Master's Thesis

Title

Design of QoE Control Alleviating Cognitive Bias in Video Streaming Services

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Abstract

With the increase in video traffic, it is required for video streaming services to enable users to watch videos as comfortably as possible. User satisfaction depends not only on the network quality but also on various factors such as the video content, feelings, or viewing environment. Therefore, estimating the user's Quality of Experience (QoE) and using it for bitrate control can efficiently improve satisfaction with limited network resources. Meanwhile, humans can make irrational decisions apart from rational probabilities, such as statistical or memory errors, called cognitive bias. QoE while watching videos could be affected by cognitive bias, which leads to a decline in it. Thus, we need QoE estimation considering cognitive bias and the bitrate control to prevent the QoE drop caused by it. In this paper, we propose a QoE model that includes the cognitive bias of video viewers. We introduce cognitive biases into the QoE model that occur after the beginning of the video and changes in video quality, such as the primacy effect and the order effect. Then we simulate the QoE with a video dataset to show that our model can estimate it accurately and represent these cognitive biases. We also analyzed the cognitive bias of actual video viewers that causes QoE reduction. Finally, we provide a design of the QoE control policy to avoid QoE decline because of cognitive bias. Then we simulated a video player and estimated QoE with and without bitrate control considering cognitive bias. As a result, when we apply bitrate control that avoids QoE decline because of cognitive bias, the QoE improves than when it is not used.

Keywords

QoE

Quantum Decision-Making

MPEG-DASH

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1 Introduction

Recently, the traffic of video has been rapidly increasing with the growing popularity of video streaming services [1]. This trend leads to congestion and poor network quality, which annoys users of these services. Service providers need to maintain and improve users' satisfaction with their services in limited communication resources to operate the service sustainably. For a better service experience, it is necessary to control the network according to how users feel. Since measuring users' satisfaction level while using the service is not practical, we need to estimate it. User satisfaction with streaming video services mainly depends on network quality. However, other factors also affect it, for example, the video content, user's mood, or viewing environment. Measuring network quality is not enough to estimate it.

For this reason, we use Quality of Experience (QoE) to quantify and express the user's satisfaction level. QoE stands for the subjective evaluation of the service experience by users. Various QoE models with factors such as those mentioned above have been proposed [2, 3] to quantify how users feel correctly.

Meanwhile, humans sometimes make irrational decisions, including statistical and memory errors. Those errors are caused by both internal and external factors, such as their experience, feelings, how information is provided, or other environments. This kind of irrational decision-making is called cognitive bias in cognitive science. Since QoE is a subjective evaluation, it is left to individual decisions, which means cognitive bias can influence the QoE. For example, Sackl A et al. [4] show that cognitive dissonance occurs in video viewers. Specifically, even though video content is the same quality, the QoE differs when users themselves select the video quality or not. Cognitive dissonance avoids contradiction in our brain when there is a conflict in recognized content. In the case of video viewing, users assume that the quality selected by themselves is better than selected automatically because of this bias. Since video viewers may be affected by a variety of cognitive biases as well as this bias, it is required to consider the influence of cognitive bias in the QoE.

Therefore, we propose a QoE model including cognitive biases to estimate video viewers' satisfaction precisely in this paper. While there are many types of cognitive biases, we introduce the following biases into the QoE model, which we found through our analysis of the cognitive biases in video viewers.

- Order effect: the bias points to the effect produced by the order of information instead of the content [5]. We show a schematic of this bias in Fig.1. For applying it to real video users, if there is a temporary change in the bitrate during video playback, the user's QoE will be higher after the quality recovery than before the quality decrease.

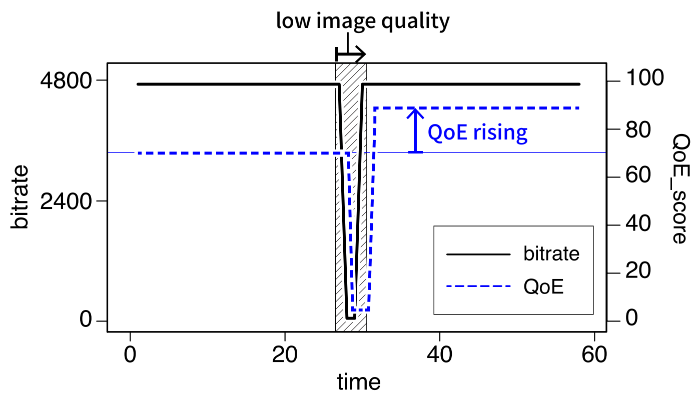


Figure 1: A schematic diagram of cognitive bias before and after video quality change

- Primacy effect: the bias where impressions based on initial information can also influence later impressions after other information has been given [6]. In the case of video viewing users, the impression received from initial video quality and content appears in the QoE, which may influence the subsequent QoE.

Furthermore, video viewers may have other cognitive biases as well as those listed above; thus, we need a model that can be applied to cognitive biases in general. To comprehensively model a variety of cognitive biases, we use quantum decision-making to model cognitive biases. It models human cognitive states by mapping them to quantum states in quantum theory. It is expected to be a general-purpose model for cognitive biases because it has a common nature with decision-making. Here, we emphasize that decision-making is not always rational and probabilistic, depending on the context. Similarly, the mathematics of quantum theory also has the nature of probability entanglement, which can naturally represent uncertainty in decision-making. With this advantage, several studies have used quantum decision-making to model various cognitive biases [7–10].

On the other hand, there is a problem applying quantum decision-making to the QoE model. While watching videos, the cognitive state of viewers changes as new information is given. Therefore, it is required to represent the change in cognitive state over time in the QoE model. However, quantum decision-making is still not suitable to directly apply for video viewing because it targets two instantaneous cognitive states; before and after decision-making. Time evolution of the state as receiving new information has not been sufficiently discussed in previous quantum decision-making-related studies. We solve this problem by introducing a cognitive bias that is inherently time-evolving in nature into the model. More specifically, we introduce the anchoring effect. The anchoring effect means that information given immediately before has a significant impact on subsequent decision-making [11]. It is shown that the bias occurs while watching TV, which suggests it may be found while watching video streaming [12]. Therefore, we represent cognitive state change over time in the QoE model by installing the anchoring effect with quantum decision-making. We also evaluate the accuracy of the QoE estimation by the QoE model and the reproducibility of the cognitive bias by simulation.

Moreover, bitrate control that considers cognitive bias may improve QoE, as cognitive bias may unconsciously reduce the QoE of video viewers. Therefore, we propose a control policy to avoid QoE drop due to cognitive bias to summarize. We analyzed the cognitive biases in actual video viewing users and extracted the factors that caused the QoE decrease. We give causes of QoE decline and solutions for each moment when the video starts playing and during playback;

- The QoE decrease due to the primacy effect is that the initial QoE tends to be lower when the bitrate is low at the start of video playback, and the subsequent QoE also tends to decrease.

- When rebuffering occurred, the QoE sometimes improved due to the order effect mentioned in Figure 1. Still, when rebuffering was repeated many times in a short period, the impact of the repetition effect exceeded the QoE, and the QoE could be decreased.

Based on these observations, we can identify the following policies for bitrate control to alleviate the impact of cognitive biases on the QoE:

- Maximize the bitrate at the start of video playback
- Set the bitrate so that rebuffering will not occur again within a certain period to reduce the frequency of rebuffering

We also simulate the QoE with and without bitrate control considering cognitive bias to evaluate the impact of bitrate control on QoE improvement.

The rest of this paper is organized as follows. We describe related work of cognitive bias, QoE models, quantum decision-making in section 2. Then we propose a video viewing users' QoE model with cognitive bias based on quantum decision-making in section 3. In section 4, we evaluate the accuracy of QoE estimation and representation of cognitive bias by simulating QoE using the proposed method. We also propose a bitrate control that takes into account cognitive bias then evaluate how much QoE improves in section 5. Finally, we summarize the results and discuss challenges for future work in section 6.

2 Related Work

2.1 Cognitive Bias

Cognitive bias is a systematic error in thinking, such as statistical and memory errors when humans process and interpret information, affecting decisions or judgments. While there are many kinds of cognitive biases, we focus on the order effect, the primacy effect, and the anchoring effect in this paper.

2.1.1 The Order Effect

The order effect is a statistical error that people make different judgments from the same information relying on the order they are given [5]. Namely, if there are two pieces of evidence and some subjects tell an opinion after seeing the information in the order A-B, others receive the information backward. The order effect occurs when opinions differ among two groups of subjects. An example of applying this bias on the Internet is the impact on online reviews (yelp.com), which results in falling review helpfulness because of the order of review. [13]. There is the order effect in the actual QoE collected from the video viewers, and we propose the QoE model with it.

2.1.2 The Primacy Effect

The primacy effect is a memory error that people retain the impression they gained from the initial information [6]. Examples of situations where this bias can occur are impressions of new people [14] or lists of candidates in an election [15]. It is also shown that the primacy effect emerges during video viewing; in TV programs, the earlier the commercial was aired, the more people remembered it [16]. Moreover, we found the primacy effect observed in the actual QoE collected from the video viewers. Thus, we include the primacy effect in the QoE model.

2.1.3 The Anchoring Effect

The anchoring effect is a bias that information provided just before a decision strongly influences the decision [11]. Information given in such a situation is called an anchor. The anchoring effect has many applications in economics, such as auctions and price negotiations [17,18]. It can affect cognition over a long time and has inherent time-evolving nature. Therefore, we introduce the anchoring effect as a cognitive bias with time evolution into the QoE model to describe cognitive states change during video viewing with quantum decision-making. We build a model of the anchoring effect of quantum decision-making based on the model in previous work [19]. In the following, we describe the previous model in Ref. [19].

It is suggested that the brain uses a sampling-like calculation in inference problems, allowing humans to estimate the value of an unknown quantity X using only one sample from a subjective probability distribution $P(x|K)$ that expresses their beliefs [20]. Sampling is often approximated by Markov chain Monte Carlo (MCMC) methods in fields such as statistics, machine learning, and artificial intelligence [21]. We can use probabilistic approximate sample sequences to sample from complex distributions in MCMC. Here, we model the anchoring effect assuming that people answer numerical estimation problems with similar thought processes as in MCMC.

Given the initial estimate $\hat{x}_0 = a$, where a is the anchor, MCMC is performed through the following two operations.

1. Take the current estimate and modify it probabilistically to generate a new estimate δ.

2. Compare the posterior probability of the new estimate with that of the old estimate, and update the cognitive state if the posterior probability grows. (Eq.(1))

$$x_{t+1} = x_t + \delta \quad (\text{if } P(x_t + \delta|K) > P(x_t|K)) \tag{1}$$

After repeating these operations, the distribution of the estimates converges to the posterior distribution $P(x|K)$. In other words, if the cognitive state is updated over a sufficient time t, the estimation result will be equal to the distribution of estimates $P(x|K)$ under all knowledge K. Inversely, if the state update terminates before the complete knowledge about the estimated target x is obtained, the initial sample x_0 influences the estimation result. This initial value $x_0 = a$ becomes an anchor, and the anchoring effect occurs.

2.2 QoE Models

QoE is used as an evaluation metric for video streaming applications. QoE influence factors include the type and characteristics of the application or service, the context of use, the user's expectations for the application or service and their fulfillment, the user's cultural background, socio-economic issues, psychological profiles, emotional state of the user, and other factors whose number will likely expand with further research [22]. Barman and Martini categorized influence factors into system IFs, human or user IFs, context IFs and Content IFs [23]. Previous QoE models mainly utilize system IFs such as network-related (metrics, bandwidth, delay, jitter, packet loss) [2, 3, 24]. However, human IFs such as cognitive biases that appear while recognizing QoE also influence it. Besides system IFs, taking cognitive bias into account enables more accurate QoE estimation and effective QoE control.

In this context, the QoE model with the Memory Effect, as an example of cognitive bias, has been proposed [25]. The memory effect denotes a bias that users' experience influences the QoE in the paper. The authors showed that the memory effect occurs while watching videos and affects the QoE, and their proposed model describes it to some extent. On the other hand, their model can only be applied to the Memory effect and is not comprehensive enough to include other cognitive biases. Quantum decision-making may help solve this problem since it can deal with various cognitive biases. We propose a QoE model with quantum decision-making to illustrate cognitive biases in this paper.

2.3 Quantum Decision-Making

Quantum decision-making is a model that represents cognitive states by mapping them to quantum states. In this model, decision-making is modeled by the probability theory that quantum follows. Decision-making is probabilistic based on various contexts, and quantum states are also defined probabilistically. Thus quantum theory has the same property as uncertainty in decision-making. It has attracted attention as a comprehensive model of cognitive biases. Some cognitive biases have been modeled with quantum decision-making. For example, a model of order effect that also appears on video viewers based on quantum decision-making has been proposed [7]. Moreover, other cognitive biases, such as the

Ellsberg paradox or gambler's and hot hand fallacies, have been modeled by quantum decision-making [8–10]. Quantum decision-making is suitable for modeling the QoE of video viewers since they may have multiple cognitive biases.

In this paper, we estimate the QoE of video viewers with cognitive bias by constructing a QoE model with quantum decision-making. We construct the QoE model by introducing time evolution in quantum decision-making (Section 3.1) then applying it to the QoE model of video viewers (Section 3.2). In the following, we describe the basics of quantum decision-making to prepare for our QoE model. Firstly we explain the mapping between quantum states and cognitive states. Then we describe how the cognitive state shifts and the decision-making process in quantum decision-making.

2.3.1 Mapping quantum states to cognitive states

In quantum decision-making, cognitive states correspond to quantum states. The quantum state is expressed as the source of the Hilbert space $|\psi\rangle \in \mathscr{H}$. The quantum state $|\psi\rangle$ means a probabilistic choice for an option. For example, we consider a decision-making problem with two options $i(i = 1, 2)$. When we have not decided which option to choose, the cognitive state is denoted as:

$$|\psi\rangle = p_1|\pi_1\rangle + p_2|\pi_2\rangle \tag{2}$$

where $|\pi_i\rangle$ is a basis and p_1, p_2 are probability amplitude. When the Eq.(2) holds, quantum state $|\psi\rangle$ is called the superposition of $|\pi_1\rangle$ and $|\pi_2\rangle$. This state corresponds to the cognitive state that option π_1 is chosen with probability $|p_1|^2$ and option π_2 is chosen with probability $|p_2|^2$.

2.3.2 Decision-making and Cognitive State Change

In quantum theory, when the quantum state is in the superposition state such as the Eq.(2), physical quantities of the system are not fixed. When an observer observes a specific physical quantity, the superposition state is resolved then a physical quantity fixes. As for decision-making, decision-makers do not know which option to choose first. The cognitive state is updated when they decide upon a trigger such as a question or asking themselves. This update of the cognitive state is called "decision-making," and "observation" in quantum theory refers to the trigger for decision-making.

In the following, we describe a mathematical model corresponding to the update of cognitive state. Decision-making is represented by Hermitian operator $\hat{A}$ on Hilbert space $\mathscr{H}$ and eigenvector $|a_1\rangle, |a_2\rangle, ..., |a_n\rangle$ of $\hat{A}$ corresponds to each cognitive state selecting option $a_1, a_2, ..., a_n$. Probability $P(a_i)$, which mean selecting a_i in cognitive state $|\psi\rangle$, is defined as:

$$P(a_i) = \||a_i\rangle\langle a_i||\psi\rangle\|^2 \tag{3}$$

where $\langle x|$ is transposed the complex conjugate of $|x\rangle$ and $|x\rangle = \sqrt{\langle x\|x\rangle}$ denotes norm on Hilbert space. Here, we define $\hat{A}$ as making a decision and consider $\hat{A}$ in cognitive state $|\pi_i\rangle$. When a_i is selected by $\hat{A}$, cognitive state $|\psi\rangle$ is updated to $|a_i\rangle$ discontinuously. In other words, decision-making lets cognitive state $|\pi_i\rangle$ update as:

$$|\psi\rangle \rightarrow |a_i\rangle \text{ with probability } P(a_i). \tag{4}$$

For which $|b\rangle$ different from $|a_1\rangle, |a_2\rangle, ..., |a_n\rangle$, $P(b)$ has a deviation from the classical probability $p(b) = \sum p_i p(b|a_i)$. This deviation $P(b) - p(b)$ is called interference term. It represents cognitive biases in quantum.

3 QoE Model of Video Viewers with Quantum Decision-Making

3.1 Quantum Decision-Making with Time Evolution

Considering the cognitive state of video viewers, we need to include cognitive state change over time in the QoE model because cognitive state changes during viewing videos. However, the quantum decision-making described in the previous section 2.3 is insufficient to describe it. We solve this problem by incorporating the cognitive bias with cognitive state change over time into quantum decision-making. One such cognitive bias is the anchoring effect. Therefore, we model the anchoring effect by quantum decision-making based on the idea of sample update in the previous model of the anchoring effect (Section 2.1.3).

In quantum, the change of state with time (time evolution) is expressed by the following Schrodinger equation:

$$i\hbar \frac{d}{d_t}|x(t)\rangle = \hat{H}|x(t)\rangle \tag{5}$$

where i is the imaginary unit, $\hbar$ is the Dirac constant, and $\hat{H}$ is the Hermitian operator for the energy of the system, also called the Hamiltonian. Let $|x^*_{t+1}\rangle = x(t+\tau)\rangle$ be the solution of the Schrodinger equation shown in Eq.(5) for a small time interval τ, the cognitive state is updated by updating the sample in the following equation.

$$|x_{t+1}\rangle = \begin{cases} |x^*_{t+1}\rangle & \text{(when update)} \\ |x_t\rangle & \text{(when stay)} \end{cases} \tag{6}$$

The cognitive state gets closer to the state with all knowledge K as updating samples repeatedly. The anchoring effect is the deviation between the state with all knowledge K and the one without sufficient update. Therefore, the anchoring effect becomes weaker as time passes. In addition, the update of samples is probabilistic, depending on whether it gets closer to the cognitive state under all knowledge K. The probability of updating samples is:

$$\begin{aligned} &P(|x^*_{t+1}\rangle|K) > P(|x_t\rangle|K)) \text{: always update} \\ &P(|x^*_{t+1}\rangle|K) \leq P(|x_t\rangle|K)) \text{: update with a probability} \\ &\qquad\qquad\qquad\qquad\qquad\qquad \text{of } \frac{P(|x^*_{t+1}\rangle|K)}{P(|x_t\rangle|K))} \end{aligned} \tag{7}$$

3.2 Applying Quantum Decision-Making to Video Viewers

3.2.1 Modeling of the Order Effect

In this section, we model the order effect (Fig.1) in video viewers. Quantum probability is a theory that describes how to assign probabilities to events [7, 26, 27]. Information given by the same source (e.g., good and bad) can be represented on the same subspace, while information from different sources (e.g., true and good) cannot be represented on the same subspace. When considering a new source of information, we can change our perspective by rotating to a new set of basis vectors that can be used to represent beliefs from the perspective of a new source. Psychologically, people have belief states, and they can evaluate the state from different perspectives. Therefore, unlike classical probability, quantum probability allows events to be incompatible. In other words, it allows for multiple events to exist simultaneously. The Hamiltonian $\hat{H}$ in Eq.(5) is defined as follows to have a dependency on the bitrate at the time.

$$\hat{H} = \begin{pmatrix} b & -(a+c(t)) \\ -(a+c(t)) & b \end{pmatrix} \tag{8}$$

$$\begin{aligned} c(t) &= \frac{d(t) - N_1}{N_2} \\ (d(t) &: \text{bitrate on time } t, \\ N_1 &: \text{threshold of } |g\rangle \text{ and } |b\rangle, \\ N_2 &: \text{normalized constant}) \end{aligned} \tag{9}$$

where $d(t)$ is bitrate on time t, N_1 is threshold of $|g\rangle$ and $|b\rangle$ and N_2 is normalized constant.

3.2.2 Definition of QoE

We define what QoE is in our QoE model. We define two states of QoE of video viewers: the good state $|g\rangle$ and the bad state $|b\rangle$. QoE calculated from the model is defined as $P(g)$, probability of selecting $|g\rangle$. P(g), the probability of selecting g, is expressed by Eq.(3) the same as when selecting one of several cognitive states in present quantum decision-making. Since $P(g)$ does not contain the interference term, we can estimate the size of the interference term with the deviation from $P(g)$. In the evaluation, we use $P(g)'$, which is $P(g)$ normalized to fit the range of actual QoE. $P(g)'$ is expressed as:

$$P(g)' = \frac{P(g) - \min P(g)}{\max P(g) - \min P(g)}(\max Q - \min Q) + \min Q \tag{10}$$

where Q is the actual QoE score in a video. As a result, QoE is expressed as a number in [0,100].

To illustrate the distribution of QoE, we show the normal Q-Q plot of QoE scores in the dataset [28] in Fig.2. It shows how well the distribution of QoE for a particular bitrate fits the normal distribution. The more the distribution of QoE overlaps with the normal distribution, the closer the QoE is to the normal distribution. The QoE at any bitrate overlaps with the normal distribution. Although the tail of the distribution deviates from the normal distribution for higher bitrates, they can be roughly approximated by the normal distribution so that we can assume the QoE follows a normal distribution depending on bitrates.

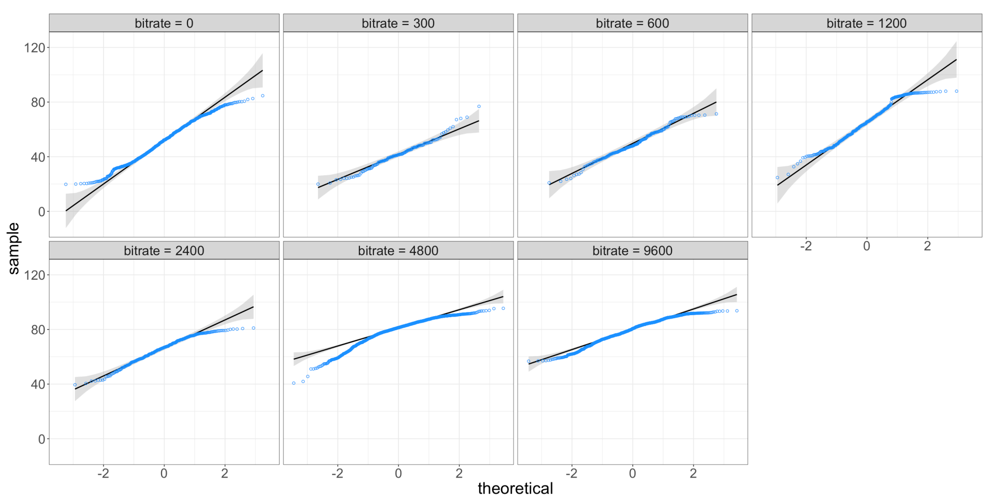


Figure 2: The distribution of the QoE in the dataset

According to the distribution of QoE scores in the dataset [28], we assume that $P(x_t|K)$ in the state update (Eq.(7)) is given in a normal distribution as shown in Fig.3, depending on the bitrate of time t. In other words, assuming that r is the bitrate of time t, $P(x|r)$ is given by the following Eq.(11). All knowledge K refers to the bitrate from the start to the end of a video. The mean of the normal distribution is given by the monotonically increasing function $\mu(r)$ for bitrate r. $\mu(r)$ is represented by Eq.(12), where R is the

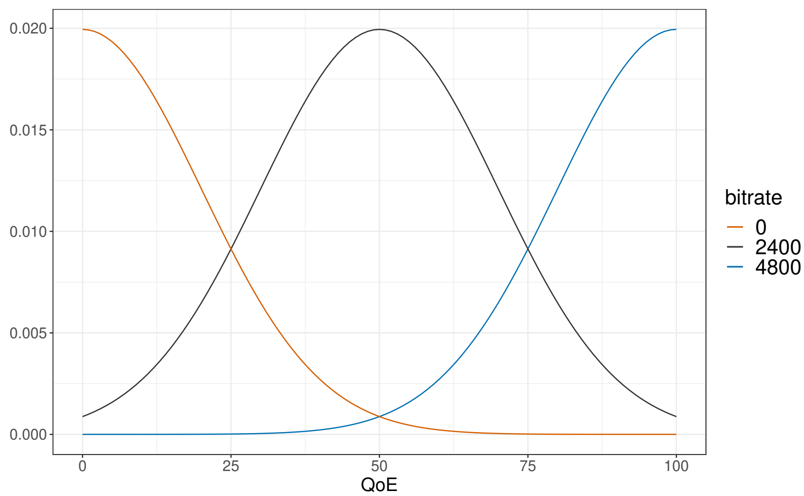


Figure 3: Example of bitrate and QoE distribution

maximum bitrate of the video to normalize the bitrate. In addition, the variance was set to $\sigma^2 = 0.17$ in the evaluation.

$$P(x|r) \sim N(\mu(r), \sigma^2) \tag{11}$$

$$\mu(r) = \frac{r}{R} \tag{12}$$

3.2.3 Input to the QoE Model

We use bitrate as the input to the QoE model. The QoE is supposed to be mainly influenced by the most recent video quality. However, each person's speed of recognizing quality and feedback QoE to the device is different. Thus, there are individual differences in the bitrate's time range reflected in the QoE. To express these differences in QoE, we take the moving average of bitrate between the last few seconds as the input. The time range of the bitrate is randomly set from 0.5 to 5 seconds in increments of 0.1 seconds for each simulation. For example, in one simulation, we use the bitrate of the previous 2.0 seconds as input, then we use the bitrate of the previous 4.1 seconds in another simulation, and so on. The difference in the time range can be regarded as differences in QoE according to each individual.

4 Evaluation of QoE Model

In this section, we evaluate our QoE model by the accuracy of QoE estimation and the ability to express cognitive biases. Simulations are performed to estimate the QoE of video viewers using a dataset. We evaluate them by comparing the actual QoE obtained by the experiments in a dataset with the QoE estimate by the model.

4.1 Simulation Setup

We simulated the video viewer's QoE with our proposed model and a dataset that includes videos, bitrate values, and QoE scores. In the simulation, the QoE was estimated from the bitrate of the dataset. We also evaluated the QoE estimation accuracy by comparing the estimated QoE scores of the QoE model with the users' actual QoE scores.

4.1.1 Dataset

We used LFOVIA Video QoE Database [28] in the simulation. The dataset contains 36 videos. Videos are processed to include decreasing and increasing bitrates to affect user satisfaction. The dataset also includes bitrate and QoE scores per second to apply these videos to QoE simulations. QoE scores of the dataset were obtained from subject experiments. In the experiment, 21 Subjects reported their QoE with a slider on their smartphones while watching videos. QoE in the dataset is the average of the values reported by the subjects. Bitrate and QoE were recorded every second.

In the following, we use f as the decreasing interval of bitrate and t as the duration of low bitrate. f means the number of times that bitrate decreases per minute and t means the duration for which the bitrate is zero. The title of videos consists of its quality, framerate, the decreasing interval of bitrate, and duration of low bitrate. For example, " TV01(FHD, 30fps), $f = 1, d = 7$" means a Full HD video with a framerate of 30 and decreasing bitrate 7 seconds per minute.

4.1.2 Calculation of QoE

We calculate the QoE score per second with our proposed model. The input to the model is the time-series bitrate of the dataset. The estimated QoE score ranges from 0 to 100, the same as QoE scores in the dataset. In addition, the estimated QoE differs for each simulation because whether updating cognitive states or not is determined probabilistically as shown in Eq.(7). Therefore, we run the simulation 10 times and use the average of estimated QoE scores.

4.1.3 Parameters

This section describes the parameters settings in Eq.(9).

- a: was formulated into two types with the average of the bitrate change speed in each video. The videos in the dataset are divided into two groups: fast and slow groups of video quality change. The group with the slower quality change contains 19 out of 36 videos in the dataset. In this group, a is defined as:

$$a = -0.0003301x + 76.17 \tag{13}$$

  where x is the amount of video quality change per second. The group with faster quality change contains the rest 17 videos of the dataset. In this group, a is defined as:

$$a = -0.0003781x + 76.44 \tag{14}$$

  where x is the amount of quality change per second as well as the former equation.

- N_1: was set to 600 because the poor quality was perceived when the bitrate was 600 or less in most videos.

- N_2: was set to 1300.

4.2 Results

4.2.1 Estimation Accuracy of QoE

We evaluated the accuracy of QoE estimation with our QoE model by comparing the estimated QoE and the actual QoE. The actual QoE was taken from the dataset [28]. The average of the simulation results for all videos in the dataset is shown in Table 1. To compare with our model, we also show the simulation results with the Memory Effect model [25] in the table. Estimation accuracy is compared by COR(correlation coefficient) and RMSE(root-mean-square error) with actual QoE. The correlation represents the match of estimated QoE with actual QoE transition over time, which evaluates how close to the actual QoE our model can estimate for the same bitrate transition. RMSE represents the difference from actual QoE and evaluates how close the QoE scores are at the same timing. When rebuffering is short or frequent, the Estimation accuracy is lower.

	COR	RMSE
Quantum Decision Model	0.5969	6.2106
Memory Effect model [25]	0.7664	4.6538

Table 1: Average of simulation results for LFOVIA Video QoE Database

We also give the average of the results only including videos without such situations in Table 2. COR is higher than the previous Memory Effect model in Table 1, which

	COR	RMSE
Quantum Decision Model	0.7857	7.2207

Table 2: Average of simulation results for LFOVIA Video QoE Database - Only videos with slow quality change

indicates our QoE model can predict the QoE transition accurately for videos with long and less frequent rebuffering. Meanwhile, RMSE is high because the QoE is not estimated precisely at the intermediate bitrate with min-max normalization (Eq.(10)).

4.2.2 Cognitive Bias of Rebuffering

We evaluate the ability of the model to simulate cognitive biases that appear during video viewing by referring to the individual simulation results. In the following result, the bitrate transition of the video, the QoE of the dataset, and estimated QoE with the model are plotted. First, we look at the order effect, a cognitive bias in rebuffering as mentioned in Fig.1. As an example, we present the result of a video in the dataset [28] in Fig.4, which contains the order effect in Fig.1. In this video, rebuffering occurs multiple times. Specifically, after 60 seconds each time rebuffering occurs, the QoE of the dataset rises

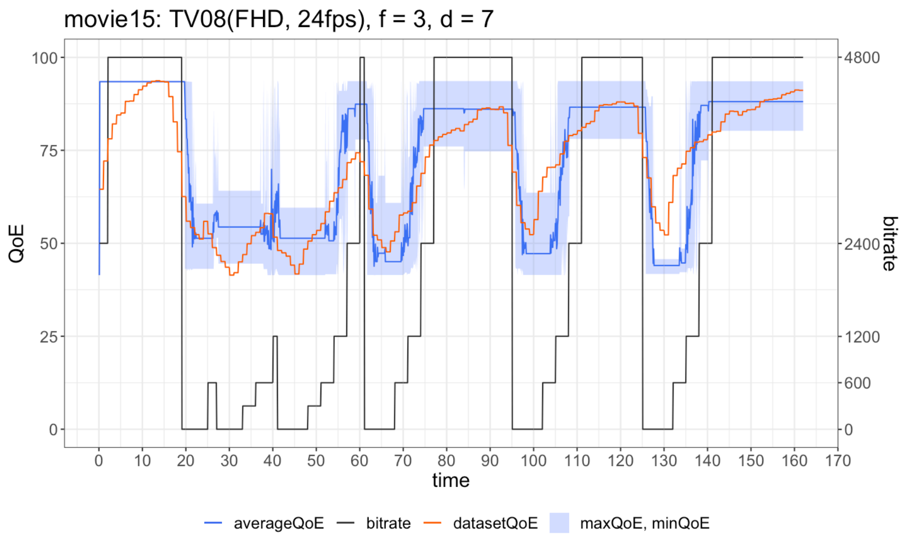


Figure 4: The simulation result for movie15 ($r = 0.8557$)

slightly. The estimated QoE also rises slightly, which means our model can describe the order effect.

4.2.3 Cognitive Bias in Initial Scene of the Video

Secondly, we look at the primacy effect, a cognitive bias that initial QoE influences subsequent QoE. From this property, we can recognize the primacy effect if initial QoE and subsequent QoE are highly correlated. We first examined the existence of the primacy effect in the QoE of the dataset. We show the results of analysis on QoE of the dataset in Fig.5, changing the duration of the initial and subsequent periods to evaluate if they are correlated. In particular, there is a high correlation with subsequent QoE when the initial phase is set to 20-60 seconds. Therefore, the primacy effect exists for the video viewing user.

We also verified if the estimated QoE with our QoE model has the same primacy effect as the actual QoE. QoE simulations were performed for each of the videos in the dataset [28]. The correlation between the QoE estimates in the initial part and the subsequent QoE estimates are shown in Fig. The initial QoE estimates are also correlated with the subsequent one, particularly when the initial part is set to 20 to 30 seconds. As a result, the proposed method can describe the primacy effect.

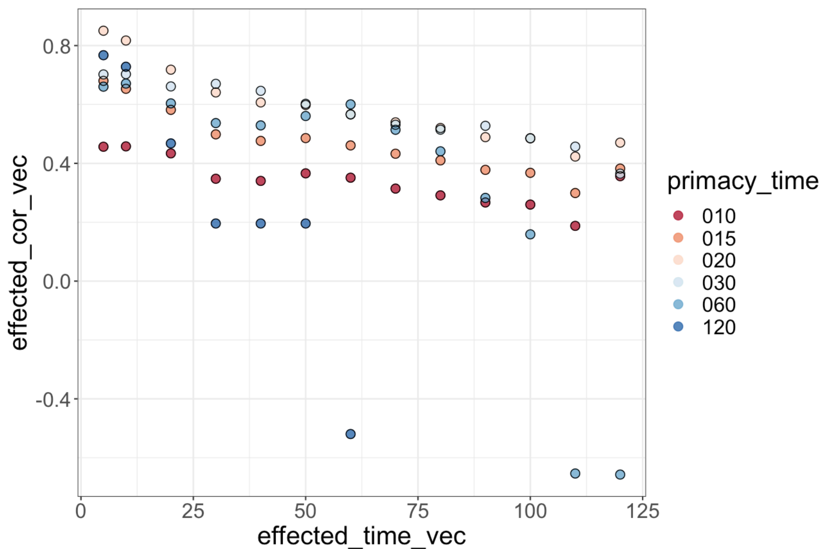


Figure 5: The primacy effect in the dataset QoE

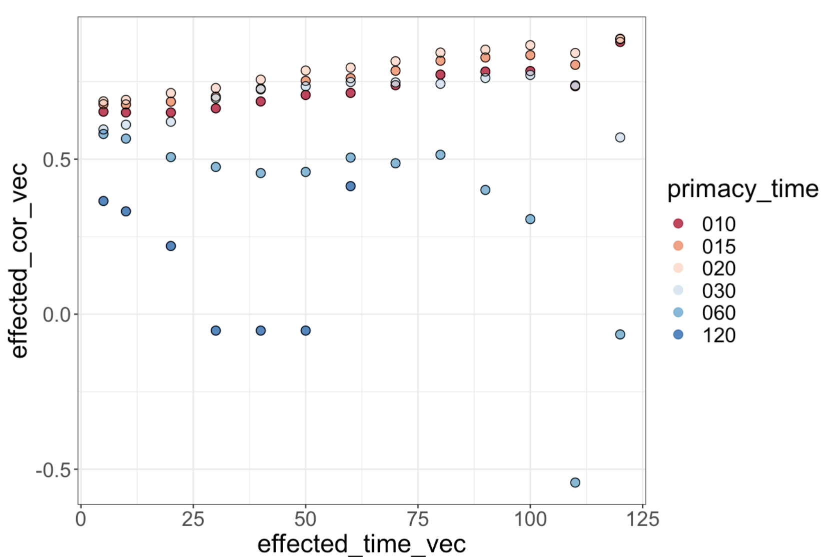


Figure 6: The primacy effect in the estimated QoE by the QoE model

5 Design of Bitrate Control to Avoid QoE Decline

In this section, we summarize the situations where cognitive bias may reduce QoE and propose strategies to avoid them. We also provide several scenarios where the control policy is applied and where it is not and compare the QoE estimates for each.

5.1 Bitrate Control Policy to Prevent Cognitive Bias

First, we summarize the cognitive biases that occur during video viewing that may lead to a decrease in QoE, and then we propose the bitrate control design to avoid them. The following is a feature of the QoE for each cognitive bias occuring situation.

- At the start of video playback: If the initial video quality is poor, the QoE becomes lower at the beginning, and the QoE afterward may also become worse because of the primacy effect. On the other hand, the QoE tends to be tolerant of some video playback delays.

- During rebuffering: If rebuffering is repeated for a short time, about 10 seconds, the QoE drops. On the other hand, the QoE is tolerant of one rebuffering being somewhat longer.herefore, when rebuffering is necessary, set the bitrate so that rebuffering will not occur again within 10 seconds.

Secondly, we propose the following two bitrate control policies based on these features.

- Bitrate control policy 1: Increase the initial video quality as much as possible. To start playback with high quality and then continue playback, buffers are stored, then playback is started. Meanwhile, this makes it longer to start playback, which may cause lower QoE. Thus, the bitrate is set so that the loading time is 5 seconds or less to prevent QoE drop.

- Bitrate control policy 2: When rebuffering is needed, continue it until a certain amount of buffer is accumulated, thereby reducing the frequency of rebuffering; prevent rebuffering within 10 seconds.

5.2 Simulation with Scenarios of Watching Video Streaming

5.2.1 Simulation Settings

Bitrate Control Assuming the actual scenario of streaming video through the Internet, we evaluate the gap in QoE whether we use bitrate control considering cognitive bias or not. To emulate the playing environment, we simulate the bitrate behavior when a video is streamed in a specific network environment and the QoE at that bitrate [29]. We start with simulating a video player that uses throughput and buffer as input to determine the playback bitrate. Supposing that each of the control policies listed in the previous section is applied or not, output the bitrate in each case. In other words, different playback quality patterns are generated by multiple control methods given the same throughput.

Moreover, we expected the situation where rebuffering occurred due to decreased throughput and compared QoE whether we apply bitrate control to prevent QoE decrease due to cognitive bias. The following four patterns of control were applied to separate the effects of control implemented at the start of playback and during playback.

- Bitrate control policy A: Not apply either policy 1 or 2.
- Bitrate control policy B: Apply policy 1, not policy 2.
- Bitrate control policy C: Apply policy 2, not policy 1.
- Bitrate control policy D: Apply both policies 1 and 2.

Throughput Three throughput patterns (throughput pattern 1,2,3) were given as input to emulate the network environment. We assume that the network environment is bad enough to cause playback stops (rebuffering) to compare the behavior during rebuffering and corresponding changes in QoE. The throughput changes periodically. In pattern 1, high throughput and disconnection are repeated in turn. Pattern 2 is a variant of pattern 1 with a lower peak throughput. Pattern 3 is a modified version of pattern 1 with a more extended period so that the disconnection duration is longer.

QoE We also estimated the QoE based on the generated playback bitrate patterns and compared the estimates with different control policies. Ultimately, it is desirable to evaluate the results of the control by actual human subjects, but this involves great difficulty in preparing for the experiment. However, since we already have a model that reproduces the time series of human QoE, we can use this model to estimate the goodness of the control results. Therefore, in this thesis, we will evaluate the behavior of the control by using the model as a substitute for the subject as a simple evaluation of the design concept of the bitrate control policy.

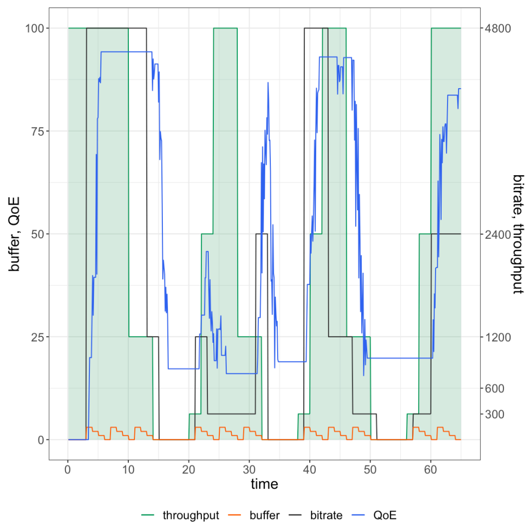
5.2.2 Results

First, we will describe the simulation of the video player. Three patterns (pattern 1,2,3) of throughput were prepared. We applied control based on the four control policies listed in the previous section for each pattern and output the bitrate; bitrate control without considering cognitive bias (a), perform bitrate control considering cognitive bias only at the start of playback, not during playback (b), perform bitrate control considering cognitive bias only during playback, not at the start of playback (c), bitrate control with considering cognitive bias (d).

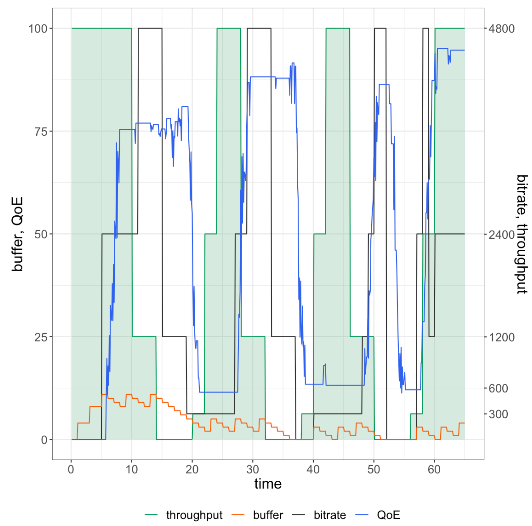
When we apply bitrate control policy A (Fig.7(a), Fig.8(a), Fig.9(a)), rebuffering occurs immediately upon throughput lowering because of no preparation for throughput reduction, resulting in a longer QoE fall. In addition, the bitrate fluctuation is frequent, which causes the QoE to be unstable. In contrast, when we apply bitrate control policy D (Fig.7(d), Fig.8(d), Fig.9(d)), the number of rebuffering is the least, and the rebuffering duration is the shortest. Namely, this control helps to avoid situations where the QoE drops.

We also look at how individual control policies (1,2) can improve QoE. Applying bitrate control policy B (Fig.7(b), Fig.8(b), Fig.9(b)) takes longer for the QoE to rise. However, storing the buffer at the beginning prevents rebuffering within 20 seconds after starting playback, thus keeping the QoE high. Furthermore, it prevents QoE decrease over the full playback. Therefore, the average QoE is higher than bitrate control policy A. Then we discuss the case where bitrate control policy C is used (Fig.7(c), Fig.8(c), Fig.9(c)). Since the bitrate control does not take into account the cognitive bias at the start of playback, rebuffering appears just after playback starts. However, the video quality is controlled to avoid playback stops afterward. The QoE decrease due to repeated rebuffering is eliminated, and its average has increased than bitrate control policy A. To sum up, these results of bitrate control policies B and C show that the QoE can improve for each control with consideration of cognitive bias at the start and during playback.

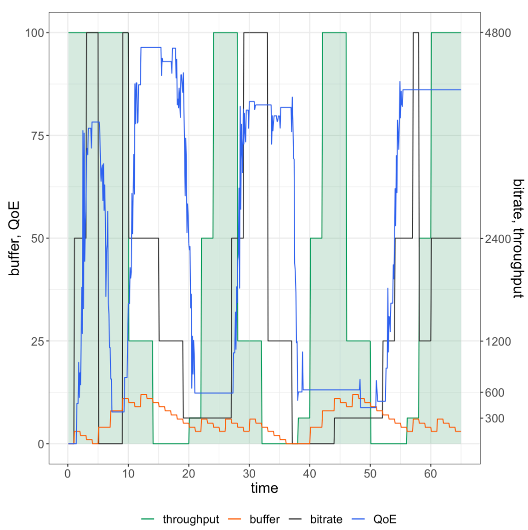
When bitrate control policy D is applied under bitrate pattern 3 (Fig.9(d)), the average QoE is slightly lower than when bitrate control policy B or C is used (Fig.9(b), Fig.9(c)). This is because the time of QoE being low is longer to prepare for avoiding QoE drops afterward. However, we can prevent a QoE drop from becoming too long in the targeted situations, even in a reasonably severe network environment like bitrate pattern 3.



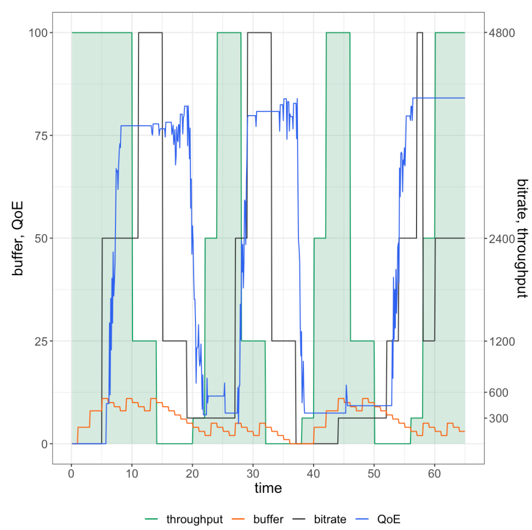
(a) Bitrate control policy A (Average QoE: 41.56)



(b) Bitrate control policy B (Average QoE: 44.10)

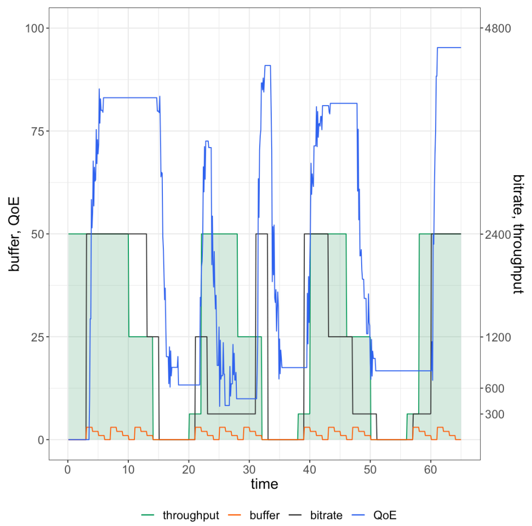


(c) Bitrate control policy C (Average QoE: 47.51)

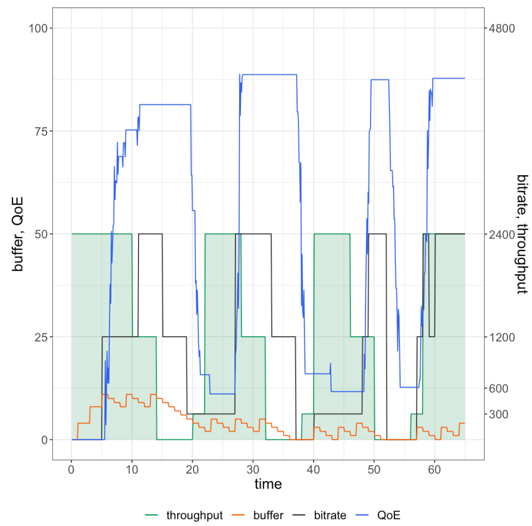


(d) Bitrate control policy D (Average QoE: 49.47)

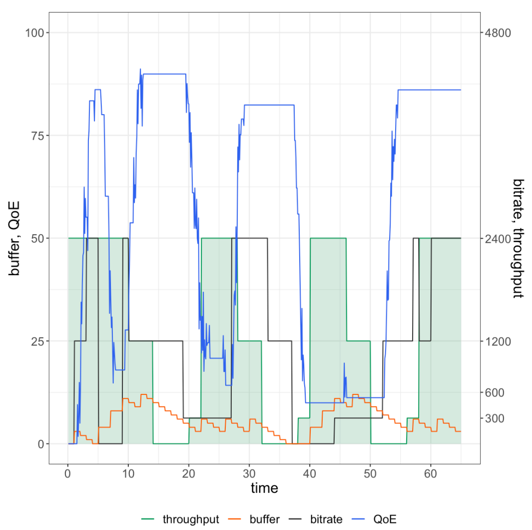
Figure 7: throughput pattern 1



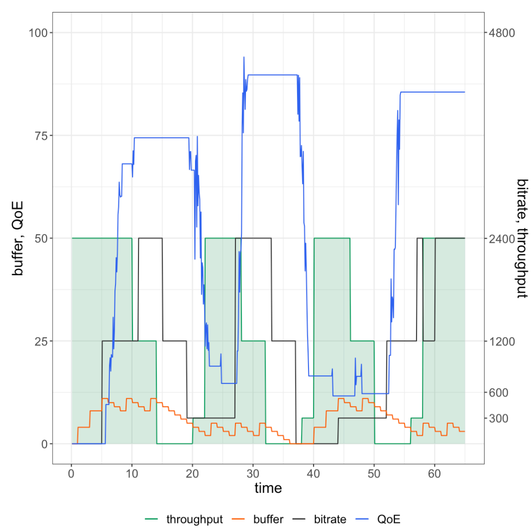
(a) Bitrate control policy A (Average QoE: 43.83)



(b) Bitrate control policy B (Average QoE: 50.39)

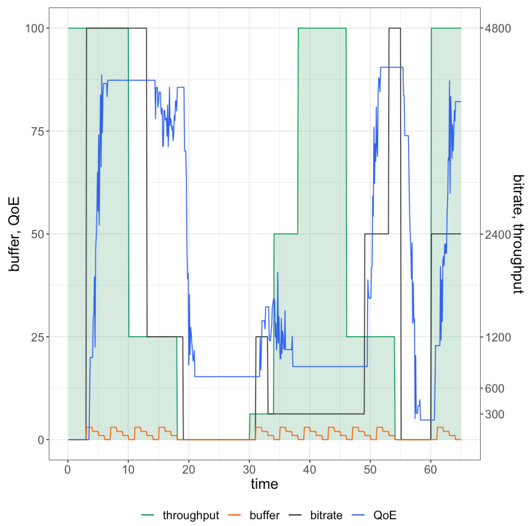


(c) Bitrate control policy C (Average QoE: 52.79)

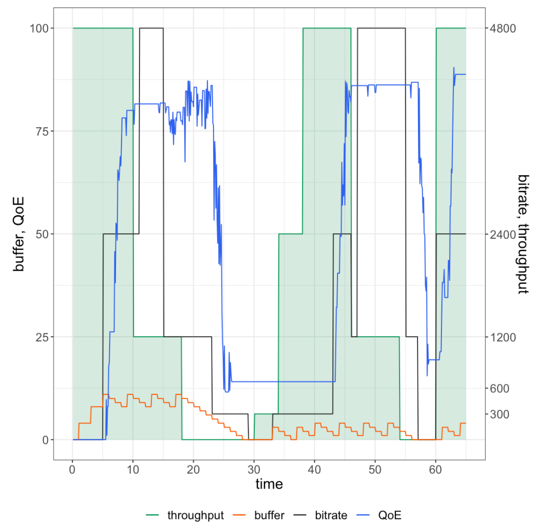


(d) Bitrate control policy D (Average QoE: 54.30)

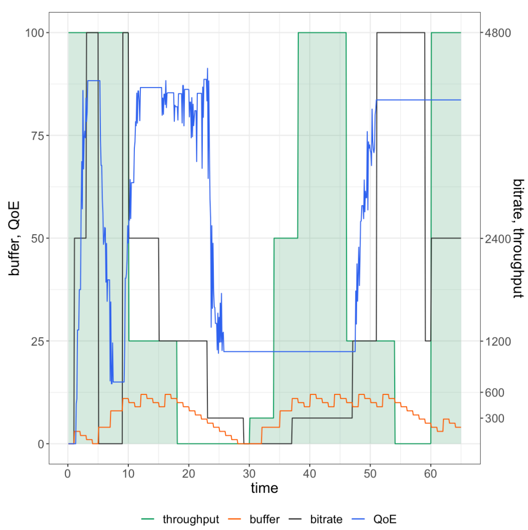
Figure 8: throughput pattern 2



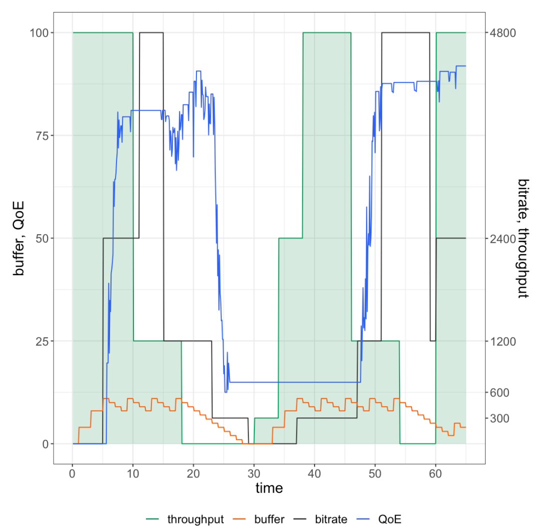
(a) Bitrate control policy A (Average QoE: 41.42)



(b) Bitrate control policy B (Average QoE: 49.96)



(c) Bitrate control policy C (Average QoE: 47.51)



(d) Bitrate control policy D (Average QoE: 49.32)

Figure 9: throughput pattern 3

6 Conclusion

In this paper, we proposed a QoE model that includes cognitive bias based on quantum decision-making to estimate QoE more precisely. We also simulated the QoE with our QoE model and estimated the QoE over time. As a result, our proposed model with quantum decision-making can express the anchoring effect, the order effect, and the primacy effect of the cognitive biases of video viewing users. We showed that the model could estimate the QoE precisely from actual video viewers. Furthermore, we evaluated how bitrate control with cognitive bias can improve QoE. We simulated the behavior of a streaming video player in a specific network environment, assuming an actual video viewing environment. We then compared the QoE of the different bitrate control policies. The results showed that the bitrate control considering cognitive bias helped avoid the decline in QoE because of the cognitive bias, and the QoE was improved than without the control. On the other hand, the model could not deal with fast bitrate changes. The future work is to improve the response of the model to these bitrate changes and introduce more cognitive biases into the model.

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