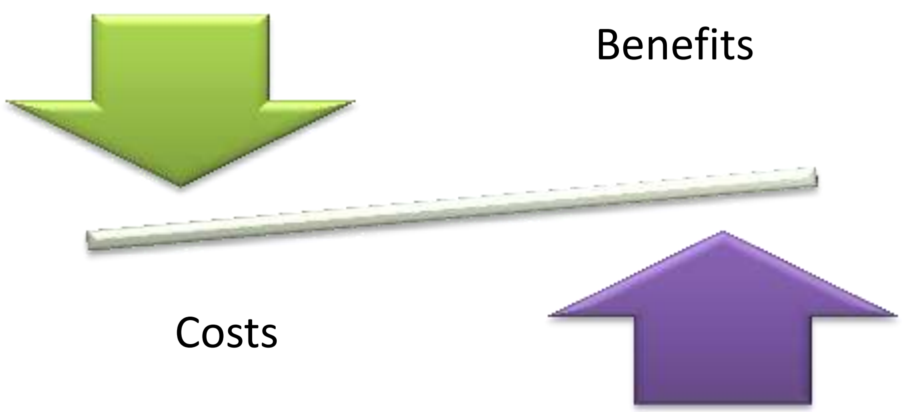

Figure 6: Rational behind human behavior

Social exchange theory

Whilst Economic Exchange Theory concerns extrinsic benefits, Social Exchange Theory (SET) concerns the intrinsic benefits (Bock & Kim, 2002). Similar to Economic Exchange Theory, SET proposes that all human behaviour involves benefit maximisation and cost minimisation, however in social exchanges (See Figure 6), the obligations to receive future returns are not clearly specified (Chen & Hung, 2010). The intrinsic benefits of sharing information in the health information market can be altruism and empathy, which are derived from the intrinsic enjoyment of helping others.

In the setting of this research, it is important to distinguish between two types of factors influencing information sharing in the abovementioned theories: motivational factors and prerequisite factors. Motivational factors refer to intrinsic or extrinsic benefits of information sharing such as altruism or reputation; however, prerequisite factors refer to requirements in information sharing which do not play a motivational role.

For example, self-efficacy which is defined as one’s perceived capability to perform actions and complete tasks (Bandura, 1997:21) is obviously a prerequisite of information sharing. People who do not feel confident about their ability of providing valuable information are less likely to contribute. However, people who have high-efficacy do not contribute if they are not motivated. Similarly, trust, which refers to an individual's expectation that members in a community will follow a generally accepted set of values, norms, and principles (e.g. keeping promises, avoiding taking advantages of others) (Chiu et al. 2006) is a necessity in information sharing (Chen & Hung 2010), but it does not play a motivational role. Likewise, shared language and shared vision are classified as prerequisite factors. Although both motivational and prerequisite factors can be influenced by the design of the platform, the focus will be on the motivational factors as the aim of this research is to design an incentive mechanism to motivate information providers to contribute high quality health information.

Based on the effect they could have on design of the platform, the motivational factors extracted from information sharing theories are categorised into intrinsic, social and financial motivations. The next section further elaborates on these categories of motivation based on the empirical research which studied them.

3.5.4.2 *Intrinsic Motivation*

Intrinsic benefits refer to those motivations stemming from factors inside individuals (Ryan & Deci, 2000). The main intrinsic motivation of information providers to share their health information is altruism. Altruism is defined as the opposite of selfishness and refers to doing something for benefit of others at some cost to oneself (Ozinga, 1999). A person who acts out of altruism aims solely to benefit others without any intent to promote, gain or improve his or her situation (Friedman et al., 2003). Altruism was the most influential factor for health answerers in social health Q&As (Oh, 2012). Empathy is a kind of altruism and refers to the ability to understand the feelings or situations of others. It has been reported as an important motivation of members of health groups for sharing and listening to personal experiences and stories of others (Preece, 1999). In social health Q&A, people are highly motivated by their empathy with others who are going through similar pain and stress due to certain diseases (Oh, 2012). In the context of this research, empathy is expected to be an important motivator for information sharing.

Further intrinsic motivations are enjoyment and achievement, through participating in a community, individuals have an opportunity to learn new things and exercise their knowledge (Nov. 2007). Participants of social Q&As have the opportunity to learn about best practices and be informed about changes (Oh, 2012). It is expected that the desire to learn, enjoyment and achievement will encourage participation in the online health information platform.

If information providers share their information just based on intrinsic motivations, there is no need to design a specific mechanism to incentivise information providers as the motivation stems just from factors inside individuals and there is no way to incentivise them externally.

3.5.4.3 *Social Motivation*

Social motivations refer to motivations derived from the networks of relationships between individuals and their community. Community refers to a group of people who regularly interact with each other and share a common set of values, acquiring a sense of common purpose and belonging that unites them into one community. This community in turn fosters a motivation to contribute, for example through sharing information, and thus helping the collective to which one belongs (Kuznetsov, 2006). A community of users has been observed as a critical factor in the success of Q&A sites. Yahoo! Answers, which enjoys a large community, outperforms sites that depend on specific individuals to answer questions, such as library reference services. It provides better answers compared to other

Q&A sites with a very similar design but a smaller community (Harper et al., 2008). Oh (2012) considered people's need of connecting to others and belonging to a social group as a motivation for sharing information in social health Q&As and called it social engagement. Chang & Chuang (2011) named it social interaction and showed that it has a positive effect on the quality (but not quantity) of knowledge sharing.

Reciprocity is the second social motivation, which is defined as a form of conditional gain; that is, people expect future benefits from their present actions. This means that a behaviour is done in response to previous friendly actions (Fehr & Gachter, 2000). According to Social Capital Theory, a norm of reciprocity is formed over a long period of time within and across groups and individuals will reciprocate others' efforts to share knowledge by contributing more (Hung et al., 2011). In the information sharing context, people who expect reciprocity will share more ideas with higher quality (Hung et al., 2011; Kuznetsov, 2006; Chang & Chuang, 2011). In this research, people might not expect to receive the returned help from the original person that they had helped, but they might believe that someone else in the community will help them in the future. This is called "generalised reciprocity" (Ekeh, 1974).

Social recognition is another important social motivation for information providers of the platform. People in all fields strive to be recognised for their work and information sharing is not an exception. A reputable identity is truly rewarding for it signifies success and accomplishment (Kuznetsov 2006). Chen et al. (2010) argue that having a system allowing exchange parties to build reputations is a crucial feature for achieving efficiency in online knowledge markets. In a world of anonymous interactions, reputation becomes the most powerful way of signalling quality and gaining a reputation through the point systems or being the top answerers, and can be an important motivation for answerers to contribute their information (Oh, 2012). Hung et al (2011) showed that reputation feedback has a significant effect on both the quantity and quality of contributions of individuals in a team setting. However, reputation is found to have positive effects on the quality, but not the quantity, of shared knowledge on the internet (Chang & Chuang, 2011). In addition to allowing the participant to build an online reputation, the platform can encourage the users to reveal their real identity and leverage it to generate high quality information. The users, in this way, have higher incentives to cooperate as they can gain offline reputation.

Tausczik & Pennebaker (2011) showed that the offline reputation of contributors in MathOverflow, a social Q&A site dedicated to math, is related to quality of their contributions.

In order to socially motivate information providers, the platform needs to build and nurture a community of users to foster a sense of belonging and shape a norm of reciprocity among participants. Furthermore, the platform should stimulate social recognition motivation through signalling the level of contribution of information providers to the community. Different mechanisms ranging from simple techniques such as posting a list of 'top contributors' each week, to complicated 'reputation systems' are used to socially incentivise information providers.

3.5.4.4 *Financial Motivation*

Financial motivation refers to any form of monetary reward paid to information providers to stimulate their participation. The effect of financial incentives on the quality of shared information is examined in several empirical studies. For example, Google Answers as a platform that motivates information providers using financial motivation has been studied in several researches. The answer quality and responsiveness of Google Answers was found to be superior to the free Q&A sites (e.g. Yahoo Answers, Live QnA) (Harper et al., 2008). However, it was showed that financial motivation leads to a significantly longer, but not better, answer in Google Answers and the study highlighted the limitation of monetary incentives in designing mechanisms of information exchange (Chen et al., 2010).

Monetary reward is the most obvious form of extrinsic motivation that will increase the benefit of information sharing, however it may have a negative effect on intrinsic benefits of information sharing especially when it has been used as a controlling instrument. Monetary rewards have both a controlling aspect and an informational aspect. If rewards are perceived as controlling, they will crowd-out intrinsic motivation by inducing a shift in the perceived locus of causality from internal (self-determined) to external (other-determined) (Wang et al. 2012). This "hidden cost of reward" (Leper and Greene, 1978) is observable if a previously intrinsically-motivated task is rewarded by external incentives.

Forker et al. (2013) extended the applicability of the crowding-out principle and applied it to the relative increase or decrease in community involvement.

Intrinsic motivation has effect on health information sharing behaviour. Therefore it is important to know if monetary reward imposes some hidden cost to the platform. In the context of this research, the choice of financially incentivising information providers may crowd out or crowd in both intrinsic and social motivations of sharing information. That is, if information providers are paid for the information they share, the crowd-out effect is observable as the monetary reward plays a controlling role. That is, monetary reward has a negative effect on intrinsic and social motivations such as altruism or reciprocity. In this case, the monetary reward should be stronger than the crowding-out effect to cover the hidden cost of reward. However, if monetary reward is used to highlight the effort of those who contribute a large number of high quality information, a crowd-in effect is observable as the rewards play an informational role. That is, monetary reward reinforces the intrinsic and motivations such as self-achievement and social recognition.

If economic motivation is the main most effective way of incentivising information providers, the platform needs to establish a payment system. The payment system should address the features such as the price of information or who determines the price, information provider, information seeker or the platform; etc.

3.5.4.5 *Summary*

The participation of information providers to share their information is one of the main conditions under which online health information markets work efficiently. Individuals' participation is dependent on the intrinsic and social or financial benefits expected from information sharing. Different types of motivation ask for different types of mechanism design. Table 3 summarises the design consequences of each way of motivating health information providers.

Table 3: Design consequences of different types of motivation

Motivation type	Incentive mechanism

Intrinsic	No specific mechanism
Social	Build a community of users/ reputation system
Economical	Payment system

In order to design an efficient incentive mechanism to bring information providers to the platform, it is important to identify which type of motivation (intrinsic, social, and economic) is more influential than the other. The information sharing theories on their own and empirical researches do not clearly specify which motivation is the most important factor in information sharing. Therefore, an important empirical research question is:

RQ1: What motivation or incentive works best in maximising the quality of health information?

3.5.4.6 *Incentives for Information Seekers*

The high quality participation of information seekers is as equally important as the information provider contribution for the viability of the platform. If the overall volume of questions is small or the platform is full of low quality questions, it may not provide enough value to become a preferred destination for information providers. Hsieh & Counts (2009) argue that one source of inefficiency in the information market is the existence of spam and non-serious questions on the platform that waste valuable time and the attention of the potential answerers that otherwise could be spent on real question that truly need answers.

The platform offers several benefits for the participation of information seekers. People have convenient access to health information in the privacy of their own homes, at the time they wish and for as long and as many times as they wish. It also saves money if they would otherwise need to pay for a consultation with a doctor or miss work to do so. Patients are eager to know more about their conditions, possible treatments and preventive actions. Furthermore, given the reported possibilities for medical errors and misdiagnoses, online health information is able to help people to identify such errors more easily (Nuffield Council on Bioethics, 2010).

Information seekers face particular challenges for their participation. The first problem of information seekers is related to quality of information exchanged in the market. It is very hard for users without medical background to assess the quality of health information. Platforms need to deploy mechanisms that ensure the quality of information to attract sufficient information seekers. Section 3.5.6 particularly looks at mechanisms that ensure quality in our platform.

The second difficulty of seeking information is related to question formulation. It is argued that users without medical training have difficulties in formulating their request as lay people describe disease and conditions in simple terms and their vocabulary does not match with medical terminology (see Section 3.4.3). This problem can be relieved if questions are asked in natural language rather than keyword searching. Furthermore, information seekers and providers are able to question back and forth to clarify their intention.

Given the several benefits that might incentivise information seekers, the platform may get more than the desirable number of information seekers on board. This phenomenon is called market congestion (see 3.4.2) .One possible solution to this problem is making the participation costly for information seekers. The cost can be in two types: social and/or financial. For example, in Google Answers, information seekers are needed to pay a price to get their question answered. In Yahoo Answers, the asker loses some points when they ask questions. The social and financial incentive makes the information seeker more selective in asking their questions. This approach leads to a trade-off between quality and quantity of information seekers' contributions for the platform designer. The platform designer may increase the cost for information seekers' contribution if the quality of information seeking is important and vice versa. From a designing point of view, it is very important to know what type of cost (incentive) increases the quality of information seeking. Therefore, an important empirical research question is:

RQ2: What disincentive works best in maximising quality of health information?

3.5.4.7 *Network Effect*

An influential factor on information sharing behaviour in a two-sided platform is the effect of information seekers' behaviour on the behaviour of information providers. The quantity and quality of questions raised by information seekers affects the contribution of information providers. Information providers are discouraged if there are not a sufficient number of high-quality questions to answer on the health information platform. For example, if the information seekers post unserious questions they automatically discourage those information providers who are motivated by "altruism"; or if they post boring questions, they discourage those who are motivated by "self-enjoyment", etc. Therefore, an important empirical question is:

RQ3: Does the quality of information seekers' contributions (question side) have an effect on the quality of information providers' contributions (answer side)?

3.5.5 Revenue Model

As a part of platform design, it is needed to design a revenue model for the platform. Platform owner is a primary player of the platform and should have enough incentive to participate. Revenue can be considered as the platform owner incentive. The platform needs to have enough revenue to cover the cost of establishing, maintaining and improving the market. Furthermore, the design of a revenue model affects participation and quality of participation of both sides of the platform. There are several concerns that are specific to the health information platforms that should be carefully considered in designing the appropriate revenue model.

There are two primary incentives for establishing this platform. The first is simply making profit. The revenue of an information platform can be generated from advertisements, membership fees, trading information itself, selling the information to third parties or a combination of these approaches. The second incentive is promoting high-quality health information.

Either to promote high quality information or make profit the platform objective is to maximise the number of information providers and seekers and the quality of exchanged information. However, each structure of revenue model causes certain advantages and disadvantages which necessitates different ways of designing. The following section discusses the possible alternatives which are summarised in Table 4.

Table 4: Revenue model alternatives

Revenue Model	Characteristics	Advantages	Disadvantages
Transaction-based Google Answers	Information seekers pay information providers and the platform gets a fraction of total paid amount per transaction	• Dis-incentivises low quality contributions of information seekers • Increase the number of information providers • Incentivises high quality contributions of information providers	• Decrease the number of information seekers as they are needed to pay • Risk of crowding out intrinsic motivation of information providers • Hard to apply due to structure of information(expensive to produce first copy and easy to copy)
ISR- model Yahoo Answers!	Asking is free and providers answer the question based on intrinsic motivations. The platform earns money from independent sources such as advertisement, selling health data, etc.	• Increase the number of information seekers as they can get information for free	• No disincentive for information seekers not to as low quality questions • lack of incentive for information suppliers to provide information, so many posted questions may remain unanswered • Conflict of commercial interest may cause a negative impact on perception of information providers and seekers

Revenue Model	Characteristics	Advantages	Disadvantages
ISR model which pays good providers YouTube	Similar to ISR model, asking is free but the platform pay a cut of its generated revenue from independent source to its best providers It relaxes the problem of unanswered questions and improves the problem of quality of information	• Increase the number of information seekers as they can get information for free • Increase the number of information providers • Incentives for high quality contributions of information providers	• No disincentive for information seekers not to raise unserious questions • Conflict of commercial interest may cause a negative impact on perception of information providers
Donation-based Model Wikipedia	Providers share their information for free and seekers find information for free and the incurred cost is covered based on donation	• Increase the number of information seekers as they can get information for free • No conflict of commercial interest	• No disincentive for information seekers not to ask low quality question • lack of incentive for information suppliers to provide information, many posted questions may remain unanswered • Difficulty in covering the cost of platform • Lack of incentive for platform owner to invest on services

3.5.5.1 *Transaction-based Model*

In this model, information seekers pay providers to answer their questions. The platform gets a fraction of the total price per transaction. The downside to this approach is the difficulty of generating revenue from trading information itself due to the structure of information. The production of the first copy of the information may be expensive; the cost for the creation of additional copies tends to be approximately zero (Rose, 1999, Shapiro and Varian, 1998). Therefore, reselling information is difficult.

Google Answers, which was in operation in the US from 2002 to 2006, is an example of a transaction based question and answer service where Google Researchers answer questions posted by askers. Google Answers was discontinued by Google as of December 1, 2006. No special reason was given by Google for this move (Raban, 2008). Recently, Google has launched Helpouts, a marketplace of live video-based help services. Unlike Google Answers, copying information for free is not the case in this service as information is exchanged in the form of live video.

The effect of this revenue model on the quality of answers is studied in several studies. Harper et al. (2008) argued that answer quality was typically higher in Google Answers (a fee-based platform) than in the free sites and paying more money for an answer led to better outcomes (Harper et al., 2008); however, Chen et al. (2010) showed that price has no significant effect on answer quality (Chen et al., 2010). To resolve this inconsistency, Jeon et al. (2010) re-analysed data from these two studies and indicated that the price effect on answer quality is two-fold. Firstly, a higher price significantly increases the likelihood that a question receives an answer. However, for questions that receive an answer, price has no effect on answer quality (Jeon et al., 2010).

This model naturally provides a solution to the problem of low quality questions (e.g. non-serious and spam questions) as information seekers are required to pay for raising questions. As a result, they are forced to be more selective in the questions they ask. Furthermore, this model acts more efficiently regarding balancing the need of the asker with the availability of the answerer because in this model questions that are more important to askers, as signalled by a higher price, should receive more attention from potential helpers (Hsieh & Counts, 2009).

3.5.5.2 *Independent Source of Revenue (ISR) Model*

In information, providers contribute their information just based on intrinsic motivation and seeking information is free; however, the platform generates revenue from independent sources such as advertisements or selling information. In this model the platform owner aims to increase the number of visitors to maximise its profit.

There are many examples of successful use of advertisement as the main source of revenue in information exchange platforms. Examples include Yahoo! Answers, Naver Knowledge–iN, Answerbag, etc. Yahoo! Answers features more than 10 million questions and has attracted a community of 120 million users in early 2007 (Koutrika et al., 2008). However in health information platforms, the HON code of conduct (1995) and information standard guidelines (2009) both emphasise that it is important to avoid conflicts of commercial interest for any organisation that produces health information. According to their codes of conduct, if advertising is a source of funding for a website, this must be clearly stated. Furthermore, advertising and other promotional material should be differentiated from the original material. It should be noted that direct direct-to-consumer advertising of pharmaceuticals is prohibited in the European Union (EU). Therefore, the platform based in the EU is not able to advertise pharmaceutical products.

Another independent source of revenue for a health information platform can be selling the shared information in the market to industry. Pharmaceutical companies, research institutes, and medical device makers are interested in paying for such information. PatientsLikeMe is good example of this revenue model. PatientsLikeMe is a patient network that describes itself as a for-profit company with a 'not just for profit' attitude. It does not allow advertising on its site. Instead, the company generates revenue from aligning patient interests with industry interests. PatientsLikeMe sells aggregated, de-identified data that patients share about their conditions to its industry partners. This information is valuable for the industry to better understand the real-world experiences of patients as well as the real-world course of disease (https://www.patientslikeme.com).

Obviously, selling health information arises several privacy concerns. Confidentiality of data relating to individual patients and visitors to a medical/health Web site, including their identity, should be respected by this website. The website owners undertake to honour or exceed the legal requirements of medical/health information privacy that apply to the country and state where the website and mirror sites are located (HONCode principles, 1995). Furthermore, one of the principles of efficient market operation is market safety. Market owners need to make it safe for those who have been brought together to reveal or act on confidential information they may hold. When a good market outcome depends on the disclosure of conditional information, the market must ensure conditions or offer incentives that make market participants willing to disclose their information (Roth, 2007). Selling market participants' data may have negative effects on information seekers to reveal their personal health information in the market.

As the information providers are not paid in this model, answering a question and the quality of the answer depends on the ability and willingness of volunteer information providers to address the asker's needs. It was found that a significant fraction of the questions may remain unanswered in advertisement-based question and answer sites (Shtok et al., 2012). This phenomenon is called "question starvation". It was showed that in Yahoo! Answers that only 17.6% of questions receive satisfactory answers within 48 hours. For those unresolved questions, nearly 1/5 of them receive no response (Li & King, 2010). Another study suggested that general-purpose question and answers sites have answer rates of between 66% and 90%; and often attract non-factual, conversational exchanges of limited archival value (Mamykina et al., 2011).

Another problem associated with the revenue model is the low quality of information seekers' contribution. For example, when asking questions is free, information seekers do not have any disincentive not raise non-serious and spam questions in question and answer websites. When browsing through these sites, visitors will notice questions that are not serious questions or do not make sense. Potential answerers may spend valuable time and attention on these non-serious questions, missing out on more serious questions that really need answers (Hsieh & Counts, 2009).

3.5.5.2.1 ISR model which pays good providers

A solution to relaxing the problem of question starvation could be paying a cut of its generated revenue from independent sources to the best information providers. In this way, information providers receive additional incentives to share their information. YouTube launched the "YouTube partner earnings" programme in 2007, which offers the video creators a cut of its advertisement revenue and increased the quality of its video.

3.5.5.3 *Donation-based Model*

Donation-based models can be considered as a form of earning revenue from an independent source, which are donations in this model. However, the goal in this case is earning money to cover costs rather than making profit. In this model, similar to the ISR model, information providers share their information for free and information seekers have access to information free of charge and the incurred cost to platform owners, such as server fees, administration costs, etc. is covered through donations. The successful example of this model is Wikipedia, which is the 6th most visited website (alexa.com, 2013), paid for by half a million donors and could be worth $5 billion if it tried to make money (Business Insider, 2013).

There are some organisations or schemes aimed at addressing the concerns over the unequal quality of online health information. For example, the ‘Health on Net’ organisation promotes and guides the deployment of useful and reliable online health information and its appropriate and efficient use. It is accredited to the Economic and Social Council of the United Nations and funded by the State of Geneva, several European projects, the French National Health Authority (HAS), the Provisu foundation and the Geneva Hospital. Similarly, the Health department of the UK-commissioned the Information Standard Scheme to encourage the health information providers to produce clear, accurate, balanced, evidence-based and up-to-date information and help the public to verify the quality and reliability of health information. These organisations have the motivation to finance the online health information market that facilitates the exchange of relevant, trustworthy and high quality health information.

Furthermore, it is extremely important for platforms that produce health information to be free of any commercial conflict of interest (HON code principles, 1995 & information standard certification, 2009). Thus, this incentive model seems ideal for exchanging online health information; however, relying on donations as a main source of revenue may risk the sustainability and improvement of the market. The platform needs to attract a large community of information providers and seekers. It also requires investing on mechanisms which improve the quality of the exchanged information, reduces search costs and facilitates match making between information seekers and relevant high quality information. Obviously, establishing and maintaining such a platform imposes costs such as server fees, administration costs, designing a mechanism for the market to work efficiently, etc.

For example, Wikipedia runs annual campaigns to seek donations using banners at the top of Wikipedia pages asking for money to cover the costs. It raised $16 million in 2010, which was double the amount generated in 2009. However, this amount is a change compared to the $500 million invested in Facebook, nearly at the same time (NBCNEWS, Jan. 3, 2011[2]). This amount causes a little incentive for Wikipedia to invest in improving its services. Maybe this explains why everything has remained nearly the same in Wikipedia since its foundation. Wikipedia's design was appropriate in 2001 and it is very different from the easy-to-use social and commercial sites that dominate the internet today (Simonite T., 2013). [3]

3.5.5.4 *Summary*

To summarise, there are two possible structures for incentivising platform owners: (1) for profit model; (2) non-for-profit model. In order to maximise profit, platform owners can either earn their revenue out of transactions occurring over the platform or find an independent source of revenue such as advertisement or selling information to pharmaceutical companies in this case. The platform can choose to pay a cut of its revenue earned from independent sources to information providers to increase market efficiency.

It should be noted that the design of revenue models and incentive mechanism are intertwined. For example, transition based models naturally use financial incentives for information providers and financial disincentives (cost). ISR models cannot financially incentivise the information provided and should rely on intrinsic or social incentives, etc.

From a design point of view, it is important to empirically investigate the effect of revenue models on the quality of contribution of both information providers and information seekers. Therefore, an important empirical question is:

RQ4: What type of revenue model is associated with high quality information (both questions and answers)?

[2] Jimmy Wales' creepy stare rockets $16 million in Wikipedia donations
[3] http://www.technologyreview.com/featuredstory/520446/the-decline-of-wikipedia/

3.5.6 Quality Signal Mechanism

Although incentive mechanisms and revenue models have an effect on the quality of information, the platform may use specific mechanisms to overcome quality concerns such as information asymmetry due to the high importance of ensuring quality in our platform. In the following, the appropriateness of these mechanisms for our platform should be analysed:

3.5.6.1 *Reputation Systems*

The common solution to solve information asymmetry issues in online markets is deploying a reputation system. Reputation systems are online mechanisms that aggregate feedback from users' past experiences, to enable more informed decisions of other users in the future. Examples of websites using reputation systems are eBay, Amazon, Yelp, Digg.com etc. (Parkes & Seuken, 2011). Reputation systems elicit information form past users and shares it with the community and in this way helps the community to get better decisions. Since the contributions of users are recognised through reputation systems, users have more incentive for high quality contributions.

There is a particular challenge for designing a reputation system for our platform due to controversy related to the ability of patients (lay users without medical background) to provide accurate feedback about the quality of care they have received. There is a controversial view in the literature about whether patients are able to provide feedback on the technical quality of healthcare or not. One view argues that patients cannot report the technical quality of care (Frank, 2004) (Chang et al., 2006); another view suggests that there is a meaningful relationship between the technical quality of health care and patients' feedback (Greaves, Felix et al., 2013 & Bardach et al., 2013).

Reputation system works based on uses' feedback. In the setting of this research user/patient feedback can be in the form of "like", "follow", etc. that users give to the piece of information or the information provider. These feedbacks are later aggregated and publicized as an reputation of a particular user in the online platforms. Prior to the design of the reputation system for online health information platforms, it is important to know if there is a relationship between information seekers' feedback on quality of health information and objective measures of health information quality. Therefore, an important empirical question is:

RQ5: Does patient feedback indicate quality of online health information?

3.5.6.2 *Certificates*

The platform can verify the medical certification of information providers and publicise it to signal quality in our platform. It is possible to try to draw some conclusions about the ability of an expert to give advice on the basis of their certifications. Statements from experts about education or certificates can be checked as a part of quality assurance by the platform. This again is no guarantee of good advice (Muller, 2005). This approach is not applicable to those who do not have any certification but might be able to contribute high quality information such as chronic patients.

3.5.6.3 *Guarantees*

Money-back guarantees are often-used means of increasing an information seeker's confidence beforehand. However, as it is difficult for an information seeker to give knowledge back, there is a danger that guarantees will be abused. Opportunistic behaviour of advice seekers can be expressed as a misuse of guarantees. Since information cannot be returned when the transaction is cancelled, it is appropriate that a guarantee is combined with a review of the information through a trusted-third party. In an electronic marketplace, the complete interaction between information seeker and information provider can be recorded and evaluated in case of conflicts (Muller, 2005). This is a common approach in medical advice giving platforms in which information providers are certified physicians.

3.5.6.4 *Previewing*

In previewing, the information seeker can get part of the goods for inspection, e.g. a trailer for a motion picture. Previewing the information in the form of an abstract allows information evaluation for relevance, but not necessarily for quality. Another problem with previewing is that it is difficult to ensure that the information seeker does not receive too much information so that there is no longer any need to proceed with the exchange.

3.5.6.5 *Reviewing*

One form of quality testing that has been established for scientific publications and patents is reviewing. An article may only be published or a patent awarded after a review has been made by other experts. Reviewing has two major shortcomings that are applied in our platform. Firstly, a review of all answers is very costly and time-consuming; secondly, reviewing is performed after the exchange of information; however information seekers need to know about the quality of information beforehand. It is possible to review the information before it passes on to an information seeker, however it slows down the process and it is very inefficient in the cases where the information is needed urgently.

3.5.6.6 *Summary*

There are several mechanisms to overcome quality uncertainty and each has its own advantages and disadvantages. It is not clear which one works best for addressing the quality concern of our platform. The problem of information asymmetry can be addressed through a reputation system. However, it should be empirically investigated whether or not health information can be rated by lay users or not. It is worth noting that the design of a reputation system and incentive mechanism is interrelated because reputation is the social incentive for platform participants to contribute high quality information. Moreover, it should be noted that all discussed mechanisms are applicable to both sides of the market. However, the quality of the contribution of the information provider has higher importance form a health point of view.

In order to design an efficient mechanism to overcome quality concerns specific to the platform for exchange of online health information, it is important to identify which type of quality signal mechanism is the most influential mechanism in maximising quality. Therefore, an important empirical question is:

RQ6: What quality signal mechanism is associated with high quality information?

3.5.7 Combination of Mechanisms

The design of three mechanisms: the incentive mechanism, revenue model and quality signal mechanism have been discussed separately. The design of the aforementioned mechanisms are intertwined and interrelated. For example, using financial incentives and designing revenue models have mutual effects; or reputation system as a quality signal mechanism lets the participant to build a reputation online, then the reputation may incentivise the participant to contribute high quality information. The platform designer should not only think about the design of these mechanisms separately but also should consider a combination of these mechanisms to maximise the quality of information. Therefore the final empirical question is:

RQ7: What combination of mechanisms in the platform leads to high quality of information?

3.6 Conclusion

This chapter has presented a framework for the efficient exchange of online health information. The framework is grounded on the notion of 'Market design' and 'Multi-sided platform'. This chapter began by explaining why the research problem can be tackled by the aforementioned notions. Next, it identified the conditions under which the market for exchanging online health information works efficiently: 1- Market thickness, 2- Market congestion, 3- Reducing search cost and 4- Reducing shared cost. It focused on those aspects of efficiency which are relevant to maximising the quality of exchanged health information. Then, the design of the platform that maximises the quality of health information was discussed. Within the platform design section, this chapter identified three mechanisms, namely: Incentive Mechanism, Revenue Model and Quality Signal Mechanism that has an effect on the quality of exchange health information. In the incentive model section, the design features that contribute to achieving market thickness and managing market congestion were analysed. The incentives of information providers were categorised into three categories of 1- intrinsic, 2- social, 3- financial, based on the effects they have on design of the platform. Further empirical study was proposed to decide which category/categories is/are the most effect set of incentives of health information sharing. This chapter particularly looked at the effect of choosing different revenue models by platform owners on the conditions of market efficiency and highlighted the research question that helps choosing an efficient revenue model. The suitability of different quality signal mechanisms for the online health information exchange platform was analysed and further empirical study was suggested. At the end, the platform considered a unified system and the empirical question was suggested to find out which combination of mechanisms can maximise the quality of exchanged information. The next chapters are going to empirically investigate the research questions derived from the outlined theoretical framework.

4 Methodology

4.1 Introduction

This chapter is concerned with outlining and justifying the empirical approach to answering the research questions developed in the theoretical section. In the first section, the ontological and epistemological assumptions that underpin this research are stated to justify the use of the quantitative method of data collection and analysis. The next section outlines the conduct of the research and explains the data collection process. Then, the measurements of both quality of information (i.e., dependent variable) and design features (i.e., independent) are presented. The characteristics of collected data for answering the research questions are described. Finally, the final section elaborates the analytical approach and methods of data analysis to answer the research questions.

4.2 Epistemological Positioning

In God we trust, all others bring data.

–William Edwards Deming (1900-1993)

Researchers have been advised to explicitly state their philosophical assumptions before deciding on an appropriate research method. The researcher's philosophical position plays a fundamental role when they are designing their research because alternative philosophical positions contain different assumptions and each can impact on the researcher's view of the world (Easterby-Smith et al. 2008). An understanding of this helps in designing the research in a way that is most appropriate for addressing the research objectives. This study belongs to the 'post positivism' philosophical tradition.

Each tradition has certain assumptions about ontology and epistemology. Ontology refers to the philosophical understanding about the nature of reality. According to post positivism, there is a real, objective reality, but humans cannot know it for sure. Epistemology is concerned with what can be regarded as legitimate knowledge (Walliman 2006) and how it can be acquired (Snape and Spencer 2003). Epistemology of post positivism can be considered as modified objectivism. It asserts that social phenomena and their meaning have an existence that is independent of the social researcher and the goal is to understand reality for sure but this is impossible. Therefore, results are just probably true.

This study believes in objective measurements of quality of health information. That is, a piece of health information has higher or lower quality that can be measured regardless of users' interpretation about the quality of it. Accordingly, it suggests criteria to measure quality of health information (see Section4.4.2). Therefore, this study can be categorised as a post-positivist study.

Many scholars find it helpful to distinguish between quantitative and qualitative research. Quantitative research can be constructed as a research strategy that emphasises quantification in the collection and analysis of data. By contrast, qualitative research usually emphasises words rather than quantification. This research follows a quantitative research strategy.

In this research, actual questions and answers were collected from question and answer platforms. The data collection method can be described as non-participant observation. This term is used to describe a situation in which the observer observes but does not participate in what is going on in the social setting (Bryman & Bell 2015, p281). The collected data were evaluated and quantified by human assessors. In order to analyse the data, this study utilises algorithmic statistical modelling. **Table 5** summarises the research approach of this study.

Table 5: Summary of research approach

Attribute	Research approach
School of thought	Post positivism
Research strategy	Quantitative
Data collection method	Non-participants' observation
Data analysis	Algorithmic statistical modelling

4.3 Research Design

The purpose of this research is to design a bottom-up approach to provide users with high quality health information. In order to achieve the research objective, this research argues that the 'market design' approach is the suitable theoretical lens. The literature review section of this research translates the research problem into a market design problem.

Accordingly the aim of this study developed into designing a market for exchange of online health information that maximises the quality of exchanged information. The literature review section critically assesses and analyses the knowledge sharing and online mechanism design literature and identifies the knowledge gaps of the literature for designing a health information market and proposes empirical research questions to fill the gaps.

This research has an exploratory nature and does not propose hypotheses; it raises research questions instead due to several reasons. First, the literature related to the research problem is insufficient to formulate a hypothesis. For example, the first question asks: “RQ1: What motivation or incentive works best in maximising quality of health information?” (See Section3.5.4). Although there are several studies about the motivations that have an effect on the quality of information sharing, the literature does not conclusively address which one is more effective than the other and as a result makes formulating a hypothesis an undesirable approach. Second, the data analysis methods that this research uses such as regression trees and random forest do not work based on hypotheses. Last but not least, this study used 31 predictors for predicting quality of health information. Formulating a list of 31 hypotheses is not favourable in terms of readability. The next section explains the design of the empirical section of this research.

4.4 Conduct of Empirical Research

Based on the proposed theoretical framework, (1) Incentive Mechanism, (2) Quality Signal Mechanism and (3) Revenue Model determine the quality of produced health information in Multi-sided platforms (MSPs). The goal of the empirical section is to assess how these mechanisms affect the quality of information exchanged in the health information platform. The research uses actual questions and answers exchanged on Q&A platforms. Question and answer (Q&A) platforms are a form of community platform that allow users to both ask and answer questions. They attempt to efficiently link the askers to answerers. Q&A platforms have become popular: people can share information and find answers for both general and specific questions. People seek information from a Q&A platform because they find it hard to formulate their information query as a web search request, or the content is not available on the Internet, or they would prefer to get help from people. Popular Q&A

platforms include Yahoo Answers and Naver. Yahoo Answers for example attracted millions of users and over 100 million answers for more than 20 million questions in just two year since its launch in 2005 (Jurczyk & Agichtein, 2007) (Jurczyk & Agichtein, 2007).

Different Q&A platforms embody different types of mechanisms. Furthermore, the quality of information is uneven, ranging from relevant and detailed to irrelevant and misleading. Thus, Q&A platforms can be utilised to test which mechanism or design feature is associated with high quality of information. Forty Q&A platforms were carefully analysed in order to find those which represent mechanisms extracted in the theoretical chapter. Table 6 indicates the 40 reviewed platforms and mentions the reason for exclusion of the platforms not chosen. The criteria for selecting Q&A platforms was mainly based on checking whether or not they are representing variation in the mechanisms they use in their platform because the empirical aim of this study is to investigate the effect of different mechanisms on the quality of generated health information. In case of similarity of mechanisms of platforms, popularity of the platform both among Internet users and in the literature made a platform more favourable for selection.

Platforms such as Google Answers and Mahalo Answers which are not active anymore have been included in the research sample as they represent different mechanisms. The inclusion of these platforms can be specifically interesting because it investigates the relationship between the design of these platforms and quality of information generated within them. This will reveal whether the inefficient mechanism design affects the quality of generated information within these platforms and finally led to discontinuation of this service or not.

Table 6: Reviewed platforms for selection

Platform Name	Web address	Why not chosen?
1. Able2Know	http://www.able2know.org	Access to data
2. AllExperts	http://www.allexperts.com	Chosen
3. Answer.com	http://answers.ask.com	Answers are generated partly by scraping and crawling

Platform Name	Web address	Why not chosen?
4. Answerbag	http://www.answerbag.com	Chosen
5. AOL Answer	http://aolanswers.com	Similar to Yahoo Answers and Answerbag
6. Ask a librarian	http://www.askalibrarian.org	It focuses on education not health
7. Ask Me Help Desk	https://www.askmehelpdesk.com	Similar to Yahoo Answers and Answerbag
8. Ask Meta Filter	http://ask.metafilter.com	Contains a lot of community features rather than Q&A platform
9. Ask The Answer	http://www.asktheanswer.com	It focuses on entertainment (horoscope) not health
10. Askville	http://askville.amazon.com	Similar to Yahoo Answers and Answerbag
11. Baidu Knows	http://zhidao.baidu.com	Chinese
12. Blurt it	http://www.blurtit.com	Chosen
13. ChaCha	http://www.chacha.com	Chosen
14. Cramster	http://www.cramster.com	It focuses on education, not health
15. Dizzay	http:// www.dizzay.com	Access to data
16. Expert Exchange	http://www.experts-exchange.com	It focuses on technology and not health
17. Fluther.com	http://www.fluther.com	Similar to Yahoo Answers and Answerbag
18. Girls ask Guys	http://www.girlsaskguys.com	It focuses on relationships and not health
19. Google Answers	http://answers.google.com	Chosen
20. Helpfulbox	http://myhelptopicsforum.com	Similar to Yahoo Answers and Answerbag

Platform Name	Web address	Why not chosen?
21. Just Answer	http://www.justanswer.com	Chosen
22. Just Ask	http://www.education.com/answers	It focuses on education not health
23. KGB	www.kgbanswers.com	Data access
24. Ask From Expert	http://www.askfromexpert.com/	Similar to Just Answer
25. Knowledge-iN	http://kin.naver.com	Korean
26. Linked In Answer	http://www.linkedin.com/answers	It is closed
27. Mahalo Answers	www.mahalo.com/answers	Chosen
28. Marchant Circle Answers	http://www.merchantcircle.com/answers	It focuses on business not health
29. Minti question and answer	http://www.Minti.com	It focuses on parenting not health
30. Questions	https://www.question.com	Similar to Yahoo Answers and Answerbag
31. Quora	http://www.quora.com	Chosen
32. Stackoverflow	http://stackoverflow.com/	It focuses on technology not health
33. The Answer Bank	http://www.theanswerbank.co.uk	It is a general purpose Q&A platform, but it does not have a health category
34. True Knowledge	http://www.evi.com/	The answers are produced through an automated procedure and not by a human
35. Trulia	http://www.trulia.com/voices/	Real state Q&A platform
36. Uclue	http://www.Uclue.com	Similar to Google Answers but less popular

Platform Name	Web address	Why not chosen?
37. WebMD	http://www.webmd.com/	Chosen
38. Wikia	http://wiki.answers.com/	Similar to Yahoo Answers and Answerbag
39. WiseGeek	http://www.wisegeek.com	It is an archive of answers for common questions
40. Yahoo Answers	http://answers.yahoo.com	Chosen

Nine websites which cover sufficient variations in mechanisms were nominated for data collection. Table 7 summarises the basic characteristics of the selected platforms and

Table 8 outlines the mechanisms embedded in them.

Table 7: Basic characteristics of the sample platforms

Q&A Platform	URL	Year	Answerers	Platform
All Experts	allexperts.com	1998 - Present	Medical Experts	Web- based
Answerbag	answerbag.com	2003 - Present	Normal users	Web- based
ChaCha	chacha.com	2006 - Present	Normal users	Mobile-based
Google Answers	answers.google.com*	2002-2006	Expert	Web- based
Just Answer	justanswer.com	2003 - Present	Medical Experts	Web- based
Mahalo Answers	mahalo.com/answers **	2008 - 2013	Normal users	Web- based
Quora	quora.com	2010 - Present	Normal users	Both
WebMD Answers	answers.webmd.com	2012- Present	Mixed	Web- based
Yahoo Answers	answers.yahoo.com	2005 - Present	Normal users	Web- based

*** Google Answers is not active anymore, however the archive of questions and answers is available online**
**** The URL does not work anymore; 'web.archive.org' (Wayback Machine service) was used to retrieve the data**

Table 8: Mechanisms embedded in the sample Q&A platforms

		Quality Mechanism		Incentive Mechanism	
Q&A Platform	**Revenue Model**	**Reliability feature**	**Reputation Type**	**Asking Cost**	**Answering reward**

AllExperts	Advertisement	Certification Reputation Mechanism Influence on Profile	Average rating on 1-10 intervals	Free	Social – Fixed*
Answerbag	Advertisement	Reputation Mechanism Rewarded report of fraudulent behaviour	Point, level, leader board	Free	Social - Fixed
ChaCha	Advertisement which pays answerers	Training Answerers Report of fraudulent behaviour	No reputation system	Free	Financial - Fixed
Google Answers	Transaction-based	Reputation Mechanism Training Answerer Money back guarantee	1-5 Star	Financial - Flexible	Financial-Flexible**
Just Answer	Transaction-based	Certification Reputation Mechanism Money back guarantee	number of satisfied customers	Financial -Fixed	Financial-Fixed
Mahalo Answers	Mixed (Ad & Transaction)	Reputation Mechanism Report fraudulent behaviour	Point, Belt	both-Flexible	Financial
Quora	Not established yet	Reputation Mechanism Influence on Profile Report fraudulent behaviour	number of followers	Social-Flexible	Social-Flexible
WebMD Answers	Advertisement	Reputation Mechanism Report fraudulent behaviour	number of followers	Free	No reward
Yahoo Answers	Advertisement	Reputation Mechanism Report fraudulent behaviour	Point, level, leader board	Social - Fixed	Social - Fixed

*** Fix means that it is predefined by the platform while **flexible means it is determined by users.**

4.4.1 Nominated Q&A Platforms

This section elaborates the dynamism of asking and answering questions on the nine nominated websites and explains how quality is managed by them. The information in this section has been gathered from multiple sources. The main source was the platform itself and guidelines available for users. The author also created an account and joined the community to understand how asking and answering is occurring there. In the case of ambiguity the asking service of the website was used to get an answer from the community members. Furthermore, the platforms were contacted directly to verify the reliability of information. Community blogs such as yanswersblog.com, which is a blog for Yahoo Answers members, were also examined as another source of information.

4.4.1.1 *Google Answers*

Google Answers is a transaction-based information market launched by Google in 2002. Although the service was closed in late 2006, archived questions and answers are still accessible online. According to the online archive (http://answers.google.com/answers/) 53087 questions were asked across 10 categories[4], out of which 2398 were under the health category. Users could post a question and specify how much they were willing to pay for an answer, from $2 to $200. Google retained 25% of the researcher's reward and a 50 cent listing fee per question. A client who was not satisfied for whatever reason could receive a refund less the listing fee. However, a satisfied client could leave a tip of up to $100. Answers were provided by Google Answers Researchers who were experts at locating hard-to-find information on the web. Researchers were required to go through an application process that tested their research skills and the quality of their answers. However, there was no claim for subject expertise of the researchers (Y. Chen et al., 2010). In addition to researchers, non-researchers could comment on the questions for free. Google claimed researchers could be recruited from commenters (Y. Chen et al., 2010).

Google Answers utilised a reputation mechanism to increase the quality of researchers' contributions. Right after receiving an answer, clients were asked to rate the answer on a 1 to 5 stars. These ratings were averaged and shown as a part of the researcher's reputation. The following information was available about the researchers: (1) 'Average answer rating' (1 to 5 stars): Right after receiving an answer, clients were asked to rate the quality of the answer on a one- to five-star system; (2) 'Questions answered': Total number of questions answered by the researcher; (3) 'Total number of refunds': Google Answers

[4] The 10 categories are: (1) Arts and Entertainment, (2) Business and Money, (3) Computers, (4) Family and Home, (5) Health, (6) Reference, Education and News, (7) Relationships and Society, (8) Science, (9) Sports and Recreation, and (10) Miscellaneous

guaranteed money back in case of dissatisfaction by the provided answer; (4) All the questions answered by the researcher along with their respective ratings.

4.4.1.2 *Yahoo Answers*

Yahoo Answers is a social question and answer platform offered by Yahoo. It is recognised as the most widely used social question and answer platform on which more than 300 million questions have been posted in seven years since its launch in 2005 (yanswersblog.com). Registered users can post their question in a wide range of 26 categories[5] (including health) defined by Yahoo Answers and get an answer from fellow users. Posting questions and answers is free of any financial charge and Yahoo Answers generates its revenue out of advertisement. Yahoo Answers has a system of points and levels to manage participation of its users. Once a user begins participating on Yahoo Answers, he gets 100 points. Asking a question costs 5 points and providing an answer earns 2 points. A question may receive several answers and the original asker has the right to pick 'The best answer' among them which gives 3 points to the asker and 10 point to the answerer (for a complete list of points and levels see Appendix C4). If the asker does not pick the best answer in a particular time, the community votes for picking the best answer. Any user can express their opinion about an answer by either commenting or casting thumbs up or thumbs down.

In order to allow everyone to recognise how active and helpful a user has been in Yahoo Answers, the following information is available on the profile of every user: (1) Points: They are calculated based on users' activities and cannot be used to buy or redeem anything (see Appendix C4); (2) Best answers: it represents the percentage of best answers provided by the user; (3) Answers: Number of answers; (4) Questions: Number of questions; (5) The

[5] (1) Arts & Humanities, (2) Beauty & Style, (3) Business & Finance, (4) Cars & Transportation (5) Computers & Internet, (6) Consumer Electronics, (7) Dining Out, (8) Education & Reference, (9) Entertainment & Music (10) Environment, (11) Family & Relationships, (12) Food & Drink, (13) Games & Recreation, (14) Health, (15) Home & Garden, (16) Local Businesses, (17) News & Events, (18) Pets, (19) Politics & Government, (20) Pregnancy & Parenting, (21) Science & Mathematics, (22) Social Science, (23) Society & Culture, (24) Sports, (25) Travel, (26) Yahoo Products

user may decide to make all the questions and answers she provided publicly available. For a snapshot of a user profile see Appendix C4.

Leader board is another mechanism to encourage participation. It ranks and advertises the top contributors based on their accumulated points.

4.4.1.3 *AllExperts*

AllExperts is an expert question and answer platform founded in early 1998. It claims that all of its experts are volunteers with knowledge in their area of expertise. In order to volunteer, experts need to apply and state their educational credentials, organisations to which they belong, publications, etc. Accepted applicants are allowed to answer questions in AllExperts. As AllExperts advertises the incentive of volunteering is 'getting traffic and attention'[6] and helping others; however, the revenue model is based on advertisement. To ask a question, users must first find an appropriate "expert" by navigating through a taxonomy of a wide range of categories provided by AllExperts. Questions will become publicly available if the asker allows.

Users can look at experts' personal profiles and the ratings of their past answers before asking their questions. The reputation system on AllExperts uses the following aspects: (1) Knowledgeable, Clarity of Response, Timeliness and Politeness: these ratings are given in the interval [1, 10]. The score in each aspect is simply the numerical average of ratings received; (2) the number of questions an expert has received; (3) prestige score: volunteers get 30 prestige points every time they receive a knowledge rating over 7; (4) all the questions answered by the expert along with their respective ratings. For a snapshot of a user profile on AllExperts please see Appendix C4.

4.4.1.4 *Just Answer*

Just Answer is an online expert question and answer platform launched in 2003. It provides answers in several categories[7] including Health & Medical. All experts must complete an

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[6] AllExperts has been mentioned in over 60 publications such as The New York Times, New York Newsday, Family, PC Magazine and Yahoo (both a "Pick of the Week" and "Incredibly Useful Site").

7 (1) Health & Medical, (2) Legal & Tax, (3) Cars & Vehicles, (4) Vets & Pets, (5) Home & Appliances, (6) Computer, (7) Life & Personal

application and have their credentials verified to be able to answer questions. A question costs £11 to £48 based on 'urgency' and 'level of detail' required for the answer and in case of dissatisfaction with the answer money back is guaranteed, however £5 is charged and retained by Just Answer upon posting a question. New experts earn 25% of what a customer is offering for an answer and this amount goes up to 50% as the experts get more experienced.

Upon receiving an answer, the customers are asked to rate the expert in 5 rating options: a score of one and two shows dissatisfaction and refund request while providing a rating of three (OK service), four (good service) or five (excellent service) authorises payment to the experts. The following information is available about the experts on their profile: number of satisfied customers; number of excellent services, good services and OK services provided by the expert in 3 months, in 12 months and in a lifetime period; in addition to the answers they provided.

4.4.1.5 *Answerbag*

Answerbag is a social question and answer platform where questions are asked and answered by users about any topic including health. Similar to Yahoo Answers, posting questions and answers is free of financial charge and the revenue model is based on advertisement. Unlike Yahoo Answers' point system, users do not lose or earn any points for simply asking and answering; rather, earning points is for submitting good questions and answers. For instance: receiving likes on a question or answer yields 1 point, and if an answer is marked as 'great' by staff, moderators or community leaders, the answerer receives 5 points. Reporting in appropriate content is encouraged in Answerbag by a flagging mechanism. Flagged questions/answers are reviewed by moderators, and if they agree with the flag, they will give the user who flagged the question/answer 5 points.

Users have profile pages where their participation statistics are posted, including the categories in which they post answers, along with points and levels, and a list of their friends.

Users can rate both questions and answers by giving positive or negative points, from plus or minus 1 for beginners, to plus or minus 6 for very experienced users. Through their contributions to the site, users can "level up," and earn the right to give or take away more points from other users' questions and answers. Users can also accumulate points by flagging questions and answers as "Wrong Category", "Nonsense", "Spam/Offensive", and "Duplicate". Flagged questions/answers are reviewed by moderators, and if they agree with the flag, they will give the user who flagged the question/answer 5 points. Users have profile pages where their points and submissions are reviewable by other users.

4.4.1.6 *ChaCha*

ChaCha is a free and mainly mobile-based question and answer platform in the US launched in 2006. Users can send their question via text messaging[8], online or using mobile applications. Asking questions in ChaCha is free and questions are provided by guides who earn $0.02 per completed transaction. The ChaCha revenue model is based on advertisement while it pays a cut of its earning to guides to provide high-quality, accurate answers. A ChaCha guide applicant must complete a two-hour evaluation assessing how quickly and efficiently one can search the Internet for answers to questions (Bliss, Lodyga, Bochantin, & Null, 2010); however, no information is publicly available about the reputation of the guides.

4.4.1.7 *Mahalo Answers*

Mahalo launched a question and answer service called Mahalo Answers in late 2008 which was discontinued for no announced reason in 2013. Mahalo Answers allowed users to post questions regarding a wide variety of subjects including health, and those questions could be answered by fellow users. Similar to Yahoo Answers and Answerbag it used a point and level system. For instance, answering a question earned 2 points while posting a question cost no points (please see Appendix C4 for a complete list of points). A key distinction was allowing questioners to give a monetary reward in Mahalo Dollars to the user who provides the best answer. The original asker had the right to select the best answer or choose "no best answer" within four days, then the community voted for the best answer. Once answerers had earned more than 40 Mahalo Dollars, they could choose to cash out and Mahalo Answers took a 25% cut (10 Mahalo Dollar was redeemable to 1 US Dollar).

[8] ChaCha shifted its focus from text messaging service to mobile app. It also made a mobile app in which anybody can answer a question.

Advertisement was another source of revenue for Mahalo Answers. One key difference between Google Answers and Mahalo Answers is that Google Answers only allowed for one answerer to provide the official answer; however, multiple answers were allowed in Mahalo and the reward went to the best answer.

Every user had a profile page in which the following information was posted: earned points, number of questions and answers, number of best answers, tips given and received along with the ranking of the users based on mentioned features. Followers, friends and following were also showed.

4.4.1.8 *WebMD*

WebMD Answers is a health question and answer service which in contextually integrated through a health public website called WebMD. It is certified by HONCode and URAC9 for the quality of health information it provides. Users can post their question for free and they may receive an answer from their fellow users, health experts or organisations who participate on a voluntary basis. The main stream of revenue comes from online advertising.

WebMD has a simple and transparent reputation system for answers. The following information is visible for each answerer on their profile page: total number of questions answered; number of followers; number of Helpful Answer Votes they received and all answers provided by them.

4.4.1.9 *Quora*

Quora is a question and answer website launched by two former Facebook employees in 2010 and its revenue model is not established yet. Quora allows users to ask, answer and edit questions and answers. That social element is what makes Quora different from other question and answer sites like Yahoo Answers. Quora focuses on leveraging social connections to get questions answered (Ovadia, 2011). Similar to the Yahoo Answers point system, Quora uses a credit mechanism to encourage participation. Everyone on Quora starts with 500 credits and users can earn credits when people like their answers or follow

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[9]URAC, an independent, non-profit organisation, is a well-known leader in promoting healthcare quality through its accreditation, education, and measurement programmes.

their questions, however, the unique feature of Quora is that users can specify how much credit they would like to get to answer a question and askers can pay with their credits to have their questions answered. Askers can also promote their questions by spending some credits e.g. to promote a question to 100 people, 500 credits should be spent. Please see Appendix C4 for a complete list of credits.

Quora summarises all activates of its users on their profile page to help other users judge their peers' reputation, including: number of questions, number of answers, number of posts, number of edits, number of followers and following and all their public questions and answers. However, the users' credit remains confidential and the amount charged to provide an answer appears at the asking point.

4.4.2 Measurements

Quality measures are used to define and quantify the quality of questions and answers on question and answer platforms. The next section clearly defines measures of answer quality and question quality.

4.4.2.1 *Measures of Answer Quality*

The quality of health information available online has been a concern since the World Wide Web was introduced to the public. Many attempts have been made to identify and develop a set of criteria to evaluate online health information (Deshpande& Jadad, 2009). This set of criteria provides a solid basis to define a measure of answer quality. The Health on the Net Foundation Code of Conduct (HONcode) was developed in the mid-1990s by the HON Foundation, a Swiss-based non-governmental organisation. The stated aim was to encourage the dissemination of quality health information for patients and professionals, and to facilitate access to the latest and most relevant medical data. The HONcode specifies eight principles for the presentation of medical and health information on the Internet (http://www.hon.ch/HONcode/Conduct.html). Similarly, the UK Department of Health launched a health information accreditation system called the 'Information Standard'. The Information Standard requires that information be accurate, impartial, balanced, based on evidence, accessible and well written (http://www.theinformationstandard.org/scheme-rules). This scheme remains the same for all types of health documents and does not capture the dynamism of the Internet.

Eysenbach et al. (2002) systematically reviewed 79 journal articles to compile criteria actually used to measure the quality of health information on the Internet. They showed that accuracy, completeness, readability, design, disclosures, and references are the most common set of criteria. Stvilia et al. (2009) developed a quality model of consumer health web pages consisting of five constructs of information quality criteria derived by exploratory factor analysis of empirical data. These initiatives and studies have tried to evaluate the quality of health information provided through websites, webpages and documents but they do not consider the social aspect of the Internet, highlighted by the emergence of Web 2.0.

In the context of Web 2.0, several studies examined the quality of information exchanged on question and answer platforms. Zhemin Zhu (2009) developed and tested a multi-dimensional model for assessing the quality of answers specifically for social question and answer websites. Oh et al. (2013) investigated how good the quality of health answers on social question and answer site is. They selected a set of 10 criteria from the literature. Table 9 summarises measures used to assess the quality of health information in the literature.

Table 9: Measures of answer quality in the literature

Source	Context	Measures of information quality
(Eysenbach et al., 2002)	Health websites and webpages	Accuracy, Completeness, Readability, Design
Health on the Net Foundation Code of Conduct for medical and health web sites available at: http://www.hon.ch/HONcode/Conduct.html	Health websites	Authoritative, Complementarity (Information should support, not replace, the doctor-patient relationship), Privacy, Attribution, Justifiability , Transparency, Financial disclosure, Advertising policy
Information Standard (2010) Scheme rules, available at: http://www.theinformationstandard.org/scheme-rules	Health information not necessarily online	Health information should be: Accurate, Impartial, Balanced, Based on evidence, Accessible, Well written

Source	Context	Measures of information quality
(Stvilia et al., 2009)	Health webpages	Accuracy, Completeness, Authority, Usefulness, Accessibility
(Zhu, 2009)	General Question and Answer	Informativeness, Politeness, Completeness, Readability, Relevance, Conciseness or Brevity, Truthfulness (Credible/Feasible/Convincing), Level of Detail, Originality, Objectivity, Novelty, Usefulness or Helpfulness, Expertise
(Oh et al., 2013)	Health Question and Answer	Accuracy, Completeness, Relevance, Objectivity, Readability, Source Credibility, Politeness, Confidence, Empathy, Efforts

Since the context of Oh et al. (2013) is similar to this research, their set of criteria is used as a basis for evaluation of answers. This set is compared with other criteria to make sure no measure is ignored. Furthermore, these measures have been refined after two pilot studies. Table 10 summarises the measures and their definitions.

Table 10: Quality measures and definitions

Answer Quality Criteria *	Explanation
Accuracy	The answer provides correct information.
Completeness	The answer includes all key points.
Relevance	The answer is relevant to the question.
Objectivity	The answer provides objective and unbiased information.
Readability	The answer is easily readable
Source Credibility	The source of information is authoritative. Not applicable when no source is provided.
Politeness	The answerer is polite. Is this answer offending?
Confidence	The answerer is confident in the answer
Empathy	The answerer expresses his or her empathy to the asker.

Efforts	The answerer puts effort into providing this answer.
Archival Value	This answer is useful for others. It is worthwhile to archive this answer.

*** A 5-point Likert scale was used where 1 is very low, 3 neither high nor low and 5 is very high**

4.4.2.2 *Measures of Question Quality*

Fewer studies have been published on question quality within Q&A platforms compared with answer quality and most of them focused on question type. Harper et al. (2009) differentiated between two types of questions: 'informational' and 'conversational'. Informational questions are asked with the intent of getting information. Conversational questions are asked with the intent of stimulating discussion. They used two other dimensions, 'writing quality' and 'archival value' using Likert scales.

Automatically extracted features such as question length and relative importance of individual terms were used in text mining and machine learning literature mostly to determine what features contribute to creating a quality question and to predict answerability of questions (Agichtein et al. 2008; Kitzie et al. 2013; Shah et al. 2014; Choi & Kitzie 2013; Shah et al. 2012). Since the aim of these studies was to develop automated techniques and they have technical concern, they did not address the value dimension of question in their studies.

(Hsieh, Kraut, & Hudson, 2010) used three dimensions: perceived sincerity, urgency and difficulty of the question, to evaluate the value of a question. Sincerity refers to the extent to which question askers wanted answers to their questions. They also used politeness and archival value to evaluate quality of questions.

To the best of the author's knowledge, there was no specific health question quality measure in the literature. For the purpose of this study, the Harper et al. (2009) and Hsieh et al. (2010) measures were initially merged to include all relevant measures. Table 11 indicates the question quality measure along with their definition.

Table 11: Health question rating

Quality Criteria *	Explanation
Importance	How **seriously/sincerely** did the question asker want an answer to the question?

Perceived Urgency	How urgently did the question asker want an answer to the question?
Difficulty	How much work would it require to answer this question? Please rate: *Low and very low:* Anybody can answer the question *Neither High nor Low:* An average high school educated person is able to answer the question *High:* Someone with general medical background can answer the question *Very high:* specialist can answer the question
Question Politeness	How rude or polite is the question?
Question Archival Value	How valuable is the question for archiving? ; Or the high-quality answers to this question will provide information of lasting/archival value to others.
Writing Quality	How well-written is the question?

*** A 5-point Likert scale was used where 1 is very low, 3 neither high nor low and 5 is very high**

4.4.2.3 *Design Feature Measures*

A set of intertwined design features in an online platform constructs a platform Mechanism. In this research based on the reviewed literature, the mechanisms which have effect on quality of health information are Incentive Mechanism, Quality Signal Mechanism and Revenue Model of the platforms. In order to measure the design features of the Q&A platforms, the nine nominated platforms were carefully investigated to extract the design features related to Incentive Mechanism, Quality Signal Mechanism and Revenue Model of the platforms. Table 12 lists the design features and clearly defines them.

Table 12: Question design feature

Design feature	Meaning	Abbreviation
Advertisement-based revenue model	Is advertisement used as the main source of revenue on the platform?	advertise1
Answer financial incentive	Is answering questions financially rewarding for the answerer?	afin
Answer financial incentive determined by platform	Does the platform determine financial benefit of answering?	afinfix
Answer social incentive determined by users	Does asker determine social benefit of answering?	afinflex

Design feature	Meaning	Abbreviation
Following mechanism	Does the platform have following feature?	afollow
Answer social incentive	Is answering socially rewarding?	aso
Answer social incentive determined by platform	Does the platform determine social benefit of answering?	asofix
Answer financial incentive determined by user	Does the asker determine social benefit of answering?	asoflex
Voting mechanism for answers	Do community members vote for answers?	avotew
Best answer mechanism	Does the platform use best answer feature?	best
Certification of information provider	Does the platform use information providers with medical certification?	certify
Commenting mechanism	Does the platform allow commenting?	comment
Expertise of information provider	Do experts (medical or non medical) answer the questions?	expert
Money back guarantee	Does platform guarantee money back?	gurantee
Mobile-based platform	Is the platform mobile-based?	mobile
Multiple answering mechanism	Does the platform allow multiple answering?	multi
Offline reputation of information providers	Does the platform allow information providers to build offline reputation?	offrepu
Payment for answering	The amount which is paid to information provider?	pay

Design feature	Meaning	Abbreviation
Point system	Does the platform use point system?	pointsys
Price of question	The amount which is cost to ask a question in the platform?	price
Question financial incentive	Is the question financially costly?	qfin
Question financial incentive determined by platform	Does the platform determine financial cost of asking?	qfinfix
Question financial incentive determined by user	Does asker determine social cost of asking?	qfinflex
Question social incentive	Is the question socially costly?	qso
Question social incentive determined by platform	Does the platform determine social cost of asking?	qsofix
Question social incentive determined by users	Is asking question financially costly?	qsoflex
Ranking system	Does the platform rank the users based on their activity?	ranksys
Reporting mechanism for fraudulent behaviour	Does the website encourage members to report fraudulent behaviour?	reportfradu
Reputation system of the platform	Does the platform use reputation system?	reput
Transaction-based revenue model	Is transaction the main source of revenue?	transaction
Number of votes/likes	The number of likes a particular answer has received	anvote
Online reputation of the participants	The normalised reputation of a particular participant	zscore

It is important to note that different Q&A platforms use different ways to calculate and indicate the online reputation of their participants such as 5-star rating in Google Answers, point system in Yahoo Answers, etc. The most explicated indicator of the online reputation by the platform has been used as online reputation. Table 13 indicates that which has been used as reputation measure in the Q&A platforms. Since this measure has different scales in different platforms, the collected data for the measure were standardized. The formula for calculating the standard score is the score, minus the mean score, divided by the standard deviation.

Table 13: Measures of online reputation in different Q&A platforms

Q&A Platform	Measures of online reputation of participants
AllExperts	Number of points
Answerbag	Number of points
ChaCha	It does not show any information about the participants' activity
Google Answers	5-star rating
Just Answer	Number of satisfied customers treated by the participants
Mahalo Answers	Number of points
Quora	Number of followers
WebMD Answers	Number of followers
Yahoo Answers	Number of points

4.4.3 Human Assessors

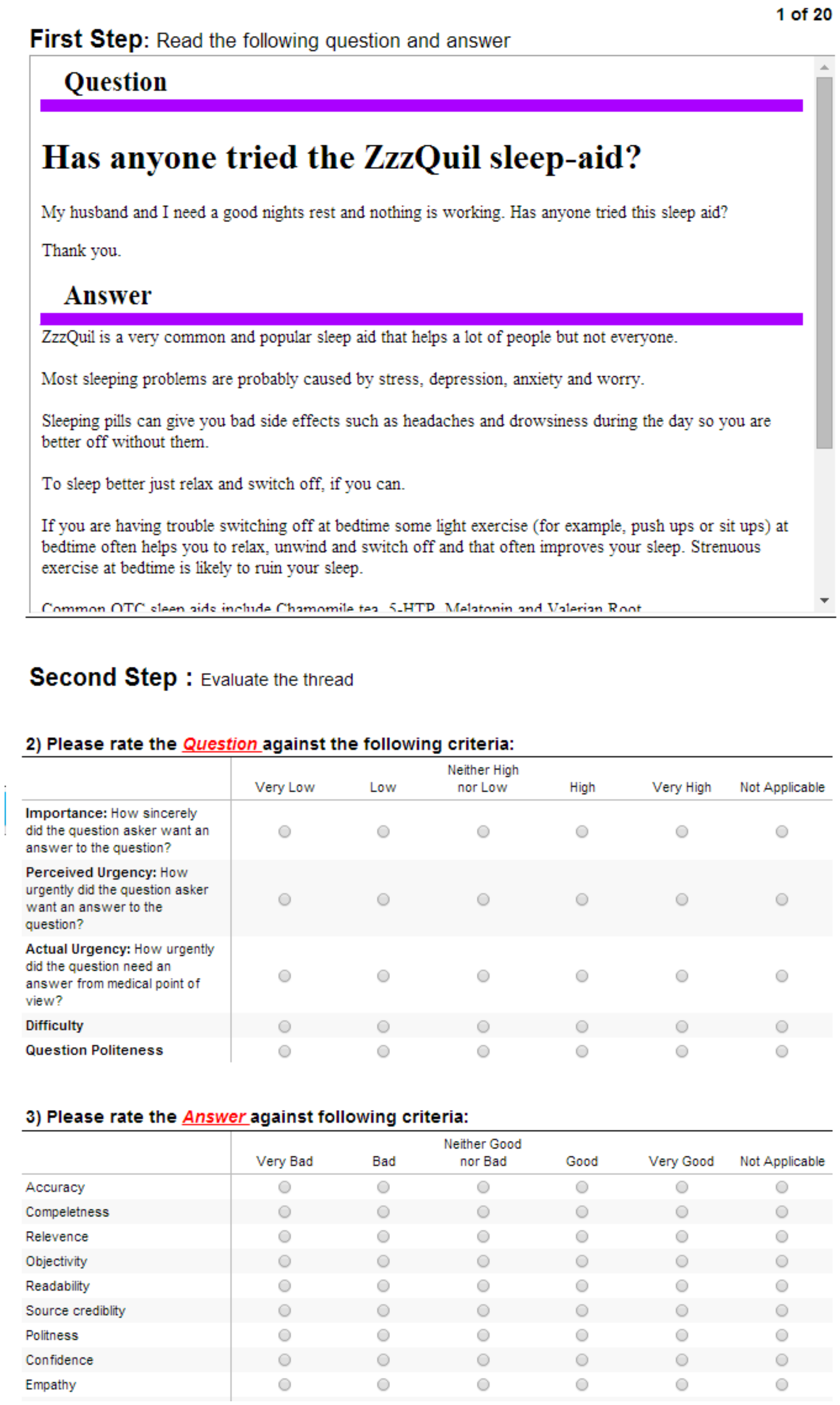
In this research human raters are used to determine quality of information which is a common procedure in evaluating quality of questions and answers in both social Q&As (Hsieh et al. 2010; Oh & Worrall 2012; Kitzie et al. 2013) and non-social Q&As (Y. Chen et al., 2010). In this study, raters are expected to provide objective assessments of the quality of health information, so two physicians were hired to rate the health questions and answers. They participated in both pilot studies and the main study of this research. In the first pilot study they were trained to have a clear understanding of the measurements; in the second pilot study they were trained to use the online tool to rate the health information. Their time and effort were compensated by £15 per hour.

4.4.4 First Pilot Study

The first pilot study aimed at clarifying the meaning of each quality criterion to be used in a health context. A random sample of 20 questions and answers were selected from Yahoo Answers and Just Answer. Two physicians were invited to take part in the pilot study. The meaning of each rating criterion was explained before rating to both of them. Then, they were asked to rate 10 questions and answers separately. The rating session was followed by a two-hour discussion on challenges and ambiguities of the quality criteria. Their provided ratings were checked to point out the different ratings and the coders were asked to explain the reasons for their ratings. The participants rated another 10 questions to check if the rating guidelines had become more meaningful after the discussion session. The feedback from the raters was used to refine the measures and guideline accordingly. The rating guideline for the raters is available at Appendix C4, Section 9.2.

4.4.5 Second Pilot Study

The aim of the second pilot study was to overcome the technical concerns of data collection and clarify the data collection process and ratings. A random sample of 80 questions and answers were selected from four Q&A platforms. In order to facilitate the process of rating, a website was designed and launched. The samples of questions and answers were uploaded to this website. This website has been integrated with Qualtrics Survey provided by The University of Manchester (see Figure 7). The same physicians were recruited to rate the Q&As. Data were collected over a period of one week. The features of question and answer platforms were also collected manually. At the end of this pilot study, choice of websites and features of websites were refined and finalised.



1 of 20

First Step: Read the following question and answer

Question

Has anyone tried the ZzzQuil sleep-aid?

My husband and I need a good nights rest and nothing is working. Has anyone tried this sleep aid?

Thank you.

Answer

ZzzQuil is a very common and popular sleep aid that helps a lot of people but not everyone.

Most sleeping problems are probably caused by stress, depression, anxiety and worry.

Sleeping pills can give you bad side effects such as headaches and drowsiness during the day so you are better off without them.

To sleep better just relax and switch off, if you can.

If you are having trouble switching off at bedtime some light exercise (for example, push ups or sit ups) at bedtime often helps you to relax, unwind and switch off and that often improves your sleep. Strenuous exercise at bedtime is likely to ruin your sleep.

Common OTC sleep aids include Chamomile tea, 5-HTP, Melatonin and Valerian Root

Second Step : Evaluate the thread

2) Please rate the *Question* against the following criteria:

	Very Low	Low	Neither High nor Low	High	Very High	Not Applicable
Importance: How sincerely did the question asker want an answer to the question?						
Perceived Urgency: How urgently did the question asker want an answer to the question?						
Actual Urgency: How urgently did the question need an answer from medical point of view?						
Difficulty						
Question Politeness						

3) Please rate the *Answer* against following criteria:

	Very Bad	Bad	Neither Good nor Bad	Good	Very Good	Not Applicable
Accuracy						
Compeletness						
Relevence						
Objectivity						
Readability						
Source credibility						
Politness						
Confidence						
Empathy						

Figure 7: Snapshot of online coding tool used for second pilot study

4.4.6 Unit of Analysis

Some platforms of the sample allow multiple answering. Accordingly, either a thread of a question and multiple answers or a thread of a question and one answer can be considered as a unit of analysis in this research. It was deemed more appropriate to focus on a thread of a question and one answer because (1) this research is looking at how reputation of a respondent may affect the quality and quantity of generated information. However, evaluating a thread of answers does not show how well a particular respondent did in terms of quality; (2) it is important to be consistent with those platforms which do not allow multiple answering.

4.4.7 Data Collection

The data were collected over a period of three weeks from 1st of July to 21st of July 2014. In the first round, question, answer and a link were collected to be able feed the webpages. To ensure that the sample selection was random, two approaches were adopted.

> (1) For the platforms which had a health category and provided a list of questions and answers raised in their platform such as Yahoo Answers, Google Answers, WebMD: Since the overall number of Q&A in these platform is unknown, 100 random numbers with a value between 1 and 1000 were generated. The questions and answers were selected in respect to generated numbers from the list of questions and answers available in their health category.

> (2) For those platforms where questions and answers were accessible by a searching tool such as Quora and Just Answer, a list of 264 health-related keywords was produced to search and find health-related questions and answers. For a complete list of keywords see Appendix C4. The procedure of nominating questions and answers was as follows: a keyword was randomly selected from the health keyword list and it was searched using the search tool of the Q&A platform under study. Out of the search results, random questions and answers were chosen. For those platforms that had multiple answers for a question, one random answer was selected.

It is important to note that Mahalo Answers data were not available on the website itself as this service is not active anymore and an Internet archive[10] service (web.archive.org) was

[10] Internet Archive is non-profit organisation which digitally archives the World Wide Web and other information on the Internet for researchers, historians, scholars and the general public.

used to download the data. Similarly, Google Answers is no longer accepting new questions; however, existing questions and answers are accessible at www.answers.google.com.

All questions were carefully reviewed and questions related to health insurance or a healthcare system such as: ‘why insurance cover Viagra not birth control pills?’ or ‘Is average life expectancy the best way to measure effectiveness of a given country’s healthcare system?’ were excluded, because different expertise is needed to evaluate the answers to these questions.

Two sets of information were needed for each Q&A thread: (1) quality rating and (2) design feature associated with Q&A (see Figure 8). Quality ratings were completed by human assessors and design features were downloaded from the Internet.

After reviewing the questions and answers, they were fed into webpages and integrated with Survey Qualtrics to make an online tool for coding. The questions and answers were classified into groups of 20 each. The assessors were trained to be able to use the tool for coding efficiently in a one to one session. The questions and answers were sent to the assessors over a period of two and half months to be rated. The raters were blinded from the name of the Q&A website where the question was asked or any other attributes associated to the questions and answers, in order to ensure that information was graded independently of any site specific bias. Ten percent of the data were rated by both participants to be able to measure inter-rater consistency. Coding and data collection were completed over a three-month period.

When data on both design features and quality ratings were collected the two data sets were merged. A random sample of the collected data was checked to make sure that the data had been merged correctly.

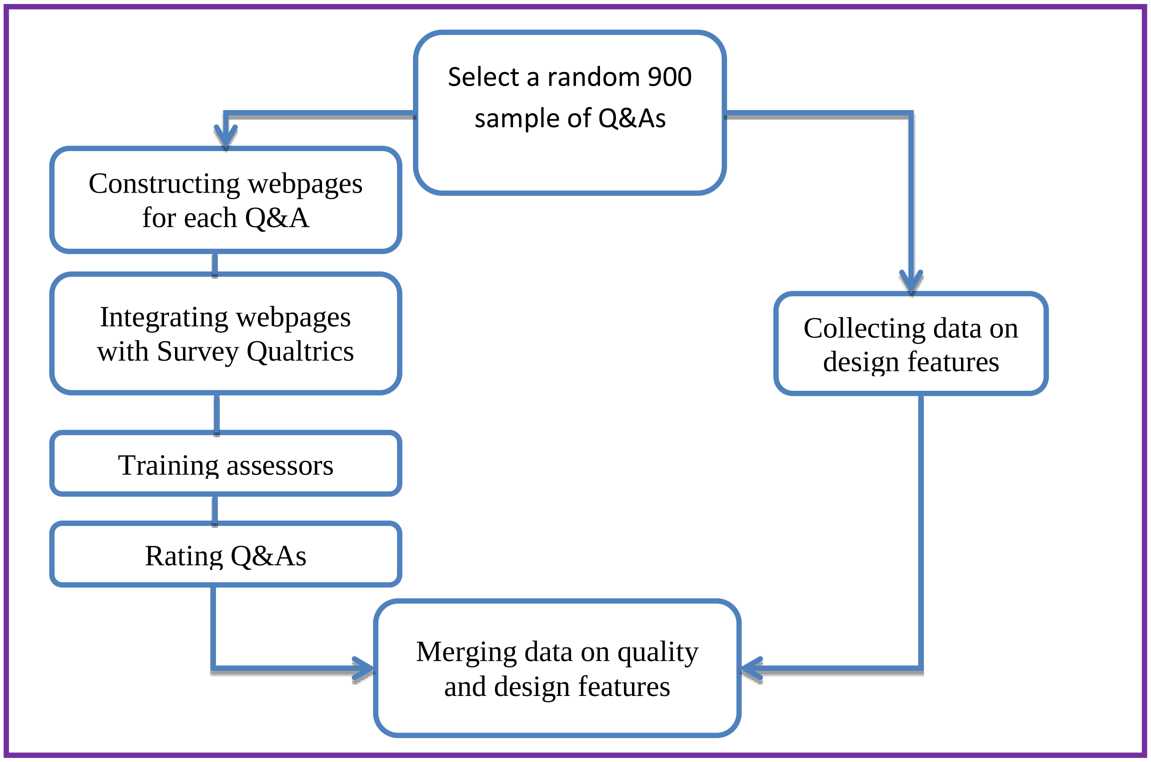


Figure 8: Data collection stages

4.5 Data

Table 14 summarises the median, mean, and standard deviation and the number of missing values for 10 measures of answer quality and Table 15 present the same measures for quality of questions.

4.5.1 Answer

Table 14: Basic statistics for quality of answer

	Answer accuracy				**Completeness**			
	MD	Mean	NA's	STD	MD	Mean	NA's	STD
AllExperts	4	3.44	2	0.86	3	3.06	2	0.89
Answerbag	2	2.478	10	1.25	2	2.333	10	1.18
ChaCha	3	2.948	3	1.07	2	2.526	3	1.00
Google Answers	4	3.528	11	1.04	3	3.225	11	1.19
Just Answer	4	4.35	3	0.83	4	4.11	2	0.98
Mahalo Answers	4	3.4	5	1.06	3	3.189	5	1.04
Quora	4	3.208	4	1.06	3	2.875	4	0.95
WebMD Answers	4	3.213	25	1.14	3	2.893	25	1.07
Yahoo Answers	2	2.526	3	1.05	2	2.299	3	0.95
	Relevance				**Objectivity**			

	MD	Mean	NA's	STD	MD	Mean	NA's	STD
AllExperts	4	3.86	2	0.51	4	3.66	2	0.74
Answerbag	3	2.867	10	1.29	3	2.607	11	1.32
ChaCha	4	3.354	4	0.98	3	3.103	3	1.08
Google Answers	4	3.864	12	0.81	4	3.64	11	0.97
Just Answer	4	4.4	3	0.66	4	4.43	3	0.71
Mahalo Answers	4	3.758	5	0.90	4	3.532	6	1.08
Quora	4	3.708	4	0.80	4	3.427	4	0.95
WebMD Answers	4	3.653	25	1.02	4	3.413	25	1.09
Yahoo Answers	4	3.255	2	1.09	3	2.794	3	1.10

	Readability				**Source credibility**			
	MD	Mean	NA's	STD	MD	Mean	NA's	STD
AllExperts	4	3.96	3	0.35	3	3.019	46	1.10
Answerbag	3	2.867	10	1.31	2	2.361	39	1.39
ChaCha	4	3.49	4	0.90	2	2.256	57	0.90
Google Answers	4	3.807	12	0.84	4	3.662	35	1.08
Just Answer	4	4.333	1	0.66	4	3.828	13	1.00
Mahalo Answers	4	3.723	6	0.93	3	3.338	20	1.11
Quora	4	3.802	4	0.76	3	2.879	42	0.97
WebMD Answers	4	3.64	25	1.01	3	2.625	60	0.98
Yahoo Answers	4	3.378	2	1.09	2	2.294	32	0.98

	Readability				**Politeness**			
	MD	Mean	NA's	STD	MD	Mean	NA's	STD
AllExperts	4	3.96	3	0.35	4	3.98	3	0.28
Answerbag	3	2.867	10	1.31	3	2.742	11	1.26
ChaCha	4	3.49	4	0.90	4	3.375	4	0.83
Google Answers	4	3.807	12	0.84	4	3.843	11	0.86
Just Answer	4	4.333	1	0.66	4	4.37	4	0.57
Mahalo Answers	4	3.723	6	0.93	4	3.819	6	0.91
Quora	4	3.802	4	0.76	4	3.708	4	0.80
WebMD Answers	4	3.64	25	1.01	4	3.587	25	0.97
Yahoo Answers	4	3.378	2	1.09	4	3.429	2	1.04

	Confidence				**Empathy**			

	MD	Mean	NA's	STD	MD	Mean	NA's	STD
AllExperts	4	3.75	2	0.61	4	3.745	2	0.71
Answerbag	3	2.744	10	1.27	3	2.506	19	1.17
ChaCha	3	3.247	3	0.93	3	2.941	15	1.06
Google Answers	4	3.64	11	0.95	4	3.667	13	0.63
Just Answer	4	4.38	4	0.64	4	4.3	3	0.85
Mahalo Answers	4	3.713	6	0.94	4	3.596	6	0.94
Quora	4	3.49	4	0.97	4	3.404	11	0.92
WebMD Answers	4	3.467	25	1.04	4	3.417	28	1.05
Yahoo Answers	3	2.99	3	1.04	3	2.969	3	1.07
	Effort				**Archival Value**			
	MD	Mean	NA's	STD	MD	Mean	NA's	STD
AllExperts	4	3.43	2	0.82	3	3.21	2	0.88
Answerbag	2	2.427	11	1.19	2	2.209	9	1.27
ChaCha	2	2.505	3	1.07	3	2.629	3	1.14
Google Answers	4	3.489	12	1.08	4	3.348	11	1.18
Just Answer	4	4.23	3	0.81	4	4.178	10	0.96
Mahalo Answers	4	3.442	5	1.06	4	3.232	5	1.13
Quora	3	3.115	4	1.00	3	3.01	4	1.04
WebMD Answers	3	3.093	25	1.12	3	3.107	25	1.16
Yahoo Answers	2	2.429	2	1.03	2	2.276	2	1.06

4.5.2 Question

Table 15: Basic statistics for quality of question

	Importance				**Perceived Urgency**			
	MD	Mean	NA's	STD	MD	Mean	NA's	STD
AllExperts	4	3.83	0.65	4	3	3.24	0.82	3
Answerbag	3	2.44	1.22	3	1	1.67	0.87	1
ChaCha	3	3	1.11	3	2	1.838	0.86	2
Google Answers	4	3.404	0.93	4	2	2.44	0.97	2
Just Answer	4	3.86	0.70	4	3	3.267	0.90	3
Mahalo Answers	4	3.34	1.01	4	2	2.29	1.02	2
Quora	4	3.36	0.88	4	2	2.11	0.87	2
WebMD Answers	4	3.714	0.62	4	3	2.827	1.01	3
Yahoo Answers	4	3.35	1.11	4	3	2.91	1.22	3

	Difficulty				**Perceived urgency**			
	MD	Mean	NA's	STD	MD	Mean	NA's	STD

AllExperts	4	3.86	2	0.67	4	3.89	0	0.40
Answerbag	3	2.657	1	1.21	3	3.14	0	0.91
ChaCha	3	3.232	1	0.80	3	3.306	0	0.63
Google Answers	4	3.63	1	0.75	4	3.68	0	0.51
Just Answer	4	3.78	1	0.76	4	3.91	0	0.64
Mahalo Answers	4	3.35	1	0.89	4	3.74	0	0.60
Quora	4	3.46	1	0.83	4	3.59	0	0.65
WebMD Answers	4	3.714	2	0.63	4	3.786	0	0.45
Yahoo Answers	4	3.57	1	0.98	4	3.49	0	0.70
	Archival Value				**Writing Quality**			
	MD	Mean	NA’s	STD	MD	Mean	NA’s	STD
AllExperts	4	3.869	1	0.51	4	3.608	3	0.79
Answerbag	3	2.483	13	1.25	3	3.011	13	0.93
ChaCha	3	3.21	19	0.91	3	3.2	20	0.72
Google Answers	4	3.59	1	0.65	4	3.717	1	0.57
Just Answer	4	3.99	1	0.66	4	3.7	10	0.77
Mahalo Answers	4	3.612	20	0.87	4	3.57	21	0.67
Quora	4	3.62	1	0.46	4	3.545	1	0.57
WebMD Answers	4	3.837	2	0.73	4	3.704	2	0.80
Yahoo Answers	4	3.475	20	0.86	4	3.412	20	0.91

4.6 Inter-Rater Agreement

Many research designs require the assessment of inter-rater reliability or agreement to demonstrate the degree of agreement among ratings provided by multiple coders. This study used two physicians to determine quality of questions and answers generated on health Q&A platforms. Ten percent of whole data were randomly selected and evaluated by both raters to be able to run an inter-rater reliability test.

The aim of reliability is to check how much homogeneity is in the ratings given by the two assessors who make independent ratings. The assessment of inter-rater agreement provides a way of quantifying the degree of agreement between two or more. Different statistics tests are appropriate for assessing inter-rater agreement such as Cohen's Kappa, Fleiss’ Kappa, intra-class correlation, etc.

The selection of the most appropriate statistical test to measure inter-rater consistency depends on the metric in which a variable was coded (e.g., nominal vs. ordinal, interval, or ratio) and the number of coders (e.g. two, multiple). For example, Cohen's Kappa evaluates agreements between two raters when the data is nominal; Fleiss's Kappa, which is an extension of Cohen’s Kappa, evaluates agreements between multiple raters, etc. (Hallgren, 2012).

In the context of this research raters were supposed to rate the questions and answers separately using a 5-point Likert scale. These ratings were later averaged and formed an overall quality index for questions and answers. It is argued that weighted Cohen’s Kappa and Intra-class Correlation Coefficient (ICC) are appropriate statistical tests to measure inter-rater agreement in this research.

4.6.1 Cohen's Kappa

Cohen's Kappa is a measurement of agreement between two raters or methods of measurement. This method can be applied to data that are not normally distributed, binary (no/yes) and a close ended ordinal scale, such as the 5-point Likert Scale (Cohen, 1968).

There are two ways of calculating Cohen's Kappa, and these produce different results. The first is by Cohen's original 1960 algorithm, now generally known as the unweighted Kappa (Cohen, 1960). The second is by the weighted method, also described by Cohen in 1968, which includes a weighting for each cell (Cohen, 1968). Cohen argued that the weighted Kappa should be used particularly if the variables have more categories than binary (more than yes and no), because the distance from agreement should be taken into consideration. Fleiss's Kappa is an extension of Cohen's Kappa to evaluate concordance or agreements between multiple raters, but no weighting is applied (Fleiss, Cohen, & Everitt, 1969). Since in this study two raters coded the health information using a 5-point Likert scale, weighted Cohen Kappa was calculated and summarised in Table 16 for every measure of quality in this study. Conventionally, a Kappa of <0.2 is considered poor agreement, 0.21-0.4 fair, 0.41-0.6 moderate, 0.61-0.8 strong, and more than 0.8 near complete agreement. The inter-rater agreement for this study is in the fair and moderate range.

4.6.2 Intra-class Correlation Coefficient (ICC)

This is a general and the most commonly-used statistical method for assessing agreement or consensus. It can be used for ordinal, interval, and ratio variables. Coefficient represents agreements between two or more raters or evaluation methods on the same set of data (Hallgren, 2012). Intra-class Correlation Coefficient was calculated and summarised in Table 16 for every measure of quality in this study. ICC can be interpreted as follows: 0-0.2 indicates poor agreement: 0.3-0.4 indicates fair agreement; 0.5-0.6 indicates moderate agreement; 0.7-0.8 indicates strong agreement; and >0.8 indicates almost perfect agreement. Similar to weighted Cohen Kappa, the inter-rater agreement for this study is in the fair and moderate range.

Table 16: Inter-Rater agreement

	Cohen's Kappa Weighted	Intra-class Correlation Coefficient
Question		
Importance	0.4325	0.6165
Perceived Urgency	0.3869	0.538
Difficulty	0.3290	0.548
Question Politeness	0.3056	0.4068
Question Archival Value	0.7604	0.7805
Writing Quality	0.8108	0.8361
Answer Quality		
Accuracy	0.4525	0.6387
Completeness	0.4122	0.625
Relevance	0.4196	0.5373
Objectivity	0.4694	0.6711
Readability	0.3554	0.5432
Source Credibility	0.4570	0.6819
Politeness	0.5299	0.6665
Confidence	0.4103	0.5916
Empathy	0.3966	0.5925
Efforts	0.4440	0.6481
Archival Value	0.5434	0.738

It is very important to note that it is more appropriate to report inter-rater agreement measures for variables in the form that they will be used for model testing rather their raw form (Hallgren, 2012). In this study questions and answers are rated based on different quality criteria or dimensions by two raters. Then the averages of the coder ratings for different quality dimensions are calculated and used for running regression trees. Therefore, the most appropriate statistics test for inter-rater agreement in this study is Intra-class Correlation Coefficient for overall question and answer quality indexes. Intra-class Correlation Coefficients for overall question quality index and overall answer quality index were calculated and summarised in Table 17. The inter-rater agreement for both question and answer quality indexes is more than 0.7 which shows a strong agreement between the two raters and confirms that these two indexes are sufficiently reliable for further data analysis.

Table 17: Inter-rater agreement for overall quality indexes

		Intra-class Correlation Coefficient
Overall Indexes		
	Answer Quality	0.7643
	Question Quality	0.7205

4.7 Methods

This section clarifies the approach and method of data analysis.

4.7.1 Two Cultures of Statistical Modelling

There are two cultures in the use of statistical modelling to reach conclusions from data: (1) The Data Modelling Culture and (2) The Algorithmic Modelling Culture. The first one assumes that the data are generated by a given stochastic data model. Popular data modelling approaches such as linear regression, logistic regression, Cox model etc. belong to this category. They assume that response variables (y) are generated based on function of predicator variables (x), random noise and parameters. In the next step the values of the parameters are estimated from the data and the model is used for purposes such as prediction (see Figure 9). On the other hand, the algorithmic modelling treats the data mechanism as unknown. In this type of modelling the focus is on finding an algorithm that operates based on dependent variables to predict the response (see Figure 10). Decision trees and neural nets are examples of this culture. Breiman (2001) argues that algorithmic modelling, also called statistical learning, is a more accurate and informative alternative to data modelling and can be used both on small and large complex data sets.

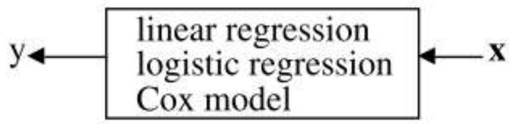


Figure 9: Data modelling

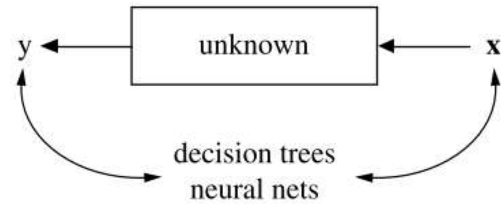


Figure 10: Algorithmic modelling

Extracting information from the data about the underlying mechanism producing the data is one of the important goals of statistics. The advantage of data modelling is that it produces a simple and understandable picture of the relationship between the predictors and responses. However, the data could result in different models which are equally good. This problem is called multiplicity and yields to different pictures of the relation between the predictor and response variables. It is very difficult to recognise which model is the most accurate reflection of the data. Therefore, Breiman et al. (2001) argue that data models suffer from loss of accuracy and information compared to algorithmic models.

Statisticians in the data modelling approach invent a parametric class of models for a complex mechanism through imagination and by looking at the data. In the next step, they estimate parameters and draw conclusions. The issue is that when a model is fitted to data to draw quantitative conclusions, the conclusions are about the model's mechanism rather than nature's mechanism. It follows that if the model is a poor emulation of nature, the conclusions may be wrong. Breiman et al. (2001) argue that these axioms have often been ignored in the enthusiasm for fitting data models in the data modelling culture.

Nonetheless, in the algorithmic modelling culture, nothing is assumed about the data or the true mechanism that generates the data. The only assumption about the data is that the data are independently and identically distributed from the population. The goal is to find a function f(x), an algorithm that operates on x to predict the response y. The best function f(x) is selected on the basis of predictive accuracy or on the basis of minimising the loss function L(Y; f(x)). This research carries out data analysis using algorithmic modelling techniques due to the advantages of this way of modelling.

4.7.2 Positioning of the Research in the Setting of Statistical Learning

Statistical/machine learning studies the algorithms that can learn from data. It is a subfield of computer science stemming from artificial intelligence. The ideas of machine learning have had a long pre-history in statistics. Machine learning tools are classified as supervised or unsupervised. Supervised statistical learning involves building a statistical model for predicting, or estimating, an output based on one or more inputs. Problems of this nature occur in fields as diverse as business, medicine, astrophysics, and public policy. With unsupervised statistical learning, there are inputs but no supervising output; nevertheless it is possible to learn relationships and structure from such data (James, Witten, Hastie, & Tibshirani, 2013).

This research aims at understanding the way that quality of health information produced on different question and answer platforms is affected by design features embedded in the platform; more specifically, it is interesting to answer the following questions:

- Which design features are associated with quality of answers?
- Which design features are associated with quality of questions?
- Which design features generate the biggest boost in quality of answers?
- Whether the quality of questions is associated with quality of answers?

In the setting of this research, the design features are independent or input variables and are denoted by x_1,..., x_p and quality of questions and quality of answers are dependent variables or response and are denoted by Y_1 and Y_2.

Generally, statistical learning deals with the problem of finding an unknown function that relates the response to the predictors based on data for two main reasons: prediction and inference. The goal of prediction problems is to predict the value of dependent measures based on a number of independent measures; however, in inference problems the goal is to understand the relationship between dependent measures and independent measures. In other words, statistical learning problems wish to fit a model that relates the response to the predictors, with the aim of accurately predicting the response for future observations (prediction) or better understanding the relationship between the response and the predictors (inference).

The aim of the research is to understand the relationship between design features i.e. independent variables and quality of answers and quality of questions; i.e. dependent variables. Therefore, the empirical questions fall under the inference category rather than that of prediction problems.

The research question is described as a supervised learning problem since the dependent variable is present to guide the learning process. In the unsupervised learning problem, the predictors are only observable and there is no measurement of the response to supervise the analysis such as clustering problems. Moreover, the research problem is considered as a regression problem as the response is quantitative. In summary, the empirical problem under is inference, supervised learning and regression problem.

4.7.3 Regression Trees

Simple linear regression is the most straightforward approach for predicting a quantitative response Y on the basis of independent variable X. It assumes that there is approximately a linear relationship between X and Y:

$$Y = \beta 0 + \beta 1X + e$$

Simple linear regression is a useful approach for predicting a response on the basis of a single predictor variable. However, in practice there is more than one independent variable. Multiple regression allows multiple independent variables $x_1, \ldots, x_p$ and assumes that independent variables have a separate and additive effect on Y.

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_p X_p + e$$

Linear regression is called global model because there is a single predictive formula holding over the entire data space. When the data has several independent variables which interact in complicated and nonlinear ways (like this research), finding a single global model is very difficult.

An alternative approach is to sub-divide, or split, the space into smaller regions, where the interactions are more manageable. The sub-divisions are then split again. This process is called recursive splitting and it is continued until finally one gets to sections of the space which are so tame that it is possible to fit simple models (like a constant) to them. It is computationally infeasible to consider every possible split of the data space. For this reason, binary splits occur in each step. The recursive binary partitioning is also called a tree as it can be well represented by a tree analogy. Splits are considered as branches of the tree, regions represent leaves of the tree and the first split is the root of the tree. Figure 11 and Figure 12 visualise the splitting and tree analogy. In the case that response variable is continuous (like this research), a regression tree is grown; for categorical responses classification trees are built.

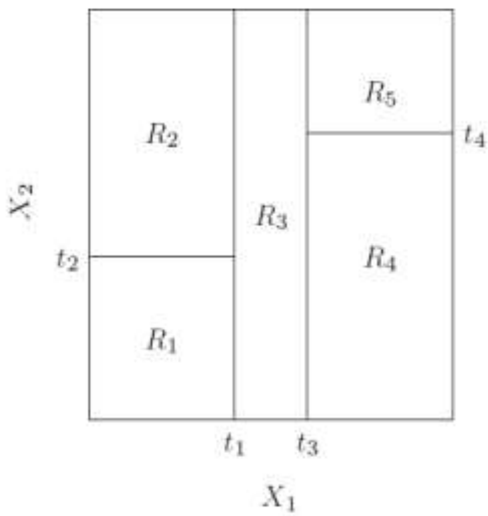


Figure 11: A partition of a two-dimensional feature space by recursive binary splitting applied to some fake data.

Source: (James et al. 2013, p 306)

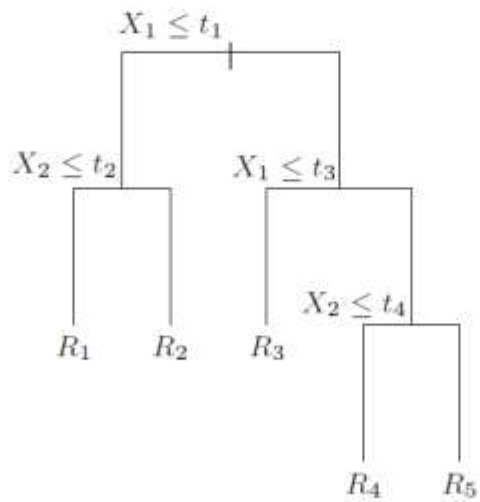


Figure 12: The tree corresponding to the partition in the left figure

Source: (James et al. 2013, p 306)

Tree models are computationally intensive methods that are used in situations where there are many independent variables and guidance is required about which of them to include in the model. The advantage of trees is that they are nonlinear and make no assumption. They are very simple and give a very clear picture of the structure of the data. Finally, they reveal interactions between variables.

Trees have application in different disciplines including medicine, computer science, psychology, etc. The oldest and most popular algorithm which performs based on the tree methodology is the Classification And Regression Tree (CART) algorithm which was first developed by Breiman et al. (1984).

The CART algorithm works based on binary recursive partitioning. The process of building a regression tree based on CART contains two steps:

1. The predictor space is divided into J distinct and non-overlapping regions R1, R2 ,…Rj
2. For every observation that falls into the region Rj, the mean of the response values for all observation which are in Rj is considered as the predicted value

In step 1, the regions R_1, R_2,…, R_J could have any shape, but for simplicity and ease of interpretation they are considered as high-dimensional rectangles. The regions are shaped in a way that they minimise the residual sum of square, given by

$$\sum_{j=1}^{J} \sum_{i \in R_j} (y_i - \hat{y}_{R_j})^2$$

where $\hat{y}_{R_j}$ is the mean response for entire observations within the jth region. It is computationally infeasible to consider every possible partition of the feature space into J region. For this reason, a top-down, greedy approach is used in the CART algorithm (James et al. 2013, p 306).

However, CART has two fundamental problems: over-fitting and selection bias (Hothorn, Hornik, & Zeileis, 2006). Over-fitting refers to the situation that the model describes the errors instead of the underlying relationship. It is undesirable because the fit obtained will not yield accurate estimates of the response on new observations that were not part of the original training data set (James et al. 2013, page 22). Selection bias happens because trees adopt a greedy method for variable selection. It means that at each step of the tree-building process, the best split is made at that particular step, rather than looking ahead and picking a split that will lead to a better tree in some future step (James et al. 2013, page 306).

The conditional preference methodology proposed by Hothorn et al. (2006) is applicable to all kinds of regression problems and provides a solution for the problem of selection bias, and pruning procedures are able to solve the over-fitting problem.

Conditional inference trees estimate a regression relationship by binary recursive partitioning in a conditional inference framework. The algorithm works as follows:

1) Test the global null hypothesis of independence between any of the input variables and the response. Stop if this hypothesis cannot be rejected. Otherwise select the input variable with strongest association to the response. This association is measured by a p-value corresponding to a test for the partial null hypothesis of a single input variable and the response.

2) Implement a binary split in the selected input variable.

3) Recursively repeat steps 1 and 2 (r help).

Using the test statistic p-values to determine a candidate split has several advantages over the CART methodology. Firstly, predictors that are measured on distinct scales can be compared since the p-values are on the same scale. Secondly, multiple comparison corrections can be applied to the raw p-values within a predictor to reduce the bias resulting from a large number of split candidates. These corrections attempt to reduce the number of false positive tests that are incurred by conducting a large number of statistical hypothesis tests. Therefore, predictors are increasingly penalised by multiple comparison procedures as the number of splits (and associated p-values) increases. For this reason, the bias is reduced for highly granular data. The unbiased trees can be implemented using the party package in R and a threshold for statistical significance is used to determine whether additional splits should be created where the default is 95% (Kuhn & Johnson, 2013).

4.7.4 Random Forests

The Random Forests algorithm was developed by Leo Breiman and Adele Cutler (Breiman 2001) and it is based on earlier work of Breiman and his colleague on Classification and Regression Trees (Breiman et. al. 1984). Despite the advantages of trees discussed in the previous section (see the Regression Trees section), trees can be very unstable. It means that small changes in the data can result in a completely different tree. This happens because when a particular split changes then all the other splits that are under it change as well. In other words, if one randomly splits the data space into two parts, and fits a decision tree to both splits, completely different trees could result. To overcome this problem, random forests algorithm averages the results of random trees which are fitted on different parts of the data space. Random forests improve predictive performance of trees substantially. However, this comes at the expense of some loss of interpretability.

This research uses regression trees to examine the interaction between variables and random forest is used to come up with an importance ranking of design features based on their predictive effect. The result of random forest is utilised as part of robustness analysis to test the robustness of tree models.

4.7.5 Model Performance

In order to evaluate a model performance, the prediction error associated with a given model should be estimated. The prediction error is the average error that results from using a statistical learning method to predict the response on a new observation. Therefore, the use of a particular statistical learning method is acceptable only if it results in a low prediction error.

In the absence of a very large test set that can be used to directly estimate the prediction error, the available training should be used to estimate this quantity. A class of methods estimates the prediction error by holding out a subset of the training observations from the fitting process, and then applying the statistical learning method to those held out observations.

The validation set approach randomly divides the data space into two parts, a training set and a validation set or hold-out set. The model is fitted on the training set, and the fitted model is used to predict the responses for the observations in the validation set. The prediction error is estimated by using mean square error for quantitative response.

The validation set approach is conceptually simple and is easy to implement but it has two potential drawbacks: (1) the prediction error estimation can be highly different, depending on which observations are included in the training set and which observations are included in the validation set; (2) Only a subset of the observations—those that are included in the training set rather than in the validation set—are used to fit the model. Since statistical methods tend to perform worse when trained on fewer observations, this suggests that the validation set error rate may tend to overestimate the prediction error for the model fit on the entire data set (James et al., 2013).

4.7.6 Leave-One-Out Cross Validation (LOOCV)

This is similar to the validation error approach but it attempts to address that method's disadvantages. For a dataset of n observation, LOOCV fit the model for n times. In each run n-1 observation is used for fitting the model and the single remaining example is used for testing. The prediction error is calculated using root mean squared error (RMSE):

$$\sqrt{\frac{\Sigma(\hat{y}_i - y_i)^2}{n}}$$

This procedure is repeated n-times for the n observation and therefore it results in test errors ($\mathrm{RMSE}_1, \ldots, \mathrm{RMSE}_n$). At the end, the average of prediction errors is estimated:

$$\frac{1}{n}\sum_{i=1}^{n}\mathrm{RMSE}_i$$

LOOCV has less bias over the validation set approach; however it has the potential to be expensive to implement, since the model has to be fitted n times (James et al., 2013).

In the setting of this research leave-one-out cross validation has been used to evaluate the performance of statistical models.

4.8 Conclusion

This chapter began by stating the philosophical assumption underlying this research and positioned the study as a post-positivistic research. Then, the theoretical and empirical design of the research was explained. In particular, the conduct of the empirical research, including the sampling logic, measures, pilot studies and the data collection process, was outlined.

In order to reduce concerns regarding the reliability and validity of the collected data, all the measurements were extracted from literature and were discussed by two medical experts. The raters received comprehensive training before evaluating health information and inter-rater agreement was conducted to check the consistency of the ratings. The results show a satisfactory level of agreement and reliability of collected data.

Finally, it was argued that this research has adopted the algorithmic modelling culture as it is a more accurate and informative alternative to statistical data modelling. This chapter closes with a presentation of data analysis methods including regression trees and random forest and methods of evaluating model performance.

5 Findings

5.1 Introduction

This chapter presents the empirical findings of this research. The first section highlights the shortcomings and the questions the empirical part of this research is going to address. Next, the results of exploratory analysis, tree-based models and robustness analysis for both question side and answer side of the platform will be presented. At the end, the summary of findings will be presented.

5.2 Empirical Research Questions

The aim of this study is to design an efficient platform for exchange of online health information that maximises quality. The high willingness to share health information online and high demand to find this information makes the Internet instrumental in the exchange of health information. However, this exchange is not efficient as the quality of information is not guaranteed. The exchange of online health information is a form of transaction and can be studied using the notion of 'market design'. Market design provides a framework to study the inefficiency of markets (Roth, 2007). Generally, it explains the rules of the game by which different forms of exchange can occur efficiently (Gans & Stern, 2010). This study focuses on the problem of quality as the main driver of efficiency in an online health information market.

Market design is particularly relevant to the design of a health information platform because it is particularly concerned with situations where markets do not spontaneously emerge or work efficiently and a business is needed to create the market or fix it to function efficiently. A market is required for exchange of online health information that brings health information providers and seekers together and establishes rules that facilitate efficient exchange of online health information.

This study further identifies the online health information market as a multi-sided platform. Since the platform has two distinct types of contributors, i.e., health information seekers and providers, and the contribution of each side depends on the participation of the other side, this research adopts a multi-sided platform (MSP) as the theoretical framework to conceptualise systematically the drivers of market efficiency and introduce relevant design adjustments.

Inspired by the theory of ‘market design’ and ‘multi-sided platform’ a theoretical framework was proposed in the theoretical chapter. In the proposed theoretical framework, the conditions of market efficiency in the online health information market were extracted and in the next step market design features were suggested to achieve an efficient market for exchange of online health information.

An Internet-based multi-sided platform embodies a design that defines the architecture of the services offered and the infrastructure that facilitates the interaction between the participating sides, and a set of rules, such as terms and the rights and obligations of the participants. The design of a platform determines the value to potential participants on each side of the platform. As a result, the design of the platform affects the efficiency of the platform.

Informed by the theoretical framework, in the empirical section, this research investigates which design features maximise the quality of health information. Based on the proposed theoretical framework (1) Incentive mechanism, (2) Quality Signal Mechanism and (3) Revenue Model determine the quality of produced health information. However, the literature has overlooked the effect of different designs of these mechanisms on quality of information exchanged in the health information platform. The goal of the empirical section is to assess how various designs of these mechanisms affect the quality of information exchanged in these platforms. Data for analysis were collected from question and answer platforms because they are apparent examples of the proposed framework.

Different types of Q&A platforms embody different designs. Social Q&A platforms allow anyone in the community to answer questions, while expert Q&A platforms allow qualified individuals to provide information. Transaction-based Q&A platforms charge askers and pay answerers, while free Q&A platforms use social incentives such as points, credit or stars to encourage answering. Design decisions such as these are likely to have a substantial impact on quality of questions asked, as well as the quality of the answers. Thus, the data are collected from Q&A platforms with different design to be able to study the effect of different mechanisms on the quality of generated health information. From an empirical point of view, this study wants to find out what are the specific effects of these decisions on quality. In the following section the nature of effect that design may have on the quality of health information will discussed and the questions that the empirical investigation is going to address will be highlighted.

The viability of the health information market depends on the ability of encouraging sufficient high quality contribution. Therefore, the platform should create enough value for the health information provider to encourage their participation. However, it is unclear which type of incentive results in better quality of health information. Is there any difference between information providers with and without medical background? Furthermore, in the absence of financial incentive what type of motivation can encourage participants to contribute to the health information market?

One source of inefficiency in the health information market is the existence of spam and unserious questions on the platform that waste the valuable time and attention of the potential answerers that otherwise could be spent on genuine questions that truly need answers. Unserious questions become a more serious issue in the absence of extrinsic motivations such as monetary rewards. If the information seekers post non-serious questions they automatically discourage those information providers who are motivated by "altruism"; or if they post boring questions they discourage those who are motivated by "self-enjoyment", etc. Thus, it is interesting to know what mechanisms in the platform result in high quality questions; do users ask better questions when asking a question is costly?

There has been insufficient research on the relationship between quality of questions and quality of answers. It is unclear if the askers receive better answers when they ask better questions. This issue becomes even more relevant when information providers are not incentivised financially. In other words, is it possible for the asker to incentivise the answerers by asking high quality questions in absence of financial incentives? Do answerers provide high quality information irrespective of question quality when they are paid?

As a part of platform design, it is necessary to design a revenue model for the platform. The platform owner needs to have enough revenue to cover the cost of establishing, maintaining and improving the market. Furthermore, revenue model design affects participation and quality of participation. However, it is still unclear which type of revenue model leads to high quality of contributions of both information providers and information seekers.

There are several mechanisms to overcome quality uncertainty, including: reputation system, providing a money back guarantee, and certification. The empirical studies about which quality mechanism works better are not conclusive. It should be investigated whether expert Q&A platforms (i.e. certified information providers) outperform social Q&A platforms in terms of quality, and also if there is any difference between the answers provided by paid and unpaid experts.

There is a particular challenge in designing an online reputation system in a health information market. An online reputation system works based on users' feedback about quality of health information; however, there is a debate in the literature about whether users without medical background can provide correct feedback about technical aspects of healthcare. Therefore, it is important to know if there is a gap between perceptions of users about quality of health information and experts' perception. In other words, are the users likely to follow or vote for questions and answers of high quality, or not? Due to the fact that health information is credence good, whose quality is difficult or impossible for patients to ascertain, there is still vagueness about whether or not patients are able to recognise quality of health information. Thus, it should be investigated if there is a relationship between users' feedback, such as number of followers and number of likes, and quality of questions and answers.

The designs of the incentive model, revenue model and quality signal mechanism are interrelated. Therefore, it is important to investigate which combination of mechanisms results in best quality of health information.

5.3 Answer Side Results

This section will investigate possible effects of the design features of a platform on the quality of questions and answers generated in the platform. It uses the data of the design features of nine health question and answer (Q&A) platforms and quality of health information produced on these platforms to conduct the analysis. Such an extensive study of possible effects of platform design on online health information has, to the best of the author's knowledge, not been conducted before. First the answer side of the platforms is analysed as the quality of answers is more important from the healthcare point of view. Next, the quality of questions as a predictor of the quality of answers is added to previous predictors to check if there is any relation between the quality of questions and the quality of answers. Finally, the robustness analysis will be presented. The same methods will be utilised to analyse the question side of the platform. Figure 13 summarises the data analysis phases for both answer side and question side of the platforms. The analyses were implemented using R package version 3.1.1 which is an open source tool and freely available. All codes are available at Appendix C5 Section1010.1.

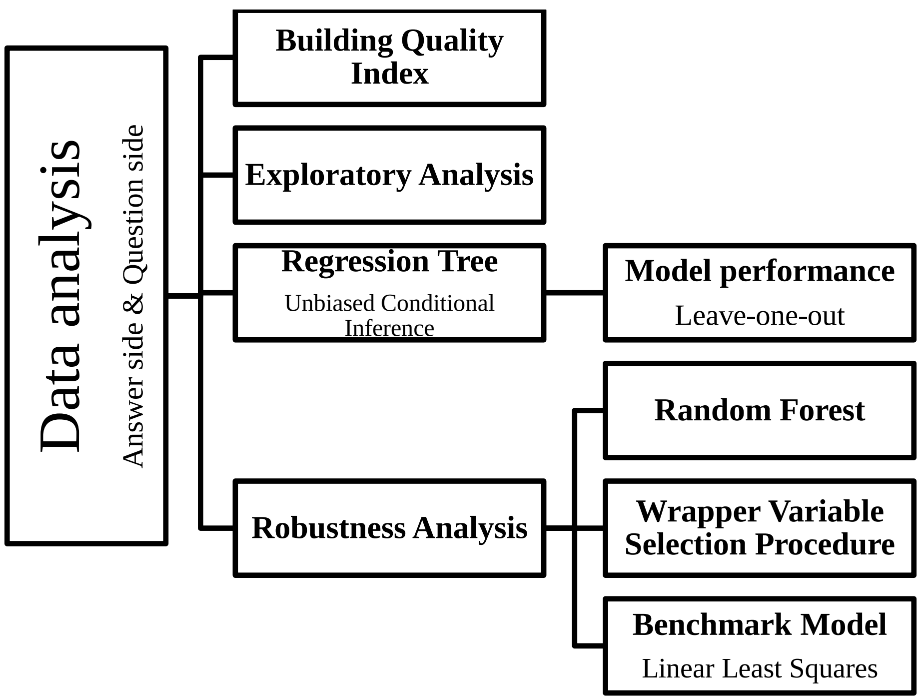


Figure 13: Data Analysis Phases- Repetitive for Answer Side and Question Side

5.3.1 Quality Index for Answers

The quality of answers was measured based on the following characteristics: Accuracy, Completeness, Relevance, Objectivity, Readability, Source Credibility, Politeness, Confidence, Empathy, Efforts, and Archival Value (for complete description of characteristics see Methodology chapter Section 4.4.2.1). In order to build one index for quality of answers, an average of these measures has been calculated. This index has been used as the dependent variable in the analysis of answer quality in the following analysis.

5.3.2 Exploratory Analysis

Table 18 summarises descriptive statistics of the quality of answers for the nine platforms of the sample. Figure 14 gives a visual representation of Table 18.

Table 18: Quality of answers across nine Q&A platforms of the sample

	Min	1st Quartile	Median	Mean	3rd Quartile	Max	Standard Deviation
AllExperts	2.2	3.273	3.668	3.576	3.909	5	0.511
Answerbag	1	1.191	2.7	2.566	3.6	5	1.156
ChaCha	1	2.545	3.1	2.99	3.636	4	0.874
Google Answers	1	3	3.818	3.593	4	5	0.875
Just Answer	3.273	3.907	4	4.274	4.818	5	0.678
Mahalo Answers	1	3.273	3.727	3.52	4	5	0.894
Quora	1	2.8	3.545	3.34	3.839	5	0.785
WebMD Answers	1	2.85	3.7	3.32	3.905	4.818	0.953
Yahoo Answers	1	2.455	2.9	2.809	3.364	5	0.879

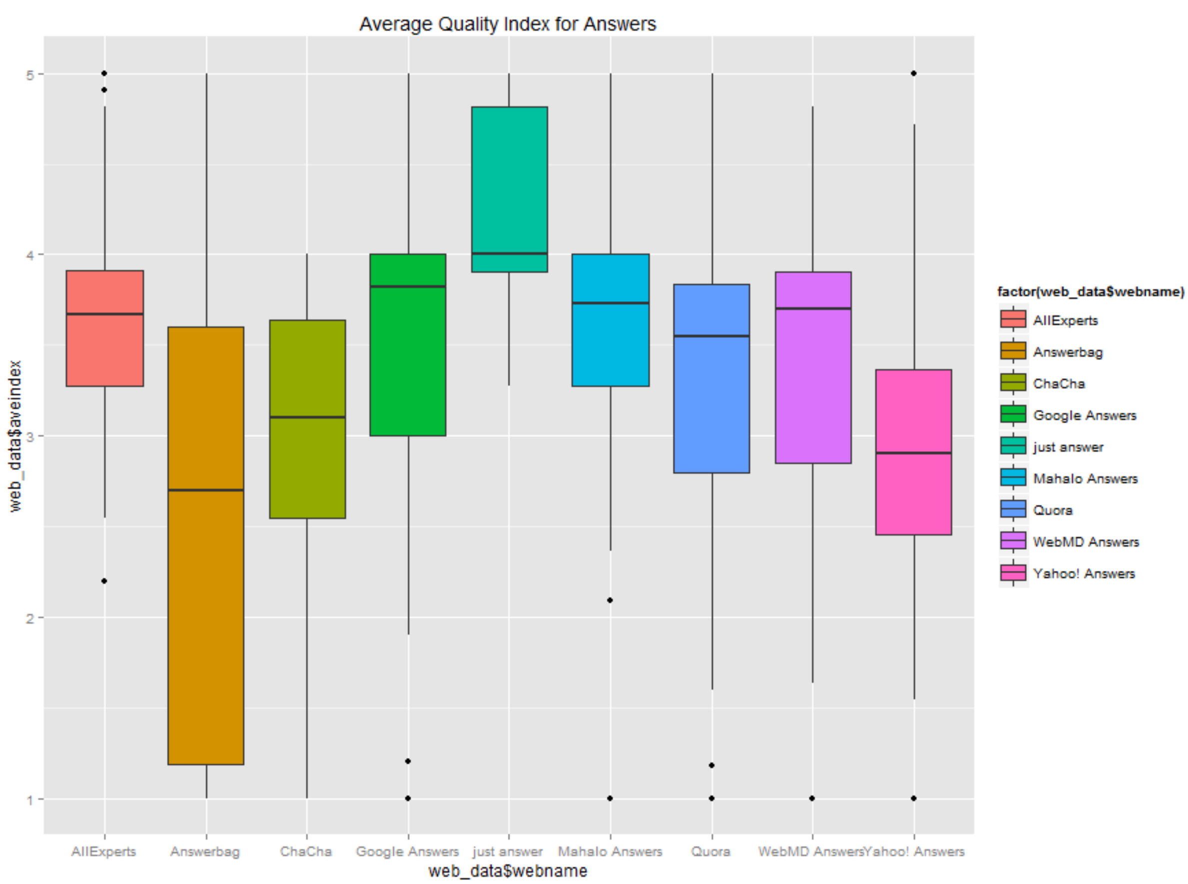


Figure 14: Quality of answers across nine Q&A platforms of the sample

The Just Answer platform has the highest mean and median for quality of answers. As depicted in Figure 14, the averages of quality of the Just Answer platform are skewed toward the higher end of the graph. That is, most of the answers in the Just Answer platform have received approximately 4 or higher score of quality by the raters. Just Answer is an online expert question and answer platform. All respondents of Just Answer have their medical credentials verified before answering health questions. The real identity of the experts is not revealed which means they cannot gain offline reputation by their contribution in Just Answer. A question costs £11 to £48 based on ‘urgency’ and ‘level of detail’ required for the answer and in case of dissatisfaction with the answer money back is guaranteed. Respondents are paid based on their experience, from 25% to 50% of the question price. The platform works based on the transaction-based revenue model. No community-based design feature including point system, ranking system, best answer, or following are used in Just Answer. For a complete explanation of Just Answer Q&A, please see Methodology chapter, Section4.4.1.4.

The quality of answers in Google Answers shows more variation in ratings comparing with Just Answer. But as depicted in Figure 14 still 75% of ratings are evaluated as higher than a 3 score. In Google Answers (no longer in operation), the questions were answered by two groups: (1) researchers; (2) commenters. Researchers were experts at locating hard-to-find information on the web. They were required to go through an application process that tested their research skills and the quality of their answers. However, there is no claim for medical expertise of the researchers (Y. Chen et al., 2010). Users could post a question and specify how much they were willing to pay for an answer, from $2 to $200. A client who was not satisfied for whatever reason could receive a refund. Commenters voluntarily provided answers. They were incentivised neither by monetary reward nor by reputation. Their incentive was to become a researcher as Google stated that people who commented might be selected to become researchers, therefore inspiring high quality comments. Google Answers does not reveal the real identity of either researchers or commenters (for a complete explanation of Google Answers, please see Methodology Chapter, Section4.4.1.1). The high variation in the rating may be the result of a different type of answer providers in Google Answers.

The average quality in AllExperts is 3.57 and 75% of the answers got more than a 3.27 score in ratings of answer quality which is a relatively high quality score. The questions in AllExperts are answered by volunteers with medical expertise. Unlike Google Answers and Just Answer, answerers in AllExperts can reveal their real identity and gain offline reputation through their contribution in the platform (for a complete explanation of AllExperts, please see Methodology chapter, Section 4.4.1.3.).

In Mahalo Answers the average quality is 3.52 and most of the answers have a quality higher than 3.27 which is very close to the AllExperts quality measurement. The askers and answerers in Mahalo Answers are able to gain or lose online reputation based on their contribution. A key distinction is allowing askers to give a monetary reward to the user who provides the best answer. The revenue model of the platform is semi-transaction-based as advertisement is another source of revenue. Similar to Yahoo Answers and Answerbag, a point and level system is used in Mahalo Answers.

The quality of answers in Quora has high variation from ~1.6 to a 5 score. The average quality is 3.34 and most of the answers have more than a 2.8 score of answer quality which is a moderate score. The revenue model of Quora has not been established yet. There is no financial incentive involved in this platform. Similar to the Yahoo Answers point system, Quora uses a credit mechanism to encourage high quality participation. The unique feature of Quora is that users can specify how much credit they would like to get to answer a question and askers can pay with their credit to have their questions answered. Users of Quora are able and highly encouraged to gain offline reputation by revealing their real identity.

In WebMD the average quality is 3.32 and most of the answers have a quality higher than 2.85 which is very close to the Quora quality score. WebMD Answers is a health question and answer service which is contextually integrated throughout a health public website called WebMD. Two types of answerers are providing answers in this platform: lay users and health experts. There is no financial incentive involved for both type of answerers; however, answerers are able to gain offline reputation based on their contribution in the platform. The revenue model is purely advertisement-based. WebMD uses community-based features including following and voting mechanisms.

The average quality in ChaCha is 2.99 and 75% of answers got more than 2.54 which is a moderate score. ChaCha is a free and mainly mobile-based question and answer platform. Asking questions in ChaCha is free and questions are provided by guides who earn $0.02 per completed transaction. The ChaCha revenue model is based on advertisement while it pays a cut of its earnings to guides to provide high quality, accurate answers. There is no information publicly available about offline and online reputation of the guides. No point and ranking system is embedded in the platform.

In Yahoo Answers the average quality is 2.809 and most of the answers have a quality less than 2.809 which is a relatively low quality score. Yahoo Answers is a social question and answer platform. Posting questions and answers is free of any financial charge and Yahoo Answers generates its revenue out of advertisement. Yahoo Answers has established a system of points and levels to manage participation of its users. Once a user begins participating on Yahoo Answers, he gets 100 points. Asking a question costs 5 points and providing an answer earns 2 points. Best answer, voting and reporting fraudulent behaviour are other mechanisms which are used in this platform. Users mostly use a nickname in the platform and their contribution is not linked with their offline reputation.

The lowest average of answer quality (mean= 2.566) and the highest variation of quality (Standard Deviation = 1.155844) belongs to Answerbag. Answerbag is a social question and answer platform where questions are asked and answered by lay users. Similar to Yahoo Answers, posting questions and answers is free of financial charge and the revenue model is based on advertisement. Unlike Yahoo Answers' point system, users do not lose or earn any points for simply asking and answering; rather, earning points is upon submitting good questions and answers. Best answer, voting and reporting fraudulent behaviour are other mechanisms which are used in this platform.

Generally the higher quality of answers belongs to those platforms which use experts as answerers in their platform such as Just Answer, Google Answers, and AllExperts. The platforms which are using a transaction-based model including Just Answer, Google Answers and Mahalo Answers have better answers compared with advertisement-based revenue model platforms such as Answerbag and Yahoo Answers. The platforms which financially incentivise answering have higher quality of answers. For example, Just Answer and AllExperts both use experts with medical background to answer the questions; however, the key distinction is Just Answer pays the experts but the incentive for experts in AllExperts is not financial. Clearly, Just Answer enjoys a higher quality of answer. Another example is Mahalo Answers and Answerbag or Yahoo Answers. The key distinction between Mahalo Answers and the other two platforms is use of a financial incentive by Mahalo Answers while the other two just rely on social incentives such as points and ranking system. The descriptive statistics clearly show that Mahalo Answers generates answers with higher quality. There is not considerable difference between qualities of answers in platforms which use different social mechanisms. For example, in Yahoo Answers asking is socially costly and answering is financially rewarding; however, in Answerbag, users do not lose or earn any points for simply asking and answering. There is not a substantial difference between qualities of answers in these two Q&A platforms.

5.3.3 Results of Answer Trees

A series of regression trees are conducted in order to investigate the exact nature of the relationship between the design features (i.e. independent variables) and quality of answers (i.e. the dependent variable). The tree building procedure in this research is implemented using R package (party library) and is based on the unbiased conditional inference methodology proposed by Hothorn et al. (2006).

The regression tree method is capable of dealing with a large number of predictors or features. This makes it possible to include all the predictors of this research in a single model at once to find out design features that help best to predict the quality of answers on a platform. Since the aim of the data analysis is to thoroughly understand the possible interactions between variables, Instead of including all predictors at once and building a single model, a growing model with increasing complexity is built. This approach gives more chance of exploring the patterns of data and revealing interactions between predictors and the response.

In this approach the predictors are categorised into reasonable sets. A simple set is selected and the regression tree algorithm is conducted. Then, a new set of predictors is added to previous set(s) and the algorithm is run again. This process is continued until all the predictors are included and the final tree is built. The track of changes in the models is kept for interpretation. It is more likely to extract the patterns in the data and observe the possible interactions between variables in this way compared with the approach in which all predictors are included simultaneously. When predictors are added gradually rather than at once, the interactions between variables can be observed more closely. For example, adopting this approach enables recognition of predictor(s) that appear and remain in the model and those which disappear by inclusion of more effective predictors. Furthermore, if all predictors are included at once, it is never recognisable which predictor forces out others.

In the literature review section, the design features which are considered as effective predictors of quality of health information are identified and classified under three mechanisms, namely revenue model, incentive mechanism, and quality signal mechanism. Through analysing question and answer platforms in the data collection process, the design features related to each mechanism are identified and added to the initial list of predictors (see section 4.4.2.3). The final list of 31 predictors is categorised based on their similarity into 7 sets of variables, tabulated in Table 19.

In the first step, the tree algorithm is run for the first set of predictors (i.e. Model A1: Knowledge background) then the resulted tree is interpreted. In the next step the successive set (i.e. Model A2: Reputation) is added to the previous and a new model is constructed. This process is continued and each succeeding model includes all the variables in that model as well as variables in the previous sets. The process is ended when all models are included and the final tree is grown.

It should be noted that in order to understand which set of variables is to be added in each step, different possible sets have been tried in each step and the best demonstration of the interaction between the predictors is presented. The most representative order in terms of ease of interpretation is shown in Table 19.

Table 19: Answer Models

Model	Variables
Model A1: Knowledge background	Medical Certification (certify), Expertise (expert)
Model A2: Reputation	Reputation System (reput) , Offline reputation (offrepu)
Model A3: Revenue Model	Advertisement-based (advertise1), Transaction-based (transaction), Money back guarantee (gurantee), Mobile-based platform (mobile)
Model A4: Incentive Model-Basic	**Basic incentives:** Social incentive for answering (aso), Financial incentive for answering (afin), Social price for asking (qso), Financial cost for asking (qfin), Price of question (price), Payment for answer (pay)
Model A5: Incentive Model-Variation	**Who determines answering incentives, platform or users:** aso determined by the platform (asofix), aso determined by users (asoflex), afin determined by the platform (afinfix), afin determined by the users (afinflex) **Who determines asking incentives, platform or users:** qso determined by the platform (qsofix), qso determined by users (qsoflex), qfin determined by the platform (qfinfix), qfin determined by the users (qfinflex)
Model A6: Governance Rule and Systems	voting system for answers (avotew), following system (afollow), ranking system (ranksys), best answer system (best), point system (pointsys), Reporting system of fraudulent behaviour (reportfradu), Multiple answering (multi), commenting (comment)
Model A7: Final Model (Adding Quality of question)	Quality of questions (questionavg)

5.3.4 Interpretation of Trees

The regression tree algorithm generates a set of split conditions in the form of binary rules or if-then statements. For interpretation of regression trees, a path from the top of the tree (the root) is tracked and proceeds to one of the leaves by following a succession of rules (splits). The root node as well as each split under an unbiased conditional preference tree contains information about p-value, because the unbiased conditional preference algorithm is working based on statistical hypothesis testing. For the remainder of this analysis, a significance threshold of 0.05 has been set. The R package shows the results of the regression tree in two formats. In one of the formats, the leaf nodes present a box-whisker plot of the data fallen in that particular split. In the second format, the leaf nodes present the mean of predicted values for the corresponding split. The mean of predicted values in this study is on the bases of 1-5 scale because the quality was rated against 1-5 Likert scale (see Section 4.4.2). In order to demonstrate the results of regression trees in this study, both the box-whisker format results and the predicted mean value format results are presented.

Intuitively, predictors that appear higher in the tree (i.e. earlier splits) or those that appear multiple times in the tree will be more important than predictors that occur lower in the tree or do not appear at all. If a predictor is never used in any split, the variable does not contribute to the prediction of the outcome variable. This advantage is weakened when there are highly correlated predictors. If two predictors are extremely correlated, the choice of which to use in a split is somewhat random (Kuhn & Johnson 2013). The correlation matrix of the independent variables is calculated and shown in Figure 15.

The correlation matrix (see Figure 15) shows perfect correlation between transaction-based revenue model (transaction) and financial cost of asking (qfin). This correlation is intuitively valid as all of the platforms in which asking a question is costly including Google Answers, Just Answer and Mahalo Answers also have transaction-based revenue model. Moreover, there is high correlation between medical certification of answerers (certify) and their expertise (expert). The reason behind this is that all the experts of the sample have medical certification except Google Answer experts/researchers who have expertise at locating hard-to-find information on the web. Another case of perfect correlation is between reporting fraudulent behaviour (reportfradu) and number of votes (avotew). These correlations are carefully taken into consideration in the interpretation of regression trees.

The rest of the predictors have less than 0.9 correlations. Based on Kuhn & Johnson's (2013) argument, if they do not appear in the trees, it is the result of their low effect on quality of answer, not random selection of high correlated predictors.

	certify	expert	reput	offrepu	advertise1	transaction	gurantee	mobile	aso	afin	qso	qfin	qfinfix	qfinflex	qsofix	qsoflex	afinfix	afinflex	asofix	asoflex	avotew	afollow	pointsys	ranksys	best	reportfradu	multi	comment
certify	1																											
expert	0.91	1																										
reput	0.30	0.33	1																									
offrepu	0.46	0.39	0.30	1																								
advertise1	-0.07	-0.19	0.05	-0.07	1																							
transaction	0.07	0.19	-0.05	-0.45	-0.50	1																						
gurantee	0.25	0.40	-0.18	-0.34	-0.76	0.76	1	-																				
mobile	-0.34	-0.38	-0.45	0.25	-0.19	-0.38	-0.29	1																				
aso	-0.23	-0.32	0.52	0.27	0.32	-0.32	-0.60	-0.06	1																			
afin	0.01	0.12	-0.23	-0.50	-0.12	0.61	0.35	0.14	-0.41	1																		
qso	-0.34	-0.38	0.25	0.25	-0.19	-0.38	-0.29	0.36	0.48	-0.42	1																	
qfin	0.07	0.19	-0.05	-0.45	-0.50	1	0.76	-0.38	-0.32	0.61	-0.38	1																
qfinfix	0.55	0.50	0.17	-0.23	-0.50	0.50	0.66	-0.19	-0.40	0.46	-0.19	0.50	1															
qfinflex	-0.34	-0.16	-0.18	-0.34	-0.19	0.76	0.36	-0.29	-0.06	0.35	-0.29	0.76	-0.19	1														
qsofix	-0.23	-0.25	0.17	-0.23	0.25	-0.25	-0.19	-0.19	0.32	-0.27	0.66	-0.25	-0.13	-0.19	1													
qsoflex	-0.23	-0.25	0.17	0.55	-0.50	-0.25	-0.19	0.66	0.32	-0.27	0.66	-0.25	-0.13	-0.19	-0.13	1												
afinfix	0.25	0.19	-0.45	-0.34	-0.19	0.19	0.36	0.36	-0.60	0.69	-0.29	0.19	0.66	-0.29	-0.19	-0.19	1											
afinflex	-0.27	-0.05	0.20	-0.27	0.05	0.60	0.05	-0.23	0.14	0.55	-0.23	0.60	-0.15	0.80	-0.15	-0.15	-0.23	1										
asofix	-0.08	-0.16	0.42	-0.08	0.63	-0.16	-0.48	-0.48	0.80	-0.23	0.06	-0.16	-0.32	0.06	0.40	-0.32	-0.48	0.24	1									
asoflex	-0.23	-0.25	0.17	0.55	-0.50	-0.25	-0.19	0.66	0.32	-0.27	0.66	-0.25	-0.13	-0.19	-0.13	1	-0.19	-0.15	-0.32	1								
avotew	-0.58	-0.69	0.05	-0.07	0.50	-0.50	-0.76	0.38	0.32	-0.12	0.38	-0.50	-0.50	-0.19	0.25	0.25	-0.19	0.05	0.16	0.25	1							
afollow	0.02	-0.03	0.25	0.61	-0.19	-0.38	-0.29	0.36	-0.06	-0.41	0.36	-0.38	-0.19	-0.29	-0.19	0.66	-0.29	-0.23	-0.48	0.66	0.38	1						
pointsys	-0.08	-0.16	0.42	-0.08	0.63	-0.16	-0.48	-0.48	0.80	-0.23	0.06	-0.16	-0.32	0.06	0.40	-0.32	-0.48	0.24	1	-0.32	0.16	-0.48	1					
ranksys	-0.45	-0.50	0.33	-0.45	0.50	0.00	-0.38	-0.38	0.63	-0.06	0.19	0.00	-0.25	0.19	0.50	-0.25	-0.38	0.35	0.79	-0.25	0.50	-0.38	0.79	1				
best	-0.27	-0.34	0.42	-0.27	0.63	-0.16	-0.48	-0.48	0.35	-0.23	0.06	-0.16	-0.32	0.06	0.40	-0.32	-0.48	0.24	0.55	-0.32	0.63	0.06	0.55	0.79	1			
reportfradu	-0.58	-0.69	0.05	-0.07	0.50	-0.50	-0.76	0.38	0.32	-0.12	0.38	-0.50	-0.50	-0.19	0.25	0.25	-0.19	0.05	0.16	0.25	1	0.38	0.16	0.50	0.63	1		
multi	-0.41	-0.50	0.52	0.08	0.32	-0.32	-0.60	-0.06	0.55	-0.40	0.48	-0.32	-0.40	-0.06	0.32	0.32	-0.60	0.15	0.35	0.32	0.79	0.48	0.35	0.63	0.80	0.79	1	
comment	-0.34	-0.16	-0.88	-0.34	-0.19	0.19	0.36	0.36	-0.60	0.35	-0.29	0.19	-0.19	0.36	-0.19	-0.19	0.36	0.05	-0.48	-0.19	-0.19	-0.29	-0.48	-0.38	-0.48	-0.19	-0.60	1

Figure 15: Correlation matrix of independent variables

Beside correlation which was shown in Figure 3, partial correlation is also observable in the resulted regression trees. For example, offline reputation of answerers and advertisement-based revenue model are not highly correlated (-0.07) in the outset. However, if experts are answering the questions then these two variables have perfect correlation. The reason behind this is that all of the platforms in the sample which use experts as respondents and have an advertisement-based revenue model allow their experts to gain offline reputation.

In such cases, the regression tree randomly selects one of the correlated predictor. As the number of platforms in the sample is limited (nine platforms) the intuitive knowledge about the platforms is utilised to identify these partial correlations and reflect them in the interpretation.

5.3.5 Results of Regression Trees

Model A1: Knowledge Background

Model A1 include two variables – medical certification and expertise. Figure 16 shows the unbiased regression tree with these two variables. The tree indicates that experts (expert =1) produce answers with higher quality compared with respondents without expertise (expert =0). Experts have either medical knowledge (certify= 1) or have expertise at locating hard-to-find information from online and offline resources, i.e. Google researchers. The mean of quality of answers produced by non-experts equals to 3.048. This figure for respondents with any kind of expertise is one score higher and around 4.0 on average (i.e. 4.253 for experts without medical expertise and 3.858 for medical experts). This means that the platform can increase the quality of provided answers by one score which equals to 20% through recruiting experts to answer health questions.

Interestingly, Google researchers who have advanced searching skills provided even higher quality than experts with health-related knowledge. It should be noted that many health-related questions remained unanswered in Google Answers perhaps due to the fact that searching expertise is not necessarily enough to answer health questions.

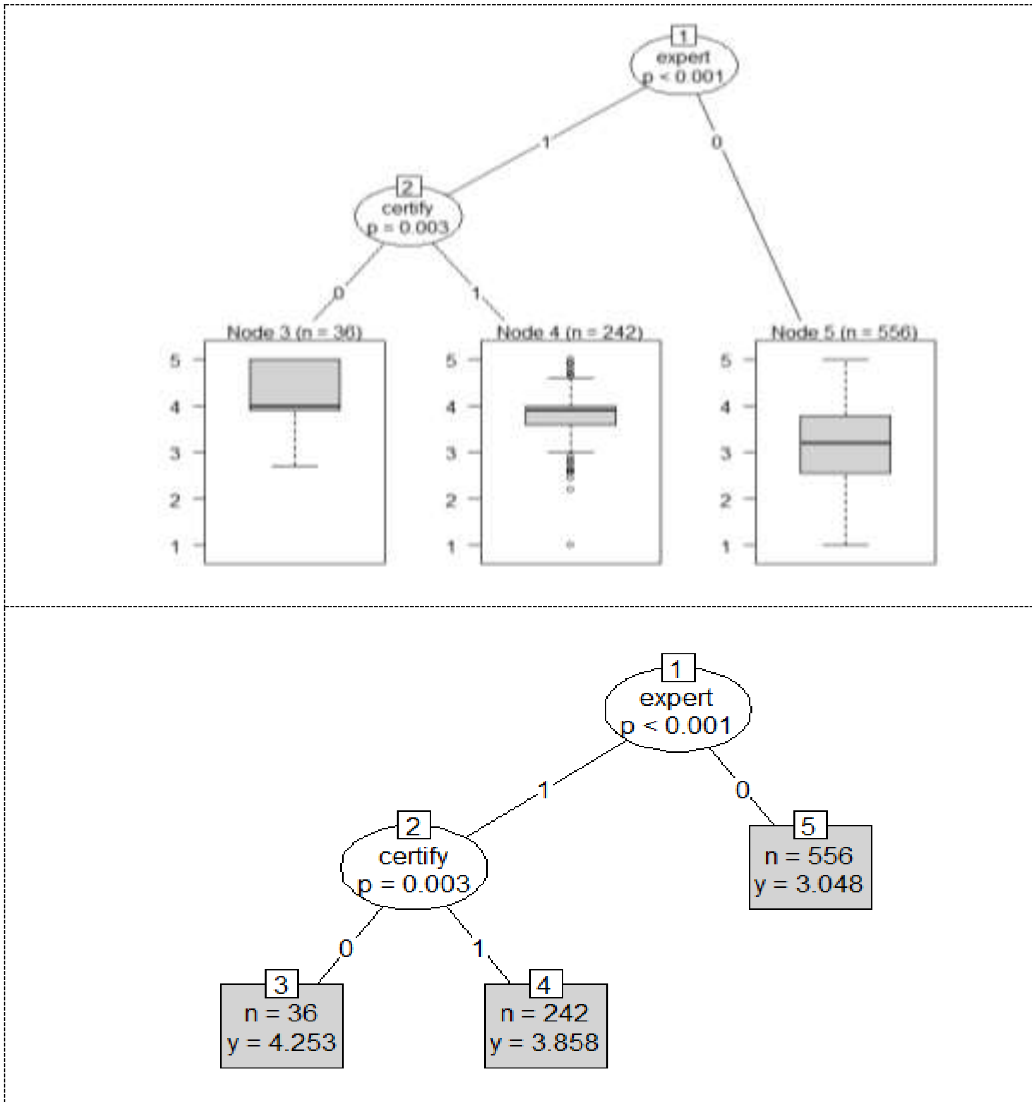


Figure 16 : Model A1 - Knowledge background

Model A2: Reputation

Model A2 adds two variables to the previous list of variables to capture the potential impact of reputation on quality of answers. Online reputation refers to the history of participants' activity inside the platform while offline reputation refers to the participant's reputation outside the platform. Platforms publicise online and/or offline reputation to signal the quality of participants' contribution for community members. Figure 17 shows the resulting tree.

The expert variable still appears at the root node which indicates the importance of expertise of respondents in determining the quality of answers. The impact of offline reputation on expert and non-expert information providers differs. If lay users provide answers (expert=0), then using offline reputation feature (offrepu=1) will increase answer quality by 0.353 quality score (equals to 7.06%). It means that when non-expert are on board and they are allowed to gain offline reputation, then the quality of answers will be 7.06% better than when non-experts are not allowed to gain offline reputation. On the contrary, experts (expert =1) who are not incentivised by offline reputation (offrepu=0) provide answers of lower quality.

As mentioned earlier (see Section5.3.4), there are some cases of partial correlations in the fitted tree models which should be considered in interpretation of the models. In the right split of Model A2 where experts are answering the questions (expert=1), there is a perfect partial correlation between offline reputation feature and financial incentive feature. There are four websites in this research sample which are using experts for answering questions: Google Answers, AllExperts, WebMD and Just Answer. AllExperts and WebMD are incentivising their experts by allowing them to gain offline reputation and the experts are not paid; but in Google Answers and Just Answer anonymous experts are financially incentivised to answer the questions. Experts are incentivised either financially or by gaining offline reputation. It means the unpaid experts are incentivised by gaining offline reputation. According to A2 Model paid experts are producing answers with 0.73 (4.268-3.565=0.73) higher quality score than unpaid experts which equals to 14.06% improvement in quality of answers. Using reputation system seems to have little effect on the quality of answers as it does not appear in the tree.

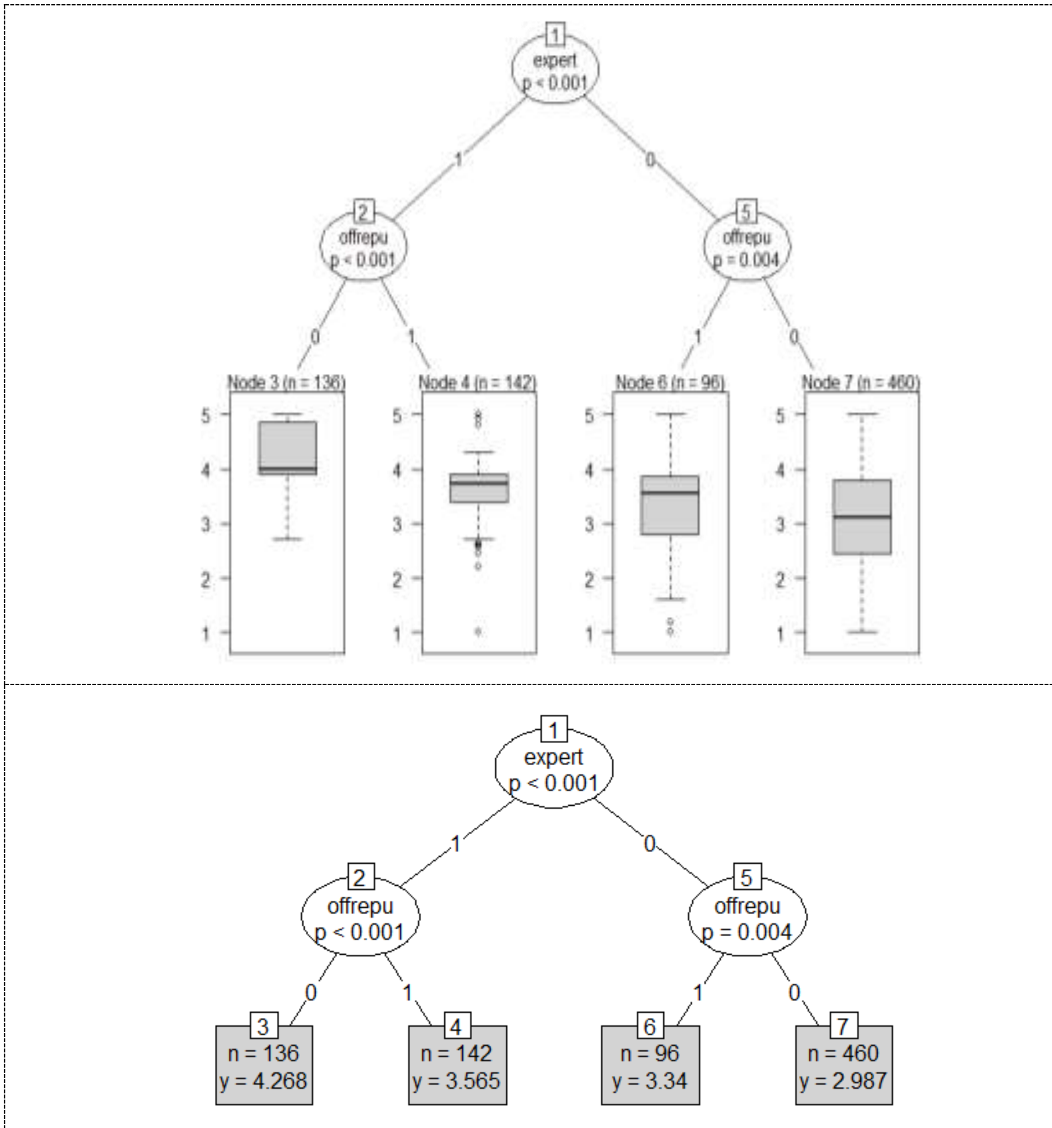


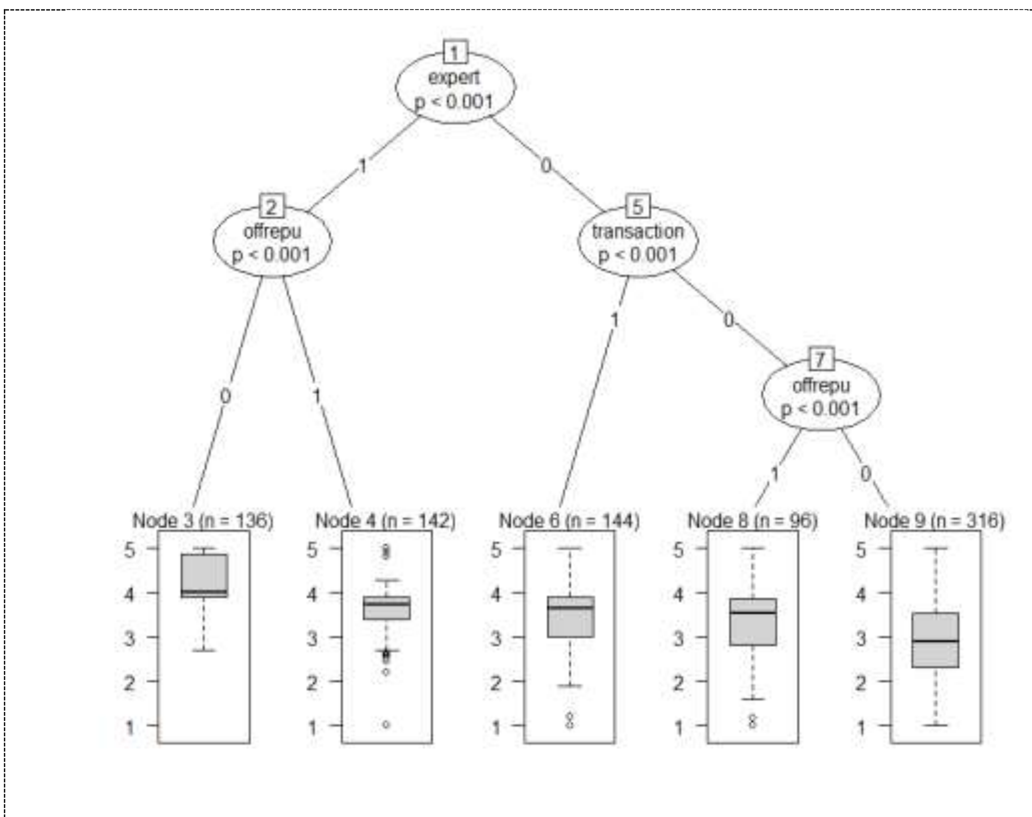
Figure 17: Model A2 - Reputation

Model A3: Revenue model

The next model adds a list of variables which captures the variables related to the revenue models of the platforms to the previous set of variables. There are two basic types of revenue model in the sample, advertisement-based and transaction-based models, and there is just one platform (i.e. Quora) that has not established its revenue model so far. It is plausible to consider the provision of a money back guarantee and having a mobile-based platform as variations of revenue model as they aim at attracting more participation (Table 19). Figure 18 shows the unbiased regression tree fitted to these variables. Revenue model variables do not appear in the branch of the tree where all answer providers are experts.

Transaction (i.e. transaction-based revenue model) appears in the non-experts branch of the tree. It can be inferred from Model A3 that participation of experts means higher quality irrespective of the type of revenue model. As mentioned in the interpretation of Model A2, transaction and offrepu can be used interchangeably due to the high correlation of these variables in the left split of the trees. It can be concluded that the transaction-based revenue model leads to higher quality in both cases of using experts and non-expert answerers. Transaction-based revenue model increases quality score by 0.73 (equals to 14.06%) in expert platforms and by 0.289 (equals 5.78%) in non-expert platforms. To summarise, the expertise of information providers is the best predictor of quality and higher quality information is provided in platforms with a transaction-based revenue model.

In the right branch of Answer Model 3, transaction-based revenue model appears in a higher split compared with offline reputation of users. It means that transaction plays a more important role in predicting quality of answers than offline reputation. In other words, if lay users answer the question (expert=0) and transaction-based revenue model is not used (transaction=0) then anonymous answerers provide information of lower quality (mean= 2.814) compared with those who are incentivised by their offline reputation (mean= 3.34).



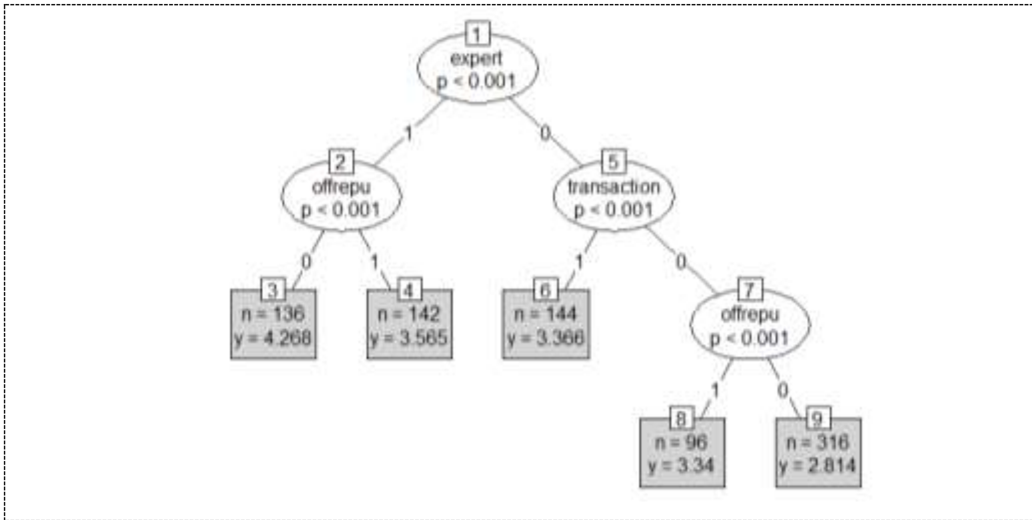


Figure 18: Model A3 - Revenue Model

Model A4: Adding basic incentive model

Basic incentives:

In this step a set of variables is included that captures basic incentives that a platform offers to the respondents. The variables represent whether financial or social incentive is used for asking and answering in the platform. Financial incentives are in the form of monetary reward. For example, in ChaCha, $0.02 is paid per answer to the respondents. Social incentives can be in the form of points or credit. For example, asking a question costs 5 points in Yahoo Answers while answering earns 2 points. In Quora, any user can determine how much credit they want to answer a question. Any user gets 500 credits upon their registration. The unbiased tree shown in Figure 19 is not very different from Model A3. The only change is that 'transaction' is replaced by 'qfin'. This is because these two variables have perfect correlation (see Figure 15). Based on Model A4, financial incentive improves quality of answer by 14.06% given than expert answer the questions. If non-expert answer questions then financial incentives improve quality by 5.78%

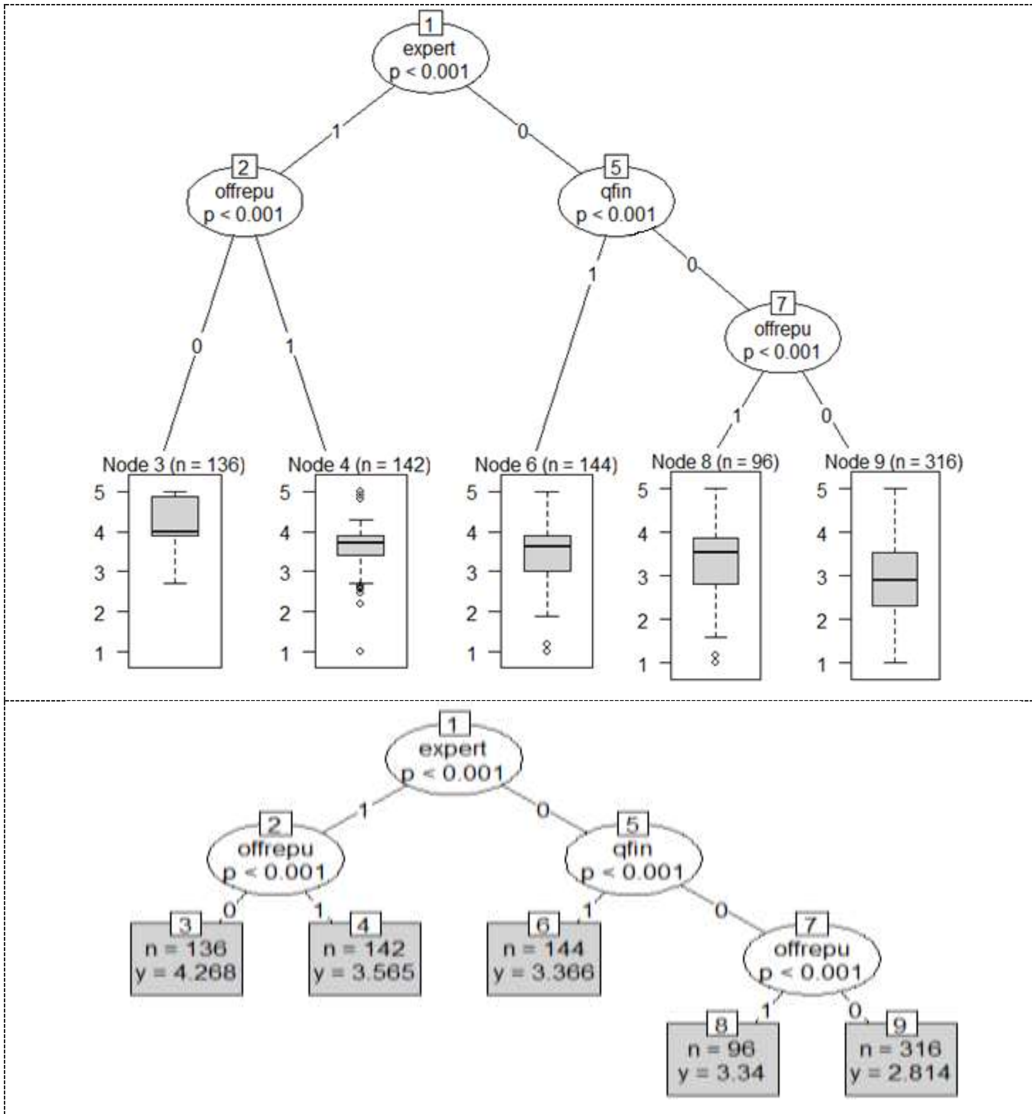


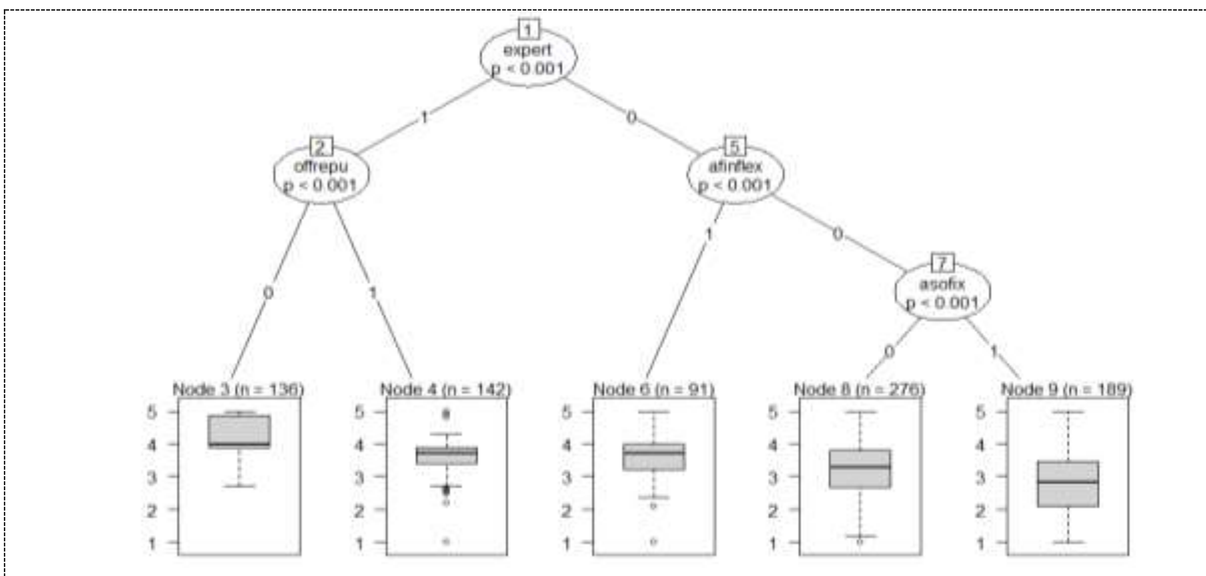
Figure 19: Model A4 - Incentive Model (Basic)

Model A5: Incentive Model- Variation

In this step, the variables relating to the incentive mechanism of the platforms were added to previous sets of variable. This step provides more detail about the types of incentives that have an effect on the quality of answers. The variation of incentives indicates whether a platform determines the amount of answering incentives (afinfix, asofix) or users themselves decide about the amount (afinflex, asoflex). For example, there is a fixed price of $0.02 per answer for answering in ChaCha. This amount is determined by the ChaCha platform. In Mahalo Answers the askers suggest a price for answering their question. Similarly, social incentives can be determined by the platforms or by the users of the platform. For example, in Yahoo Answers an asker loses 5 points per question. This rule was set by the Yahoo Answers platform, but in Quora respondents suggest the amount of credit they want in order to answer a question. The variables of whether a platform determines the amount of asking incentives (qfinfix, qsofix) or the users (qfinflex, qfinflex) decide about it are also included in Model A5.

Figure 20 depicts the unbiased tree fitting the variables. There is no change in the root (i.e. expert) and the right side branch of the tree (expert=1). In the left side branch (expert=0) variables capturing incentives determined by the users (afinflex, asoflex) appear in the model. If ‘afinflex’=1 then the expected mean quality of answers is higher and equals to 3.49. It means that the platforms which let the users decide about the payment of answers provide answers with higher 0.571 quality score (11.42% improvement).

When ‘afinflex’=0, another predictor of answer quality (i.e. asofix) appears in the model. Node 7 of the model indicates that using fixed social incentive leads to lower quality of answers (mean= 2.69) and those platforms which do not use fixed social incentive enjoy higher quality of answers (mean=3.144). It can be inferred that those platforms which are working based on social incentive and the amount of incentive is determined by the platform are producing the lowest quality answers (mean= 2.692). Yahoo Answers is an example of this type.



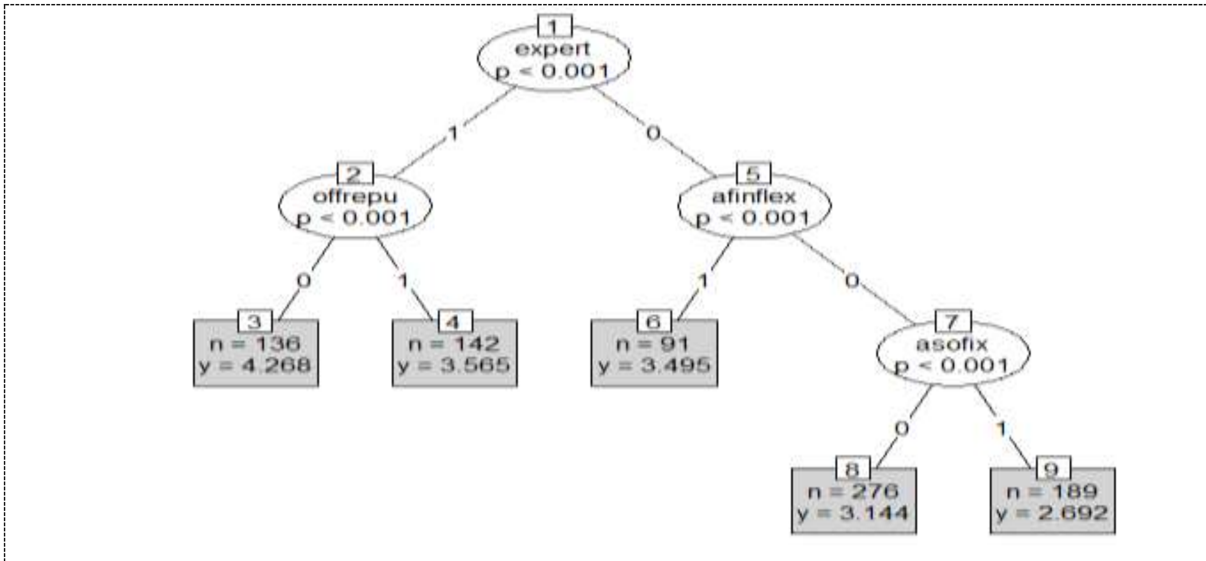


Figure 20: Model A5 - Incentive Model- Variation

Model A6: Governance rules and system

Variables related to voting, following, ranking, reporting, point systems, allowing multiple answering, commenting and best answer mechanisms are added to previous predictors in the sixth model. Fitting an unbiased regression tree to these variables yields a tree similar to Figure 20 – none of the newly added variables appear in the tree, suggesting that they do not contribute to the prediction of the quality of answers noticeably.

Model A7: Final Model

At the final stage, the quality of questions is added to the previous predictors. The average rating for measuring quality of questions is considered as a predictor of quality of answers. This model wants to check whether the quality of the asked question has effect on quality of the answers it receives. The fitted regression tree is shown in Figure 21. Adding quality of question to the model does not change the tree but the prediction error is improved (see Figure 22: Ranked prediction error for answer models). It should be noted according to random forest analysis (that will be presented in the robustness analysis (see Figure 23)), the quality of question turns out to be an important predictor of answer quality. The reason behind this is that predictors of question quality are similar to predictors of answer quality. Since the predictors of question quality already appear in the model, this variable does not turn up in the tree model.

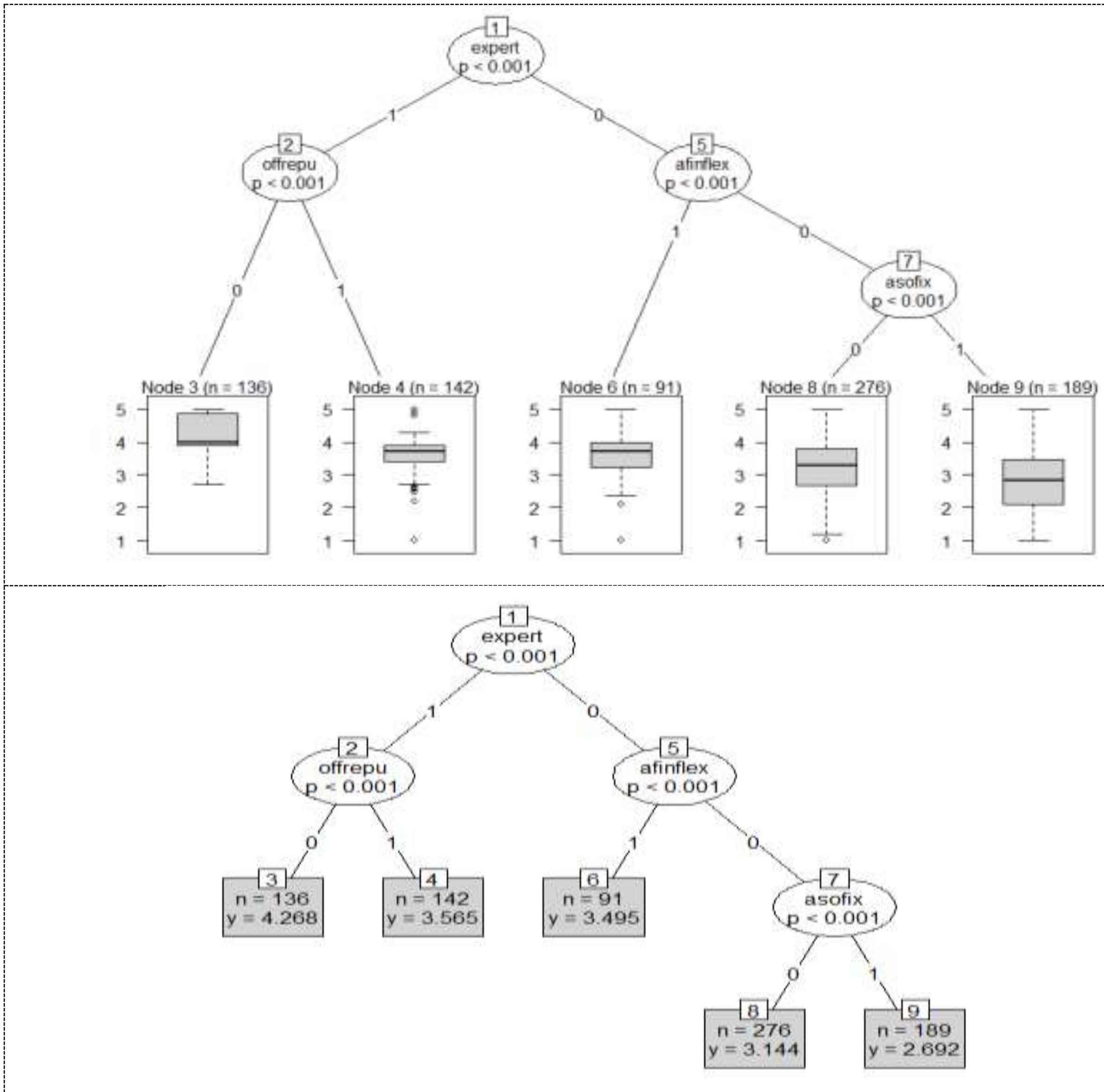


Figure 21: Model A7- Final Model

5.3.6 Predictions Errors

In order to evaluate model performance of the unbiased regression trees, leave-one-out cross validation is used to evaluate the out-of-sample predictive performance of the models. Table 7 shows the out-of-sample prediction errors for the seven tree models. Figure 22 visualises the ranked prediction errors of the answer model. The evaluation of mode performance enables comparison of the performance of the regression trees and helps in the decision of which answer model should be used as the basis for further interpretation. It is revealed that Model A4 and Model A7 have the lowest prediction error and as a result the best performance over all other models. The results of answer side will be based on these two models as they have the best model performance and lowest root mean square error (please see for calculation of RMSE section 4.7.6)

Table 20: Prediction Error for Answer Models

Model Name	Root Mean Square Error (RMSE)
Model A1: Knowledge background	0.870908
Model A2: Reputation	0.843973
Model A3: Revenue Model	0.830708
Model A4: Basic Incentive model	0.820102
Model A5: Incentive Model- Variation	0.820498
Model A6: Governance Rule and Systems	0.83212
Model A7: Final model	0.820395

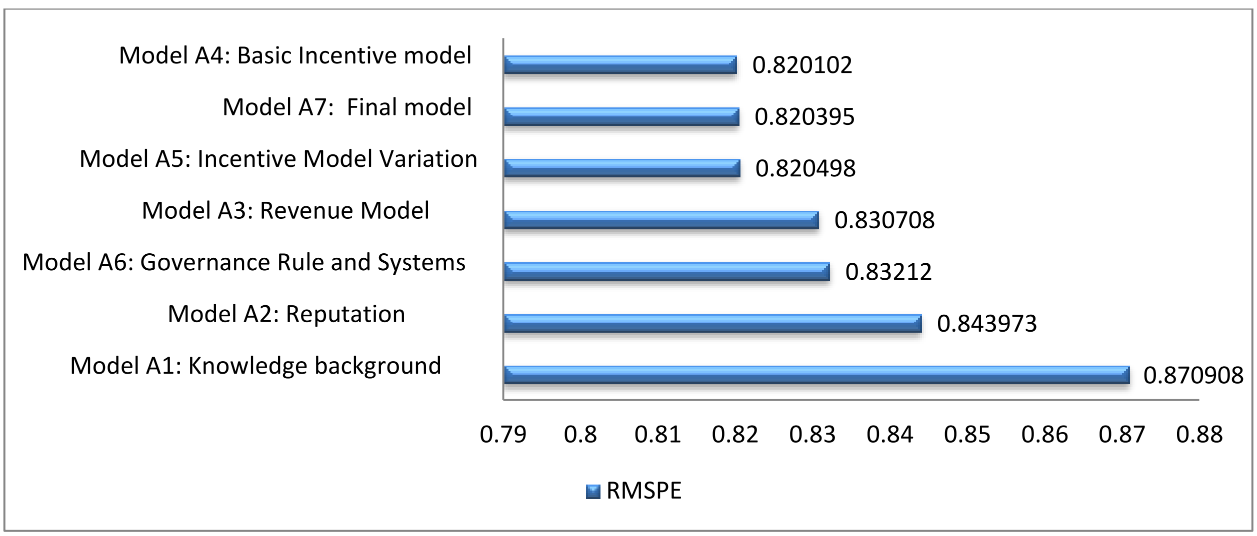


Figure 22: Ranked prediction error for answer models

5.3.7 Robustness Analysis

A common exercise in empirical studies is conducting a robustness analysis where the researcher examines how certain results are when the regression specification is modified by adding or removing variables (Lu & White, 2014). This study conducts robustness tests to examine the robustness of the results of answer trees. If the model is not robust, any inference based on it will be uncertain.

Two types of robustness checks based on a random forest algorithm are performed in this study. First, random forest is conducted to check if the results of it are consistent with that of the answer models. Second, a wrapper selection procedure is used to reduce the number of predictors and build a regression tree and check the consistency of results. At the end, a benchmark using the conventional statistical method was used.

5.3.7.1 *Random Forest*

Regression trees suffer from three disadvantages. First, trees can be very unstable. It means that small changes in the data or list of predictors can result in a completely different tree. This happens because when a particular split changes then all the other splits that are under it will change as well. Second, trees are tough estimators. It means that they use a minimum number of predictors in the model to reduce prediction error. Last, comparing to ensemble models, they have less predictive accuracy (James et al., 2013). To overcome these problems, random forest averages random trees which are fitted on different parts of the data space. Random forests are more stable than trees, their results rank all predictors and they improve predictive accuracy of trees substantially. However, this comes at the expense of some loss of interpretability. That is, random forest results do not tell that much about the interaction of variables.

Random forest is a strong regression algorithm and provides a guide to understand which independent variables have the greatest impact on the response. In the setting of this research it indicates which design features contributed most and least in estimating quality of answers. If there is a consistency between the predictors that appeared in the answer model and the top-ranked predictors in the random forest, it can be argued that the answer model was robust. Similarly, the predictors which did not appear in the answer model should be the low-ranked predictors in the random forest.

In the formula for random forest, the quality of answer (dependent variable) is specified versus all other independent variables. Beside the design feature of the platform, the average quality of questions is also used as predictor for quality of answers provided. The number of trees used was 500 (see Appendix C5, Section 10.2 that explains how this figure was calculated); the algorithm is set to calculate the variable importance so it is possible to see which predictor contributed most to estimating quality of answer. Table 21 gives a numerical representation of how important the variables are in predicting quality of answers, while Figure 23 gives a graphical representation.

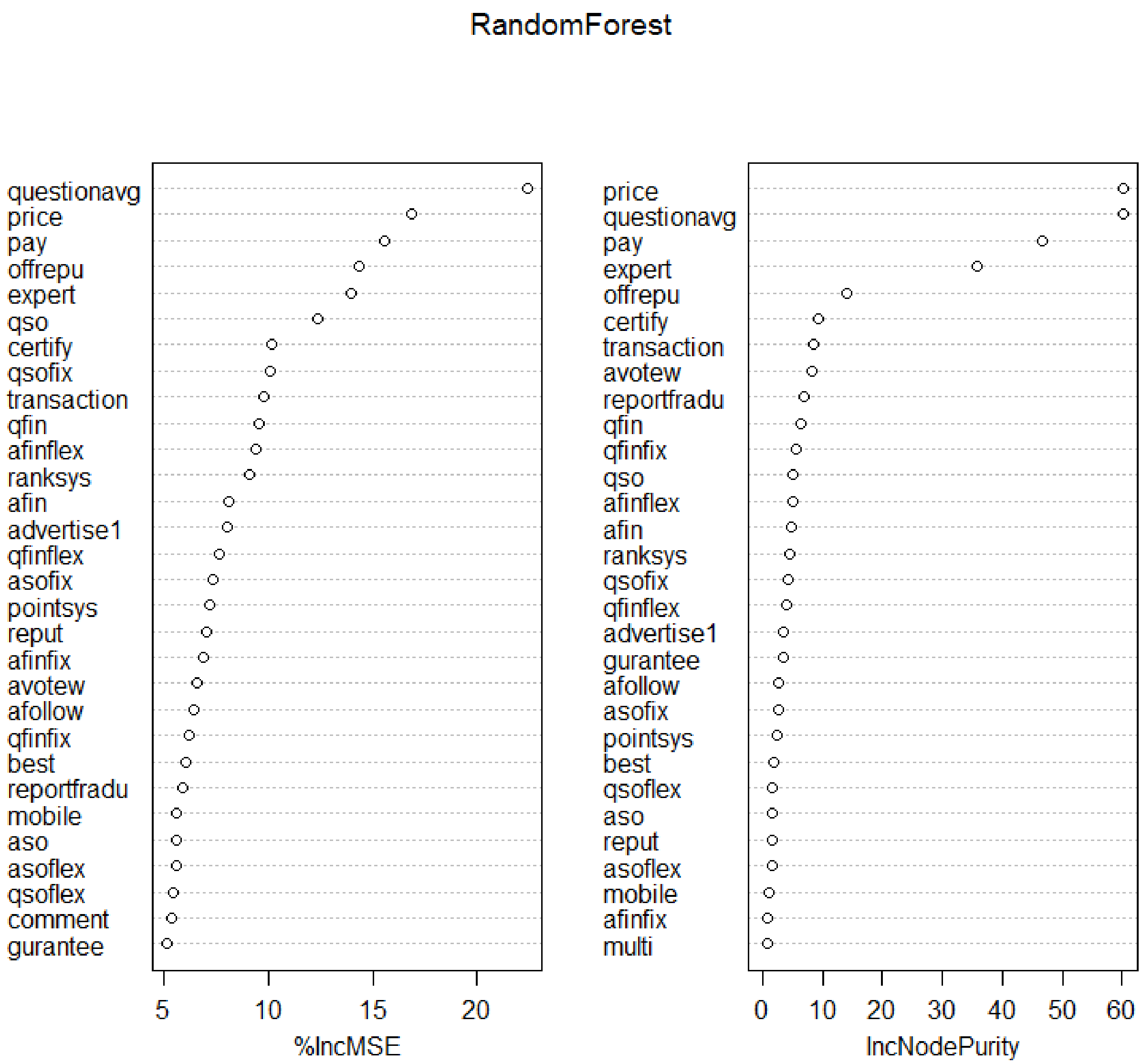


Figure 23: Random forest plot for answer quality

Table 21: Random forest result for answer quality

Predictors	Complete names	%IncMSE	IncNode Purity
questionavg	Average of question quality	22.4135	60.19906
price	Price of question	16.85781	60.22069
pay	Payment for answering	15.52612	46.74255
offrepu	Offline reputation of information providers	14.3213	14.10021
expert	Expertise of information provider	13.95002	35.71434
qso	Question social incentive	12.37914	5.107925
certify	Certification of information provider	10.17068	9.18539
qsofix	Question social incentive determined by platform	10.10615	4.205506
transaction	Transaction-based revenue model	9.758632	8.40699
qfin	Question financial incentive	9.519411	6.458449
afinflex	Answer social incentive determined by users	9.432806	5.077942
ranksys	Ranking system	9.080369	4.58323
afin	Answer financial incentive	8.135611	4.826372
advertise1	Advertisement-based revenue model	8.064516	3.571919
qfinflex	Question financial incentive determined by user	7.623631	3.947976
asofix	Answer social incentive determined by platform	7.320202	2.592827
pointsys	Point system	7.192486	2.465607
reput	Reputation system of the platform	7.021969	1.529776
afinfix	Answer financial incentive determined by platform	6.869753	0.907279
avotew	Voting mechanism for answers	6.600669	8.101585
afollow	Following mechanism	6.414096	2.661038
qfinfix	Question financial incentive determined by platform	6.187148	5.592166
best	Best answer mechanism	6.084879	1.868887
reportfradu	Reporting mechanism for fraudulent behaviour	5.912948	6.940641
mobile	Mobile-based platform	5.633821	1.016835
aso	Answer social incentive	5.593303	1.56474

asoflex	Answer financial incentive determined by user	5.571451	1.519297
qsoflex	Question social incentive determined by users	5.429796	1.714194
comment	Commenting mechanism	5.350893	0.623805
gurantee	Money back guarantee	5.139617	3.517109
multi	Multiple answering mechanism	4.078011	0.713763

Two measures of variable importance are calculated and reported in Figure 23. (1) The %IncMSE is the percentage of increase in the mean squared errors, reported on a 0 to 100 scale. It calculates the mean of decrease of accuracy in predictions when the given variable was excluded from the model, in other words, how much worse the model performs when each predictor variable is excluded and the rest of the variables are left unchanged. The worse the model performs when a given predictor variable is removed, the more important that variable is in predicting the response variable (L Breiman, 2001).

IncNodePurity is a measure of the total decrease in node impurity that results from splits over that variable, averaged over all trees. It is measured by the residual sum of squares. It can be seen from measure of importance that average of questions' quality, financial incentives (price, pay), background knowledge of the information providers (expert, certify) and the offline reputation of answerers are the most important predictors of quality of answers. However, mechanisms such as point system; best answer; social incentives (qsoflex, aso, asoflex); mobile-based platform; and providing a money back guarantee (gurantee) are the least important predictors of quality of answers. The predictors that appears in the final answer tree including: expert, offrepu, afinflex and asofix (See Figure 21) are among the most important predictors of answer quality in the results from random forest (See Figure 23: Random forest plot for answer quality). It can be inferred that there is a consistency between results of the final answer tree and random forest and the answer model is robust.

5.3.7.2 *Wrapper Variable Selection Procedure*

In supervised learning problems involving very high dimensional data, such as the case of this study that has 31 predictors, it is often desirable to reduce the number of variables given to the learning machine models. This is because the removal of irrelevant variables may improve the performance of the learning machine models. Furthermore, identifying only those variables that are important for regression may help in the interpretation of the model (Guyon & Elisseeff, 2003). A wrapper variable selection procedure is proposed for use with random forest to reduce the number of variables. The procedure is based on iteratively removing low-ranking variables and assessing the learning machine performance by cross-validation (Svetnik et al. 2004). In the context of this research, the wrapper variable selection is used as a part of the second robustness check. The procedure reduces the number of predictors and removes the irrelevant variables. Then, the relevant predictors are used to build a regression tree. The new regression tree will be compared with the final answer tree for consistency.

Accordingly, the random forest is run for all variable 31 predictors and the model performance is calculated using leave-one-out cross validation. Next, the six least important predictors (~1/5 of predictors) are omitted and the model performance is estimated again. Then, another six least important predictors are omitted and model performance is calculated. This iteration should be continued until model performance gets better. Three rounds of iteration were conducted and in the third round the model performance decreased and the iteration discontinued. Figure 24 indicates the model performances of the three rounds of conducting random forest. The lowest prediction error belongs to the second round of omitting low-ranking variables in random forest. The process of conducting the wrapper procedure is documented in Appendix C5, section10.3.

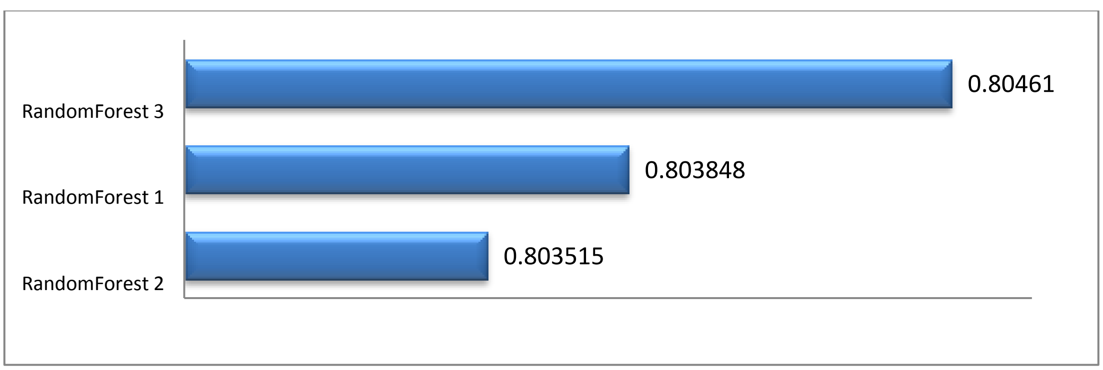


Figure 24: Comparing prediction errors of three rounds of conducting random forest

The predictors of the second round of conducting random forest were used to build a regression tree. The resulted regression tree is the same as the final answer tree (see Figure 21). It can be concluded that the final answer tree is robust.

5.3.7.3 *Benchmark using the conventional statistical methods*

As a benchmark to assess the possible impact of each variable on the average quality of responses (answers), a set of ordinary least squares linear model was also run in line with the conventional statistical literature. Figure 25 presents two models for the predictors entering the analysis of the quality of responses. The firm model in column (1) includes variables that appear in the final answer model and the key interactions present in the model. As expected, variables expert, afinflex, offrepu are all strongly significant below 1% critical significance level with positive coefficients. The interaction terms are also highly significant with negative sings consistent with the final answer tree (see Figure 21) – to give an example, experts with offline reputation on average offer lower quality responses. The second column includes all important variables based on second round of random forest (see Section 5.3.7.2) which had best model performance. The estimation results are overall consistent with the non-parametric unbiased regression analysis.

	Dependent variable:	
	aveindex	
	(1)	(2)
expert	1.28***	0.56**
	(0.10)	(0.24)
afinflex	0.78***	
	(0.10)	
certify		−0.04
		(0.18)
offrepu	0.35***	0.04
	(0.10)	(0.18)
reput		0.55**
		(0.21)
advertise1		0.43*
		(0.25)
transaction		0.84***
		(0.12)
mobile		0.64***
		(0.16)
pay		0.001
		(0.01)
qso		0.14
		(0.12)
asofix	−0.25***	−0.29*
	(0.07)	(0.17)
expertOffrepu	−0.88***	
	(0.17)	
expertafinflex	−0.80***	
	(0.19)	
avotew		−0.31
		(0.23)
questionavg1		0.12***
		(0.04)
Constant	2.99***	1.87***
	(0.06)	(0.20)
Observations	840	834
R^2	0.28	0.30
Adjusted R^2	0.28	0.29
Residual Std. Error	0.82 (df = 833)	0.81 (df = 821)
F Statistic	54.89*** (df = 6; 833)	29.25*** (df = 12; 821)
Note:		*p<0.1; **p<0.05; ***p<0.01

Figure 25: Response analysis using least squares linear model for answer-side

5.3.8 Summary of Findings (Answer Side)

The result of the data analysis of the answer side of the health platforms revealed important points about what design features are determining the quality of answers and how these features affect each other. In the results of regression tree analysis, 'expert' feature constantly appears as root node. This means that having experts in the platform as information providers overrides the other design features of the platform. In other words, the quality of answer is 16.13% higher when respondents have relevant expertise, irrespective of any other design feature. Among experts, the quality of answers provided by paid experts is 14.06 % higher than unpaid experts. Most probably, unpaid experts are incentivised by their offline reputation. Similarly, among lay respondents, the quality of answers is 5.78% higher if the respondents are paid. In the cases that the platform let its user to determine the answer price (financial incentive) the quality will improve by 11.5%. In the absence of financial incentive, offline reputation is an effective incentive that increases the quality of answers provided by lay user respondents by 10.52%. Therefore, it can be inferred that financial incentive is more effective than social incentives. As a result, a transaction-based revenue model generates better answers than an advertisement-based revenue model. The worst answer quality belongs to the platforms that does not use expert, do not financially incentives information providers and pay fixed social incentives per question to respondents. Mechanisms such as point system, ranking system, reporting and multiple answering and commenting had only little effect on quality of health information.

5.4 Question Side Results

This section investigates which design features are possibly associated with quality of questions. Analysing quality of answers, more specifically random forest results, reveals that quality of questions is a significant predictor of answer quality (see Figure 23: Random forest plot for answer quality). This finding makes it more important to investigate what design features have an effect on quality of questions. A similar approach as that used to analyse answer quality is utilised to analyse the questions.

5.4.1 Quality Index for Questions

Quality of questions is measured based on the following measurements: importance, difficulty, politeness, archival value and writing quality. In order to build one index for quality of questions, the average of these measures has been calculated. This index has been used as the dependent variable or response in the analysis of question quality.

5.4.2 Exploratory Analysis of Questions

Table 22 summarises descriptive statistics of quality of questions categorised based on the nine platforms of this research sample. Figure 26 gives a visual representation of Table 22. The highest quality of questions belongs to Just Answer and AllExperts. The lowest quality of questions belongs to Answerbag and ChaCha. Just Answer and AllExperts have experts with medical background as their respondents; however, Answerbag and ChaCha are using lay respondents. Raising a question in Just Answer is subject to financial cost determined by the Just Answer platform; however, asking question in ChaCha and Answerbag is free of any type of financial and social cost.

Table 22: Quality of questions across nine Q&A platforms of the sample

	Min	1st Quartile	Median	Mean	3rd Quartile	Max	Standard Deviation
AllExperts	2	3.625	3.833	3.718	4	5	0.466
Answerbag	1	1.667	2.792	2.575	3.333	4	0.902
ChaCha	1	2.5	2.833	2.951	3.583	4.5	0.695
Google Answers	1.667	3.125	3.5	3.411	3.833	4.167	0.567
Just Answer	1	3.5	3.833	3.793	4	5	0.560
Mahalo Answers	1	3	3.5	3.3	3.808	5	0.708
Quora	1	3	3.5	3.281	3.667	4.167	0.647
WebMD Answers	2.5	3.333	3.667	3.597	3.833	5	0.442
Yahoo Answers	1.333	3	3.5	3.387	4	5	0.778

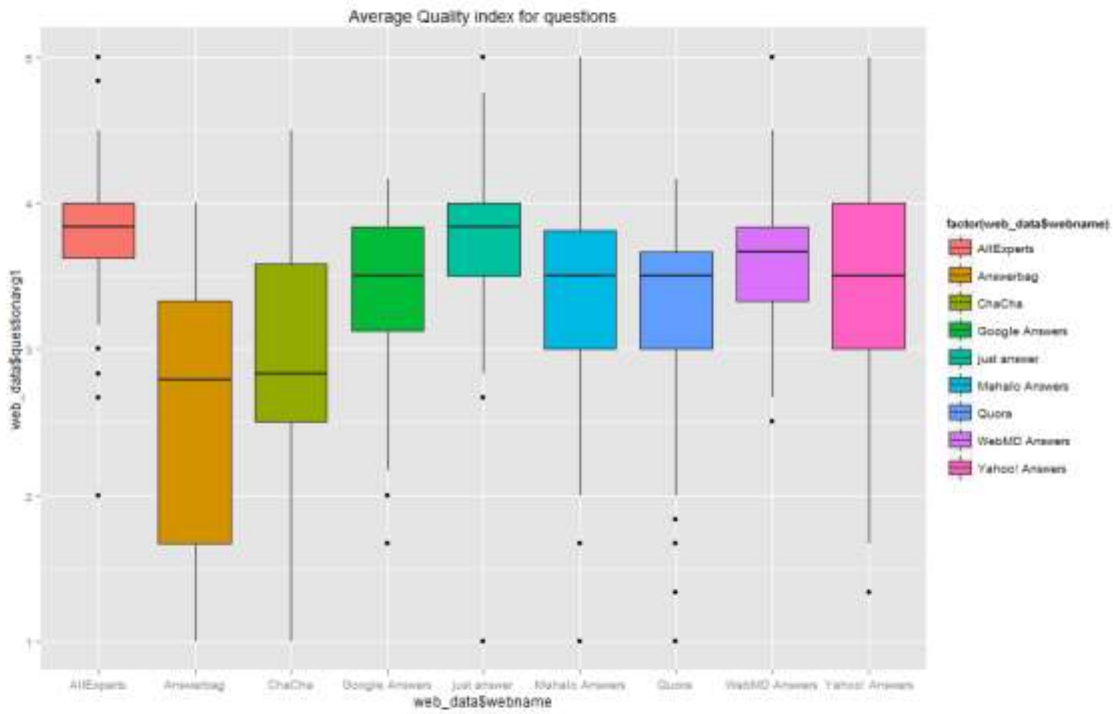


Figure 26: Quality of questions across 9 Q&A platforms of the sample

5.4.3 Results of Question Trees

Similar to the analysis of answers, regression tree algorithm based on the unbiased conditional preference methodology proposed by Hothorn et al. (2006) is used to investigate the nature of the relationship between the design features (predictors) and quality of questions (dependent variables).

Again, not all the predictors are included at once but sets of variables step by step are added to be able to understand the interaction of variables. The same categorisation used in the answer side (Table 19: Answer Models) was used as a basis. The categorisation was refined to be used for examining quality of questions. The features related to incentive mechanisms for answering the question were excluded as it is not logical to think there is a relationship between quality of questions and how information providers are incentivised to provide answers. Obviously, quality of questions was also omitted. The categorisation is tabulated in Table 23.

Table 23: Question Models

Model	Set of variables
Model Q1: Knowledge background	Medical Certification(certify), Expertise (expert)
Model Q2: Reputation	Reputation System(repu), Offline reputation(offrepu)
Model Q3: Revenue Model	Advertisement-based(adevertise1), Transaction-based(transaction), Money back guarantee(gurantee), Mobile-based platform(mobile)
Model Q4: Incentive Model-Basic	**Basic incentives:** Social price for asking (qso), Financial price for asking(qfin), Price of question (price)
Model Q5: Incentive Model-Variation	**Who determines asking incentives, platform or users:** qso determined by the platform (qsofix), qso determined by users (qsoflex), qfin determined by the platform (afinfix), qfin determined by the users (qfinflex)
Model Q6: Final Question Model (Governance Rule and systems)	following system, ranking system, best answer system, point system, Reporting system of fraudulent behaviour, Multiple answering, commenting

Similar to answer models, in the first step the regression tree algorithm was run for the first set of variables. In the next step the successive set is added to construct a new model. Each succeeding model includes all the variables in that model as well as variables in the previous sets. Overall, six question models are built. The final regression tree (Model Q6) which includes all variables captures all dynamics between the variables. Therefore, all questions trees are not presented in the main body of this research to avoid repetition. All question models are available at Appendix C5 Section 10.4.

Model Q6: Final Question Model

This model includes all the predictors of question quality. Model Q6 shows that the medical background of the information providers (certify) is the most effective predictor of question quality. It means that the means quality of questions is 0.418 higher (equals to 8.36%)

when questions are asked of physicians. In other words, when users are asking a question of medical experts, they ask 8.36 % better quality questions. In absence of medical expert to answer questions, financial cost leads to 0.111 increase in mean quality score (equals to 2.22% improvement) compared with social cost as it appears in an earlier split in the tree. Those websites which impose social cost enjoys 3.38% higher quality questions compared with those who do not use any incentive. It is worth noting that ‘qfin’ and ‘transaction’ can be used interchangeably because the platforms which are transaction-based are imposing financial cost and vice versa. It implies that higher quality of question is observed in platforms which have a transaction-based revenue model such as Google Answers and Mahalo Answers.

In the next split (node 7), afollow appears in the model. It means that in absence of medical experts, financial and social incentive, the websites which use a following mechanism observe questions with 0.807higher quality which equals to 16.14% increase in quality of questions. This might be because a following mechanism facilitates attracting an audience for a question. The website that does not apply any restriction for asking the question generates the lowest quality of question.

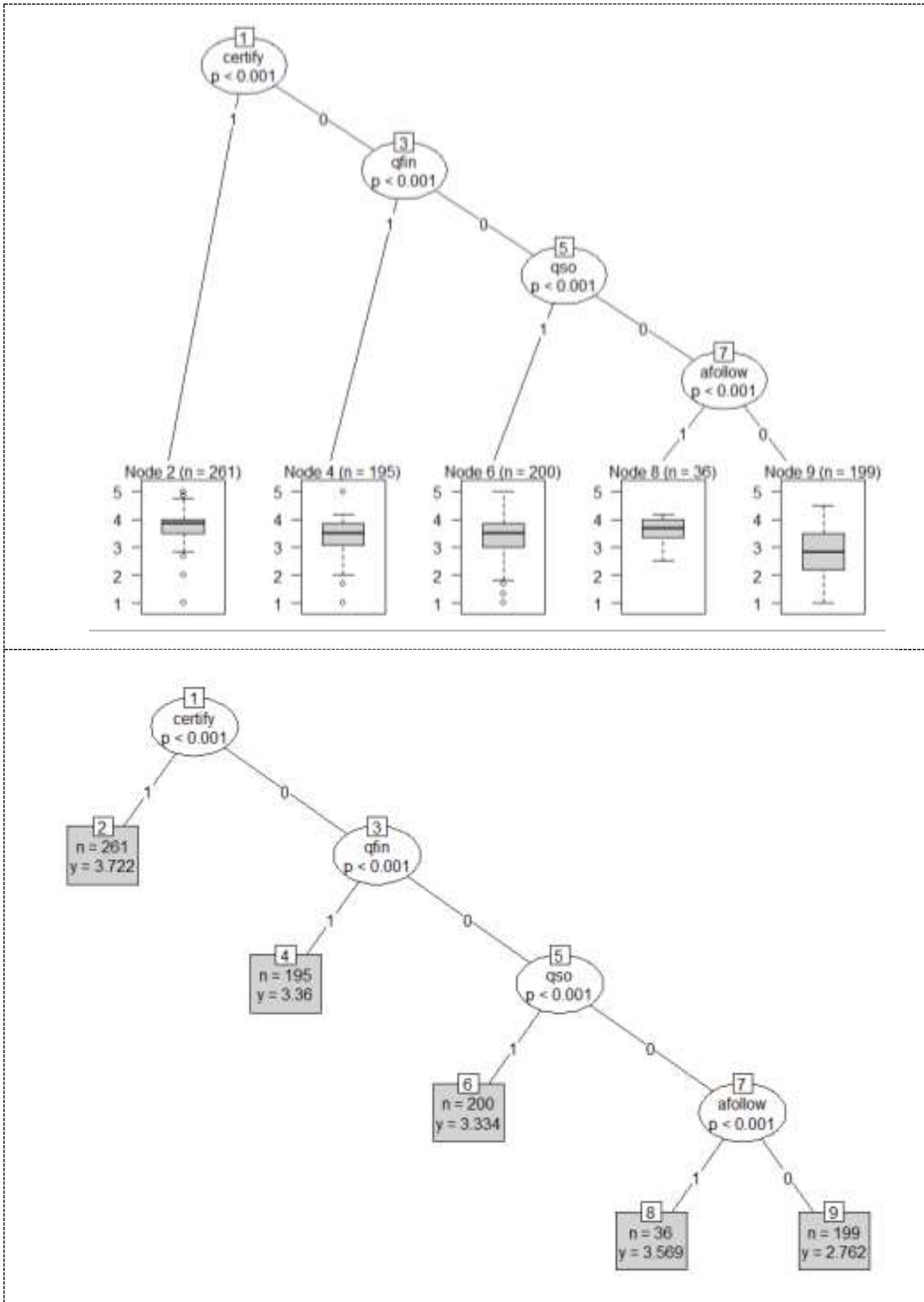


Figure 27: Model Q6 – Final Question Model (Governance Rule and Systems)

5.4.4 Predictions Errors

In order to evaluate model performance of trees, leave-one-out cross validation has been conducted. Prediction error has been calculated, ranked and shown in Table 24 for all six question models. Figure 28 visualises the ranked prediction errors of the answer trees. Prediction errors enable comparison of the performance of the trees. It was revealed that question model 6 which contains the entire variable has the best prediction error over all other question models. Question model 6 is considered as the final answer model as it has the lowest prediction error.

Table 24: Prediction error for Question Models

Model Name	**Root Mean Square Error (RMSPE)**
Model Q1: Knowledge background	0.699699
Model Q2: Reputation	0.699699
Model Q3: Revenue Model	0.699699
Model Q4: Basic Incentive model	0.675933
Model Q5: Incentive Model- Variation	0.675933
Model Q6: Governance Rule and Systems	0.659535

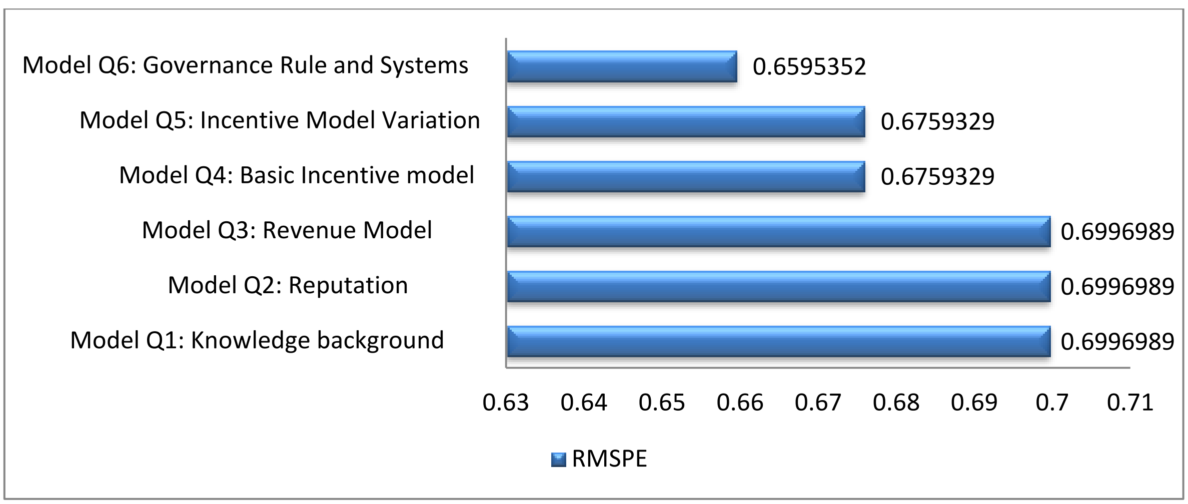


Figure 28: Ranked prediction error for question models

5.4.5 Robustness Analysis

This study conducts two robustness tests to examine the robustness of the results of the question trees. First, random forest is conducted to check if the results of it are consistent with those of the question models. Second, a wrapper selection procedure is used to reduce the number of predictors and build a regression tree and check the consistency of results. At the end, a benchmark using the conventional statistical method was used.

5.4.5.1 *Random Forest*

Similar to analysis of the answer side, random forest is conducted to check the consistency between the predictors that appeared in the final question model and the top-ranked predictors in the random forest. The predictors which did not appear in the answer model should be the low-ranked predictors in the random forest. If the results of the regression tree and the random forest are consistent, it can be argued that the final question model is robust.

In the formula for random forest, the quality of question (dependent variable) was specified versus all other independent variables. The algorithm is set to calculate the variable importance so it is possible to see which predictor contributed most to estimating quality of question.

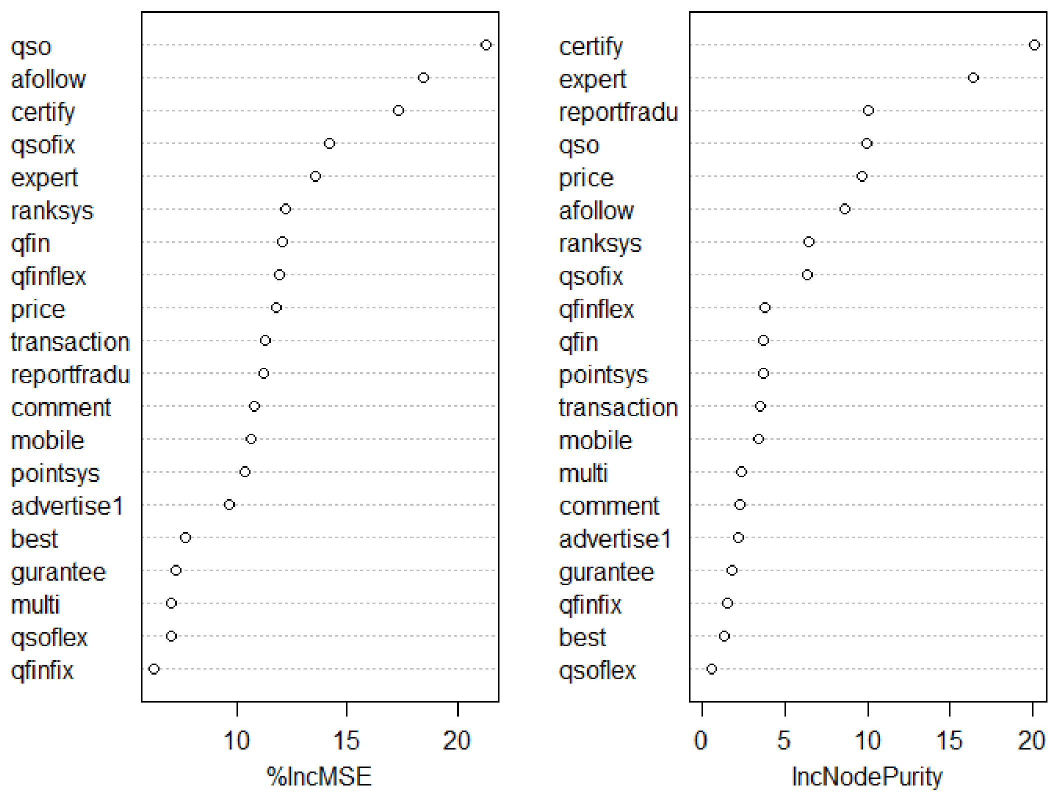


Figure 29: Random forest plot for question quality

Random forest provides a hierarchal ranking of predictors' importance in predicting quality of question. Table 25 gives a numerical representation of how important the variables are in predicting quality of questions, while Figure 29 gives a graphical representation.

Table 25: Random forest results for question quality

Variables	Complete Names	%IncMSE	IncNode Purity
qso	Question social incentive	21.26285	9.941278
afollow	Following mechanism	18.42828	8.591278
certify	Certification of information provider	17.32747	20.08233
qsofix	Question social incentive determined by platform	14.20652	6.322099
expert	Expertise of information provider	13.55578	16.34985
ranksys	Ranking system	12.19815	6.466979
qfin	Question financial incentive	12.0473	3.697502
qfinflex	Question financial incentive determined by user	11.96524	3.804768
price	Price of question	11.76501	9.61556
transaction	Transaction-based revenue model	11.31653	3.526606
reportfradu	Reporting mechanism for fraudulent behaviour	11.19458	10.00178
comment	Commenting mechanism	10.82028	2.234306
mobile	Mobile-based platform	10.68489	3.357097
pointsys	Point system	10.37735	3.681413
advertise1	Advertisement-based revenue model	9.637825	2.167836
best	Best answer mechanism	7.683068	1.27811
gurantee	Money back guarantee	7.270775	1.73277
multi	Multiple answering mechanism	7.070741	2.292495
qsoflex	Question social incentive determined by users	7.050446	0.525312
qfinfix	Question financial incentive determined by platform	6.300117	1.476151

The predictors that appeared in the final question tree including: certify, qfin, qso and afollow (see Figure 27) are among the most important predictors of question quality in the result of random forest (see Figure 29). It can be inferred that there is a consistency between results of the final question tree and random forest and the question model is robust.

5.4.5.2 *Wrapper Variable Selection Procedure*

Similar to analysis of the answer side, a wrapper variable selection procedure using random forest was adopted as part of the second robustness test. This procedure is based on iteratively removing low-ranking variables and assessing the learning machine performance by cross-validation (Svetnik et al., 2004). This iteration is continued until model performance gets better. Accordingly, in the first step random forest for all 20 predictors of question quality is conducted (See Table 25: Random forest results for question quality) and the prediction error using leave-one-out cross validation is calculated which is equal to 0.6561662.

For the second round, the five least important predictors of question quality (~1/5 of predictors) are omitted. The prediction error for this round is 0.6561847 which is worse than the first round. Therefore, the process of omitting low-ranking predictors will not be further continued. Since the first round of random forest which contained all predictors of question quality turned out to be the best model in terms of model performance, the results based on the final question tree (see Figure 27) are robust.

5.4.5.3 *Benchmark using the conventional statistical methods*

As a benchmark to assess the possible impact of each variable on the average quality of responses (questions), a set of ordinary least squares linear model was also run in line with the conventional statistical literature. Figure 30 presents two models for the predictors entering the analysis of the quality of questions. The firm model in column (1) includes variables that appear in the final question model and the key interactions present in the model (see Figure 27). As expected, variables certify, qfin, qso and afollow are all strongly significant below 1% critical significance level with positive coefficients. All interactive terms except certifyqfin drop out in this model. The reason behind this is that once the variables appearing in the model are interacted to capture the interactions present in the tree, the values of the outcome variables (interactive terms) coincide with other variables already in the model and, as a result, the interactive terms are forced out of the model. As an extra robustness check, various combinations of variables were tried. And in all regressions, the results of the final tree remain unchanged. The second column includes all variables entered to the final question tree. The estimation results are overall consistent with the non-parametric unbiased regression analysis.

	Dependent variable:	
	questionavg1	
	(1)	(2)
expert		−0.75***
		(0.24)
certify	0.76***	0.79***
	(0.07)	(0.19)
reput		0.73***
		(0.17)
price		−0.002
		(0.01)
qfin	0.49***	0.71***
	(0.07)	(0.09)
qso	0.40***	−0.07
	(0.07)	(0.19)
qfinfix		−0.36
		(0.22)
qsofix		0.89***
		(0.19)
advertise1		0.21
		(0.14)
afollow	0.13**	−0.11
	(0.06)	(0.11)
certifyqfin	−0.32***	
	(0.11)	
ranksys		−1.10***
		(0.17)
Constant	2.87***	2.74***
	(0.05)	(0.12)
Observations	897	891
R^2	0.18	0.24
Adjusted R^2	0.17	0.23
Residual Std. Error	0.68 (df = 891)	0.65 (df = 879)
F Statistic	38.98*** (df = 5; 891)	24.94*** (df = 11; 879)
Note:		*p<0.1; **p<0.05; ***p<0.01

Figure 30: Response analysis using least squares linear model for question-side

5.4.6 Summary of Findings (Question Side)

The analysis of data related to the question side of the health platforms shed light on what design features are determining the quality of question and how these features interact. The result of conducting regression trees revealed that askers raise better questions when they are asking from medical experts. Very similar to the results from the answer side, having medical experts on board overrides the other design features of the platform. It means that if the platform recruits medical experts, irrespective of other mechanisms in the platform, the quality of question will be 8.36% higher. In the question side of the platform, unlike the answer side, there is no difference in level of quality between paid and unpaid experts. Another important point is that costly questions are of 2.22 % better quality in absence of medical experts. That is, when askers need to pay per question they raise better questions. Interestingly, social cost is also effective and results in 3.38% higher quality questions in absence of medical expert and financial incentive. It means that when askers lose some points or credit they are more careful in formulating their questions. The following feature also turned out to be an important predictor of question quality that improves quality by 16.14%. The following feature engages a bigger audience for a question than just the respondents and this makes the asker more careful about the quality of the question. Generally, the predictors that affect quality of questions are very similar to the predictors that affect quality of answers. Unlike the answers, social mechanisms such as social cost of asking and following have an effect on quality of questions.

5.5 Result of Analysing Subsets of Data

This section will investigate the possible effect of customer feedback on the quality of health information. The data are just adequate to make measures for customer feedback about answers and investigating the relationship between customer feedback and quality of questions remains for future research. Another limitation is that there is not a unified and consistent indicator of customer feedback in different Q&A platforms. Therefore, building quality measures involves some subjective assumptions (see Methodology chapter Section 4.4.2.3).

Number of likes or votes that a particular answer receives (anvote) is a measure of customer feedback. Some Q&A platforms in this research sample do not use a ‘like’ feature. AllExperts, Just Answer and Google Answers which are all expert Q&A platforms do not have a 'like' feature. Therefore, the effect of customer feedback on just a subset of data can be investigated.

In other to investigate the relationship between number of likes and quality of answers, random forest method is used. The result shows that number of likes occupies a dominant position in the hierarchy of predictors that random forests produce (see Appendix C5 10.5 section).

Online reputation of respondents (zscore) can be considered as another measure of customer feedback. It should be noted that different Q&A platforms use different ways of calculating and signalling reputation in their platform. The most explicated indicator of reputation in the platform was used as the online reputation measure. Since this measure has different scale in different platforms, the collected data for the measure were normalised.

A random forest algorithm was conducted to check how great the impact of the zscore is on quality of answers. The result (see Section10.5 in Appendix C5) shows that zscore is among the most influential predictors of answer quality.

The analysis of both number of likes and online reputation of respondents suggests a strong correlation between quality of answers and customer feedback. This means that participants without medical background could signal the quality of health information in the platform. Due to the limitation of data and measurements further research is suggested to investigate the relationship between customer feedback and quality of answers.

5.6 Conclusion

This chapter illustrated a long sequence of statistical analysis and the resultant findings. It started with restating the research question that the data analysis wants to address. Then, the results of this study were presented in two main sections: 1) Answer Side Results and 2) Question Side Results. The same series of data analysis were utilised in both sections. Inside these sections, first came a series of regression trees based on unbiased conditional preference methodology to reveal the exact nature of the relationship between design features of a platform and the quality of health information. Then, the robustness analysis based on a random forest algorithm was conducted. Next, the main findings based on the data analysis were highlighted. At the end, the result of analysis based on subsets of data was presented.

6 Discussion

6.1 Introduction

This chapter comprehensively discusses the results of the empirical analyses presented in the findings chapter. It clarifies how the results address the research questions, and proposes four design scenarios for an online health information platform based on the empirical findings.

6.2 Discussion of Findings

This section presents the discussion of key empirical findings of this research. It particularly discusses how the aims and objectives of the research, especially the empirical questions raised in the literature review chapter, are answered by the data analysis. An aim of the research is to identify the conditions of market efficiency that maximise the quality of exchanged health information. To this end, seven empirical research questions were derived from extensive literature review in Chapter 3. In this section, it will be discussed how the findings in Chapter 5 answer these questions.

6.2.1 Incentive Model: Motivations and (Dis) Incentives in Maximising the Quality of Health Information Questions and Answers

6.2.1.1 *The Role of Incentives*

The viability of the online health information market depends on the ability of encouraging sufficient high quality contributions (i.e., ensuring market thickness). People's time, energy and information are personal assets and limited. The platforms should provide enough incentive for participants to contribute their information. 'Incentive mechanism' refers to sets of design features utilised in the platform to achieve market thickness. The first logical step to design a suitable incentive mechanism is to understand what motivates people to participate in health information exchange platforms. Therefore, the first research question was:

RQ1: What motivation or incentive works best in maximising quality of health information?

In order to answer this question, the theoretical part of this research reviewed the knowledge sharing theories and classified the motivation of information providers to share their high quality health information into three categories of intrinsic, social and financial (see Section3.5.4). The categorisation of motivation was based on the effect the motivations have on the design of the incentive model.

Intrinsic motivations such as altruism and empathy refer to those motivations stemming from factors inside individuals (Deci & Ryan, 1980). If the primary motivation of information providers to participate is intrinsic, then there is no need to design a specific incentive mechanism. If social motivations such as reputation and social recognition are the main motivations for information sharing (Kuznetsov, 2006), then the platform should build a large community of participants and use mechanisms such point system or reputation system to be able to socially incentivise participants by the accumulation of reputation or points. Finally, if financial incentive is an important motivation for information sharing, as several studies suggest (e.g. Hsieh et al. 2010; Chen et al. 2010; Chen & Hung 2010), then the platform should earn enough revenue to pay the information providers and design a proper payment system. Although fairly rich literature exists about motivations of information sharing, there was not sufficient literature to figure out which motivation is primary.

This research attempted to investigate this in the empirical section. The result of conducting regression trees revealed that financial motivation is the most effective incentive. It turned out to be more important than intrinsic and social motivations (see Section5.3.5 Figure 21: Model A7- Final Model). Financial incentive increases the quality of exchanged information in both answer side and question side of the platform. In the answer side of the market, sufficient incentive is required to persuade information providers to spend their time and energy and share their personal information; it was found that financial incentive works best in maximising quality of health information. The results suggest that there is no difference between information providers with and without expertise; in both cases paid respondents provide higher quality information. It should be noted that the amount of money the platform is required to pay the expert is much higher than for lay users (see Methodology chapter, Section 4.4.1). In summary, the financial incentive for information providers is the best motivation for maximising quality of health information. It works better than social and intrinsic motivations. From a design point of view, the online health information platform needs to establish a payment system and set up pricing rules to be able to financially incentivise health information providers. More importantly, it should consider how the cost of financial incentives can be covered. For discussion of different types of revenue model see Section6.2.2.

This result reinforces the findings of Harper et al. (2008) that suggest answer quality was typically higher in fee-based online Q&A sites than in the free sites. However, it contradicts the findings of Wang et al. (2012) that showed there are no significant quality differences between paid and unpaid online reviews. Online reviews are becoming an increasingly prevalent way for consumers to publish and share their personal experiences with products and services. Product reviews can be generated by volunteers or paid employees and critics. Wang et al. (2012) explored whether the provision of explicit monetary payments would affect the quality of reviews and showed that paid and unpaid online reviews are of the same quality (J. Wang et al., 2012). Cabral & Li (2015) ran a series of controlled field experiments on eBay where buyers were financially rewarded for providing feedback and showed that rebates decrease the quality of reviews. This is in contrast with the findings of this study that show a significance difference between quality of health information generated by paid and unpaid participants (Cabral & Li, 2015).

The effect of financial incentive on quality is particularly interesting and has been debated for many years. In this research, financial incentives refer to any form of monetary reward paid to information providers to stimulate their participation. It is the most obvious form of extrinsic motivation that will increase the benefit of information sharing, however it is argued to have a negative effect on intrinsic benefits of information sharing. According to the motivational crowding out theory, financial incentive may undermine intrinsic motivation (Deci & Ryan, 1980). If financial incentive is perceived as controlling, it will crowd out intrinsic motivation by inducing a shift in perceived locus of causality from internal to external and reducing the level of self-determination (Deci & Ryan, 1980). This "hidden cost of reward" (Leper and Greene, 1978) is observable if an intrinsically-motivated task is rewarded by external incentives. In this case, the monetary reward should be stronger than the crowding out effect to cover the hidden cost of reward.

The results of conducting regression trees showed that the financial motivations are more effective than intrinsic and social motivations in sharing health information. This is in contrast to Wang et al. (2012) and Lam & Lambermont-Ford (2010), both studies suggesting extrinsic motivation and particularly monetary award crowd out intrinsic motivation of individuals to share their information. Yet, the result of the current study suggests that quality of health information is higher in platforms that financially incentivise information providers. It means that either the intrinsic motivation plays a limited role in sharing health information or the financial incentive is stronger than the crowding out effect and covers the hidden cost of reward. It is hard to conclude with certainty which option was the case because there is not a Q&A platform that purely works based on intrinsic motivations in the current research sample.

Roth (2007) highlights the importance of dealing with “repugnance”. Some markets are constrained by social norms or legal restrictions that limit the price system as an allocation mechanism (Gans & Stern, 2010). There are some transactions that are not repugnant as gifts and in kind exchanges, but they become repugnant when money is added to the transaction, such as a market for sex or kidneys (Roth, 2006). Intrinsic motivation such as altruism was argued by Oh (2012) to be amongst the most influential motivations for most of the health information answer givers. It was expected that adding money to the online health information market would discourage volunteer health answerers from participating in the market. However, the results showed a higher quality of contribution from both experts and non-expert respondents in the health information market in presence of a financial incentive. It can be inferred that money does not make a market for exchange of health information repugnant as there is no strong social norm or legal restriction that constrains money.

Kissick (1994) argues that quality, cost, and access are three essential aspects of health care systems. The problem is that they are in competition with each other. That is why it is called the iron triangle in health policy. It means that if a policy decreases the cost of health services, it would inevitably lower quality of health care and/or access to health care services. The result of this study confirms the triangle notion in accessing online health information as the evidence is that high quality information is accessible for payment rather than being freely available.

6.2.1.2 *The Role of Disincentives*

The online health information market faces a congestion problem as a result of market thickness that makes the market inefficient. An efficient market needs to overcome the congestion that thickness can bring. This means that the market should give market participants enough opportunity to make satisfactory choices when faced with a variety of alternatives (Roth, 2007). In the question side, the online health information platform offers several benefits that incentivise information seekers to participate. This may encourage more than a sufficient number of information seekers to come on board. Consequently, many respondents face the problem of reviewing and evaluating many questions to find those questions that really need an answer. Low quality contributions from information seekers such as spam or unserious questions waste the valuable time and attention of the information providers that otherwise could be spent on high quality questions that truly need answers (Anderson & Palma 2012; Anderson & Palma 2009; Hsieh & Counts 2009). The platform designer needs to try to reduce the amount of low quality contribution of information seekers. Therefore, it is very important to know what incentive discourages the information seekers from producing low quality questions. Accordingly, the second research question was:

RQ2: What disincentive works best in maximising quality of health information?

In order to answer this question, the theoretical part of this research reviewed design studies and analysed questions and answer platforms (see Section4.4.1) to find solutions for addressing market congestion. A possible solution to this problem is making the participation costly for information seekers (Kraut, Sunder, Telang, & Morris, 2005). For example, in Just Answers, information seekers are required to pay a fixed price to get their question answered. In Quora, askers are required to pay some credit to get their questions answered. The present research categorised the cost of getting answered into two categories of social and/or financial costs based on the effect they have on design of the platform (See section 3.5.4.6 l). The social and financial cost makes the information seeker more selective in asking their questions. The literature was not conclusive about which type of cost (social or financial) increases the quality of information seeking. This research attempted to investigate this issue in the empirical section.

The results of conducting a regression tree on the data related to the question side of the platform, (see Section 5.4.3) suggested that financial cost rather than social cost is more effective in discouraging low quality contribution. It means that when information seekers need to pay per question, they raise higher quality questions. In other words, financial cost is an effective feature to solve the market congestion problem in an online health information market by making information seekers more selective when they want to raise a question. From a design point of view, these findings mean that the online health information platform needs to establish a payment system and consider pricing rules to be able to impose financial cost for asking questions.

The problem of low quality questions is similar to the problem of spam email, which is not a mere nuisance. Spam is growing rapidly and threatens to choke off email as a reliable and efficient means of communication over the Internet. Kraut et al.(2005) investigated the effect of economic cost on solving the problem of spam emails. Similar to the findings of the current study, their research confirms that charging a price for sending messages disciplines senders from demanding more attention than they are willing to pay for. Furthermore, price may also credibly inform recipients about the value of a message to the sender before they read it.

Notwithstanding, the results of regression trees for the question side data revealed that although financial cost is more effective than social cost, social cost is also effective (see Figure 27: Model Q6 – Final Question Model (Governance Rule and Systems)). This means that the quality of question is higher in the platforms that make asking socially costly, for example by reducing some points from the asker’s credit in Yahoo Answers. Using social cost is considered costly because it limits the number of questions a participant can ask. This is similar to use of virtual roses in the Internet dating market. Virtual roses are financially free but they are costly because they are in limited supply. If there is no cost (such as limited number of virtual roses) for sending a message to initiate a date in the online dating market, participants send messages to everyone without sufficient scrutiny. In this case, message recipients will spend unaffordable time and attention on irrelevant messages and may lose their interest or overlook a qualified message. Using the virtual rose mechanism makes the participants selective (S Lee, Niederle, & Kim, 2009). Lee et al. (2014) showed that introducing roses to the Internet dating market has a sizable impact and improves market efficiency (Soohyung Lee & Niederle, 2014). This is in line with the result of this research that shows using social cost has an effect on quality of questions and improves the efficiency of an online health information platform. From a design point of view, this finding means that the second desirable choice for increasing the quality of the information seekers' contribution (in absence of financial cost) for the online health information platform is to impose a kind of social cost to limit the number of questions the information seeker can raise, for example, through a point system similar to Yahoo Answers or a credit system similar to Quora.

The result of conducting regression trees for the question side of the platform revealed that the lowest quality of contributions on the question side belongs to those platforms that do not use any social or financial cost for discouraging low quality questions, such as ChaCha or Answerbag.

Nevertheless, it should be noted that in any information platform, the platform designer should make a trade-off between quality and quantity of the information seeker's contribution. If no disincentive is embedded in the platform, the quantity of contribution will increase but the shortcoming is that, as the results of this study show, the quality of the contribution will decrease. On the other hand, if the platform socially or financially disincentivises information seekers' contributions, the quality of questions will increase, but the quantity will decrease. The platforms such as Just Answer and Google Answers focus on quality and set up financial cost for asking questions. Contrariwise, ChaCha and Answerbag prefer to minimise the cost of contribution for information seekers to maximise the number of contributions on the question side. The way the platform handles this trade-off has direct implications for designing the revenue model of the platform. The interaction of incentive mechanism and revenue model will be discussed in the final research question (see Section 6.2.4).

6.2.1.3 ***Expert vs Non-Expert Respondents***

A nuance in these results that should be noted is that the social and financial cost on the question side has an effect on quality in the platforms that are using lay respondents *without* medical background. On the contrary, the results show that the quality of questions is always high when respondents are experts with medical certification. In other words, information seekers ask better questions when an expert such as a physician, nurse, etc. is expected to answer the question. This is irrespective of financial and social cost associated with asking. Even if no disincentive is utilised on a platform to discourage low quality contribution of information seekers, the quality of question is high when information providers have medical certification.

6.2.1.4 *Effects of Quality of Information Seeker Questions on the Quality of Answer*

In a multi-sided platform, the behaviour of one side of the platform affects the behaviour of the other side. In the health information platform, it is expected that the quality of question has an effect on the quality of the answer. In this case, information seekers can incentivise the information providers by asking high quality questions. Therefore, the third research question was:

RQ3: Does the quality of information seekers' contributions (question side) have an effect on the quality of information providers' contribution (answer side)?

The result of conducting random forest analyses on the answer side of the platform confirms that the quality of question is an influential predictor of answers (see Figure 23: Random forest plot for answer quality). This means that askers get high quality answers if they raise a high quality question and vice versa. The findings endorse the well-known concept "Wise question contains half of the answer". This result is in line with the viewpoint of Hsieh & Counts (2009) and Harper et al. (2009) that the quality of questions in Q&A portals has an impact on the quality of answers. This finding becomes particularly important in the absence of other types of incentive such as financial and social and provides the asker with a means to encourage respondents to provide high quality information. Therefore, if the platform designer aims at increasing quality at the answer side of the platform, then encouraging production of good questions is a type of incentive alongside financial incentives.

6.2.2 Revenue Model: Association between Type of Revenue Model and Information Quality

The revenue model can be considered as the platform owner's incentive. A suitable and effective revenue model is an important element of online marketplaces and can take various forms (Zuiderwijk & Loukis 2014; Ferro & Osella 2013). Two types of revenue model are probable for incentivising platform owners: for-profit and not-for-profit models. The design of the revenue model is believed to have effects on quality of health information in the platform. However, there is not sufficient literature to decide what type of revenue model has more effect on quality of information in question and answer sides of the platform (see literature review chapter, section 3.5.5). Accordingly, the fourth research question sought to fill this gap:

RQ4: What type of revenue model is associated with high quality of information?

The result shows that a transaction-based revenue model leads to higher quality of information in both question and answer sides of the platform (see Figure 21: Model A7-Final Model and Figure 27: Model Q6 – Final Question Model (Governance Rule and Systems)). In a transaction-based revenue model, information seekers are supposed to pay for their question to get answers and information providers are paid and the platform owner gets a commission fee per transaction. This concurs with the results for both question and answer sides in regards to question/answer quality. Obviously, the incentive model and revenue model are interrelated. It means that in a transaction-based revenue model, the information providers are incentivised financially and on the question side asking questions is financially costly. Section 6.2.1 discusses the findings that financial incentive is the most effective type of incentive on both sides of the platform. Consistently, the transaction-based revenue model is found to produce higher quality questions and answers.

It is important to note that the transaction-based revenue model is superior in terms of quality in both expert and non-expert Q&As. However, when medical experts are being asked, the quality of question is high irrespective of type of revenue model.

The platform can either earn revenue from transactions or find an independent source of revenue to cover its costs (i.e., ISR model). In the sample of this study, advertisements were the independent source of revenue for health Q&A platforms. In the advertisement-based revenue model, asking and answering is free and the platform earns money from advertisement. The results of conducting a regression tree revealed that in the advertisement-based revenue model, lower quality of information is produced compared with the transaction-based model. This finding supports the other findings of this study and is in line with Harper et al.'s (2008) findings that suggest quality of answers is typically higher in a fee-based site such as Google Answers than in the free sites such as Yahoo Answers.

An advertisement-based platform is interested in increasing the number of questions and answers as much as possible to make the platform a favourable target for advertisements. As the results of this study confirm the quality of question and answer decreases in this model, then the viability of the platform will be at risk. One solution to this problem is paying a cut of the platform's revenue to information providers to incentivise information quality. The results of this study confirm that the quality of answers is higher in such platforms (see RQ1 in section 6.2.1); however, the quality of questions remains the same.

6.2.3 Quality Signal Mechanisms and Information Quality

Ensuring high quality of information in a health information platform has such an importance that the platforms usually design specific features to address quality. Certification, providing guarantees, and reputation systems are examples of quality signal mechanisms. The literature is not conclusive about which quality mechanism works better than others (see literature review chapter section Quality Signal Mechanism).Therefore, an important research question was:

RQ6: What quality signal mechanism is associated with high quality of information?

The results of conducting regression trees show that having experts as information providers is the most effective predictor of information quality in both sides of the market (see Figure 21 and Figure 27). This is in line with Clauson & Polen (2008) who suggest the strongest signal of high quality in an online book market is certification of seller by a respected third party. There are two types of experts in this research sample: those with medical expertise and those with expertise in finding hard-to-locate information. In the answer side, those platforms that use experts as respondents produce high quality answers. It should be noted that paid experts provide better answers than unpaid experts. On the question side, askers provide high quality questions when experts with medical certifications are on board and no difference between paid or unpaid respondent was observed (See Section 6.2.1.3).

This finding suggests that expert-generated content has higher quality compared with user-generated content. This result provides further support for Clauson & Polen's (2008) viewpoint that considers user-generated information such as Wikipedia as less complete and narrow and consequently not a good source of drug information. However, it challenges the body of literature (e.g. Giles 2005 and Reavley et al. 2012) that argues user-generated content such as Wikipedia has comparable quality with or even better quality than expert-generated content.

Providing a money back guarantee turned out to be of very little importance. In other words, no difference in quality of information is observed in platforms that offer money back guarantees and those which do not use this feature. This evidence supports the findings of Clauson & Polen (2008) that found little impact of warranties such as money back guarantees in online book markets. There are two possibilities explaining why money back guarantee is not an effective feature with regards to quality. First, it may be felt that the costs of enforcing the warranties are too high to make them effective. Second, there are stronger signals of quality in the platform, certification especially, that have an effect on quality of information (Clauson & Polen, 2008).

There are two types of reputation: offline and online. Offline reputation refers to the reputation of the participant outside the platform. Some platforms allow and encourage the participants to reveal their real identity. Through revealing real identities participants have less incentive to perform a malicious behaviour because their behaviour affects their reputation outside the platform itself, as well. Moreover, the offline reputation feature helps participants, particularly experts, to get attention in the offline world. For example, physicians can advertise their capabilities and expertise and attract patients to their private clinics using this platform. This gives extra incentive to participants to provide high quality information.

The results show that offline reputation of information providers is an important predictor of quality on the answer side of the platform (see Figure 17). It is observed that in the absence of financial incentive for information providers, offline reputation is the critical incentive for experts to contribute high quality health information in the platform. In the platforms with lay respondents, higher quality of answers is produced when the platform allows and encourages participants to reveal their real identity. This finding is in line with the findings of Tauscizik & Pennebaker's (2011) research that showed offline reputation of participants of Q&A platforms is related to the quality of their contribution. However, the result does not support the impact of online reputation on quality of health information. This may be due to the limitation of this research data because all the Q&A platforms of the sample use online reputation except ChaCha. Therefore, there is not enough variation in the sample data to investigate the impact of online reputation and further studies should address this gap.

Online reputation systems work based on the history of participant contributions inside the platform. They store feedback from users' past behaviour such as the number of likes their answer received or number of questions they answered, etc. Reputation systems aggregate this feedback and signal it to the community to help members recognise the quality of participants' contribution. There is a particular difficulty in utilising an online reputation system for health information platforms. It is the controversial question about whether people without a medical background are able to evaluate technical aspects of healthcare or not. In the present case, whether information seekers are able to recognise the correctness, completeness and objectiveness of the answers is still vague. If there is no relation between quality of information and user feedback, then user feedback does not reflect the quality of health information and the reputation system performance is questionable, therefore, an important research question to bridge this gap in knowledge was:

RQ5: Does patient feedback indicate quality of online health information?

The results suggest a strong correlation between user feedback and quality of health answer. This means that the feedback from participants without medical background could signal the quality of health information in the platform. This finding is more in line with Greaves et al. (2013) and Bardach et al. (2013) who empirically showed that there is a meaningful relationship between technical quality of health care and patient feedback on quality of care. From a design point of view, this finding suggests that there is no need to design a specific reputation system for a health information market and a typical reputation system can signal quality in this platform.

It should be noted that since the data for this research are not adequate to define more precise and objective measures for patient feedback, it is suggested that future research investigate this relationship thoroughly with more tailored and adequate data.

6.2.4 Combination of Mechanisms for High Quality Information

A platform is a unified system and the design of mechanisms is highly intertwined. Thus, the type of incentive mechanism (for example) will confine the options of the revenue model and vice versa. The platform designer should consider the design of incentive mechanism, revenue model and quality signal mechanisms separately but also needs to consider the best combination of these mechanisms for optimal performance. Therefore, the final research question was:

RQ7: What combination of mechanisms in the platform leads to high quality of information?

The superiority of using a regression tree algorithm is that it gives a very clear picture of the structure of data and reveals the interaction of different variables. This advantage helps the researcher to consider the design features as a whole and investigate the interactions between the mechanisms in the platform. The result for the present research shows that having experts as respondents in the platform overrides the other design features of the platform (see sections Figure 21 and Figure 27). In other words, the quality of answers is high when there are experts on board irrespective of revenue model and incentive model. However, the experts who are paid (i.e., incentivised financially) provide even higher quality answers compared with those who are not paid. On the question side also, askers raise high quality questions when they are asking experts with medical background and there is no difference in this advantage between situations of paying or not paying respondents.

Financial incentives have a high impact on quality of answers in both absence and presence of experts in the platform. However, the amount of financial incentive for experts is much higher than for lay users. Financial incentives have high impact on quality of question only in the absence of medical experts on the platform. In cases of medical experts answering the question, no differences between costly and free questions were found.

In the absence of financial incentives, offline reputation is the critical incentive for quality of answer when lay users are answering the questions. There is not enough variation in the sample data to undeniably conclude that offline reputation is the main incentive of information providers in absence of monetary reward when experts are answering health questions. There was only one platform, namely AllExperts, in which medical experts provided answers for free in the sample of this study. In AllExperts, the experts are allowed to gain offline reputation by answering questions. However, other factors such as 'altruism' or 'helping others' may play a role. Investigating this issue calls for future research.

The designer of an online platform to exchange health information faces a serious trade-off between quality and quantity of information. The platform can create value from either quality or quantity of health information. For example, in advertisement-based platforms, the platform attempts to maximise the number of views of the platform to make it a favourable place for advertisers. Therefore, it minimises the cost for information seekers to contribute. The downside is that the information seekers do not have any incentive to raise high quality questions and the platform may be flooded by low quality information. That is, the market thickness leads to market congestion. In this case, the time and attention of information providers is wasted on questions of low quality. In a less congested market, time and attention of information providers is assigned to real questions which truly need answers.

On the other hand, if a platform creates its value from quality of contribution, the problem will be reversed. When a platform sets up a financial or social barrier as a disincentive to low quality contribution, the market congestion issue is resolved but the platform faces a thickness problem. It means that the platform may not attract enough contributions to make the market satisfactorily thick. Table 26 summarises the interaction of revenue model and drivers of market efficiency, i.e., market thickness and market congestion.

Table 26: Revenue model and market efficiency

Sources of platform efficiency / Revenue Model	Market thickness Provider-side	Market thickness Seeker-side	Market congestion Seeker-side
Transaction-based	*Increase* (↑)	*Decrease* (↓)	*Increase* (↑)
Independent Source of Revenue (ISR)	*Decrease* (↓)	*Increase* (↑)	*Decrease* (↓)
ISR which pays providers	*Increase* (↑)	*Increase* (↑)	*Decrease* (↓)

6.3 Four Scenarios of Design to Maximise Quality of Health Information

The aim of this study was to design an online health information platform that maximises quality of exchanged health information. Mechanisms and design features of an online platform are interrelated and intertwined. This means that the choice of any mechanism or feature affects and may restrict the choice of other features and mechanisms. From a design point of view it is important not only to understand which mechanisms maximise the quality of health information but also to consider the interactions between design features and provide a comprehensive solution that proposes a consistent combination of mechanism and feature to design an online health information platform.

Based on empirical findings of final answer and question regression tree (see Figure 21, Figure 27), this section proposes four scenarios of platform design and speculates on the quality of health information in the proposed scenario. Each scenario is discussed based on combination of incentive model; revenue model and quality signal mechanism and considers the effects and restrictions that choice of design features and mechanisms has on each other. Table 27 summarises these scenarios and Figure 31 indicates the means score of quality for questions and answers generated in each scenario.

1. **Best case scenario: Paid experts with medical background**

The best case scenario that produces the highest quality of health information in both question and answer sides of the platform is when paid experts with medical background are answering health questions. In this scenario, the platform owner needs to verify the medical certification of information providers and publicise it to signal the quality of answers in the platform.

The platform can earn its revenue either from transactions or from an independent source (ISR). In the case of the transaction-based revenue model, information seekers pay information providers to answer their questions. It means that a financial incentive model is used in both sides of the platform. The platform gets a fraction of each transaction. The platform owner does not allow the experts to reveal their real identity because this puts the platform at risk of being cut out by experts and clients and losing the commission fees as the main source of revenue. Therefore, experts are not able to gain offline reputation. Just Answers is an example of using this scenario.

In the case of having an independent source of revenue, a cut of platform revenue should be paid to the information providers but the information seekers are not required to pay. Since they ask questions of a medical expert the quality of question will be high. There is no risk of being cut out and losing the commission fee for the platform owner. Therefore, the platform may allow the respondents to gain offline reputation. This way the respondents may have even more incentive to provide high quality health information. To the best of the author's knowledge, there is no platform that uses this form of design. The mean score of answer quality in this scenario will be 4.88 out of 5 and the mean score of question quality will be 3.772.

2. Mediocre scenario: Unpaid experts with medical background

Using experts with medical background as respondents leads to relatively high quality of health information. In this scenario asking is free of charge and answering is not financially rewarded. The platform owner verifies the medical certification of information providers and advertises it in the platform to signal the quality of answers. The incentive for information providers to participate is mainly to gain offline reputation. Quality of question would be high in the scenario because medical experts are answering questions. The platform should find an independent source of revenue. All Experts is an example of this scenario in which the revenue model is advertisement-based. The mean score of answer quality in this scenario will be 3.565 out of 5 and the mean score of question quality will be 3.772.

3. Mediocre scenario 2: Paid lay respondents or unpaid lay users with social incentive

Although the findings confirm that having experts as respondents overrides the other mechanisms of the platform, the quality of health information is not the same in lay user platforms. It means that there are still some design features that can increase the quality of health information in the absence of experts in the platform. Three sub-scenarios are probable:

(C1) Financial incentive for information providers can increase the quality of answers in the platform. Apparently, financial incentive for lay users is significantly less than financial incentive for medical experts. The platform can make asking questions financially costly and pay the respondents. In this case the platform gets a commission fee per transaction and therefore the revenue model is transaction-based. In this case the quality of information in both sides of the platform is high. Mahalo Answers is an example of this case. The mean score of quality in this case will be 3.495 for answers and 3.36 for question quality.

(C2) The platform can pay a cut of its revenue from an independent source to respondents and keep asking free of financial cost, as ChaCha does. In this case the quality of information is high in the answer side but low in the question side. If advertisement is the independent source of revenue, the platform owner tries to attract high number of views to maximise revenue from advertisement to cover the cost of paying information providers. In this case the platform does not impose any cost for asking question to maximise quantity of participation. The mean score of quality in this case will be 3.36 for answers and 2.762 for question quality.

(C3) The platform can incentivise information providers by encouraging them to use their real identity and gain offline reputation. In the question side, the platform owner can increase the quality of questions by making asking questions socially costly. Quora and WebMD are examples of using this design feature. The mean score of quality in this case will be 3.34 for answers and 3.34 for question quality.

4. Worst case scenario: Unpaid lay users without social incentive

The worst case scenario which produces the lowest quality of health information in both sides of the market is when there is no form of social or financial cost in the question side of the platform and the platform utilises social incentive to encourage the information providers in the platform. In this case the participants are lay users without any special expertise. The platform owner earns revenue from an independent source such as advertisement. In this case the lowest quality is expected in both sides of the platform. ChaCha in the question side and Answerbag in the answer side are examples of this scenario. The mean score of quality in this scenario will be 2.692 for answers and 2.762 for question quality.

Table 27: Four design scenario

	Incentive Model	Revenue Model	Quality Signal Model	Answer Quality	Question Quality
Best case scenario	Financial incentive in answer side	Transaction-based ISR which pays providers	Certification	4.268	3.722
Mediocre scenario1	Offline reputation	ISR	Certification	3.565	3.722
Mediocre scenario2	Financial incentive in answer side Offline reputation	Transaction-based ISR which pays respondents	Not certification	C1:3.495, C2:3.36, C3: 3.34 Avg=3.398	C1:3.36 C2:3.34 C3: 2.762 Avg=3.154

Worst case scenario	Social incentive in answer side; intrinsic in question side	ISR	Not certification	2.692	2.762

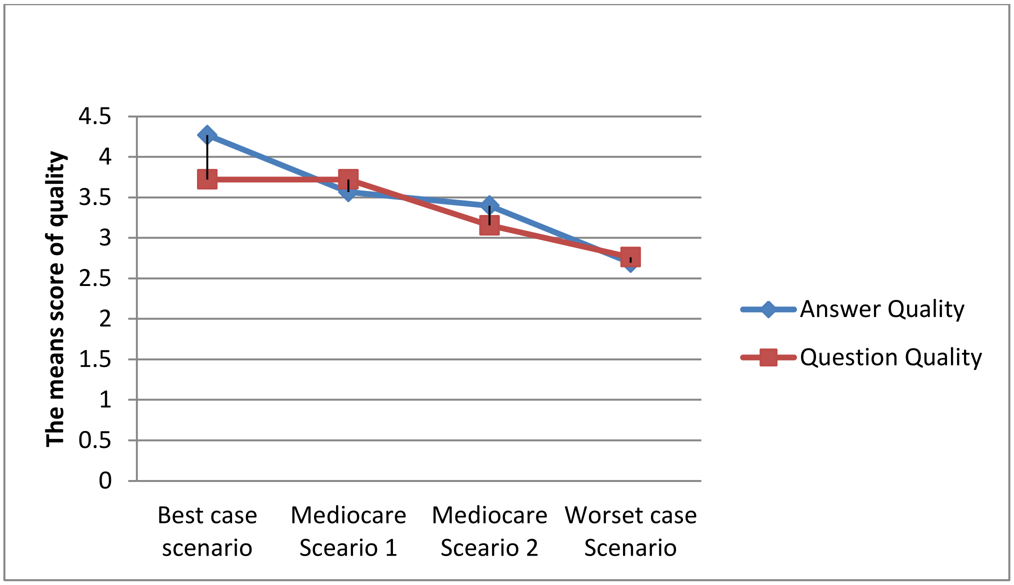


Figure 31: The mean score of quality in the four design scenarios

This research argued that maximising quality is an essential driver of efficiency and it has particular importance in health context because it has effect on human health, however, it is very important to highlight that ensuring quality does not guarantee the success of a platform for exchange of online health information. In other words, ensuring the quality of health information is a necessary, but not sufficient condition for success of an online platform. The success of an online health information platform should be considered in a wider context that includes other elements such as quantity of participation, competition, etc.

It was argued earlier in the discussion of "combination of mechanisms" (see Section 6.2.4) that the designer of an information platform faces a trade-off between quality and quantity of participants' contributions. If a platform follows the best case scenario to maximise quality, there is still a possibility of failure if they fail to generate enough traffic and consequently sufficient revenue.

Google Answers could be a very good example of this situation. Google decided to shut down its Google Answers service despite being successful in terms of quality of generated information. The limited size of the community was the reason, as declared in its closure announcement[11]. It should be noted that size of the community and level of revenue are not objective measure and can be different in different platforms. For example, Uclue.com uses the similar design that Google Answer used to have and it is now active.

It is worth mentioning the Mahalo Answers case as another unsuccessful example that had an acceptable level of health information quality. Mahalo Answers can be categorised under mediocre scenario 2 which can be considered as an acceptable level of health information quality. However, this service was discontinued due to external factor which was to relevant to the design of the platform. Google changed its search algorithm; this change resulted in a decrease in number of views and consequently Mahalo Answers' advertising revenue dropped by 75%, which led to discontinuation of the whole service[12].

[11] http://www.metafilter.com/56634/Google-loses-one-battle-to-the-competition

[12] Mahalo Answers had experienced substantial growth since its launch in 2007. Its traffic had increased from ten thousand visitors a month to two million visitors a month in 2008. In 2011, Mahalo's president announced that the recent changes in the Google search algorithm had significantly reduced traffic, resulting in the need to lay off about 10% of Mahalo employees. Mahalo's Google generated search traffic declined by over 75% since these changes and the service was disconnected by then.

7 Conclusion

This chapter first presents the concluding remarks regarding this research. Then, it outlines the contributions of the study to theory and practice. Next, the implications of the study are highlighted, and the final section discusses the limitations of the study and suggests future research.

7.1 Concluding Remarks

Advances in information technology have had a significant influence on healthcare. Among technological breakthroughs, the Internet has revolutionised the way people access health information. People are increasingly using the Internet to search for, exchange and post health information. The amount and variety of health information available on the Internet offers extraordinary benefits to its users; however, it also gives rise to concerns about quality of online health information. The Internet has made it easy to publish and disseminate misinformation and, in turn, adversely affect the quality of health information available to patients, caregivers, and medical professionals.

The top-down approaches to control the quality of online health information proved to be neither probable nor desirable (See Background Chapter, Section 2.3.2). The advent of web 2.0 (read and write version of the Web) enabled user-driven approaches to improve the quality of information through 'bottom-up' approaches. Having established the capability of bottom-up approaches to tackle quality issues, the important question and research gap identified in this research is 'what type of bottom-up approach is suitable to offer optimal design of websites to provide online users with high quality health information?'

Market design is considered as an engineering side of economics. It goes beyond just understanding and analysing economic structures to looking at designing and building them. This thesis argued that the market design approach has a substantial potential to contribute to design of a bottom-up approach to address the issues related to the quality of online health information available on the Internet.

The theoretical aim of this research was to propose an analytical framework to study the design of a market for exchange of online health information. To achieve this aim, Chapter 3 translated the research problem into a market design issue and further specified the market as a multi-sided platform that brings health information providers and seekers together and establishes rules that guarantee the high quality of exchanged health information. Next, based on multi-sided platform and market design literature, this research extracted the conditions under which a platform for exchange of online health information works efficiently, namely: market thickness, market congestion, search cost reduction and shared cost reduction. Then it focused on those aspects of efficiency conditions that maximise the quality of health information. In the next step, the mechanisms to achieve the efficiency conditions and maximise quality were suggested. Inside the analytical framework, knowledge sharing literature was critically analysed to identify the motivations for generating high quality information. The online mechanism design literature was also critically reviewed to identify the design features that contribute to generation of high quality health information. The knowledge gaps in the literature related to the design of a health information platform were highlighted in terms of seven empirical researchable questions to fill the knowledge gaps.

In order to answer the empirical research questions, this study developed a unique research design outlined in Chapter 4. The research used real data from real websites whose design features and mechanisms have evolved over time, that is, actual questions and answers exchanged in Q&A platforms. This provided natural representations of the results of using such mechanisms and designs. Question and answer (Q&A) platforms are forms of community platforms that allow users to both ask and answer questions. They attempt to efficiently link the askers to answerers. The data were collected from Q&A platforms that provide examples of the different theoretical facets of the proposed analytical framework. Different Q&A platforms embody different types of mechanisms. Furthermore, the quality of information is uneven ranging from relevant and detailed to irrelevant and misleading. Thus, Q&A platforms can be utilised to test which mechanisms or design features are associated with high quality of health information in the real world rather than artificial experimental conditions.

After carefully analysing forty Q&A platforms, a purposeful sample of nine Q&A platforms was found that represented mechanisms extracted in the theoretical chapter. One hundred actual questions and answers from each Q&A (900 questions and answers in total) were randomly selected. Using an online tool designed and implemented for the purpose of this research, the quality of health information (collected questions and answers) was determined by medical expert assessors.

The design features present on and related to the platforms were also collected. The data related to design features of the platforms and the data about quality of health information were merged and formed an extensive and unique dataset to investigate the effect of design features on quality of health information.

A statistical algorithmic modelling approach with supervised learning and regression tree methods was used to investigate the relationship between dependent variable (i.e., the quality of health information) and independent variables (i.e., design features of the platforms). The robustness of the results was checked by conducting a random forest algorithm. The unique and extensive data and conducting regression trees enabled investigation into the interactions of different design features that affect quality of health information.

The result of studying the relationship between design features of the platform and the quality of health information in Chapter 5 revealed important empirical evidence about the design features that contribute to the generation of high quality questions and answers. It was shown that expertise of information providers, providing financial incentives and offline reputation of participants increase the quality of answers generated in an online health information platform. Furthermore, mechanisms such as point system, ranking system, reporting system, multiple answering system and commenting system have little effect on quality of health answers. The analysis of data related to the question side of health platforms shed light on what design features are determining the quality of question. It was shown that participation of medical experts in the platform, financial cost, social cost and following mechanism are contributing to generation of high quality questions. Moreover, the effect of using multiple answering, point system, and commenting mechanism on quality of questions is low.

Conducting a series of regression trees made it possible to study the interaction between the design features that contribute to the quality of health information. The results showed that participation of experts in the platform as information providers overrides all the other design features of the platform. The platform designer can improve the quality of information generated by experts through financial incentives and the best answers are provided by paid experts. Financial incentive is also an effective predictor of answer quality when lay users answer questions. In the absence of financial incentive, offline reputation is the critical incentive for participation of non-experts in providing high quality answers.

The results showed that information seekers ask higher quality questions of medical experts than of non-experts. Costly questions are of higher quality. Financial cost leads to higher quality of questions compared with social cost. In other words, presence of medical experts, financial cost and social cost are able to increase the quality of questions with presence of medical experts as the most effective feature and social cost the least effective.

Based on the empirical results presented in Chapter 5, in the discussion section, it was comprehensively discussed how the empirical results address the research questions. Furthermore, four scenarios for designing an online health information market were proposed based on the interaction between design features, and the quality of health information in each scenario was predicted. These scenarios provide market engineers with clear guidance on how to handle quality in an online health information market.

7.2 Contributions

This research criticises the top-down approach to controlling quality of health information on the Internet and proposes a framework to understand and address the problem of quality of online health information. Translation of the research problem into a market design issue is one of the main contributions of this study that provides a basis to understand and think about the quality problem. The proposed theoretical framework in this research goes beyond understanding the research problem and suggests possible solutions and evaluates them for addressing the research problem.

After translating the research problem into a market design issue, the problem is further specified by defining the health information market as a multi-sided platform. Inside this devised theoretical framework, this study integrates different streams of literature to speculate on the conditions under which the market or platform for exchange of online health information works efficiently through maximising quality. Knowledge sharing theories were used to find out under which conditions the platform's participants share high quality information. Then, online mechanism design literature was utilised to speculate on what mechanisms are contributing to achieving efficiency conditions and maximising quality of health information. Literature gaps relating to design of a health information market were highlighted and empirical research questions were proposed to be addressed in the empirical section. Integration of knowledge sharing theories and online mechanism design literature and applying them within market design theory to speculate on the conditions that maximise the quality of exchanged information in the health information market is a unique aspect of this research. Furthermore, the proposed framework provides empirically researchable questions to design an online health information platform that maximises the quality of exchanged information. It particularly highlights empirical questions about incentive, revenue and the quality assurance model of the platform.

The methodological novelty of this research is its unique research design. This study constructed a unique and comprehensive dataset. The data for this study were collected from differently designed health question and answer platforms. One hundred questions and answers from nine question and answer websites (900 questions and answers in total) were selected and their design features extracted. One of the biggest downsides of experimental data is that they reduce reality. When people are part of an experiment, their normal behaviours are limited because of the experiment environment. Much of the validity of the experimental data can be compromised by small human errors that can ruin any conclusion based on the data. Using actual questions and answers and applying a non-participatory data collection method results in very accurate and reliable data that improve the breadth of issues that can be addressed and the precision of the research results.

An online tool was exclusively designed for the purpose of this study and the 900 selected questions and answers were fed to the tool to be evaluated by medical experts. The quality of health information was assessed by experienced medical doctors who received comprehensive training to be able to produce consistent and reliable evaluation of information.

The unique data, besides using an algorithmic statistical approach, made it possible to investigate the interactions of different design features that have an effect on quality of health information sharing. Such an extensive analysis of the effect of design features of the platforms on the quality of health information has, to the best of the author's knowledge, not yet been conducted.

This research provides empirical answers to some contradictory findings in the literature by using real data from websites whose mechanisms have evolved over time and provide natural representations of the results of using such mechanisms and designs over time. No experimental research studies can provide such a breadth and depth of information as they are necessarily narrow in design to permit control.

The empirical section of this study contributes to the knowledge sharing literature by providing evidence that financial incentive is the most effective incentive for high quality health information sharing. The empirical result of this study does not support the notion of a crowding-out phenomenon that argues that extrinsic motivation such as monetary reward crowds out the effects of intrinsic motivation such as altruism.

The results also contribute to the online mechanism design literature by empirically recognising the mechanisms that are associated with high quality of online health information. This study also provides empirical evidence about how different mechanisms interact with each other and as a result it gives a realistic picture about how different mechanisms lead to different quality of health information.

7.3 Implications

This research has numerous practical implications for different audiences. It opens a new perspective for researchers as well as managers/designers about how to tackle the problem of quality of online health information by framing this problem as a market design issue. By analysing the effect of different mechanisms on quality of online health information, this research proposes four design scenarios and predicts the quality of health information. It gives recommendations to designers on how to devise their platform to maximise quality and provides examples of these at work. Findings of the current study about design feature that affect both information seekers and information providers shed light on ways to encourage the active participation of both sides in social and commercial Q&A platforms. . The findings of this study highlight the importance of financial incentives in enhancing health information quality. This finding is particularly important for platform designer because it shows that generation of high quality health information is costly and they need to find a way to cover the costs of improving quality of health information.

This research also has implications for policy makers, for example organisations or schemes such as Health on Net Foundation, the Health Information Standard (a health information accreditation scheme) or the Utilization Review Accreditation Commission that aim at addressing the concerns over the unequal quality of online health information. The findings of this thesis give them empirically supported guidance for recognising and promoting online procedures that lead to production of high quality online health information.

The results of this study confirm the triangle notion that argues quality, cost, and access are three essential but competitive aspects of health care systems (Kissick, 1994) in accessing online health information. The evidence is that high quality information is accessible for payment rather than being freely available. Consequently, those who are less well-off are potentially disadvantaged in accessing high quality information. This research contributes to the growing body of criticism of the idea of the Internet as a leveller through freedom of information and raises serious questions about the viability of the free market in health information as a generator or catalyst of citizen empowerment, at least as far as healthcare is concerned. That there were examples of most theoretically derived types of information website available for study, including those where information quality is likely to be low, suggests that the concerns about whether people can access high quality information and likely confusion about the varying information are still valid. The health policy makers should take this finding seriously by monitoring whether this issue significantly affects the access of disadvantaged social-economic groups and provide subsidisation when it is required.

7.4 Limitations and Future Research

The current study provides a broad understanding of the mechanisms that maximise the quality of online health information. However, there are some limitations to this study that could lead to ideas for future research. First, the empirical aim is investigate the effect of different mechanisms on the quality of generated health information. The criteria to include a Q&A platform in the sample were mainly based on variation representation of the mechanisms. This research tried to include as much variation as exists on the Internet. However, there may still be some theoretically possible mechanism that does not have any equivalent in the real world. For example, to the best of the author's knowledge, there is no health Q&A platform that uses a donation-based revenue model (such as the case of Wikipedia), or any platform that works based on purely intrinsic motivation of the participants. This issue limits the empirical findings of this study, especially since a donation-based model could be one way to provide high quality information for all.

Second, different Q&A platforms use different types of customer feedback such as voting, following, best answer mechanism, etc.; this feedback is integrated in different ways and publicised on the platform. Consequently, defining comprehensive measures to quantify patients' feedback in this research inevitably involved some subjective assumptions that limit the generalisability of the results. However, from a design point of view, it is extremely important to know whether or not users without medical expertise are able to provide feedback that signals the quality of health information. It is suggested that future research define more precise and objective measure for patients' feedback to investigate the relationship between customers' feedback and quality more thoroughly.

Third, the current study investigated "what" incentives have effects on participants to generate high quality health information, but did not address the question of "why" participants are responding to these incentives. These remaining questions can be further investigated in future research.

Fourth, this research mainly used a medical expert perspective to evaluate the quality of health information; this was justified as it was unclear at the start of the research whether non-experts could distinguish the technical quality of health information. However, the user's point of view as the main consumer of health information is also important. Whilst this research has established a relationship between information quality and positive feedback about the information, future research can further investigate the user's perspective about the usefulness of quality of health information. There is, for example, an argument that feelings of social support and not being alone in facing a problem are also important effects for health information users. These benefits are arguably as likely to arise from non-expert replies to questions as from expert replies.

Fifth, inclusion of inactive Q&A platform is justified but can be considered as limitation of data. This research included Google Answers and Mahalo Answers because they are no active Q&A platform which uses similar design that they are using.

Sixth, the framework of multi-sided platform is suitable just for the platform that facilitate direct interaction between information providers and information seekers and it does not fit very well with all kind of platforms which generate health information. This may affect the generalizability of proposed theoretical framework to study the design of health information market.

Last but not least, this research was the first attempt to conceptualise the problem of online health information quality as a ‘market design’ issue. Future research can further investigate other efficiency drivers of an online market for exchange of health information such as quantity of information and suggest how these mechanisms interact with each other.

This research provided a solution for the problem of online health information quality. The findings collectively provide a novel understanding of the design of an online health information market that maximises the quality of exchanged health information. This study not only enhances theoretical understanding of how the design of an online health information market affects the quality of information generated in the market, but also provides insights for design engineers into how to handle the problem of quality. Hopefully these insights will motivate academics to engage in more empirical research and study different aspects of the design of an optimal online health information market.

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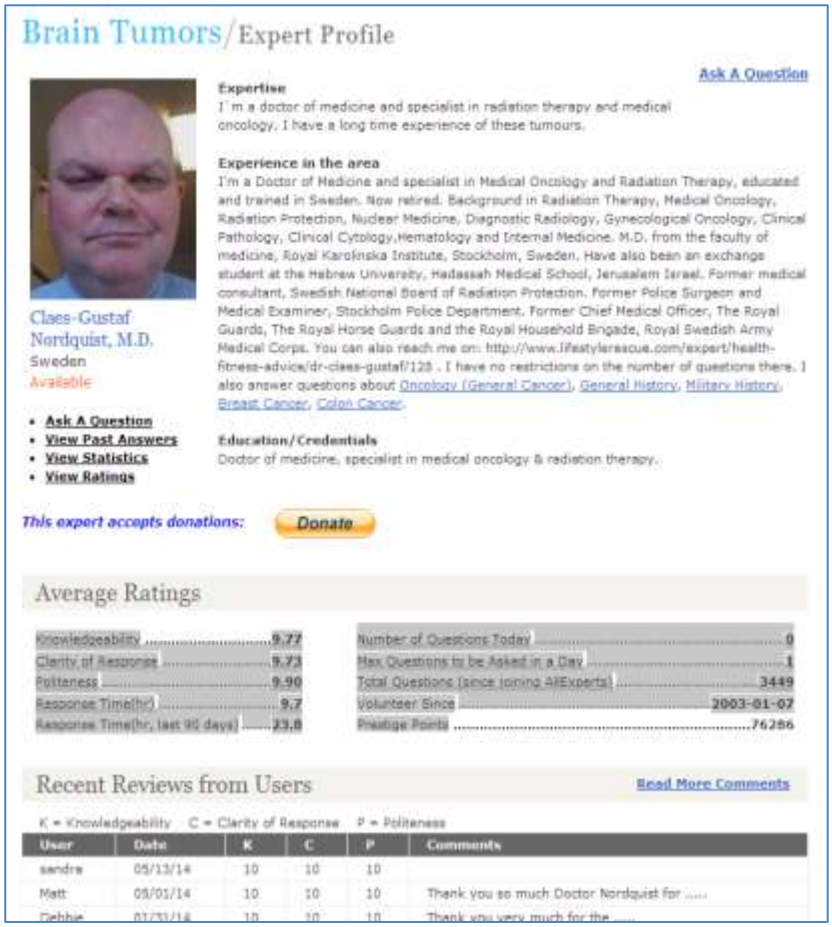
9 Appendix C4

This section includes appendices related to chapter4 – Methodology chapter

9.1 Information about nominated Q&A platforms

9.1.1 All Experts



Brain Tumors/Expert Profile

Ask A Question

Claes-Gustaf Nordquist, M.D.
Sweden
Available

- Ask A Question
- View Past Answers
- View Statistics
- View Ratings

Expertise
I´m a doctor of medicine and specialist in radiation therapy and medical oncology. I have a long time experience of these tumours.

Experience in the area
I'm a Doctor of Medicine and specialist in Medical Oncology and Radiation Therapy, educated and trained in Sweden. Now retired. Background in Radiation Therapy, Medical Oncology, Radiation Protection, Nuclear Medicine, Diagnostic Radiology, Gynecological Oncology, Clinical Pathology, Clinical Cytology,Hematology and Internal Medicine. M.D. from the faculty of medicine, Royal Karolinska Institute, Stockholm, Sweden. Have also been an exchange student at the Hebrew University, Hadassah Medical School, Jerusalem Israel. Former medical consultant, Swedish National Board of Radiation Protection. Former Police Surgeon and Medical Examiner, Stockholm Police Department. Former Chief Medical Officer, The Royal Guards, The Royal Horse Guards and the Royal Household Brigade, Royal Swedish Army Medical Corps. You can also reach me on: http://www.lifestylerescue.com/expert/health-fitness-advice/dr-claes-gustaf/128 . I have no restrictions on the number of questions there. I also answer questions about Oncology (General Cancer), General History, Military History, Breast Cancer, Colon Cancer.

Education/Credentials
Doctor of medicine, specialist in medical oncology & radiation therapy.

This expert accepts donations: Donate

Average Ratings

Knowledgeability	9.77
Clarity of Response	9.73
Politeness	9.90
Response Time(hr)	9.7
Response Time(hr, last 90 days)	23.8

Number of Questions Today	0
Max Questions to be Asked in a Day	1
Total Questions (since joining AllExperts)	3449
Volunteer Since	2003-01-07
Prestige Points	76286

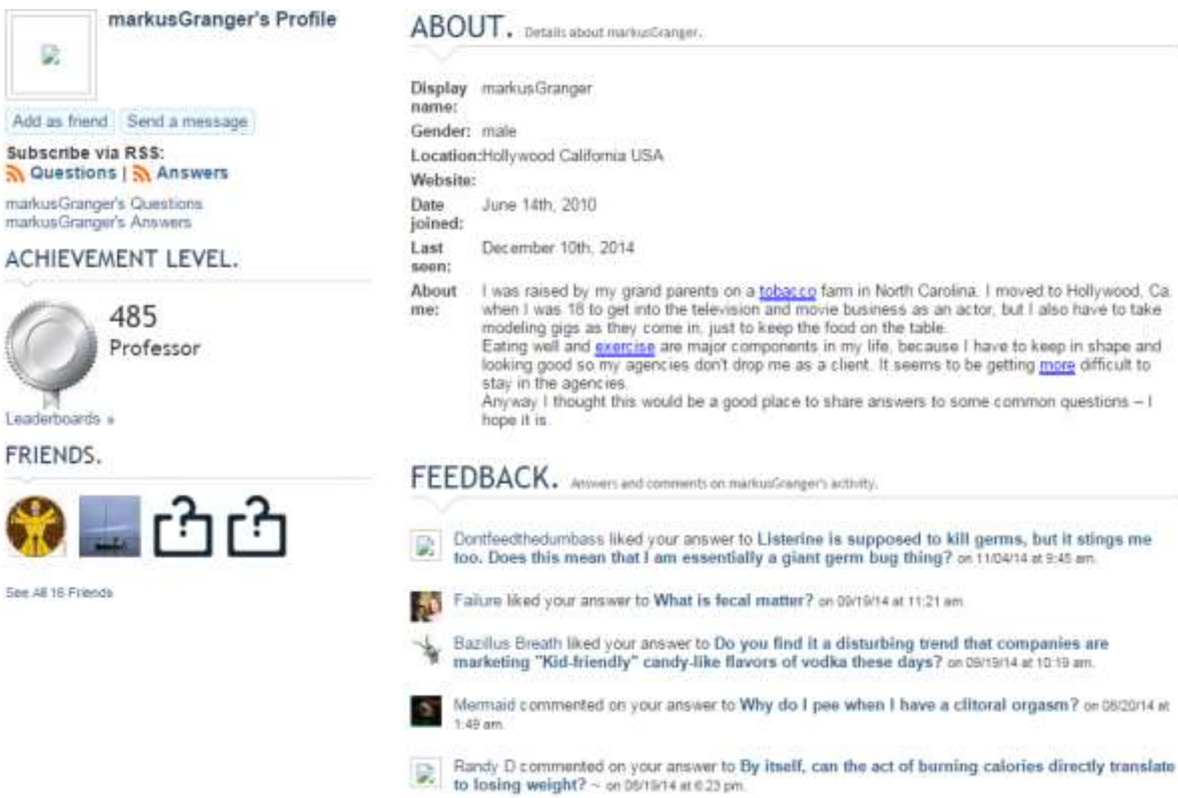
Recent Reviews from Users

Read More Comments

K = Knowledgeability C = Clarity of Response P = Politeness

User	Date	K	C	P	Comments
sandra	05/13/14	10	10	10	
Matt	05/01/14	10	10	10	Thank you so much Doctor Nordquist for .....
Debbie	01/31/14	10	10	10	Thank you very much for the .....

9.1.2 Answer bag


markusGranger's Profile

Add as friend | Send a message

Subscribe via RSS:
Questions | Answers

markusGranger's Questions
markusGranger's Answers

ACHIEVEMENT LEVEL.

485
Professor

Leaderboards »

FRIENDS.

See All 16 Friends

ABOUT. Details about markusGranger.

Display name: markusGranger
Gender: male
Location: Hollywood California USA
Website:
Date joined: June 14th, 2010
Last seen: December 10th, 2014
About me: I was raised by my grand parents on a tobacco farm in North Carolina. I moved to Hollywood, Ca when I was 18 to get into the television and movie business as an actor, but I also have to take modeling gigs as they come in, just to keep the food on the table.
Eating well and exercise are major components in my life, because I have to keep in shape and looking good so my agencies don't drop me as a client. It seems to be getting more difficult to stay in the agencies.
Anyway I thought this would be a good place to share answers to some common questions – I hope it is.

FEEDBACK. Answers and comments on markusGranger's activity.

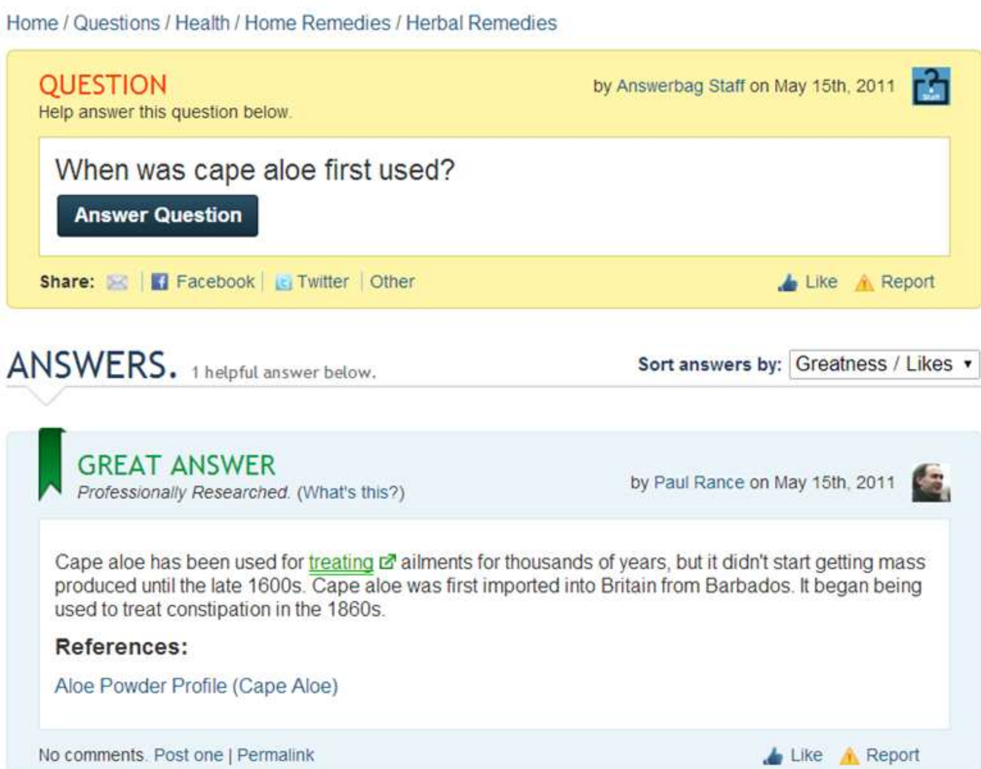
Dontfeedthedumbass liked your answer to Listerine is supposed to kill germs, but it stings me too. Does this mean that I am essentially a giant germ bug thing? on 11/04/14 at 9:45 am.

Failure liked your answer to What is fecal matter? on 09/19/14 at 11:21 am.

Bazillus Breath liked your answer to Do you find it a disturbing trend that companies are marketing "Kid-friendly" candy-like flavors of vodka these days? on 09/19/14 at 10:19 am.

Mermaid commented on your answer to Why do I pee when I have a clitoral orgasm? on 08/20/14 at 1:49 am.

Randy D commented on your answer to By itself, can the act of burning calories directly translate to losing weight? ~ on 08/19/14 at 6:23 pm.


Home / Questions / Health / Home Remedies / Herbal Remedies

QUESTION
Help answer this question below.

by Answerbag Staff on May 15th, 2011

When was cape aloe first used?

Answer Question

Share: | Facebook | Twitter | Other

Like Report

ANSWERS. 1 helpful answer below.

Sort answers by: Greatness / Likes

GREAT ANSWER
Professionally Researched. (What's this?)

by Paul Rance on May 15th, 2011

Cape aloe has been used for treating ailments for thousands of years, but it didn't start getting mass produced until the late 1600s. Cape aloe was first imported into Britain from Barbados. It began being used to treat constipation in the 1860s.

References:

Aloe Powder Profile (Cape Aloe)

No comments. Post one | Permalink

Like Report

9.1.3 ChaCha

In: Health › Vital Signs › Blood Pressure, Circulatory System, Oxygen, Body Systems
Jadyn Shumaker
Rochester, MN
When arteries become clogged which of the following may result? A. Blood pressure will increase. B. Oxygen supply to the tissues increases. C. Cholesterol blood levels increase. D. All of the above.
May 22, 2014 (1 hour ago)
Rochester, MN
Report Abuse
Ads by Google
Lower Your Cholesterol
Information, Recipes, Advice & More to Help you Lower Your Cholesterol.
www.benecol.co.uk/lower-cholesterol
ANSWERS
Aadori Rk
1 hour ago
Tucson, AZ
When arteries become clogged, blood pressure will increase.
0

9.1.4 Google Answers

Researcher Ratings for pinkfreud-ga

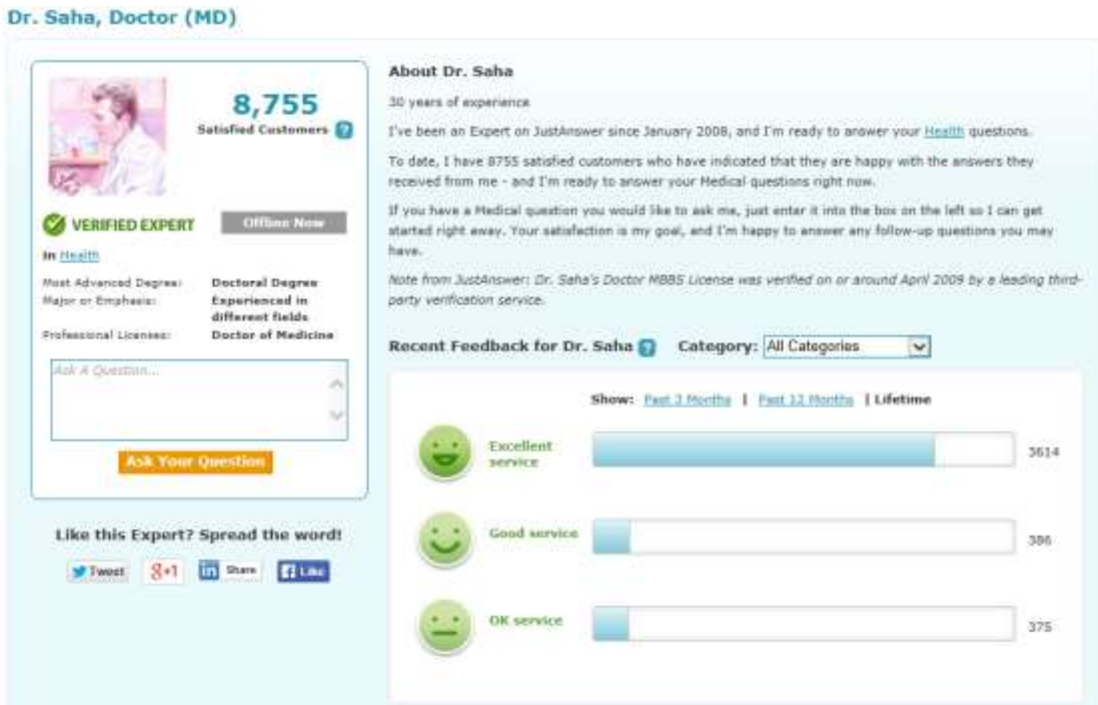
Average Answer Rating: ★★★★☆
Questions Answered: 2354
Number of Refunds: 13
Showing **Researcher Ratings** 1-50 of 2354

Subject: Unable to process request. Please try again later.
Category: Relationships and Society > Cultures
Rating and comments by: **siliconsamurai-ga**
This answer has not been rated.

Subject: Law of Software Development
Category: Computers > Programming
Rating and comments by: **johndnz-ga**
★★★★★
Awesome! Exactly what I wanted, and a lot more.

Subject: For PinkFreud: What Next?
Category: Reference, Education and News > Current Events
Rating and comments by: **thaumaturge-ga**
★★★★★
PinkFreud,

9.1.5 Just Answers



9.1.6 Mahalo Answers

potterarchy
★ 4

118 Asked
891 Answered
432 Best

1 year, 2 months ago

Can adult acne be treated with a special diet? Or is there only hope in topical creams and oral medication?

3

follow | report

Tip for best answer: M$0.17

acne | conditions | health | treatments

What is Your Answer?

0 0 0

Submit Your Answer

1 Answer

Best Answer by popular decision

$0.17 tip awarded

princm42 | 1 year, 1 month ago
★ 3

1

Scientist do not believe that acne can be cured through diet but her are some ffod to stay away from: Sugary foods, excessive caffeine, and greasy, fatty snacks. Not drinking enough water also does not help in skin repair and formation of new tissue. If your skin is particularly susceptible to acne, having a poor diet will definitely not help the situation.

report | permalink

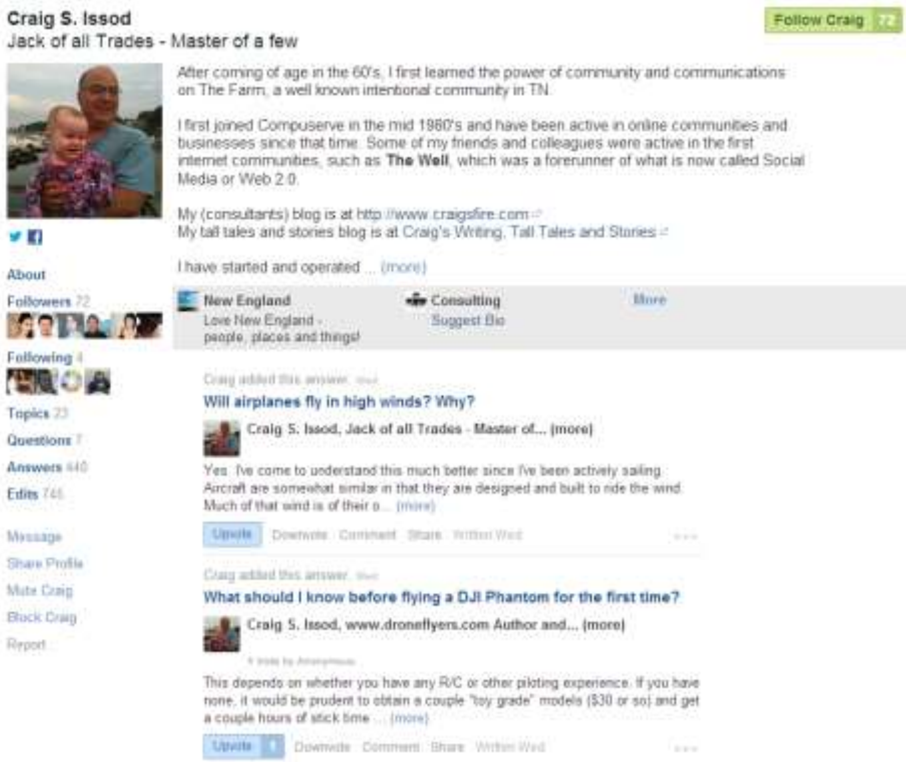
+ show 1 comment

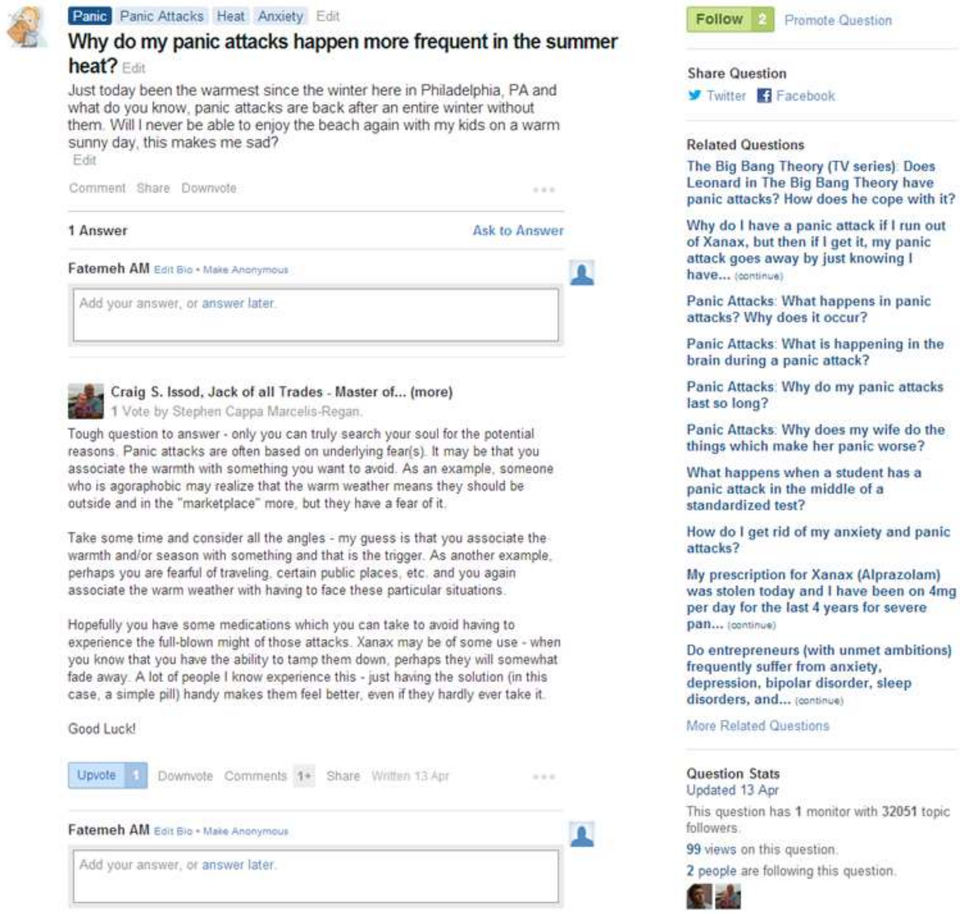
Mahalo Answers has a points and levels system to encourage helpful participation. The table below explains all the different ways you can earn points.

How to earn points in Mahalo Answers

Action	Points
Join Mahalo Answers	One time: **50**
Ask a question	**0**
Choose a best answer for your question	2
Rate the answer to a direct question you asked	2
Answer a question	2
Answer a question within one hour of when the question was asked	4
Log in to Mahalo Answers	Once daily: **1**
Vote for a best answer	1
Your answer is selected as the best answer	10
Comment on an answer by adding a source or refuting a fact	1
Receive a tip	**2** points for each **M$1** you receive in tips (*up to belt level limit)
Give a tip	**2** points for each **M$1** you give in tips (*up to belt level limit)
View up to 500 pages in a day	Once daily: **1** for every 20 pages you view (limited to 25 points a day)
Embed the answers widget on your blog or website	One time: **50**

9.1.7 Quora


Craig S. Issod
Jack of all Trades - Master of a few
Follow Craig 72
After coming of age in the 60's, I first learned the power of community and communications on The Farm, a well known intentional community in TN.
I first joined Compuserve in the mid 1980's and have been active in online communities and businesses since that time. Some of my friends and colleagues were active in the first internet communities, such as The Well, which was a forerunner of what is now called Social Media or Web 2.0.
My (consultants) blog is at http://www.craigsfire.com
My tall tales and stories blog is at Craig's Writing, Tall Tales and Stories
I have started and operated ... (more)
About
Followers 72
Following 4
Topics 23
Questions 7
Answers 440
Edits 745
Message
Share Profile
Mute Craig
Block Craig
Report
New England
Love New England - people, places and things!
Consulting
Suggest Bio
More
Will airplanes fly in high winds? Why?
Craig S. Issod, Jack of all Trades - Master of... (more)
Yes. I've come to understand this much better since I've been actively sailing. Aircraft are somewhat similar in that they are designed and built to ride the wind. Much of that wind is of their o... (more)
Upvote Downvote Comment Share
What should I know before flying a DJI Phantom for the first time?
Craig S. Issod, www.droneflyers.com Author and... (more)
This depends on whether you have any R/C or other piloting experience. If you have none, it would be prudent to obtain a couple "toy grade" models ($30 or so) and get a couple hours of stick time ... (more)
Upvote Downvote Comment Share



Quora terms and condition to earn credit

Whenever you add interesting content other people appreciate.

- You get 10 credits when people follow questions you ask
- You get 10 credits when people upvote your answer
- You get 10 credits when people upvote answers you requested from another person (via Ask-to-Answer). This reward may be split with others if multiple people have requested the answer from the same person.
- You get 50 credits when the person who asked the question upvotes your answer

9.1.8 WebMD

NOHARD

3,493 Answers
54 Followers
80 Best Answers
2,432 Helpful Answer Votes

My Favorite Quote

Your penis is affected by every aspect of your physical, mental and emotional life, and that's a fact. Men's talk.

My Story

Hi Folks, well the picture you see, is me to a turn, just love being naked, yes at heart a true naturist, but if you look you will see there face less, just like a lot of us on here, were just faceless people.

So for me I live here in Greece, in a village of Aristomenis, were near Kalamata, yes were all the nice big olives come from, I do have my own olive grove and do have eating olives which I do some each year, we do our own olive pick about mid January, and produce around 40 sacks a year.

Back to List | Next Question

Posted: 15 hours ago | Report This |

Q. How do I know if the piercing in my nose is rejecting?

I've had my nose piercing for almost four years. No mater how many times I have cleaned it it still feels sore, and when I take it out to clean it it feels like the skin has closed in a matter of seconds and I have to force it back in.

Related Topics: Piercing, Nose, Skin

Answer This | Follow Question | Post new Question

Answers from Contributors (1)

NOHARD
3,493 Answers
2,432 Helpful Votes
54 Followers
Follow

A. Hi Have you thought of going back and have the hole made bigger, doing this should stop you problem.

Good Luck

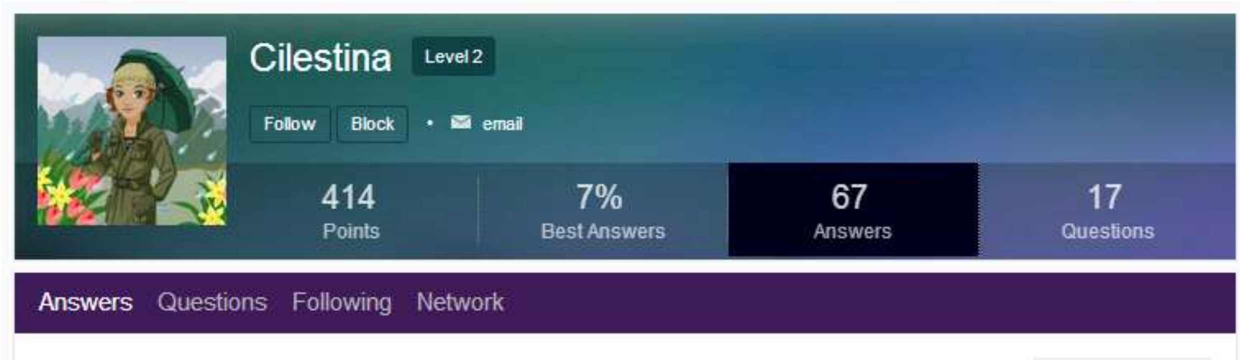
The opinions expressed here are solely those of the User.

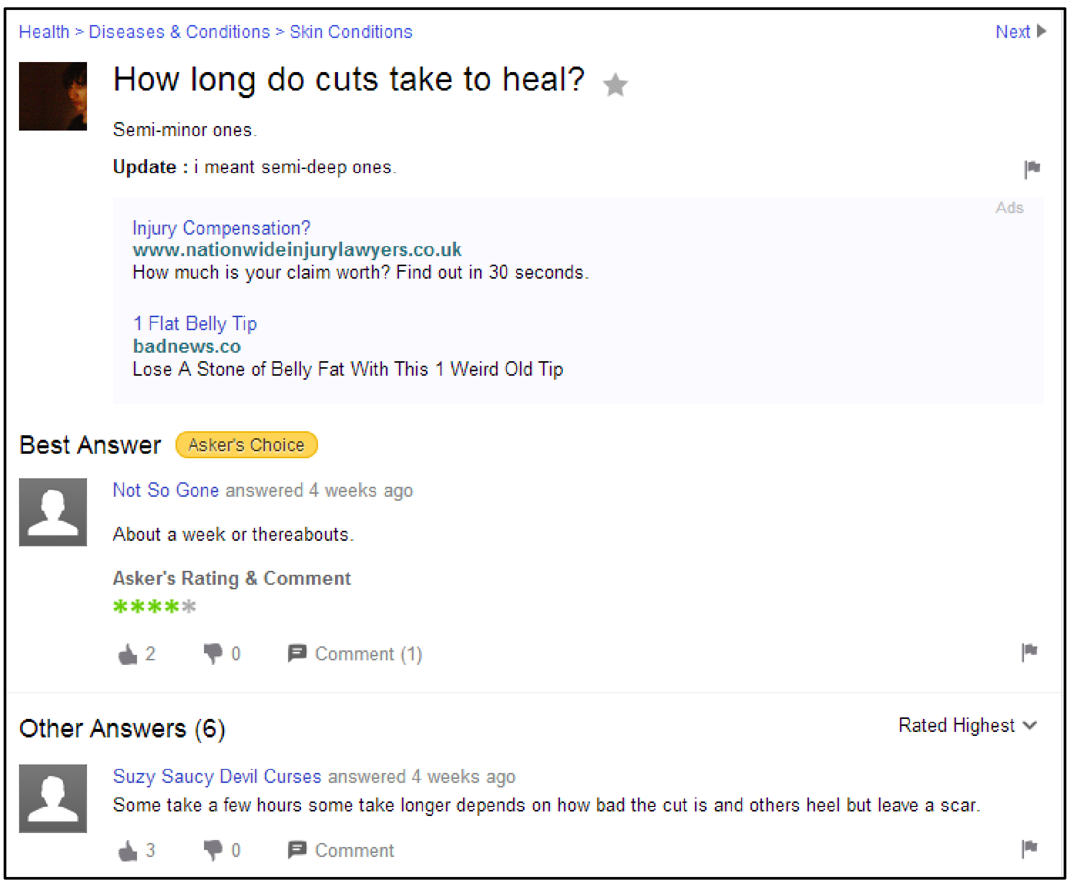
Posted: 2 hours ago | Report This

Was this helpful? Yes No

1 Answer

9.1.9 Yahoo Answers





Points Table

Points and Level system in Yahoo Answers

To encourage participation and reward great answers, Yahoo Answers has a system of Points and Levels. The number of points that you get depends on the specific action that you take. The Points table below summarizes the point values for different actions. While you can't use points to buy or redeem anything, they do allow everyone to recognize how active and helpful you've been. (And they give you another excuse to boast to your friends.)

Action	Points
Begin participating on Yahoo Answers	One Time: 100
Ask a Question	-5
Choose a Best Answer for your question	3
Answer a Question	2
Self-deleting an answer	-2
Log in to Yahoo Answers	Once daily: 1
Have your answer selected as the Best Answer	10
Receive a "Thumbs-up" rating on a Best Answer that you wrote (up to 50 "Thumbs-ups" are counted)	1 per "thumbs-up"
Receive a violation	-10

Levels

Levels are another way to keep track of how active you (and others) have been. The more points you accumulate, the higher your Level. Yahoo Answers recognises your Level achievements with our special brand of thank you

And finally, as you attain higher levels, you'll also be able to contribute more to Yahoo Answers - you can ask, answer and rate more frequently.

Level	Points	Questions	Answers	Follows
7	25,000+	20	160	100
6	10,000-24,999	20	160	100
5	5000-9999	20	160	100
4	2500-4999	20	160	100

Level	Points	Questions	Answers	Follows
3	1000-2499	15	120	100
2	250-999	10	80	100
1	1-249	5	20	100

*All limitations are per day

9.2 Rating criteria guideline for human assessors

A. Quality of questions

Question Type

General Health: Seeks for knowledge/information about general health topic (**Example:** What is the origin of HIV?)

Personal Health: Seek for knowledge/information about personal health issue (**Example:** Why do I have pain in my back?)

Conversational: Seeks for starting a discussion/conversation; these questions do not have a "correct" answer (**Example:** Do you give blood?)

Emotional: they seek passion or empathy (***Example:*** *Is it scary to have brain cancer?*)

Spam/Non-question: The question is spam / not a question.

Question Rating

1. **Importance:** How **seriously/ sincerely** did the question asker want an answer to the question?
2. **Perceived Urgency:** How urgently did the question asker want an answer to the question?
3. **Actual Urgency:** How urgently did the question need an answer from medical point of view?
4. **Difficulty:** How much work would it require to answer this question? Please rate:
    a. *Low and very low:* Anybody can answer the question
    b. *Neither High nor Low:* An average high school educated person is able to answer the question
    c. *High:* Someone with general medical background can answer the question
    d. *Very high:* specialist can answer the question
5. **Question Politeness:** How rude or polite is the question?
6. **Question Archival Value:** How valuable is the question for archiving? ; Or the high-quality answers to this question will provide information of lasting/archival value to others.
7. **Writing Quality:** How well-written is the question?

B. Criteria for quality of answers:

1. Accuracy: The answer provides correct information.
2. Completeness: The answer includes everything. There is nothing to add.
3. Relevance: The answer is relevant to the question.
4. Objectivity: The answer provides objective and unbiased information.
5. Readability: The answer is easily readable.
6. Source Credibility: The source of information is authoritative. **Please rate "Not Applicable" if no source is provided.**
7. Politeness: The answerer is polite.
8. Confidence: The answerer is confident in the answer
9. Empathy: The answerer expresses his or her empathy to the questioner.
10. Efforts: The answerer puts effort into providing this answer.

11. Archival Value: This answer is useful for others. It is worth to archive this answer.

9.3 Health keywords

ABDOMINAL PAIN
SPINAL PAIN
Abortion
Acne
AIDS
Alcohol
Alcoholism
Allergies
Alternative Medicine
Alzheimer's
Alzheimer's Disease
Amnesia
AMPUTATION
Anemia
Anesthesiology
Anxiety
Anxiety Disorders
ARM AND LEG PAIN
Arthritis
Artificial insemination
Asthma
Atherosclerosis
Athlete's Foot
Atopic Dermatitis
Attention Deficit Disorder
Attention Deficit Hyperactivity Disorder
Audiology
Autism
Avian flu
Back Injury
Back Pain
Bacterial
Bacterial Vaginosis
Bacterium
Baldness
Bedbug
Benign Prostatic Hyperplasia
Biology
Biotech
Bipolar Disorder

Blindness
Blood
BLOOD PRESSURE
Blood vessels
BODY TEMPERATURE
Bone grafting
BONE PAIN
Brain Tumor
Breast Cancer
BREAST PAIN
Breasts
Broken Bone
BURN
Cancer
Cardiology
Cataract
Celiac Disease
Chewing Tobacco
Chickenpox
Chlamydia
Chronic Disease
Chronic Fatigue Syndrome
Chronic Pain
Cigarettes
Cigars
Circulation
Cold
Coldness
Colitis
Colon Cancer
Condom
Congestive Heart Failure
Corpulence
COSMETIC SURGERY
Crohn's Disease
Cystic Fibrosis
Deafness
Dealing with terminal conditions
Death
Dementia
Dentistry
Depression
Dermatology
Diabetes

Diarrhea
Diet
Digestive
DILATION AND CURETTAGE
Disability Issues
Donation
Drowsiness
Drug Overdose
Drugs
Ear
Eating Disorders
Eczema
Emphysema
Epilepsy
Exercise
Fats
Female Ejaculation
Fertility
Fever
Fibromyalgia
First Aid
Flu
Food Allergy
FRACTURES
Gallstone
Gastroenteritis
Genital Herpes
Genital warts
Gonorrhea
GROIN PAIN
Gynecologic Cancers
Gynecology
Hair Loss
HAND AND FOOT PAIN
Hangovers
Hard of Hearing
Harmful
Headaches
Health
Health Care
Healthy
Heart
Heart Disease
HEART RATE

Muscle
MUSCLE PAIN
Nausea
Neck Injury
NECK Pain
Nephrology
NERVE PAIN
Neuralgia
Neurological conditions
Nose
Nursing
Obamacare
Obesity
Obsessive-Compulsive Disorder
Obstetrics
Oncology
Organ donation
Organ transplants
Orphan Diseases
Orthopedics
Osteoarthritis
Osteoporosis
Otolaryngology
Paget's Disease
Pain
PAIN MANAGEMENT
PAINKILLERS
Pancreas
Panic
PAP tests
Parkinson's Disease
Pediatrics
Penicillin
Pharmacology
Physical Therapy
Pipes
Plastic Surgery
Pneumonia
Poisoning
Postpartum Depression
Pregnancy
Prostate Cancer
Prostatitis
Psoriatic Arthritis

Psychological
Public Health
Pulse rate
Quitting smoking
Radiation Surgery
Rash
Reaction
RESPIRATORY RATE
Ringworm
Schizophrenia
Senior Health
Sexuality
Sexually Transmitted Diseases
Sexually-transmitted diseases
Shingles
Side effect
Sinus Infection
Sleep Disorders
Smokeless ashtrays
Smoking
Sports Medicine
STOMACH Pain
Stress Management
Surgery
Swine influenza
Syphilis
TESTICULAR PAIN
Throat
Thyroid Disease
TONSILLECTOMY
Toxic Shock Syndrome
Toxoplasmosis
Transient Ischemic Attack
Traumatic Brain Injury
Trigeminal Neuralgia
Tuberculosis
Type 1 Diabetes
Type 2 Diabetes
Ulcerative Colitis
Ultrasound
Unhealthy
Urinary
Urology
Uterine fibroids

10 Appendix C5

This section includes appendices related to chapter5 – Finding chapter

10.1 Data analysis code

```
## Activate the required libraries
library(foreign)
library(MASS) ## a library of example datasets
library(ggplot2)
library(grid)
library(gridExtra)
library(tree)
library(rpart)
library(randomForest)
library(dplyr)
library(party)
library(rpart.plot)
library(Hmisc)
library(nlme)


web_data <- read.csv("C:/Users/helenomid/Dropbox/health and new approach/Data Analysis/total.csv")

names(web_data)
sapply(web_data, class)
```
===
dfta <- web_data%>%
  select(id, price, expert, mobile, advertise1, transaction,
        certify, gurantee, reportfradu, qfin, qso, qfinfix, qfinflex, qsofix, qsoflex, multi, comment, reput,
pointsys, ranksys, best, offrepu, qvotew, avotew, afollow, questionavg1)

sapply(dfta, class)
dfta1 <-na.omit(dfta)

prefix <- "questionavg1~"

# Respondant expertise
set1 <- select(dfta1, expert, certify)

# Reputation
set2 <- select(dfta1, reput)

# Incentive mechanism -Basic
set3 <- select(dfta1, price, qfin, qso)
# Incentive mechanism - Variation
set4<- select(dfta1, qfinfix, qfinflex, qsofix, qsoflex)

# Revenue model-Basic
set5 <- select(dfta1, advertise1, transaction)

# Revenue model- Variaton1
set6 <-select(dfta1, gurantee, mobile)
# Revenue model- Variaton1
```
```

```
#set7 <-select(dfta1, mobile)
# Governance Rules
set7<- select(dfta1, afollow, ranksys, best, pointsys, reportfradu, multi, comment)


# Average Quality index as an input for our model
#set5 <- select(dfta1, questionavg)


# Expertise
formula1 <- as.formula(paste(prefix,paste(names(set1), collapse="+")))

# Expertise & Reputation
formula2 <- as.formula(paste(prefix,paste(c(names(set1), names(set2)),collapse="+")))

# Expertise & Reputation & basic revenue model
formula3 <- as.formula(paste(prefix,paste(c(names(set1), names(set2), names(set5)),collapse="+")))

# Expertise & Reputation & All revenue model
formula4 <- as.formula(paste(prefix,paste(c(names(set1), names(set2), names(set5),
names(set6)),collapse="+")))

# Expertise & Incentive
#formula5 <- as.formula(paste(prefix,paste(c(names(set1), names(set3)),collapse="+")))

formula5 <- as.formula(paste(prefix,paste(c(names(set1), names(set2), names(set3),names(set5),
names(set6)),collapse="+")))

# Expertise & Reputation & basic Incentive
formula6 <-  as.formula(paste(prefix,paste(c(names(set1), names(set2),
names(set3),names(set4),names(set5), names(set6)),collapse="+")))

#Expertise & All incentive & reputation & Revenue all
#formula7 <- as.formula(paste(prefix,paste(c(names(set1), names(set2), names(set3), names(set4),
names(set5), names(set6), names(set7)),collapse="+")))

# All Possible Variables
formula7 <- as.formula(paste(prefix,paste(c(names(set1),  names(set3), names(set4), names(set5),
names(set6), names(set7)),collapse="+")))



formulae <- list(formula1,formula2,formula3,formula4,formula5,formula6, formula7)

Models <-c("formula1","formula2","formula3","formula4","formula5","formula6", "formula7")


#Trees

p <- length(formulae)
for(i in 1:p){
  fit <-ctree(formulae[[i]], data=dfta1, controls = ctree_control(mincriterion = 0.99))
  #cartree <-ctree (currentprice~., data=car1, controls = ctree_control(maxsurrogate = 3, mincriterion = 0.9,))
  plot(fit, col=9 , main= paste("Tree for",Models[i],"\n" ))
```

```
  plot(fit, col=9, type = "simple", main= paste("Tree for") )

  #fit1<- rpart(formulae[[i]],data=dfta1, control=rpart.control(cp=0.03))
  #rpart.plot(fit1,extra=1,type=1)
}

##################################Random forest

setR1 <- select(dfta1, qso, afollow, certify, qsofix, expert, ranksys, qfin, qfinflex, price, transaction,
reportfradu, comment, mobile, pointsys, advertise1)

formulaR1 <- as.formula(paste(prefix,paste(names(setR1), collapse="+")))

attach(dfta1)
set.seed(1265)
RandomForest<-randomForest(formulaR1, data=dfta1, ntree=500, importance=TRUE)
RandomForest
importance(RandomForest)
varImpPlot (RandomForest)
plot(RandomForest)
########################################
# Radnom forest cross validation

formulae <- list( formulaR1)

Models <-c("RandomForest-2")
p <- length(formulae)

```{r}
k=unique(dfta1$id)
set.seed(1265)
## Predictions with ctree ##
rctree_RMSPE_LOOCV <- matrix(NA,p,1,dimnames=list(Models,"RMSPE"))

for (i in 1:p){
  rRMSPE11=matrix(0,nrow=length(k), ncol=1, dimnames=list(NULL, "rmse"))
  rctree_pred11=matrix(0,nrow=length(k), ncol=1, dimnames=list(NULL, "pred"))
  rctree_e11=matrix(0,nrow=length(k), ncol=1, dimnames=list(NULL, "error"))
  for (j in 1:length(k)){
    test11=filter(dfta1, id==k[j])
    train11=filter(dfta1, !(id==k[j]))

    rctreeresult11<-randomForest(formulaR1,data=train11, ntree=500, importance=TRUE)
    if (dim(test11)[1]==0){
      rctree_pred11[j]= NA
      rctree_e11[j]=NA
      rRMSPE11[j]=NA
    }
    if(dim(test11)[1]!=0) {
      rctree_pred11[j]=Predict(rctreeresult11, test11)
      rctree_e11[j]=(test11$questionavg1-rctree_pred11[j])^2

    }
  }
```
```

~~~
  rctree_pred22=na.omit(rctree_pred11)
  rctree_e22=na.omit(rctree_e11)
  rctree_RMSPE_LOOCV[i]<-sqrt(mean(rctree_e22,na.rm=TRUE))
}


============================================================
### Cross Validation & Other Model Fitting Measures ###
===========================================================

### In-sample fit

## Define the vectors and matrices where results will be stored
```{r}
p <- length(formulae)

## Output matrices for REEMtree
rpart_result <- vector("list",p)
rpart_fit <- matrix(NA,nrow(dfta1),p,dimnames=list(NULL, Models))
rpart_LogLik <- vector("list",p)
rpart_AIC <- matrix(NA,p,1,dimnames=list(Models,"AIC"))
rpart_BIC <- matrix(NA,p,1,dimnames=list(Models,"BIC"))

## Output matrices for unbiased REEMctree
ctree_result <- vector("list",p)
ctree_fit <- matrix(NA,nrow(dfta1),p,dimnames=list(NULL, Models))
ctree_LogLik <- vector("list",p)
ctree_AIC <- matrix(NA,p,1,dimnames=list(Models,"AIC"))
ctree_BIC <- matrix(NA,p,1,dimnames=list(Models,"BIC"))
```

########################
## Model fit and plots ##
########################


```{r}

for (i in 1:p){
  rpart_result[[i]] <- rpart(formulae[[i]],data=dfta1, control=rpart.control(cp=0.03))
  summary(rpart_result[[i]])
  print(rpart_result[[i]])
  rpart.plot(rpart_result[[i]], main=Models[i],extra=1,type=1)
  rpart_fit[,i] <- predict(rpart_result[[i]])
  plot(dfta1$aveindex,rpart_fit[,i],main= paste("rtree fit for",Models[i],"\n"),xlab="Actual
Aveindex",ylab="Fitted Aveindex")

}
```

#####################################################
## Predictions and cross validations / Leave one out ##
#####################################################
~~~

````
## ctree

```{r}
k=unique(dfta1$id)

## Predictions with ctree ##
ctree_RMSPE_LOOCV <- matrix(NA,p,1,dimnames=list(Models,"RMSPE"))

for (i in 1:p){
  RMSPE11=matrix(0,nrow=length(k), ncol=1, dimnames=list(NULL, "rmse"))
  ctree_pred11=matrix(0,nrow=length(k), ncol=1, dimnames=list(NULL, "pred"))
  ctree_e11=matrix(0,nrow=length(k), ncol=1, dimnames=list(NULL, "error"))
  for (j in 1:length(k)){
    test11=filter(dfta1, id==k[j])
    train11=filter(dfta1, !(id==k[j]))
    ctreeresult11<-ctree(formulae[[i]],data=train11, controls = ctree_control(mincriterion = 0.9))
    if (dim(test11)[1]==0){
      ctree_pred11[j]= NA
      ctree_e11[j]=NA
      RMSPE11[j]=NA
    }
    if(dim(test11)[1]!=0) {
      ctree_pred11[j]=Predict(ctreeresult11, test11)
      ctree_e11[j]=(test11$aveindex-ctree_pred11[j])^2
    }
  }
  ctree_pred22=na.omit(ctree_pred11)
  ctree_e22=na.omit(ctree_e11)
  ctree_RMSPE_LOOCV[i]<-sqrt(mean(ctree_e22,na.rm=TRUE))
}
```

### for rpart you need to use cross validation first to select the optimal value of cp,
### and use the value to calculate the cross validation associated with the model.

```{r}
### Use cross validation to select cp
set.seed(22)
fitp1<- rpart(formula2, data=dfta1, control=rpart.control(cp=0.001))
fitp1
rpart.plot(fitp1,extra=1,type=1)

xmat <- xpred.rpart(fitp1, return.all=TRUE)
xerr <- (xmat - dfta1$aveindex)^2
z <- apply(xerr, 2, mean) # cross-validated error estimate
zp <- prune(fitp1, cp=0.03)
rpart.plot(zp,extra=1,type=1, main= "Model 2")
```

```{r}
#### rpart / cross validation errors
k=unique(dfta1$id)
rpart_RMSPE_LOOCV <- matrix(NA,p,1,dimnames=list(Models,"RMSPE"))
cpval=0.03
````
````

```
for (i in 1:p){
 RMSPE11=matrix(0,nrow=length(k), ncol=1, dimnames=list(NULL, "rmse"))
 rpart_pred11=matrix(0,nrow=length(k), ncol=1, dimnames=list(NULL, "pred"))
 rpart_e11=matrix(0,nrow=length(k), ncol=1, dimnames=list(NULL, "error"))
 for (j in 1:length(k)){
  test11=filter(dfta1, id==k[j])
  train11=filter(dfta1, !(id==k[j]))

  rpartresult11<-rpart(formulae[[i]], data=train11, control=rpart.control(cp=0.03))
  #rpartresult11<-rparttree(formulae[[i]], data=train11, cv = FALSE, random=~1|id,
tree.control=rpart.control(cp=cpval))
  rpartresult11
  if (dim(test11)[1]==0){
   rpart_pred11[j]= NA
   rpart_e11[j]=NA
   RMSPE11[j]=NA
  }
  if(dim(test11)[1]!=0) {
   rpart_pred11[j]=predict(rpartresult11, test11)
   rpart_e11[j]=(test11$aveindex-rpart_pred11[j])^2
  }
 }
 rpart_pred22=na.omit(rpart_pred11)
 rpart_e22=na.omit(rpart_e11)
 rpart_RMSPE_LOOCV[i]<-sqrt(mean(rpart_e22,na.rm=TRUE))
}
```

10.2 Out-of-bag (OOB) prediction error

The Figure 32 shows the out-of-bag (OOB) prediction error as a function of the number of trees in the ensemble. In random forests, there is no need for cross-validation or a separate test set to get an unbiased estimate of the test set error as it is estimated internally, during the run. In Breiman's original implementation of the random forest algorithm, each tree is trained on 2/3 of the total training data. In this way, each tree can be tested on the remained 1/3 of the data which was not used in building tree. The estimation is similar to leave-one-out cross validation and it is called out-of-bag error. It can be seen from Figure 32 that OOB prediction error decreases sharply form ~0.728 to 0.645 as number of trees increases from 1 to 50. Additionally, OOB error stays rather stable with minor fluctuation after 150. Therefore, any number larger than 150 results minimum OOB prediction error and improves the performance of the random forest. Initially, a relatively large value of 500 was chosen to construct the Random Forest model in this study. Figure 32confirms that there is no need to increase the number of trees to improve the model.

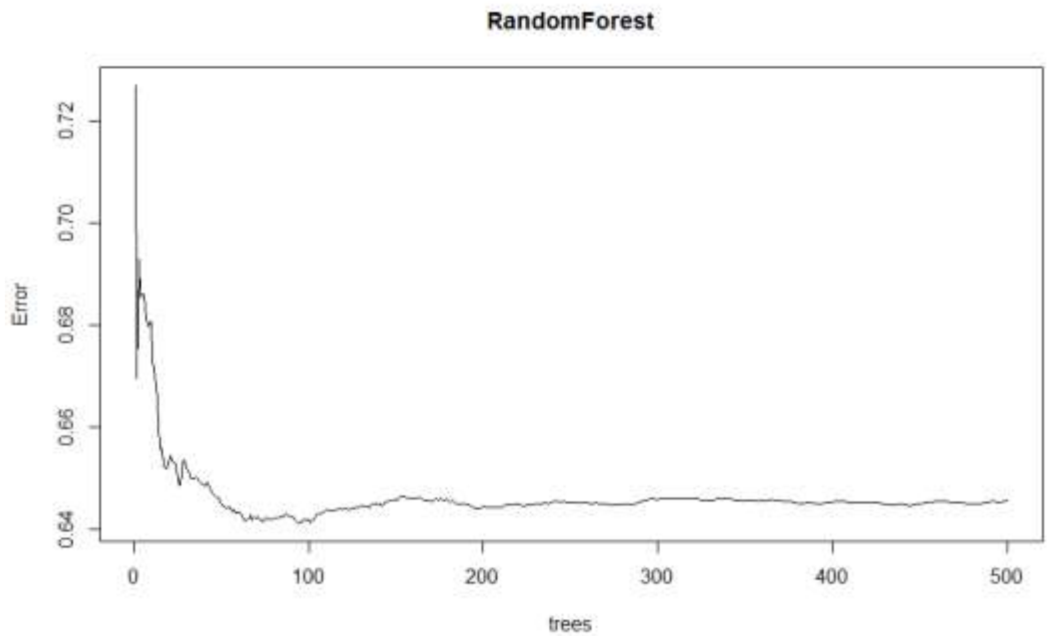


Figure 32: Out-of-bag (OOB) prediction error for random forest of answer

10.3 Wrapper selection procedure: Three rounds of conducting random forest

Random Forest1: First round of variable selection by Random Forest

In the formula for Random Forest in this round, quality of answer (dependent variable) was specified versus all other independent variables. Table 28 gives a numerical representation of how important the variables are in predicting quality of answers. It should be noted that the result of the first round of the wrapper selection procedure is the same is the result of random forest that previously conducted. Leave-one-out cross validation is run to estimate out sample prediction error which is equal to 0.8038479.

Table 28: Random forest result for first round of random forest

Predictors	Complete names	%IncMSE	IncNodePurity
questionavg	Average of question quality	22.4135	60.19906

price	Price of question	16.85781	60.22069
pay	Payment of answering	15.52612	46.74255
offrepu	Offline reputation of information providers	14.3213	14.10021
expert	Expertise of information provider	13.95002	35.71434
qso	Question social incentive	12.37914	5.107925
certify	Certification of information provider	10.17068	9.18539
qsofix	Question social incentive determined by platform	10.10615	4.205506
transaction	Transaction-based revenue model	9.758632	8.40699
qfin	Question financial incentive	9.519411	6.458449
afinflex	Answer social incentive determined by users	9.432806	5.077942
ranksys	Ranking system	9.080369	4.58323
afin	Answer financial incentive	8.135611	4.826372
advertise1	Advertisement-based revenue model	8.064516	3.571919
qfinflex	Question financial incentive determined by user	7.623631	3.947976
asofix	Answer social incentive determined by platform	7.320202	2.592827
pointsys	Point system	7.192486	2.465607
reput	Reputation system of the platform	7.021969	1.529776
afinfix	Answer financial incentive determined by platform	6.869753	0.907279
avotew	Voting mechanism for answers	6.600669	8.101585
afollow	Following mechanism	6.414096	2.661038
qfinfix	Question financial incentive determined by platform	6.187148	5.592166
best	Best answer mechanism	6.084879	1.868887
reportfradu	Reporting mechanism for fraudulent behavior	5.912948	6.940641
mobile	Mobile-based platform	5.633821	1.016835
aso	Answer social incentive	5.593303	1.56474

asoflex	Answer financial incentive determined by user	5.571451	1.519297
qsoflex	Question social incentive determined by users	5.429796	1.714194
comment	Commenting mechanism	5.350893	0.623805
gurantee	Money back guarantee	5.139617	3.517109
multi	Multiple answering mechanism	4.078011	0.713763

Random Forest2: Second round of variable selection by Random Forest

The six least important predictors (~1/5 of predictors) are omitted including: aso, asoflex, qsoflex, comment, gurantee, multi in this stage and run the random forest for the second time (see Table 29)and calculate prediction error to see if it is reduced comparing with the original random forest model. The estimated prediction error is 0.803515 which is slightly better than previous random forest model. Therefore, the process will be continued.

Table 29: Random forest result for second round of random forest

Predictors	%IncMSE	IncNodePurity
questionavg	23.563474	60.996083
price	19.338313	67.593226
pay	18.326693	50.957625
offrepu	14.728742	14.769548
expert	14.2862	30.528393
qso	12.416111	5.252621
qsofix	11.733003	3.925681
certify	10.762294	9.225552
transaction	9.459115	7.976838
qfin	9.45365	7.23573
advertise1	9.400899	4.588475
afin	9.21623	4.48217

ranksys	8.850552	5.697138
asofix	8.340554	2.590878
afinfix	8.178496	1.498213
qfinflex	8.017488	3.537723
afinflex	7.945638	3.850419
pointsys	7.137758	2.762201
afollow	7.038479	3.33016
qfinfix	6.939278	5.8077
avotew	6.721887	7.834716
best	5.988593	2.69969
reportfradu	5.762656	6.227379
mobile	5.649962	1.170436
reput	5.49912	1.486792

Random Forest3: Third round of variable selection by Random Forest

In the second round another 6 least important predictors are omitted including: qfinfix, avotew, best, reportfradu, mobile and reput. The random forest is run for the third time and prediction error is calculated which is equal to 0.8046099. As the prediction error become worse, the process of omitting low ranking predictors is not continued further and the remained predictors will be used to build a robust tree to check if the results are confirming the result of the regression trees.

10.4 Compelete question Models

Model Q1: knowledge background

In Model Q1, it is checked whether the knowledge background of information provider has effect on quality of questions asked in the platform. The model Q1 shows that the medical background of the information providers (certify) is an effective predictor of question quality. Furthermore, it shows that higher quality questions are asked from physicians. In other words, when you are asking a question from medical doctors, you ask a better quality questions.

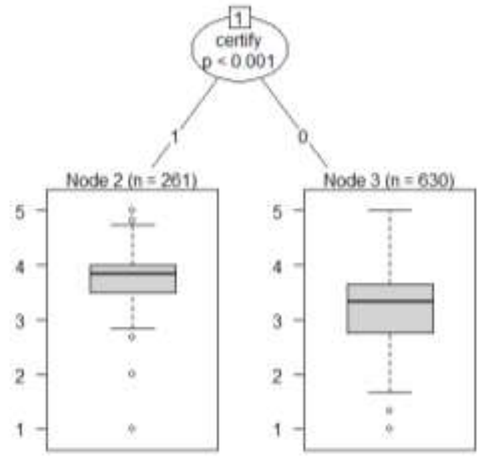


Figure 33: Model Q1 - knowledge background

Model Q2: Reputation

Two variables of reputation were added to the previous model and the resulted tree remained unchanged.

Model Q3: Revenue Model

Variables related to revenue model of the platform were added to the previous set. There are 4 variables related to revenue model in the sample: Advertisement-based revenue model, Transaction-based revenue model, providing money back guarantee and having Mobile-based platform. The result is shown in Figure 34.

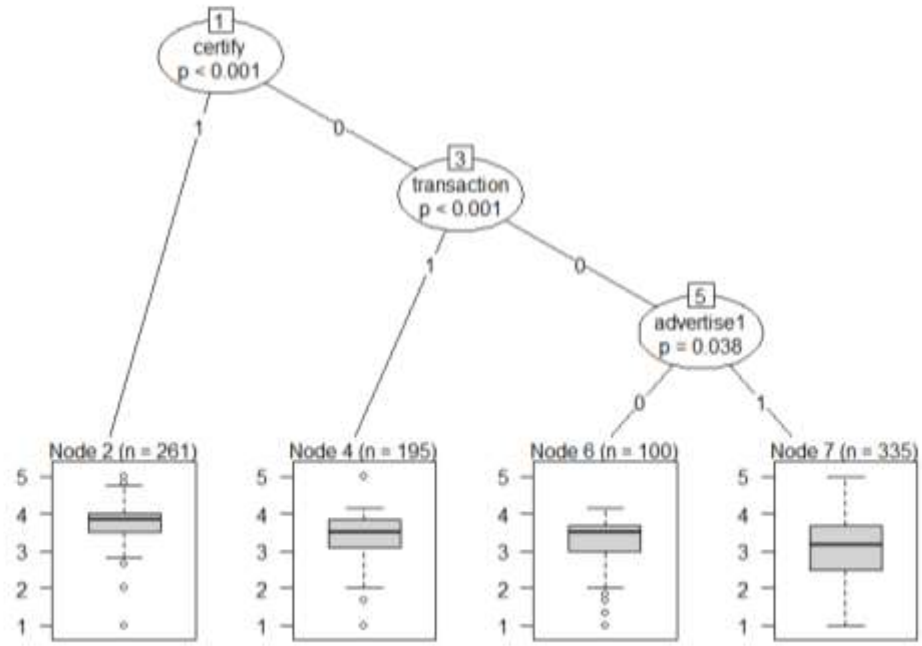


Figure 34: Model Q3 - Revenue Model

Model Q4: Incentive Model- Basic

In this stage variables related to basic inactive model used by platform was added to previous sets of data. Basic incentive model indicates that whether financial or social incentive has been used for asking question in the platform. The resulted tree is shown in Figure 35.

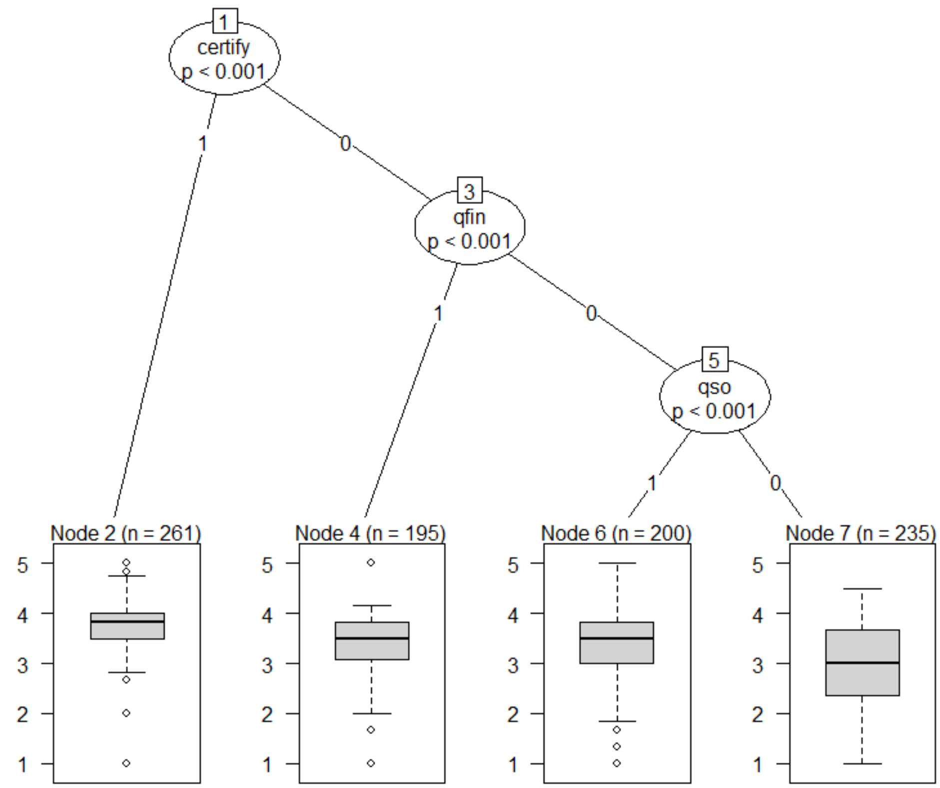


Figure 35: Model Q4 - Incentive Model (Basic)

Model Q 5: incentive Model- Variation

In this step I added more variables related to incentive model of the platforms to clarify what type of incentives have effect on quality of question. The variation of incentives indicated whether platform or user determine the asking incentives. The resulted tree remained unchanged.

Model Q 6: Governance Rule and systems

For the resulted tree see Figure 27

10.5 Random forest for number of likes and Zscore

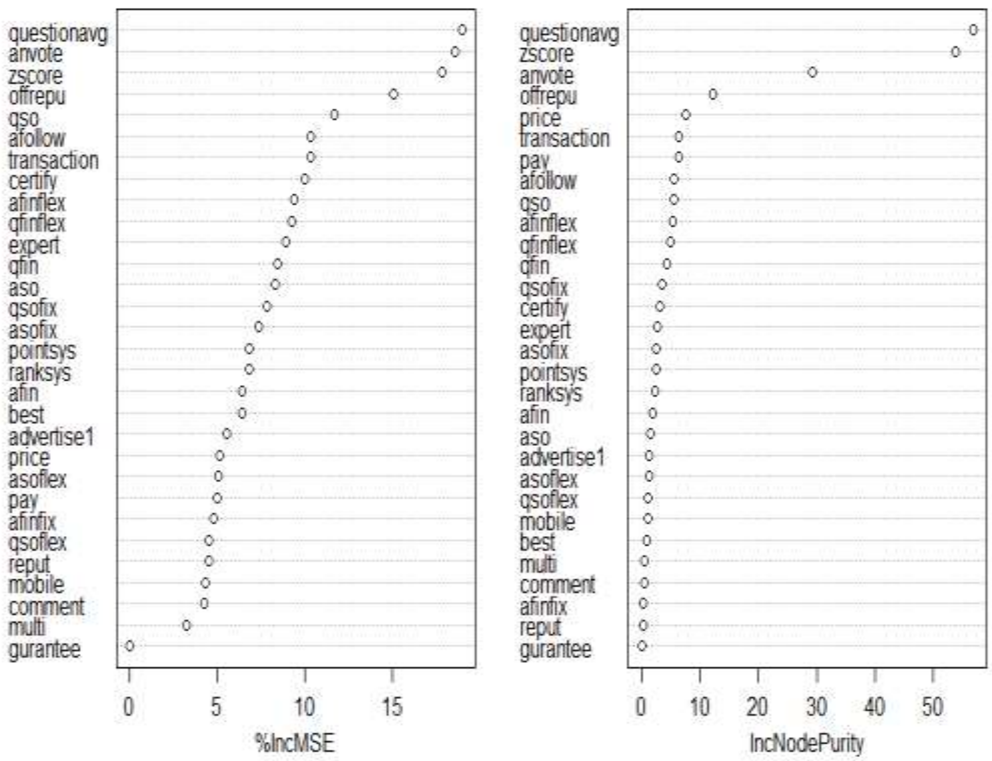


Figure 36: Random forest for number of likes and Zscore

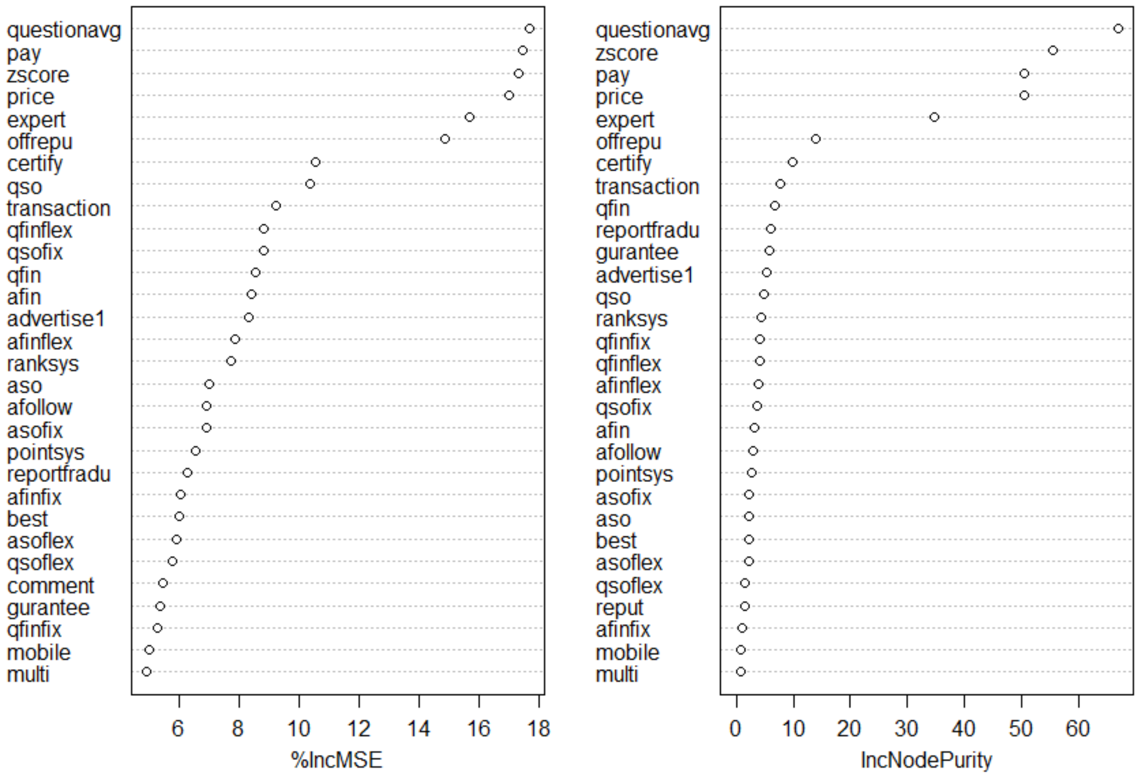


Figure 37: Random forest for online reputation of respondents (Zscore)