

# Minimising energy consumption: how does displaying the environmental impact of video quality influence user behaviour?

Benoît BERNIER

*Nantes Université*

[benoit.bernier@etu.univ-nantes.fr](mailto:benoit.bernier@etu.univ-nantes.fr)

Toinon VIGIER

*LS2N*

*Nantes Université*)

[toinon.vigier@univ-nantes.fr](mailto:toinon.vigier@univ-nantes.fr)

Mathias GUERINEAU

*LEMNA*

*Nantes Université*

[mathias.guerineau@univ-nantes.fr](mailto:mathias.guerineau@univ-nantes.fr)

**Abstract**—While the digital sector accounts for 4% of total greenhouse gas, growing by 9% per year, video streams represent 80% of worldwide data traffic. Both quantity and quality are quickly growing.

Some entertainment providers begin to provide informative choice interfaces, advising the user on the environmental impact of different levels of quality. Impact of such interfaces is still not documented, while the influence of labels on purchasing behaviour is well documented.

From a subjective qualitative test with 15 respondents, we found that using an informative interface can influence user choice behaviour, without lowering the quality of experience. We discuss the experiment and the implication from a policy point of view.

**Index Terms**—choice behaviour, environmental impact, video streaming

## I. INTRODUCTION

In a context of climate change, identifying the sources of pollution and fighting against their growth is essential. According to The Shift Project, a think tank that works towards an economy freed from carbon constraint (sic.), in 2018, the digital sector accounts for 4% of total greenhouse gas (GHG) emissions, ahead of civil aviation (around 3% of emissions). Concerns about digital sector emissions stem mainly from its growth: while other sectors are much more important in absolute terms (transport, buildings, etc.), digital-related emissions are increasing by 9% per year, and no other sector is growing as fast (Fig. 1). The think tank proposes different scenarios with or without sobriety to evaluate the growth of the digital sector's share of global GHG emissions. [1]

We can separate the global balance of energy consumption in the digital sector into two main categories: the use of equipment on one hand, and its production on the other. The use of terminals, data centres, and networks accounts for 55% of this overall balance, with the remaining 45% corresponding to the production of computers, TVs, smartphones, and other. (Fig. 2)

Data flows are responsible for just over half of the overall digital consumption in 2017, with a growth rate of over 25% [2]. Video streams accounted for 80% of global data flows in 2018, the remaining 20% are shared between extremely

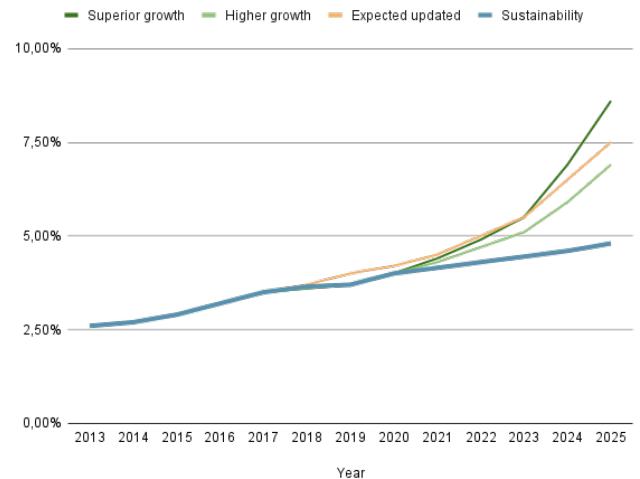


Fig. 1. Share of digital technology in global GHG emissions, from The Shift Project, 2018 [1]

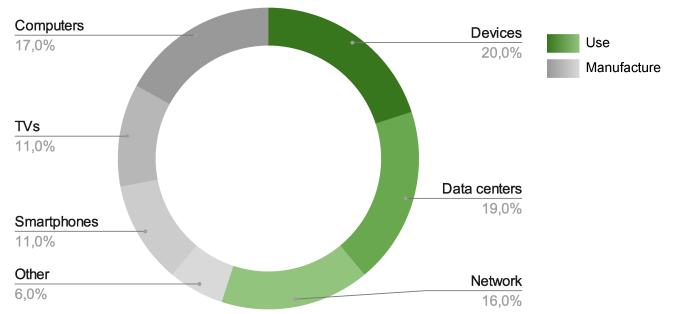


Fig. 2. Global balance of energy consumption in the digital sector.

various uses: websites, emails, instant messaging, machine to machine communication, photo storage, etc. Among video streams, online video occupies the most important part with 60% of worldwide data flows which is 1.05 zetta-bytes (1.05 trillion billion bytes), or 20% of total GHG emissions due to digital technology, or even 1% of worldwide GHG emissions. The video effect of the devices on the traffic is more pronounced because of the introduction of high definition video streaming. These technologies have a strong effect on internet traffic: 4K video bitrate is about 15 to 18 Mb/s, more than double of the HD video bitrate and nine times more than standard definition (SD) video bitrate. Cisco estimates that installed ultra-high definition (UHD) flat-panel TV sets will increase from 23% in 2017 to 62% in 2022. At the same time, UHD video is supposed to account for 22% of global IP Video traffic (Fig. 3), starting at only 3% in 2017. These projections were made in 2019 and have not been updated since.

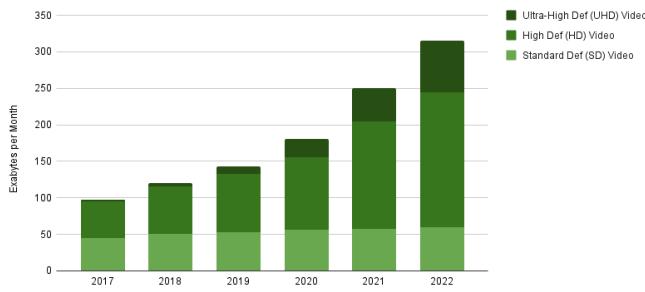


Fig. 3. Global UHD IP video traffic from Cisco VNI 2019 [2]

If ecological awareness of the public can be noticed, it remains very limited in the digital domain, and even more for the environmental impact of video streams. Nevertheless, some initiatives are emerging, mainly from digital providers to consumers. An example of this is the new interface of the web client of Canal+ that provides information about the different ecological impact between the three qualities available. [3]

As online video streams represent 1% of global GHG emissions and increase exponentially, this leads us to assess the question of the individual levers of online video consumption.

## II. LITERATURE REVIEW

In order to reduce the environmental impact of their online video consumption, individuals can act on two levers: the quantity and the quality. They can reduce the amount of video watched and they are also able to reduce, for each video seen, its impact.

### A. Quantity

The business model of many online video players is based on the economy of enjoyment [4], through the widely documented phenomenon of binge watching, with two distinct goals. For VoD (Video On Demand) oriented companies such as Netflix, Amazon Prime or Disney +, it is above all a matter of building user loyalty, with the economic model based on subscription-based offers. For companies oriented

towards Tubes (YouTube, Dailymotion) or social networks (TikTok, Facebook Watch, Instagram Reels...) which are growing rapidly, the main goal is to display advertising, or even collect personal data to refine the advertising models.

The operation of these systems is based on a process of user configuration [5], where the company tries to configure and adapt the user to its business model through the software rather than the other way round. These systems should not be analysed from a technical point of view alone, they are complex socio-technical devices. This is the point of view of the Critical Algorithm Studies.

Thus, Netflix is implementing very important means to improve its recommendation solution. It is based on two main axes: the Cinematch recommendation algorithm and the interface of its system, co-evolving and feeding each other. For its algorithm, Netflix organised for three years, between 2007 and 2009, the Netflix Prize, a competition open to developers not affiliated with the company, allowing them to improve the algorithm by 10%. For the interface, Netflix works particularly on the implementation of the algorithm's prescriptions. Thus, the sections of the interface "Continue watching", "Watched by ...", "Because you watched ..." highlight the desire for transparency and explicitness of the algorithm in order to promote user confidence [6] in the algorithm and its prescriptions. The Netflix Tech Blog reports that the personalisation of the interface by algorithms reduces the time to make a choice and helps retain users. Netflix is also working hard on the effectiveness of user feedback to the recommendation algorithm, so the "post-play" feature or looped viewing has a high weighting in the feedback loop. Since 2017, the star rating system has been replaced by a thumbs up/down system, increasing the volume of movie ratings by 200%, by incentivising the customer to provide more feedback.

In his article Captivating algorithms: recommender systems as traps [7], Seaver attempts to describe the tendency of recommender system designers to 'hook' people. He draws a parallel with traps (in the hunter sense). This parallel allows us to establish, understand and analyse recommender systems, and to think about how these systems "relate to broader infrastructural ecologies of knowledge and technology". He bases this on the American Anthropologist of 1900 where Otis Mason wrote a study of the animal traps of indigenous Americans. Here Mason establishes the key concept of the recommendation algorithm 120 years ahead of its time: persuasive technologies. The trap is not a violent mechanism, but a strong mental interaction between hunter and prey. Seaver seems to understand in this article the origin of these recommendation algorithms, and particularly the primary reason for the desire of online entertainment companies to retain users as long as possible. The algorithms used to be based on Root Mean Square Error (RMSE), an index that measures the difference between the rating predicted by the algorithm and the actual rating given by the user. The lower this measure, the better the recommendations. With the advent of development methods involving a user-centred approach and the rise of machine learning systems, the RMSE has gradually been abandoned in

favour of a combination of multiple indicators. Where RMSE was based on a completely conscious action by the user (noting the video watched, noting the quality of the system), the multi-criteria approach is resolutely unconscious: the user stops the video before the end, makes a suggestion, watches it again... It is a total paradigm shift inherited from a strong behaviourist approach. We are now looking for strong or weak signals of satisfaction in the many logs left behind. A user who stays is a user who leaves more traces, who provides more data for recommendations. For Netflix, the satisfaction of a client is measured in the time spent watching videos and the time during which he pays his subscription. There is, however, a porous boundary between user satisfaction and capture by the system, and captology is the result: rather than predicting explicit ratings, developers try to anticipate implicit ratings using the traces left, but this requires designing the system to get more.

If the issue of the quantity of videos consumed is a key point of the environmental impact of video streams, it requires very profound changes on the part of platforms. Unless the various market regulatory authorities (states, communities, etc.) decide to limit these practises, the individual levers can only be a constant struggle against the platform and the user configuration that accompanies it. It thus seems delicate, in our research framework (individual levers of online video consumption), to pursue investigations in this direction.

### B. Quality

The second dimension impacting the energy consumption of online video is the streaming quality. To define this, we often speak of definition, summarised as a number describing the number of pixels on the smaller side. Thus, we speak of 720p video for a video of 1280 pixels in length by 720 pixels in height or 1080p video for a dimension of 1920 by 1080 pixels. Note that 4K (3840 by 2160 pixels) has four times more pixels than a 1080p image, hence its name. There is also SD (up to 576 pixels high), HD (720 pixels high) and FHD or full HD (1080 pixels high) content. In addition, there are the notions of frame rate (generally 30 to 60 frames per second), the various codecs and compression techniques that we will not consider here. All this data is often summarised in bitrate, in bits per second.

The weight of videos (i.e. the bitrate multiplied by the length of the video) directly depends on the definition in a non-linear way. Thus, a one-hour video in 4K on Youtube weighs about 2.7 GB (gigabytes), i.e. 1.6 times the same video in 1080p / full HD and three times that in 720p / HD. The power consumption of the different equipment (especially the network part) also increases with the increase in quality. The main problem is related to the increase in consumed quality, as shown in Fig. 3.

The concepts of Quality of Service (QoS) and Quality of Experience (QoE) are linked to this. Quality of service corresponds to technical quality: stability of the connection, packet loss, etc. Quality of experience seeks to measure the impact of the network on user satisfaction. Thus, depending

on the type of video watched, expectations may be different and the same QoS for two different types of video may result in different QoE. This is explored by Dobrian et al. in *Understanding the impact of video quality on user engagement* [8]. They test three types of videos: short videos (less than five minutes), long videos (35 to 60 minutes) and live video. They use five objective criteria to qualify the quality of service: the percentage of time spent in the buffer (loading the video), the duration of the video launch (time spent before the video starts), the number of times the video was stopped to fill the buffer, the bitrate and the number of images rendered versus the number of possible images (some images are sometimes not displayed). The study shows that for both short and long videos, the bitrate is not important, whereas it is for live video since it is directly correlated with the filling of the buffer (the higher the quality of the video, the more the loading moments there will be). It also shows that the start-up time is not very important when we look at the scale of the video but becomes very important at the scale of the user: a user who takes time to access the videos watches less and comes less often to the site. It is also clear that fluidity and speed of playback seem to be more important than the quality of the image displayed in all cases of use. Dobrian uses user engagement (total play time and number of videos viewed) as QoE indicator, but simpler indicators exist, such as the Mean Opinion Score (MOS). Because the MOS is normalised by the Telecommunication Standardisation Sector of the International Telecommunication Union (ITU-T) [9] and is a simple to interpret scalar value, this measure is common and wide spread in quality of experience studies. It relies on the Absolute Category Rating test in which a single test condition (generally an image or a video sequence) is presented to the viewers once only. The test subjects then have to give a quality rating on an ACR scale, usually a five-point likert scale rated from bad to excellent.

Most online video services rely on an algorithm such as DASH (Dynamic Adaptive Streaming over HTTP), which allows dynamic bitrate adaptation to maximise QoE. This is based on the following principle: a video is hosted on a server. It is divided into segments, and is available in several bitrates, from the lowest to the highest. The user has an Adaptive Bitrate (ABR) algorithm in his player, whose role is to select the most suitable bitrate for each segment over time in order to maximise the bitrate while maximising other QoE indicators: video start-up time, duration and number of buffering moments, number of bitrate changes and many other indicators specific to each service provider. The use of this type of algorithm is particularly noticeable at Netflix with the cold start of episodes. As Netflix strongly favours the start time of the video, it starts with the lowest bitrate before rising on the following segments. Video consumers can choose a target quality through a selector interface, usually displaying only the target definition. Some interfaces display additional details such as frame rate, performance advice or even environmental impact information.

Canal + and 6play, in their VoD players, have already

implemented such a tool but have not communicated on the impact of this change on choice behaviour. The European Union has not yet published any information on their running experiments in this area. We are therefore looking more widely at similar systems. The nutri-score (a five-colour nutrition label displayed on food products) seems to be a good parallel to establish. The three-year evaluation of the nutri-score nutrition logo [10] allows us to establish that the number of consumers declaring to have changed a purchasing habit thanks to the nutri-score has increased: 57% in 2020 against 43% in 2019. Similarly, for those aware of the logo, more than a third said they had chosen a product with a higher score than another product on the shelf. The simplicity of the display allows all populations, even those with a low level of education or little or no knowledge of nutrition, to understand it. The application of this logo can also be beneficial to brands: for 70% of those questioned, affixing the nutri-score to the brand's products helps to improve its image.

As a simple colour label can change a choice behaviour, new interfaces such as Canal+ or 6play might have a significant impact on it. Further research is needed to determine the interaction between environmental impact of video quality labels and choice behaviour.

### III. METHODOLOGY

To assess this question, we carried out two tests. The first one aimed at getting clues on parameters and concepts that could be mobilised for the final experiment. Its objective was not to obtain significant results but simply to obtain clues to refine the final experiment. The second experiment had to answer the problem raised by the clues obtained in the first experiment. For the exploratory study, we chose a mixed method based on an experiment and on a semi-structured interview. The final experimentation used a quantitative method only based on a subjective test.

### IV. EXPLORATORY STUDY

As part of a Master's project, we had to create and carry out an experimentation, an opportunity to conduct an exploratory study. We tried to answer the question: does the disruption of video quality influence the choice (ecological or not) of future viewing quality?

#### A. Procedure

For this purpose, we decided to run a test with two independent variables (IV): interface and disruption. Interface IV showed two conditions: pure and ecological interfaces, while disruption IV showed three conditions: buffering, drop of bitrate and none.

After the video test, a 15 minutes semi-structured interview was conducted. Each participant has seen six videos, two with a drop of bitrate, two with a buffering event and two without any perturbation. For each video, the test subjects were asked in which quality they would like to watch it for a longer viewing session. The first three videos were followed by a "standard interface" as a support, inspired by YouTube quality

TABLE I  
CHOSEN QUALITIES FOR EXPERIMENTATION

Frame size (pixels)	Bitrate (Mb/s)	MOS	Abbreviation in this paper
1920 × 1080	9	7.2	Q1
1280 × 720	6	6.8	Q2
720 × 576	3	2.1	Q3

selector, and the last three with an "informative interface", inspired by Canal+ one.

To reduce variations due to the content of the videos, we decided to choose various subjects: sport, movie trailer, report, landscape, humour and scientific popularisation.

#### B. Results and analysis

The test was conducted with six participants to whom we tested visual acuity and colour perception with Ishihara colour plate test. Their age ranged from 22 to 39 with an average of 26. The introduction of a perturbation in the viewing session leads to a change in behaviour: a third of the participants tends to choose lower quality when being involved in a buffering or drop of bitrate event while best quality is always chosen with no disruption. However, the interface seems not to influence the behaviour of choice: results are equivalent between YouTube like interface and informative interface. Too many independent variables have been chosen with a too small sample size, resulting in non-significative statistical results.

While the choices made by the participants tend to show no influence of the interface on the behaviour, conducted semi-structured interviews tend to show something else. Although we tried to disregard this factor, respondents tend to mention primarily the content of videos as choice justification. Most of them corroborate our observations: "I always look for the best quality because... it's more pleasant to watch". Nevertheless, they also touched on the environmental impact: "I am aware of that, there is always an impact I know."

### V. EXPERIMENT

The results of the exploratory study led us to refine our research question: how does displaying the environmental impact of video quality influence user choice behaviour?

#### A. Experimental design

Given the results of the pre-experiment, we have seen that the subject of videos highly influences the choice of video quality. To explore the choice behaviour regardless of content, we had to find a video dataset with low variation between subjects. For replicability we used an existing video dataset: *H264 HD vs Upscaling and Interlacing*, providing three video source contents (Fig. 4) with different variations of degradation. The dataset also provides the MOS (Mean Opinion Score) of each variation.

To get significant results, we decided to limit the number of variations we will use to three. Based on the MOS provided in the dataset, we chose the quality listed in the table I.

The provided videos were packaged in an AVI container with raw video codec. In order to play videos with the native



Fig. 4. Videos used for the experimentation

Chrome player, we had to convert it to MP4(H264). For this purpose, we used ffmpeg [11] with a constant rate factor (CRF) at 18 and a slow preset for nearly lossless conversion.

We finally got nine videos  $V_iQ_j$  where  $i$  is the number of the video (from one to three) and  $j$  is the rank of the quality (from one to three).

We then introduced the two video quality choice interfaces. One had to be neutral while the other had to inform the user on the environmental impact of video streaming. For the neutral interface (which we will refer to as  $I_{\text{pure}}$ ), we decided to mimic usual tubes providers as DailyMotion, Vimeo or YouTube. Users could use radio buttons to select quality between 1080p, 720p or 576p. For the informative one ( $I_{\text{eco}}$ ), many interfaces were possible. Pictograms and colours could be used along with different ways to advise (grCO<sub>2</sub>eq, equivalence with kilometres driven, ratio of economy...). With the lack of design studies on this subject, we finally decided to take inspiration from an existing interface. Canal+ introduced a new quality menu in september 2020, which we adapted for our experiment.

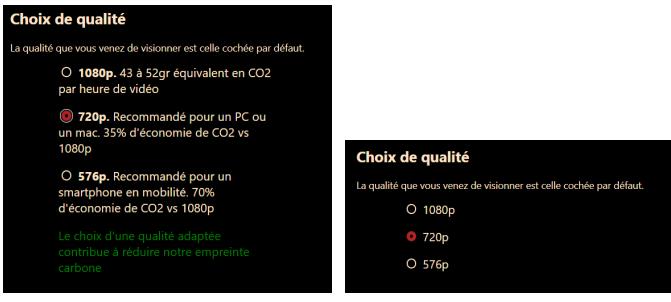


Fig. 5. Interfaces used for the experimentation

The nine  $V_iQ_j$  videos were presented in random order. For each  $V_iQ_j$ , a three seconds extract was displayed. The test subject had to set the video fullscreen then watch it once. A quality choice interface was then displayed, participants were asked to choose the quality they would like to see for a longer viewing session. The video  $V_iQ_k$  was then displayed with  $k$  the choice of the viewer. To evaluate the visual quality of this choice, we used the Absolute Category Rating (ACR) [9] with a five-point Likert Scale (Bad, Poor, Fair, Good, Excellent, coded from one to five for data processing).

The test was carried out in two parts, each presenting a different video choice interface, separated by a five minutes pause to reduce learning effect. One participant out of two

began with the ecological interface  $I_{\text{eco}}$ , the other one with  $I_{\text{pure}}$ .

a) *Questionnaire*: Besides demographics, three questions were asked to the respondents at the end of the questionnaire. The first one was on the knowledge of internet video diffusion systems (*Mon état de connaissance des systèmes de diffusion de vidéo par internet*) rated with a five-point Likert scale from no knowledge (1) to expert (5), the second one was on the knowledge of the impact of digital technology on the environment (*Mon état de connaissance de l'impact du numérique sur l'environnement*), rated as the first question. Finally, the last question was designed to evaluate the pro-environmental behaviour (PEB) [12]. We used for this purpose the Inclusion of Nature in Self [13]. Other indicators exist but are more complex to set-up, INS has the advantage of being answered with only one question.

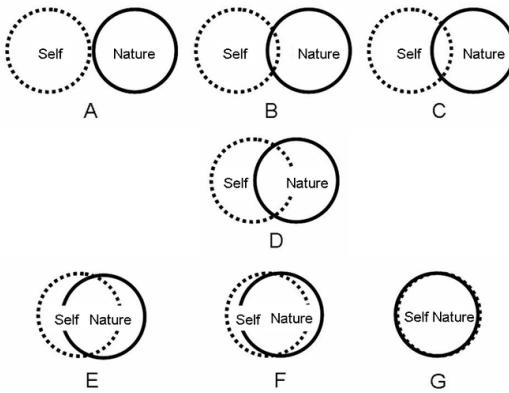


Fig. 6. INS scale from Liefländer 2013 [14]

### B. Experimental setup

For test replicability requirements and to ensure video quality, we needed software running on the device. Using a shared questionnaire on the internet was not feasible: we would not have been able to control the screen's technical characteristics and the streaming of the videos would have been dependent on the internet connection of the test subject. Existing software did not meet our needs for various reasons (poor video rendering quality, randomization of videos etc.).

We thus decided to develop our own software, based on web technologies such as JavaScript, Node.js and HTML/CSS. The program and the results are now open source and can be found on GitHub [15].

The test has been run on a Dell XPS 13 9370 with a 1080p non-touch screen running Windows 11 and Chrome 97. Environment was not controlled or measured (luminosity, colour, ambient sound), but experiments were conducted in quiet conditions. According to ITU recommendations, participants were placed at a distance with the screen of three times the height of the display (50cm). Luminosity was set to 70%.

### C. Participants

The test was presented to 15 people. Their age ranged from 17 to 52, with an average of 24 and a standard deviation

of nine, 33% of them being women. This distribution of the age range is due to the recruitment of the candidates: they are mostly students, randomly recruited at the university of Nantes. Three candidates were rejected for misunderstanding instructions and are not part of our sample.

#### D. Results and analysis

In the questionnaire, the two questions about knowledge can not be used: answers about environmental impact are below or equal to middle value which does not enable us to create two groups to check whether knowledge influences or not behaviour. Results are the same for video systems knowledge, only two respondents rated themselves above average with “advanced knowledge”. This cannot be used to create a significant group. For Inclusion of Nature in Self results, a D’Agostino normal test has been run and p-value has been interpreted against an alpha of five percent and found that the test dataset did not significantly deviate from normal distribution, centred around the middle value. As for knowledge questions, this does not allow us to create groups and demonstrate an influence of PEB on choice behaviour.

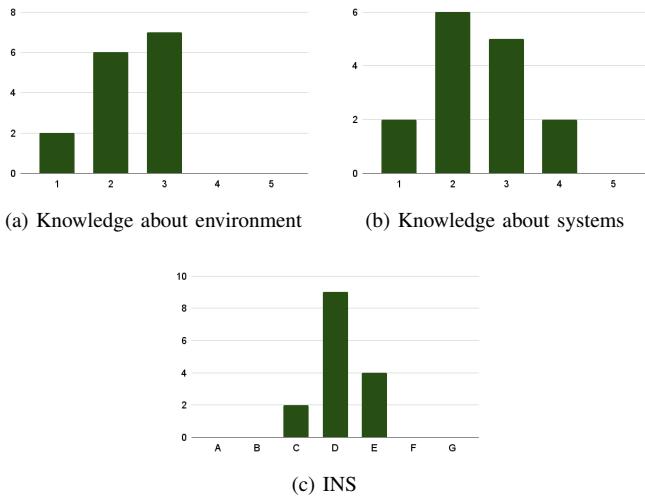


Fig. 7. Results of the questionnaire

According to Fig. 8, for the first video, V1, participants have chosen the highest quality 81.5% of the watching session with the  $I_{\text{pure}}$  interface. Behaviour with  $I_{\text{eco}}$  seems to be very different: for V1, highest quality choice drops to 44%, for V3, middle quality choice rises from 37% to 76%. The results of V2 are interesting: quality choices seem to be similar, independently of the interface. Because of the randomness of the distribution of videos between  $I_{\text{pure}}$  and  $I_{\text{eco}}$ , each video is not watched the same amount of times in each interface. If V3 is well balanced (watched 53% of times with  $I_{\text{pure}}$ , 47% with  $I_{\text{eco}}$ ), V2 is overrepresented in  $I_{\text{eco}}$  interface, where 64.4% of videos are watched. Significance of V1 can also be interrogated: repartition is 60/40. Sample size must be increased to reduce the unbalance.

Measured MOS seems to fit the results given in the dataset. Reducing the 11-point answers from the dataset to 5-point

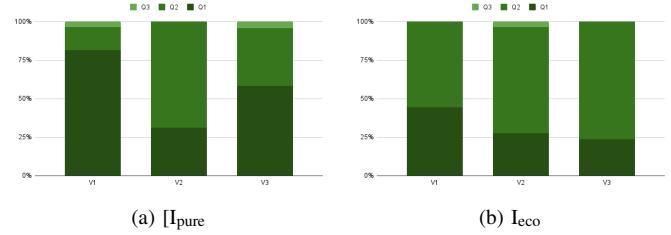


Fig. 8. Chosen quality per video

answers to compare with measured MOS shows relatively good results, even though we converted the answers linearly. A sigmoid function would be preferable.

The very small difference between Q1 and Q2 can partially explain the high adoption of Q2, as well as the poor MOS of Q3 can explain its non-adoption: regardless of the interface, Q3 seems not to be acceptable, having been chosen only three times out of a total of 135 watching sessions.

Running a two-way anova test on the ACR result-dependent variable between interface and quality concludes with a significance on the quality but not on the interface, nor on the interaction between quality and interface.

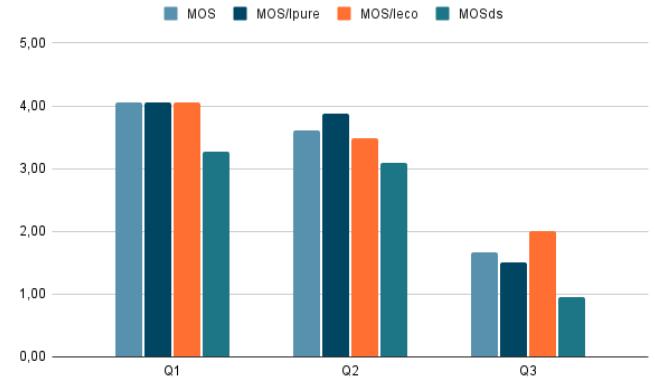


Fig. 9. MOS

#### E. Discussion

The results of the experiment shows that the difference between the interfaces can influence the choice behaviour: displaying environmental impact information on the quality selector interface leads users to reduce the quality of the videos. This information could have influenced the perceived quality of the videos watched, lowering the MOS when using an informative interface, which could result in a low adoption by content providers. The experiment we ran does not show such an interaction.

The non-ecological conditions of the experiment led to exploration effects that have been expressed through verbatims as “I want to see what 576p looks like”, first choices have probably been made randomly. This could have been mitigated

with a training session, which is usually released on ACR test method. A larger video dataset would be necessary.

Even with uninviting content and normalised videos, differences of choice are marked between videos. If this can be partly explained by the distribution of the videos between  $I_{\text{eco}}$  and  $I_{\text{pure}}$ , the exploratory study showed the importance of subjects on choice behaviour. Moreover, we proposed for our test only three levels of quality when services such as YouTube offer three times as much. Quality difference between Q1 and Q2 was not strongly marked as shown by the MOS. Further experimentation is needed, with different types of content and different levels of quality.

The MOS we used to measure the quality satisfaction is a practical and common way to convey QoE measures, and this does not show an impact of the interface on the perceived quality. Nevertheless, MOS hides important details about the results, such as the relation between quality and acceptance, that can have a significant impact on the business aspects of the service.

## VI. OVERALL DISCUSSION

### A. Limitations

The experiment we ran showed encouraging results. However, we imposed a choice to the test subjects, inducing a non-ecological behaviour. We could then try to understand the underlying mechanics that cause the need for a quality change.

As some entertainment begins to implement informative interfaces, there may be a learning effect on the part of consumers: a user who has already seen an informative interface on a platform will perhaps have a pro-environmental behaviour, even with a non-informative interface. We could assess this question by increasing our sample size and varying the length of the break.

A global introduction and adoption of informative interfaces would raise organisational issues. Such an interface would probably need a shared calculation methodology to harmonise information. From 2000 to 2015, various studies proposed calculation models for electrical intensity of data transmission over the internet with results varying from 0.004 kWh/GB to 136 kWh/GB, depending on the chosen system boundaries [16]. Differences would be even greater by trying to calculate the grams of carbon dioxide equivalent per kilowatt-hour, as in the Canal+ interface. If the introduction of a standardised method or even a third-party authority seems to be mandatory, some entertainment providers could still have complaints: Google claims to rely on renewable energy for 100% of its annual electricity use [17] and could argue that the standardised method does not fit.

With network bandwidth improvement (the average mobile network connection speed will more than triple and will be 43.9 Mb/s by 2023) [18], and streaming technologies enhancement (new codecs, better algorithms, etc.), interfaces of quality choice tend to disappear in a hidden parameter and to be totally automated. The effect of an informative interface will then be affected.

### B. Policy, perspective

In France, this experiment takes place in a favourable political context with the law n° 2021-1485 from 15 November 2021 aiming at reducing the environmental footprint of digital technology in France [19], or in the bill on combating climate change and building resilience to its effects [20]. The latter is more commonly known as Loi Climat, which came directly from the Citizen's Climate convention. First article in the first chapter of the bill provides that a display is intended to provide the consumer with information on the environmental characteristics of a product or a service.

## VII. CONCLUSIONS

In this paper, we have evaluated the impact of informative interfaces on choice behaviour for video quality through subjective tests. Results show the importance of such an interface on the behaviour of individuals.

Our contributions are manifold. Firstly, since informative interfaces will be made mandatory, we showed the usefulness of these and their real impact on usage behaviour. Secondly, as entertainment providers may be reluctant to adopt such interfaces for fear of a drop of QoE, we showed that the impact of the different interfaces on the perceived quality was not significant.

## ACKNOWLEDGMENT

I thank Toinon VIGIER and Mathias GUERINEAU for their guidance and am grateful the other members of the panel: Raphaël SUIRE and Veronique CHARRIAU. I also express my gratitude to my classmates from Master Degree and particularly Anthony GILAIZEAU. I finally thank Claire BERNIER for reviewing my report.

## REFERENCES

- [1] The Shift Project, "Pour une sobriété numérique," *Futuribles*, vol. N° 429, no. 2, p. 15, Mar. 2018. [Online]. Available: <http://www.cairn.info/revue-futuribles-2019-2-page-15.htm?ref=doi>
- [2] Cisco, "Cisco Visual Networking Index: Forecast and Trends, 2017–2022," Tech. Rep., 2019. [Online]. Available: <https://twiki.cern.ch/twiki/pub/HEPIX/TechwatchNetwork/HtwNetworkDocuments/whitepaper-c11-741490.pdf>
- [3] Info Abonné Canal, "INFO ABONNE CANAL+ sur Twitter." [Online]. Available: <https://twitter.com/InfoAbonneCanal/status/1306643958295035907>
- [4] G. Silva Mota Drumond, "La configuration des usages sur Netflix : le système de recommandation Cinematch et la représentation de l'usager," Nov. 2016. [Online]. Available: <https://archipel.uqam.ca/9253/>
- [5] S. Woolgar, "Configuring the User: The Case of Usability Trials," *The Sociological Review*, vol. 38, no. 1 suppl, pp. 58–99, May 1990. [Online]. Available: <http://journals.sagepub.com/doi/10.1111/j.1467-954X.1990.tb03349.x>
- [6] L. Quéré, "La structure cognitive et normative de la confiance," *Réseaux*, vol. 108, no. 4, pp. 125–152, 2001. [Online]. Available: <http://www.cairn.info/revue-reseaux1-2001-4-page-125.htm>
- [7] N. Seaver, "Captivating algorithms: Recommender systems as traps," *Journal of Material Culture*, vol. 24, no. 4, pp. 421–436, Dec. 2019. [Online]. Available: <http://journals.sagepub.com/doi/10.1177/1359183518820366>
- [8] F. Dobrian, V. Sekar, A. Awan, I. Stoica, D. Joseph, A. Ganjam, J. Zhan, and H. Zhang, "Understanding the impact of video quality on user engagement," *ACM SIGCOMM Computer Communication Review*, vol. 41, no. 4, pp. 362–373, Oct. 2011. [Online]. Available: <https://dl.acm.org/doi/10.1145/2043164.2018478>

- [9] ITU-T, “Subjective video quality assessment methods for multimedia applications.” [Online]. Available: <https://www.itu.int/ITU-T/recommendations/rec.aspx?rec=1482&lang=fr>
- [10] French Government, “Evaluation à 3 ans du logo nutritionnel Nutri-Score,” Tech. Rep., Feb. 2021. [Online]. Available: <https://solidarites-sante.gouv.fr/IMG/pdf/nutriscorebilan3ans.pdf>
- [11] “FFmpeg.” [Online]. Available: <https://www.ffmpeg.org/>
- [12] F. Lange and S. Dewitte, “Measuring pro-environmental behavior: Review and recommendations,” *Journal of Environmental Psychology*, vol. 63, pp. 92–100, Jun. 2019. [Online]. Available: <https://www.sciencedirect.com/science/article/pii/S0272494418307709>
- [13] P. Wesley Schultz, “THE STRUCTURE OF ENVIRONMENTAL CONCERN: CONCERN FOR SELF, OTHER PEOPLE, AND THE BIOSPHERE,” *Journal of Environmental Psychology*, vol. 21, no. 4, pp. 327–339, Dec. 2001. [Online]. Available: <https://linkinghub.elsevier.com/retrieve/pii/S0272494401902270>
- [14] A. K. Liefländer, G. Fröhlich, F. Bogner, and P. Schultz, “Promoting connectedness with nature through environmental education,” *Environmental Education Research*, vol. 19, pp. 370–384, Jun. 2013.
- [15] B. Bernier, “Experimentation,” Jan. 2022. [Online]. Available: <https://github.com/benoit-bernier/projet-recherche>
- [16] G. Rousselhe, “Siter le numérique,” de-signcommun, Tech. Rep., Nov. 2020. [Online]. Available: <https://designcommun.fr/media/pages/cahiers/situer-le-numerique/1a0a29dd3f-1624309254/situer-le-numerique.pdf>
- [17] “Commitment to a Carbon-Free Future.” [Online]. Available: <https://sustainability.google/commitments/carbon/>
- [18] Cisco, “Cisco Annual Internet Report (2018–2023),” Tech. Rep., 2020. [Online]. Available: <https://www.cisco.com/c/en/us/solutions/collateral/executive-perspectives/annual-internet-report/white-paper-c11-741490.pdf>
- [19] “LOI n° 2021-1485 du 15 novembre 2021 visant à réduire l’empreinte environnementale du numérique en France (1),” Nov. 2021.
- [20] A. Nationale, “Projet de loi n° 3875 portant lutte contre le dérèglement climatique et renforcement de la résilience face à ses effets.” [Online]. Available: [https://www.assemblee-nationale.fr/dyn/15/textes/115b3875\\_projet-loiDArticle1er](https://www.assemblee-nationale.fr/dyn/15/textes/115b3875_projet-loiDArticle1er)