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# Impact of service quality on user satisfaction: Modeling and estimating distribution of quality of experience using Bayesian data analysis

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ABSTRACT

Quality of experience (QoE) plays a crucial role in attracting and retaining users of interactive Internet applications. In this work, the relation between quality of service (QoS) perceived by users and the satisfaction level of users is carefully studied. In our experiments, users encountered certain latencies while using a photo viewing service on their mobile phone; we used the experience sampling method (ESM) to record the satisfaction level of these users on a scale of one to five. The user opinion data are ordinal; therefore, it is not meaningful to treat the data as metric. To address this issue, we used Bayesian data analysis with a generalized linear model (GLM) to estimate the overall satisfaction of the users in the form of the posterior distribution of opinions. We propose that the quality of experience of users can be represented by opinion score distribution (OSD) instead of the mean opinion score (MOS).


## 1. Introduction

In the early 1990s, Mark Weiser, a computing pioneer, wrote his vision of radical changes in the future computing systems; Weiser (1991) predicted that personal computing will evolve such that computing systems will be present everywhere, at all times, calling the new paradigm "pervasive computing". He described this new computing environment as "The deepest and most enduring technologies are those that disappear. They dissipate in the things of everyday life until they become indistinguishable".

Nearly 25 years after the emergence of the new vision of Mark Weiser, a new generation of computing systems—in the form of pervasive computing and the Internet of Things (IoT)—has found its way into people's lives, thus making his prediction a reality. These new systems, by creating smart spaces, have entered the computing environment in people's daily lives; the significant amount of research in this area and the related hardware and software developments demonstrate the imminent prevalence of the new computing systems.

Interaction with pervasive systems completely differs from interaction with desktop computers; pervasive computing systems provide dynamic context-aware responses when interacting with humans, thus differing from desktop computers that provide computing services in a static environment to a user sitting at a desk.

In 1999, the objective of using computers was to perform simple tasks such as creating documents and sending text emails. However, today, we expect pervasive computing systems to be part of a smart environment. For example, smart homes providing user services adopt a completely different approach from desktop personal computers performing computational operations.

The use of network-connected computing systems in daily life is increasing considerably; however, to satisfy user needs in an acceptable manner, pervasive computing systems must consider, in addition to functional properties of the services, non-functional properties and quality of them. Furthermore, pervasive computing systems should provide these services according to user needs.

Although system-level aspects of quality of service, such as delay, throughput and jitter, can be used to determine and improve the quality of service (QoS), the important factor for a user is the overall acceptability of the service. Quality of experience (QoE) is a measure of this acceptability and can be used to compare the service quality from the user viewpoint. A better quality of experience can guarantee more users for the system and more revenue for the service provider because QoE is a direct measure of user satisfaction with the service. Anderson et al. (2004), Clark (2007) have provided new approaches for stock value estimation of companies that

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provide services to people. They have used customer satisfaction as a measure of the stock efficiency of the company; these approaches demonstrate the importance of measuring, modeling and predicting user satisfaction.

Previous studies in this area generally used the mean opinion score (MOS) as the sole measure of user satisfaction with a service. However, user opinion is an ordinal variable; therefore, the calculation of distance for these data is not meaningful, and similarly, other arithmetic operations-such as calculating the mean, variance and ratio for these data, as well as calculating MOS-are invalid operations. Owing to this important statistical consideration, in our work, we propose the use of the discrete distribution of user opinions (opinion score distribution or OSD) as a measure of service acceptability. However, to use opinion distribution, we must overcome certain technical difficulties because it is not possible to calculate OSD using the linear regression method, which is used for calculating MOS. We adopted a Bayesian analysis of regression using a generalized linear model (GLM) of ordinal data to study the relation between QoE and the QoS attribute, delay. This method can generate the complete posterior distribution of user satisfaction for a known range of quality of service values in a certain context of usage.

Our main research questions can be specified as follows:

1. What are the shortcomings of the popular mean opinion score (MOS), and what are the possible measures that can be defined and used to overcome these shortcomings?
2. What are the main parameters that affect the QoE for a user, and how can we model and evaluate these parameters? Are the system-level parameters of QoS and QoE based on user opinion correlated, and do they have a particular relationship? Can the relationship be used to forecast QoE based on the previous QoS log of the user's service usage?
3. Is this satisfaction subjective? Can different people have completely different opinions about the same level of QoS?
4. How can we estimate the discrete distribution of user satisfaction using available data related to quality of service? Is this forecast a point forecast or a probability distribution?

The main contribution of this research is that it studies the statistical properties of QoS and QoE data and their relation; it provides provide a means of calculating user QoE from perceived QoS as a discrete distribution of user satisfaction level and parameters of the relation between QoS and user QoE. The calculation of this distribution (OSD) provides a new measure of the overall satisfaction of the users; therefore, the distribution of user opinions (OSD) is suggested as a replacement for MOS.

## 2. Related work

In this section, we discuss related work. Then, these studies are categorized according to the area of research and compared, highlighting the shortcomings that we try to address in our work.

The quality of network-based services can be measured by using two different approaches:

1. Specific modeling of quality for certain media such as voice over IP (VOIP) and video on demand (VOD).
2. Generic modeling of perceived service quality by user surveys and monitoring tools.

The first method is based on modeling the quality of media in different ways and different media, and various studies have been conducted to calculate the perceived quality of experience for users; each study, based on different needs, provides a different model. These studies are diverse, and each study is specific to a certain media. The second method is generic and can be used for a wide range of services. Our work uses the second method, and here we discuss the studies that consider the relation between QoS and QoE as a generic relationship. We analyze some existing methods in this area and their limitations.

Fiedler et al. (2010) discuss the advantages and disadvantages of general performance modeling and subjective testing; then, they provides a method for combining general performance testing with subjective evaluation. This study suggests that a generic relationships between QoE and different performance metrics is beneficial to the user and also provides better understanding of quality to the service provider. In the framework provided by Fiedler et al. (2010), personal evaluations are considered for the quality of experience criteria; thus, system-level measurements and user ratings are applicable and are used for the purpose. They went for objective measures, and converted results of subjective tests into objective measures by calculating MOS, thus removing all the personal differences.

Fiedler et al. (2010) argue that perceived QoS parameters are vital to QoE. They have provided a generic qualitative equation to relate QoS and QoE in the form of a power law that is based on a hypothesis called *IQX*. Then, this equation is evaluated and approved for stream services, and QoE is presented in the form of the mean opinion score (MOS). QoS parameters such as packet loss and packet order change are used. Then, this study discusses three different areas in the relation between QoS and QoE:

**Area 1: Constant optimal QoE.** There is no distortion. User considers perceived QoS equivalent with the reference QoS, and a slight disturbance in QoS does not cause any problems.

**Area 2: Sinking QoE.** The QoE of the user declines with decreasing QoS and can fall outside the acceptable area.

**Area 3: Unacceptable QoE.** When the disturbance in QoS goes higher than a certain threshold, QoE moves outside the acceptable area; thus, it may not be possible to provide service with adequate quality. An equation called IQX is used to obtain a differential equation that describes the relation between QoS and QoE; this equation is solved to generate a power law equation between QoS and QoE.

In general, QoE can be considered as a function of $n$ affecting variables, which can be written as: $QoE = \Phi(I_1, I_2, \ldots, n)$. However, this research focuses on only one parameter (i.e., QoS), and ignores the other parameters. In this situation, QoE can be considered as a parameter of QoS; therefore, $QoE = f(QoS)$. In general, when QoE is high, changes in perceived QoS have an obvious effect; however, when QoE is low, a slight disturbance in QoS does not have a significant effect on QoE. For example, in the real world, we can consider a 5-star hotel in which even a small amount of dirt on a table would be unacceptable from the customer perspective.

Therefore, a change in QoE can be related to the current QoE value with a minus sign. This relation can be written as: $\partial QoE/\partial QoS = -(QoE - \gamma)$. By solving this differential equation, the IQX hypothesis becomes: $IQX = \alpha.e^{-\beta QoS} + \gamma$. Then, this model is fit on real-world data, and its precision is compared with other similar approaches. The improvement of this model is measured in terms of the amount of correlation, and then, the results are discussed.

Mitra et al. (2014) discuss that the typical scale for QoE data is the ordinal scale; they argue that arithmetic operations such as the mean and standard deviation cannot be applied to these data because subjective tests consist of user opinions that do not have a constant distance between choices. Further, it is incorrect to use methods such as linear regression, which is used in highly cited works such as Fiedler et al. (2010), because simple linear