Need for Speed?
On Quality of Experience for Cloud-based File Storage Services

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Abstract

Cloud computing is receiving growing attention by researchers from a variety of disciplines. However, so far only a few studies exist that investigate the Quality of Experience (QoE) of cloud services, including the category of personal file storage services like Dropbox or Livedrive, from an end user perspective.

The contribution of this paper is a methodology and the results of four different user studies towards a *situational QoE model for file storage services*. In order to obtain insights in existing usage practices and to detect possible QoE influencing factors and relevant features, we conducted an online survey amongst users of personal cloud storage services in general (N=349) and one specifically targeted at users of one of the major popular cloud storage services, namely Dropbox (N=49). A third study (N=13) on mobile Dropbox further investigated QoE and specific use cases in a mobile context, via smartphones and tablets. Based on these results, typical usage situations as well as short-term and long-term QoE influence factors were derived which included user profile, context and situation, as well as system level influences. In a fourth lab study (N= 52) the impact of waiting times, i.e. short-term QoE influences on system level during the regular usage of Dropbox, is investigated for different situations and use cases are obtained from the first three studies. As an outcome of our studies, we formulate research questions driving the agenda towards measuring and modeling QoE for cloud-based file storage services.

Index Terms: Quality of Experience, survey research, file storage services and applications, user perspective

1. Introduction

In the last couple of years, the emergence of file storage services facilitated by cloud computing technology represented one of the trends that received particular attention in several research domains. From an end-user and market point-of-view, it cannot be ignored that the use of personal cloud storage services such as Dropbox, Google Drive and iCloud has boomed enormously. According to [1], the most important application which is responsible for this evolution, is Dropbox. From a service providers' perspective, measuring users' Quality of Experience (QoE) is critical since it is strongly tied to revenue and market success. So far however, the literature on the QoE of file storage services is very limited. As a result, it is currently still unclear what the major QoE influence factors are. Factors that have already been identified in the literature include waiting times (i.e. performance) and the possibility to utilize a service at all (i.e. availability of services) [2]. Yet, their relative impact on QoE and the role of other influencing factors, are to date poorly understood. It has also been argued that in order to estimate QoE for cloud storage services and applications, it is necessary to monitor network environment and conditions, terminal capabilities, SLAs and service and application-specific information [3]. However, not only such purely technical and QoS-related parameters influence QoE. It has been shown that human and context-related factors may also play a major role. In the context of Web QoE for instance, memory effects, i.e., the psychological influence of past experiences [4] bear a strong influence. Furthermore, a recent study on adoption of cloud services indicated that security and privacy issues impose strong barriers to user adoption [5]. Finally, personal cloud storage services and applications are increasingly used in different context and accessed from multiple devices, with distinct characteristics. This evolution does not only amplify availability problems and other technical challenges, it potentially also has crucial implications for QoE, which need to be considered.

As a result, in order to identify the major QoE influencing factors, there is a need to go beyond technical aspects and to gain a better understanding of the experiences and use practices themselves. As a first step, we therefore conducted two user surveys, one about file storage services in general and one specifically about Dropbox. The aim was to understand the actual usage of file storage services as well as to detect possible QoE influencing factors and relevant features to address the following questions. *Is it possible to define different user profiles of file storage services? What are main influence factors on QoE for file storage services? How do user profiles differ in QoE influence factors? Is the performance of file storage services (i.e. speed of data transfer) a major item influencing the QoE? So, does a need for speed exist? Do service providers solely have to focus on networking speed to improve the users' QoE or is a secure, reliable service also or even more important?*

Secondly, since Dropbox is - like personal cloud storages services in general - also increasingly being accessed via smartphones and tablets, a dedicated mobile Dropbox study was set up. The aim here was to investigate QoE in different mobile use cases and considering different devices (smartphones and tablets). Information was gathered through on-device Experience Sampling Monitoring (ESM) questionnaires and mobile sensor logs.

Finally, we also discuss approaches on modeling cloud stor-

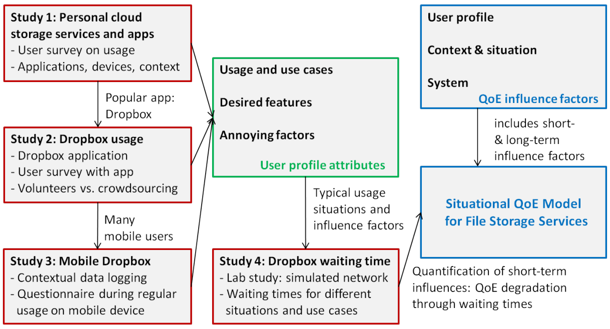


Figure 1: Methdology and conducted user studies towards a situational QoE model for file storage services

age QoE depending on the actual usage context and situation. Therefore, a QoE study on different usage scenarios of cloud storage users was conducted in a laboratory environment. The network conditions were varied in such a way that different waiting times occurred, in order to answer the following questions: *Do cloud storage users perceive waiting times differently according to the actual usage or task (e.g. synchronization or collaboration) and context (e.g. mobile device)?*

The remainder of this paper is structured as follows. Section 2 first gives an overview of our methodology and the conducted studies. Thereupon, we discuss whether crowdsourcing can be used for our Dropbox user survey and share a number of important considerations. Section 3 discusses the results of the personal cloud storage survey and the Dropbox survey. In particular, the importance of cloud storage features is evaluated, before typical user profiles of Dropbox users are derived through clustering. Section 4 approaches the Dropbox QoE model by analyzing the relevance of influence factors and by correlating contextual parameters with ratings from mobile Dropbox users, before the influence of waiting times is quantified. We propose a generic QoE model for Dropbox which is open for dicussions and formulate research questions driving the agenda for file storage QoE. Finally, Section 5 summarizes our main insights and conclusions .

2. Methodology

Four individual studies were conducted to derive typical usage scenarios and QoE influence factors for cloud storage services. Figure 1 gives an overview of how the studies relate to each other. The first three studies allow to extract user profiles including typical cloud storage use cases, desired features and annoying factors. Some of these are investigated in the fourth study on the impact of waiting times on Dropbox QoE. The findings help to understand the influence of short-term (e.g. waiting times) and long-term factors (e.g. privacy or security) on QoE and to take a first step towards a situational QoE model for file storage services.

2.1. Overview of Conducted Studies

Study 1: Personal Cloud Storage Services. In the first online survey, we focused on personal cloud storage services and applications in general. More concretely, purely use-related aspects (i.e., which applications, which type(s) of content, sharing behavior, which device(s) and connection types, in which context, etc.) and a number of expectation- and attitude-related questions were included in the questionnaire. 349 users of personal cloud storage services and applications participated. 87% of them indicated to use Dropbox.

Study 2: Dropbox Service. In the second online survey, we therefore zoomed in more concretely on the use of Dropbox storage capacities and tried to detect factors influencing Dropbox QoE. For this survey (N=49 Dropbox users), a dedicated application was installed on the participants' Dropbox account in order to gather information on available and used storage capacity. To recruit respondents, we addressed a paid crowdsourcing website, as well as volunteers, in particular members of the Qualinet-panel [6] and respondents of the first survey. In 2.2 we discuss additional methodological consideration related to the use of crowdsourcing in this study. Depending on users' goals and specific purposes for using Dropbox, their personal characteristics and the usage situation, the impact of influence factors on Dropbox QoE may differ. Therefore, the information collected in this second survey is used to define user profiles and groups of QoE influence factors by using the Expectation Maximization (EM) cluster algorithm. For modeling Dropbox QoE depending on the actual usage context and situation, we analyze the connection between these clusters to map user groups to sets of QoE influence factors.

Study 3: Mobile Dropbox. In order to gain more insight in the use practices and to explore the possible role of contextual factors, an exploratory, follop-up study (N=13) considering real usage of Dropbox in a natural context, was set up. More concretely, this study focused on the use of Mobile Dropbox on smartphones and tablets. QoE-relevant usage information was collected in users' natural enviroment by means of contextual data logging and an on-device Experience Sampling Monitoring (ESM) questionnaire [7], facilitated by the AWARE Framework [8]. During two weeks, 156 ESM questionnaires were filled in by 7 smartphone and 6 tablet users: after the use of Dropbox on the participant's device, a questionnaire was triggered. During the usage session, additional device- and context- related information (such as gps-location, network type, signal strength, duration) was collected.

Study 4: Dropbox Waiting Times Lab Study. As the above studies indicated and as is discussed in Section 4, fast synchronization and short startup times matter to end users. For this reason, a subjective lab study (N=52) was conducted at the premises of FTW in order to quantify the impact of waiting times on QoE for cloud storage and file synchronization services like Dropbox. Beyond startup delays (initialization), participants were instructed to evaluate three different storage and file synchronization operations which cover the most common activities performed in Dropbox-like applications: file storage (from device to cloud server), file sharing/retrieval (from cloud server to device), and multi-device file sync (from device A to cloud server to device B).

2.2. Results and Decision on User Panel for Dropbox Studies: Volunteers vs. Crowdsourcing

Online survey research usually draws heavily on volunteering and self-selection of participants (e.g. people volunteer to participate out of goodwill, out of interest, ...). As a result, recruiting sufficient respondents can be very challenging. Another possibility to recruit a large amount of respondents is via paid crowdsourcing platforms like MicroWorkers.com. The advantage of those platforms is that it is usually faster to recruit crowd workers than to search for volunteers. Further, crowd workers come from all around the world and it is possible to recruit workers solely from specific countries [9]. For the Drop-

Table 1: Characteristics of Dropbox accounts

		MicroWorkers	Volunteers
Used Space	Initial amount	79.14%	17.31%
	≥100MB	9.82%	67.31%
	≥1GB	2.45%	40.38%
Account size	2GB	67.48%	17.31%
	≥3GB	6.75%	71.15%
	≥10GB	1.84%	57.69%

box Survey (Study 2), we recruited 49 volunteers and we used MicroWorkers.com to gather additional information from 163 workers.

Since the survey consisted of questions for which the answers are inherently subjective (i.e. they have no right or wrong answer that can simply be verified), we used to different methods to verify the quality and reliability of all respondents (both volunteers and workers). This is a necessary pre-condition for reliable and representative results.

First, participants without a Dropbox account should not be able to complete the survey. Therefore, we used the API offered by Dropbox to develop a dedicated Dropbox application which can - with their permission - be linked to the respondents' Dropbox accounts. To this end, the participants were asked to accept the dedicated application before being able to complete the survey. Dropbox applications have access to either one folder, as is the case for our application, or to the whole account. One of the features of the application is that valid information about the participants' used, shared and available Dropbox space can be collected.

In our study, additional insights into the respondents' Dropbox accounts (and thus their use of Dropbox) were gained in this way. Table 1 depicts the percentage of workers and volunteers with different Dropbox account sizes and amounts of stored data (i.e. used space). The table shows that 79.14% of the workers only have the initial amount of data stored (example files and folders with a total size of 1.4 MB) in their Dropbox folder, see also Figure 2. For 67.48%, the available account size is the initial 2GB Dropbox space. This indicates that these workers do not use their account or that they just created a new account to complete the survey and subsequently receive the financial reward. Another possible explanation for this is that the respondents are Dropbox users, but they created a new account for privacy reasons, i.e. due to the fear that our application has access to their account. When comparing these results with those of the volunteers, we see that only 17.31% of the volunteers have the initial amount of space used in their folder. The same share has the initial 2 GB of Dropbox space available. Despite the same percentage these are not the same volunteers. Thus, some of the volunteers use Dropbox with only 2 GB space and some of them do not use Dropbox or have created a new account for the survey. Considering larger account sizes and larger amounts of stored data, we see that the percentage of workers is very low while the percentage of volunteers is still notable.

Since we assume that reliability cannot only be evaluated based on participants' Dropbox space because of inherent privacy issues, another approach to check the reliability of the respondents was to include consistency questions. The participants first had to rate annoyance (1= very annoying ... 5= not annoying) and important features of Dropbox (1= not important ... 5= very important). Different features could be rated the same. Afterwards, they were asked to make a top 3 of these features, ranking the three most annoying and three most important features. If features rated as very annoying or very important were also ranked on the first two positions, the repondent's answers were considered as being consistent. This included consistency check was also evaluated before further analysis of the data. We recruited 163 workers in multiple runs and adjusted the survey in some parts, so Table 2 refers solely to a subset of 74 workers for which the questions are comparable. The table depicts the percentage of workers and the volunteers which answered the rating and ranking questions inconsistently. At 16.3% and 10.2% of the volunteers and at 28.4% and 24.3% of the workers, inconsistencies can be found. A possible explanation for the inconsistency is that the participants did not understand the questions correctly and therefore answered inconsistently. The assumption that the workers might have randomly selected the answers just to get the financial reward could explain the difference between volunteers and workers.

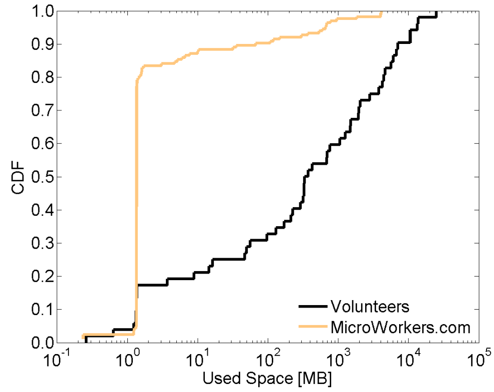


Figure 2: Used Space of Dropbox accounts

Table 2: Inconsistent Submissions

	MicroWorkers	Volunteers
Annoying Features	28.4%	16.3%
Desired Features	24.3%	10.2%

Lessons learned: The evaluation of both approaches showed that there is no certainty about the participants' reliability, confirming the need to consider this matter in online subjective studies. The volunteers also have accounts with 2GB or initial used space and - to some extent - they also answered inconsistently. On the other hand, their incentive to participate is different and on overall they seem to be more reliable than the workers. Based on the reliability check, we therefore decided to exclude the crowdsourcing workers from our sample. In the further analysis, we will only refer to the 49 volunteer respondents.

3. Usage of Cloud Storage and Dropbox

3.1. Importance of Cloud Storage Features

In Table 3, comparable results from the surveys performed in Studies 1 and 2 are shown. The most striking outcome is that the respondents of both surveys indicated the same features as being the most important. For the respondents, it is very important to be able to access data from different devices (with different operating systems), to share data (and jointly collaborate on documents) and to have backup of data. Furthermore, we can see in the table that cloud applications are used on multiple devices and in multiple contexts. They are mostly used in a fixed internet environment. However, the usage in mobile context is notable too.

We also see comparable results for usage experience: about 70% has been using the service for longer than a year. In terms of the financial dimension, we notice that only a smaller part of both samples pays for their cloud services. Moreover, in the survey on personal cloud services, the non-paying users indicated that they are satisfied with the low storage capacity (usually 5 GB) that is offered.

Table 3: Comparison of results of the Survey Studies 1 and 2

		Personal Cloud Services	Dropbox
3 key features		Accessibility Sharing data Backup	Sharing data/ Collaboration Accessibility Backup
Devices	1	10.6%	20.4%
	2 or 3	64.7%	44.9%
	4 or more	25.1%	34.7%
Context	Fixed	82.2%	85.4%
	Mobile	60.3%	62.5%
Using the service longer than a year		73.6%	67.4%
Paying for services		15.2%	6.1%

In Figure 3, we compare the average user rating on the importance of different features (going from 1=very unimportant to 5=very important). Note that the graph only shows results ranging from 3 to 5. Performance (fast upload and download times), financial aspect (free of charge), fast synchronization and security (secure Internet transmission of data and protection of data against other people) are important features of cloud services. Network conditions influence performance and speed of synchronization, which in their turn may influence QoE.

What stands out is the difference in ratings for 'privacy'. We hereby mean that data are anonymous for the service provider. At first sight, the results from the personal cloud survey could lead to the conclusion that respondents are not really concerned about privacy infringement by the cloud service provider. On the other hand, almost a third of the respondents mentioned possible violation of privacy and security issues in an open question on disadvantages of personal cloud services.

Lessons learned: Taking above results into account, and considering the fact that the respondents of the Dropbox survey indicate that privacy and security are very important, these features should be taken into account when measuring QoE. The question remains whether and how features like privacy or reliability can be measured beyond user surveys in QoE experiments (as done in Section 4.3 for waiting times).

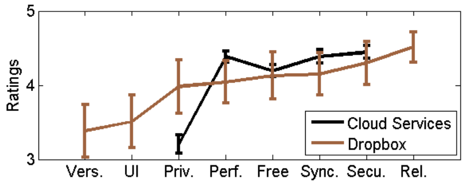


Figure 3: Average rating on the importance of different features

3.2. Clustering of Dropbox User Profiles

As argued above, the influence factors that determine QoE may be different for different kinds of users. We therefore performed a cluster analysis using the data from the 49 volunteers who participated in the Dropbox Survey (study 2). We defined a user profile by taking into account: (a) the usage duration of Dropbox (for a few days, up to one year, more than a year), (b) the number of linked devices (1,..,5, more than 5), (c) experience with in-conflict files, and (d) especially their main use case / reason to use Dropbox (backup, synchronization, collaboration, file sharing and version control). We used the Expectation Maximization (EM) cluster algorithm of the machine learning software WEKA [10] to determine different user groups. This approach resulted in six clusters containing two empty clusters and one with only three respondents who did not answer some of the questions. These three clusters were excluded from further analysis. In the following we will refer to the three remaining clusters as beginners, synchronization users and power users.

Table 4: Characteristics of User Profiles (B=Beginners, S=Synchronization Users, P=Power Users)

	B	S	P
Usage Time (Main Part)	Up to 1 Year	$>$ 1 Year	$>$ 1 Year
Number of Devices (Mean)	1.4	3.8	2.6
OS (Main Device)	Windows	Windows, MacOS	Windows, MacOS
'In-conflict' Files	10.0%	0.0%	68.2%

In Table 4 some characteristics of the different user profiles are shown. The beginners cluster contains 10 respondents using Dropbox up to one year. The synchronization users cluster consists of 14 users and is characterized by a common Dropbox usage time of more than a year (78.6%). 22 users are part of the power users cluster. In this cluster all the respondents use Dropbox for more than a year. Further, the table depicts that synchronization users push to many linked devices (mean=3.8) while power users on average use 2.6 devices for using Dropbox.

Figure 4 depicts the main use cases for the different clusters. The beginners use Dropbox mainly for collaboration (50.0%) and file sharing (40.0%) while the synchronization users make a greater use of it for synchronization (64.3%) and backup (14.3%). For the power users synchronization is still dominating (40.9%) but the use purposes are more balanced than in the other clusters. Moreover, Table 4 shows, that 10.0% of the beginners and 68.2% of the long-term users have experienced in-conflict files. This can be explained by the use of Dropbox for collaboration of the beginners and power users and the overall usage duration of the power users.

Lessons learned: Dropbox users can be allocated to certain user profiles. These clusters will be examined further towards a QoE model as shown in Figure 1.

4. Towards a Dropbox QoE Model

In this section, the importance of influence factors on Dropbox QoE is quantified by means of Study 2 (Section 4.1). For mobile Dropbox users and based on data from Study 3, the correlation between user perceived quality and contextual data is investigated (Section 4.2). Then, results from Study 4, in which the influence of waiting times was investigated in a lab study, are presented (Section 4.3). As an outcome of our studies, we formulate research questions driving the agenda towards measuring and modeling QoE for file storage services and propose a QoE model for dicussion.

4.1. Influence Factors on Dropbox QoE

In the Dropbox survey, rating questions about annoyance factors were included to gather information about possible QoE influencing factors. The annoying features (existence of in-conflict files, popups, CPU/working memory consumption, decelerated startup, reduced browsing speed), as well as their importance, are shown in Table 5.

Table 5: Shares of Users finding a certain factor annoying or very annoying including importance values (1-5, the higher the more annoying).

Factors	Percentage	Importance
'In conflict' files	31.91%	2.51
Pop-ups	29.79%	2.43
Affected browsing speed	23.91%	2.24
CPU/working memory consumption	25.53%	2.23
Decelerated startup	23.40%	2.15

Further, the important features consist of version control, reliability, security, privacy, performance, fast synchronization, GUI, and that fact that it is free of charge. The importance values of these features can be seen in Figure 3. To examine whether different groups of QoE influence factors exist, we used the EM algorithm to cluster the respondents according to their ratings of the annoying and important Dropbox features. The EM algorithm found three clusters. One cluster is excluded from further analysis as it contained only three respondents with missing data. The first cluster contains 21 respondents and is characterized by a high tolerance with respect to annoying features. In contrast to this, 25 respondents are contained in the second cluster in which the users are more annoyed by the features. Considering the important features, both clusters do not differ much. Most of the users rated these features as important or very important.

We determined the relationship between the different profile clusters and the clusters of QoE influence factors (QoE clusters). By this approach we get to know whether certain user groups are more tolerant than others. The beginners seem to be more intolerant (two beginners in the first and six in the second QoE cluster). This could be explained by the fact that those participants who have been using Dropbox just for a short time (so far), are not very familiar with all the features and settings that can be changed. Therefore, they could be more annoyed due to e.g. in-conflict files than long-term users who know how to handle this. In the second and third profile cluster an equal distribution to both QoE clusters can be found.

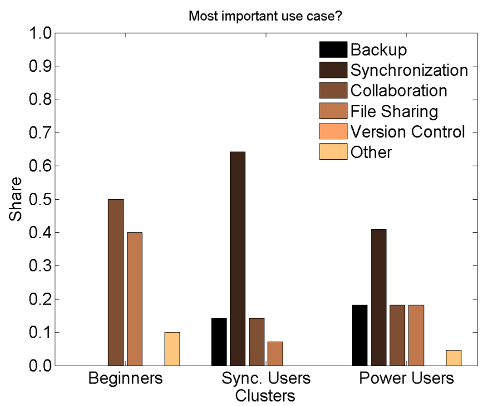


Figure 4: Main Use Purposes in Clusters

Lessons learned: A clear separation between user profiles and QoE influence factors does not exist. Therefore, we assume that the QoE of Dropbox does not depend on the user profile only. Context factors and the concrete situation also have to be taken into account in the QoE model.

4.2. Influence Factors for Mobile Dropbox Usage

Based on the participants' answers on the ESM questionnaires and the data collected with the mobile sensor logs, we are able to map the user context and link this to QoE. We divide context in geographical location, level of mobility, connectivity, social context, device and affordance of Dropbox. Moreover, we relate the occurrence of problems during Dropbox sessions to these dimensions. In order to assess Dropbox QoE, the participants were asked to give an overall rating of their experience with the application during the past session, on a 5-point MOS scale ranging from (1) Bad to (5) Excellent) [11].

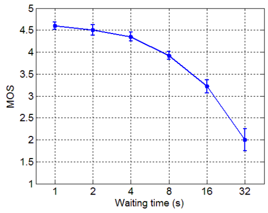
Geographical context and level of mobility. During the two-week test period, Dropbox was used most of all at home (49.4%) and at school or at work (21.8%). It was less frequently used in a mobile context (14.7%), at other indoor locations (12.8%), or outdoors (1.3%). The application was used most of all when participants were sitting or lying down (87.1%), 8.9% was nomadic and 3.8% of sessions took place while the user was standing up. Problems occurred more often in a mobile context (car, bus, train) and when the user was nomadic (going from one place to another).

Network connection. The application was used in 56.4% of sessions with a fixed network connection (WiFi). In 40.4% of the sessions, a mobile network connection such as HSPA+, HSPA (HSPA and HSDPA) or EDGE was logged. In some situations, the participants had no network connection (3.2%). In this study, we found no correlation between the logged signal strength and QoE.

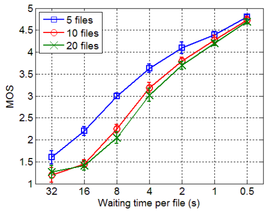
Social context. Participants used Dropbox mostly when they were alone (35.9%) or accompanied by 1 or 2 others (36.5%). In 12.2% of the cases in which other people were around, their presence was evaluated as being annoying. We also found a significant but low, negative correlation between MOS and number of people in the immediate surroundings during the Dropbox session (Spearman correlation coefficiant= -.389, p= .01). When there are less people around, the MOS scores seem to be higher and vice versa.

Affordances of Dropbox (what did you use it for?). During the Mobile Dropbox Test, participants used Dropbox most of all to watch photos (38.5%), to read text files (24.4%) and to consult other files (8.3%). In 9.6% of sessions, the application was used to upload files (photos, texts, other). A combination of tasks was however rarely made (5.8% of the sessions). Only in 2.6% of cases, Dropbox was used to share data with others. 10.9% used dropbox still for other purposes. In terms of QoE, we found a significant difference between MOS ratings for uploading files (4.47) and MOS for watching photos (3.33) (p= .02). The occurrence of problems can however not be related to specific tasks on Dropbox.

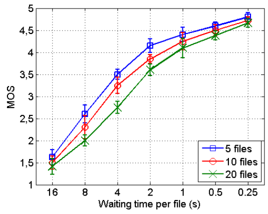
Device. The overall MOS of the tablet users in the study is slightly higher than that of the smarphone users (3.85 vs. 3.49). A possible explanation in this respect could be the difference in screen size and differences in terms of usability in general. For example, sharing files with a smartphone might be experienced as more cumbersome. Again, we found no correlation between



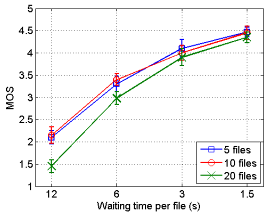
(a) Client initialization



(b) File storage (upload)



(c) File retrieval (download)



(d) Multi-device synchronization

Figure 5: MOS as function of waiting times for four difference task scenarios: initialization, storage, retrieval, and multi-device sync

the device and occurrence of problems.

Lessons learned: In mobile contexts the level of mobility and the network connection are important factors which are considered as short-term factors influencing the waiting times directly and therefore the QoE. However, social context and task are also relevant factors for a proper QoE model.

4.3. Waiting times and Dropbox QoE

As shown in the previous sections, fast synchronization and short startup times matter to end users. For this reason, a subjective lab study was conducted at the premises of FTW in order to quantify the impact of waiting times on QoE for cloud storage and file synchronization services like Dropbox considering the following tasks: initialization, storage, retrieval, multi-device sync. Figure 5 depicts the obtained results in terms of overall quality. The study results do not only show that perception (and rating) is highly non-linear and exhibits only limited saturation effects (similar to file downloads), but also that end-user sensitivity is dependent on the task context. For example, users tend to be more tolerant with slow storage operations as compared to retrieve ones, as observed in Figures 5b and 5c, and are even more patient with multi-device file synchronization, as depicted in Figure 5d. In addition, saturation effects are different for both storage/retrieval scenarios: a slight saturation effect occurs for file retrieval for waiting times below 2 seconds, which is not observed in the case of storage. For more details on this study please refer to [12].

Lessons learned and discussion: According to the actual situation S including the actual task and conditions like number of files, different shapes of curves are observed in Figure 5. Thus, the QoE model function $f_S(t)$ provides the MOS for this situation depending on the short-term influence factor waiting time t, e.g. $f_S(t) = a\log(t) + b$. However, the overall QoE $Q(S, t, \mathfrak{F})$ also needs to take into account the long-term influence factors $\mathfrak{F}$ which provides an upper bound for Q. Additional degradations during the usage of the service, i.e. through waiting times, may occur. For example, security is not affected during the usage of Dropbox, thus, it may define an upper bound for QoE, while during the usage of Dropbox mainly waiting times, but also the appearance of in-conflict files shape the user perception. For the sake of simplicity, we focus on waiting times only as short-term influence factor. Thus,

$$\frac{\partial}{\partial t} Q(S, t, \mathfrak{F}) = \frac{d}{dt} f_S(t) \tag{1}$$

and for $t = 0$ it is

$$Q(S, 0, \mathfrak{F}) = \sum_{i \in \mathfrak{F}} w_i \, . \tag{2}$$

Thus, the importance of an annoyance factor i is reflected by the weight w_i. For the example $f_S(t) = a\log(t) + b$, we arrive at $Q(S, t, \mathfrak{F}) = a\log(t) + \sum_{i \in \mathfrak{F}} w_i$ with $b = \sum_{i \in \mathfrak{F}} w_i$.

For a holistic File Storage QoE model, the different usage scenarios and the user profiles have to be taken into account which is the case for $Q(S, t, \mathfrak{F})$. However, the following questions remain. *How to quantify and measure long-term influence factors? Are long-term and short-term influence factors interacting? Are the model parameters interacting (e.g. a and b)? How to integrate long- and short-term factors in QoE model? How to integrate several short-term factors like waiting times and in-conflict files?*

5. Conclusions

This paper has explored the use of personal cloud applications to detect possible QoE influencing factors and features that need to be investigated more closely in future research. Therefore, we conducted four different user studies. As a result, identified key features of cloud storage services are accessibility, sharing data and backup of data (and in a broader perspective reliability). Our findings show that there is definitely a need for speed: performance, i.e. upload and download speed, goes hand in hand with synchronization speed and should be taken into account when measuring QoE. However, other factors beyond speed such as the financial aspect, privacy and security related issues are important, too. A clear separation between Dropbox user groups and specific clusters of QoE influence factors could not be found. Thus, despite different use contexts, all influence factors should be taken into account to ensure a good QoE. In addition, we noticed high figures for mobile and cross-device use. Therefore, we suggest that a situational QoE model is required for Dropbox taking into account QoE assessment of reliability and performance.

Open issues are new ways to properly measure aspects like reliability or security for proper QoE models and the integration of short- and long-term QoE influence factors. In particular, future research has to cope with the following research questions: *How to quantify and measure long-term influence factors? Do long-term and short-term influence factors interact? How to integrate long- and short-term factors in QoE model?*

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7. References

[1] I. Drago, M. Mellia, M. M Munafo, A. Sperotto, R. Sadre, and A. Pras, "Inside dropbox: understanding personal cloud storage services," in *Proceedings of the 2012 ACM conference on Internet measurement conference*. ACM, 2012, pp. 481–494.

[2] H. Qian, D. Medhi, and K. Trivedi, "A hierarchical model to evaluate quality of experience of online services hosted by cloud computing," in *Integrated Network Management (IM), 2011 IFIP/IEEE International Symposium on*. IEEE, 2011, pp. 105–112.

[3] T. Hoßfeld, R. Schatz, M. Varela, and C. Timmerer, "Challenges of qoe management for cloud applications," *Communications Magazine, IEEE*, vol. 50, no. 4, pp. 28–36, 2012.

[4] T. Hoßfeld, S. Biedermann, R. Schatz, A. Platzer, S. Egger, and M. Fiedler, "The memory effect and its implications on web qoe modeling," in *Proceedings of the 23rd International Teletraffic Congress*. ITCP, 2011, pp. 103–110.

[5] M. Zhou, R. Zhang, W. Xie, W. Qian, and A. Zhou, "Security and privacy in cloud computing: a survey," in *Semantics Knowledge and Grid (SKG), 2010 Sixth International Conference on*. IEEE, 2010, pp. 105–112.

[6] ICT COST Action IC1003, "European network on quality of experience in multimedia systems and services (qualinet)," 2011 - 2014. [Online]. Available: http://www.qualinet.eu

[7] J. M. Hektner, J. A. Schmidt, and M. Csikszentmihalyi, *Experience sampling method: Measuring the quality of everyday life*. SAGE Publications, Incorporated, 2006.

[8] "Aware: Android mobile context framework," 2012. [Online]. Available: http://www.awareframework.com

[9] T. Hoßfeld, M. Hirth, and P. Tran-Gia, "Modeling of Crowdsourcing Platforms and Granularity of Work Organization in Future Internet," in *International Teletraffic Congress (ITC)*, San Francisco, USA, Sep. 2011.

[10] M. Hall, E. Frank, G. Holmes, B. Pfahringer, P. Reutemann, and I. H. Witten, "The WEKA Data Mining Software: An Update," *SIGKDD Explorations*, vol. 11, no. 1, 2009.

[11] I. BS, "1534-1, method for the subjective assessment of intermediate quality level of coding systems," *International Telecommunications Union, Geneva, Switzerland*, vol. 14, 2003.

[12] P. Casas, H. Fischer, S. Suette, and R. Schatz, "A first look at quality of experience in personal cloud storage services," in *IEEE-ICC International Workshop on Mobile Cloud Networking*, Budapest, Hungary, 2013.