Published in the proceedings of the *IEEE International Conference on Advanced Learning Technologies (ICALT)* 2023, 10-13 July 2023, Orem, UT, USA, which should be cited to refer to this work.

Using Video Streaming Feeds to Encourage Informal Learning

Rania Islambouli
École polytechnique fédérale de Lausanne (EPFL)
Lausanne, Switzerland
rania.islambouli@epfl.ch

Sandy Ingram
Haute école d'ingénierie et d'architecture de Fribourg, HES-SO
Fribourg, Switzerland
sandy.ingram@hefr.ch

Isabelle Vonèche Cardia
École polytechnique fédérale de Lausanne (EPFL)
Lausanne, Switzerland
isabelle.voneche-cardia@epfl.ch

Denis Gillet
École polytechnique fédérale de Lausanne (EPFL)
Lausanne, Switzerland
denis.gillet@epfl.ch

***Abstract*—Social media have become an indispensable part of daily life, particularly among university students, who regularly browse social news feeds in their spare time. Due to their pervasiveness, social media platforms provide an opportunity for influencing user behavior and encouraging informal learning. In this paper, we present an experiment using an online video recommendation application designed to blend micro-informative content with general content according to user preferences and activity history. Based on a one-week study, we conclude that injecting micro-informative content into video streaming platforms has the potential to improve the perceived satisfaction of users and can act as a potential catalyst to motivate users to consume more informative content online.**

***Index Terms*—informal-learning, video streaming platforms, social media, well-being, user satisfaction**

I. Introduction

Around 4.62 billion people are active social media users constituting about 93.4% of the total internet users [1]. YouTube is the most commonly used online platform, and there is evidence that its reach is growing. In 2021 81% of internet-connected Americans reported using the video-sharing site, which increased from 73% in 2019, making it one of just two platforms to experience a statistically significant increase in usage [2]. It is clear that social media and video streaming platforms particularly can offer an opportunity to influence users' behavior.

Concerns over social media's effects on users' well-being have increased steadily over the past decade [3]. According to a study published in 2018 [3], social media can negatively contribute to adolescents' mental health. Social media usage has been linked to a decline in performance and intellectual abilities [4]. One approach to help regulate social media usage and, potentially increase digital well-being is to devise applications that set limits to the use of specific applications and websites [5]. On the one hand, these static non-personalized interventions are ineffective over time [6]. On the other hand, according to the literature, improving the quality of time spent online reduces the potential drawbacks of excessive digital presence [7]. To improve the quality of time spent on social media and specifically video streaming platforms, we designed MStream, a video recommendation app that blends recommended short animated micro-informative videos with general content based on users' interests and online activity. We conducted a one-week experiment with university students using MStream to investigate two research questions: Does recommending a personalized blend of micro-informative and general content (based on user preferences and online activity):

1) RQ1: Allow users to feel positive about the time they spend online?
2) RQ2: Act as a potential stimulus to grow users' interest in informative online content?

II. Background and Related Work

A. Learning and Well-being

According to Aked et al., learning is one of the evidence-based five ways to well-being. Learning may provide a sense of satisfaction, contentment, fulfillment, accomplishment, and appreciation [8]. A survey conducted by Narushima et al. showed that informal lifelong learning could positively contribute to psychological well-being [9]. It can also help deal with stress and mental problems [10]. Research has also focused on creating informal learning opportunities. Serrano-Iglesias et al. [11] tried to connect formal and informal learning experiences by integrating a mobile application about the history of art, with a recommendation system based on student position. A browser extension developed by Kovacs [12] teaches vocabulary in the context of Facebook feeds by presenting users with interactive quizzes. The study demonstrated that users were more likely to engage with learning tasks when the latter are integrated into the students' news feeds.

Taking into account the benefits of informal learning on the one hand and the prevalence of video streaming platforms on the other, we propose to inject micro-informative videos into video streaming platform feeds and study the perceived user satisfaction.

B. Recommendation Systems and Tools for Well-being

Not enough attention has been paid to the role of recommendations in digital well-being. In many cases, the focus of recommender systems is business and profit-oriented [13]. Traditional recommendation systems are optimized to enhance user engagement, leading to an increase in profit and popularity [14], without sufficient focus on long-term effects on users' well-being. Some tech companies like Meta and Google started tackling digital well-being and introduced timers in their apps to help users overcome the negative impact of technology on their well-being [5]. Various digital self-control tools exist [15]. They enable users to record the time spent online and track their activity. However, these static non-personalized interventions are ineffective over time [6]. Users are not only interested in limiting their time online but also in learning how to benefit and generate a profitable experience online [7].

Thus, we design a video recommendation app that injects micro-informative videos into a video streaming feed to test whether consuming short well-crafted informative content can enable users to feel that their time is well spent online and encourage informal learning.

III. Method

A. Dataset

The app designed recommends micro-informative and general YouTube videos. It employed YouTube videos collected throughout the YouTube API for the time spanning from 2015 to 2021 split into 6 categories: music, pets and animals, sports, travel and events, people and blogs and politics. We define micro-informative videos as short, informative clips that center around a single idea and aim to inform the users and spark their curiosity. They were streamed from the TED-Ed YouTube channel [16]. TED-Ed is an online library of short animated informative video lessons crafted in collaboration with educators. The library consists of videos from various domains including science, health, art, history, hobbies, and technology. The duration of the extracted videos ranged from 2 to 5 minutes.

B. Recommendation Approach

We model the sequential interactions between the items and users as a Markov Decision Process and utilize reinforcement learning and the Actor-Critic method [17] to dynamically update recommendations according to the users' real-time feedback. The actor generates an item to recommend. The critic evaluates the reward of this recommendation, where the reward of a clicked micro-informative item is higher than a clicked non-informative item. While a non-clicked informative item has a lower reward than a clicked non-informative item. The actor-network is modeled using recurrent neural network layers to enable the modeling of sequential consumption of informative and non-informative content. The prediction model and training procedure are based on our previous work [18]. We pre-trained our model using behavior theories and a simulation model as explained in our previous work [18].

TABLE I: Pre-study questionnaire.

Why do you use social media apps? Four possible answers:
(1) To stay in touch with friends and acquaintances
(2) To stay up-to-date with news and current events
(3) To have fun and entertain myself
(4) To develop my knowledge and skills (cooking, science, any topic))
Please indicate your level of agreement with the following statements (From strongly agree to strongly disagree):
(1) Social media negatively affects my daily activities and schedule
(2) I consider that my time online is well spent
(3) During my free time I usually enjoy acquiring new information (example: watching cooking lessons, watching "how to" videos, reading about a new topic etc.)

The recommendation system tries to learn the long and short-term interests of users while recommending both informative and non-informative content and adjusting their frequency and recommendation time to create higher rewards and increase the click rate. To avoid the cold start problem, users define their interests over multiple video categories when they first register.

C. Recruitment and Participants

We recruited participants by emailing students through our university groups. We sought active video streaming platforms users who are also English speakers. Respondents were required to sign an informed consent form that included information about the experiment and the gathering and processing of their data. Data were anonymized, and users could drop out of the experiment anytime.

Three participants were dropped at the end of the study for not having answered the final survey. We present results from the 37 participants who completed the field study and filled out the questionnaires. The participants were undergraduate university students in a variety of majors. They included 20 females and 17 males between the ages of 18 and 23.

D. Experiment Setup and Protocol

The experiment took place in February 2021 and was conducted in English. All study components were responsive, enabling participants to access the study using a variety of devices. The final experiment consisted of four main stages, detailed below.

1) **Enrollment**: The participant began by reading a general introduction about the study and compensation (15 dollar library voucher). Before participating in the experiment, respondents had to acknowledge the informed consent.
2) **Pre-study questionnaire**: In this phase, the participants were introduced to the experiment steps and rules. The introduction consisted of a generic overview of the study, asking them to use the application to watch videos for seven days and then give their feedback through a questionnaire after the seven days. Nothing was said about the nature of the videos recommended. Then, participants were asked to answer a short questionnaire before the start of the experiment (Table I).

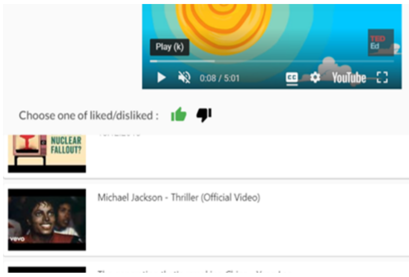

Fig. 1: In-app videos and feedback collection.

TABLE II: Post-study questionnaire.

Please indicate your level of agreement with the following statements (from strongly disagree to strongly agree):
(1) The items recommended to me in the application matched my interests.
(2) I found it easy to inform the system if I dislike/like the recommended item
(3) I enjoyed watching the informative videos recommended (if any)
(4) Through using the app, I discovered new information
(5) I felt that learning new information makes me feel good (about the time spent online)
(6) I would like to see more informative videos in the original YouTube app.
(7) I am in favor of an application that helps me balance the time spent watching pure entertaining vs informative content
(8) After this experiment, I am planning to spend more time watching informative videos

3) **Online experiment**: In this phase, participants were required to remotely access our Web application where the experiment took place over a period of one week. Participants used the application for a period of seven consecutive days. The first time they sign-up, users were asked to fill in their preferences. After that, they were presented with a list of videos from which they can choose any video to click. The recommendation system takes into account the videos the user clicked on to adapt the next recommendations. The participants were split into two groups: the control group and the experiment group. The experiment group was recommended both micro-informative videos and general videos, whereas the control group was only recommended general videos. The algorithm adapts recommendations starting from the preferences expressed by the participants and then based on click history. For analysis purposes, we recorded all user clicks on videos and collected feedback for each video (Figure 1).
4) **Post-study questionnaire**: The final phase consisted of filling out a post-experiment survey. This survey aimed at understanding the users' perceived experience beyond clicks and in-application feedback (Table II).

IV. Results

We examined three types of data, including (1) the pre-study questionnaire results, (2) the post-study questionnaire results and (3) the logged app data. We report the results of the Likert scale using means (1 = strongly disagree 5 = strongly agree) and percentages and visualize them using horizontal stacked bar charts.

A. *Pre-study Questionnaire*

The pre-study questionnaire indicated that users are not satisfied with their social media habits. Around 67% use social media to stay in touch with friends and acquaintances, 71% to stay up-to-date with news and current events, 64% to have fun and entertain themselves and 27% to develop knowledge and skills. Around 78% of the control and experiment group participants said that social media usage negatively affects their daily activities and schedule. Approximately 63% of the control group and 66% of the experiment group participants reported that they are not happy about how their time is spent online. The majority of the control and experiment group participants did not agree with the statement "During my free time I usually enjoy acquiring new information", where the median of the Likert scale was around 2.9 for the control group and 2.5 for the experiment group.

B. *Post-study Questionnaire*

Approximately 84% of the control group and 83% of the experiment group participants saw it was easy to use the application and give feedback demonstrating the usability of the app's interface and mitigating the impact of its poor design on the experiment results. A total of around 68% of the control group and 72% of the experiment group participants reported that the recommendations in the application matched their interests (Figure 2).

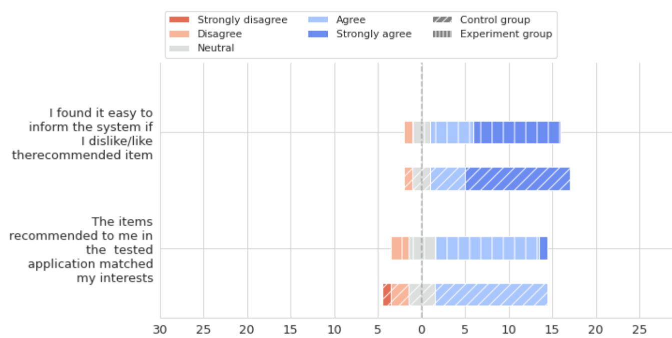

Fig. 2: Recommendation quality was the same for both groups and UI was user-friendly.

Approximately 66% of the experiment group participants enjoyed watching the informative TedEd videos, and around 66% were able to discover new information by using the application. Around 77% of the experiment group agreed with the following statement "I felt that learning new information makes me feel good (about the time spent online)". Participants were asked whether they usually enjoy acquiring new information during their free time in the pre-study questionnaire. The majority of the experiment group participants did not agree with this statement, where the median of the Likert scale was around 2.5. At the end of the experiment, we asked study participants whether they plan to spend more time watching informative videos. Most participants in the experiment group agreed with this statement, where the mean was around 4.1 (Figure 3). Results of the Wilcoxon Sign-Rank test indicated that the differences between the before and after experiment results were significant for the experiment group ($p < .002$). However, the same mean for the control group was around 2.31 (Figure 3). Results of the Mann–Whitney U test indicated that the differences between the experiment and the control group were significant ($p < 0.01$) thus, signaling the effect of injected micro-informative videos. Participants were also asked in the post-study questionnaire whether they are in favor of an application that helps them balance the time spent watching pure entertaining vs informative content, around 70% of the experiment group agreed with this statement (Figure 3). However, we could not observe this for the control group (around 30% agreed) where the p-value of the Mann–Whitney U test was < 0.03. In addition, around 80% of the experiment group said they would like to see more informative videos in the original YouTube application (Figure 3) versus 20% for the control group where the p-value of the Mann–Whitney U test was < 0.02.

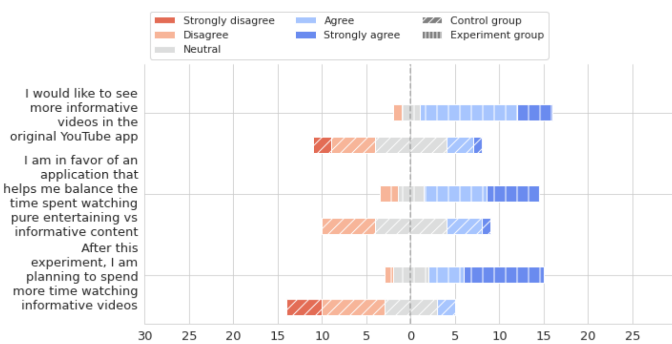

Fig. 3: Post-study questionnaire results showing the increased interest in informative content for the experiment group.

C. Logged Data

An analysis of the log files of the experiment resulted in the measurements detailed in Table III. A significant correlation was found for the experiment group between the variables "Average percentage of liked micro-informative videos by the user out of micro-informative videos recommended" and the variable "I felt that learning new information makes me feel good (about the time spent online)" using spearman correlation (corr coefficient = 0.68) signaling the effect of micro-informative content consumption on the user.

V. Discussion

A. Discussion of RQ1

Does recommending a personalized blend of micro-informative and general content (based on user preferences and online activity) allow users to feel positive about the time they spend online?

Our first research question focuses on understanding the impact of consuming micro-informative content on users and

TABLE III: Logged measurements results.

Average session length per user		24.61 minutes
Average % watched of each clicked video per user	Experiment	87.11 (of micro-informative) 84.08 (of other videos)
	Control	82.38
Average % of liked videos per user	Experiment	67.21 (of micro-informative) 66.41 (of other videos)
	Control	64.53

their perceived experience. The results reveal that participants who consumed micro-informative content relevant to their interests blended with non-informative content based on the user interactions feel positive about how they spend their time online. The answers to the post-study questionnaire revealed that the experiment group enjoyed watching the informative content (66%). The answer to the post-study questionnaire "I felt that learning new information makes me feel good (about the time spent online)" showed a 77% agreement among the experiment group with a significant difference compared to the control group indicating the effect of mico-informative consumption. The answer to the question "The items recommended to me in the tested application matched my interests" revealed similar recommendation quality for the experiment and control groups. In addition, the percentage of liked videos per user is also comparable between the experiment and the control group eliminating the effect of bad recommendation quality. The variable "I felt that learning new information makes me feel good (about the time spent online)" was positively correlated with the variable "Average percentage of liked micro-informative videos by the user out of micro-informative videos recommended" indicating the importance of personalized recommendations.

B. Discussion of RQ2

Does recommending a personalized blend of micro-informative and general content (based on user preferences and online activity) act as a potential stimulus to grow users' interest in informative online content?

The pre-study questionnaire results indicated that both control and experiment group participants do not usually enjoy acquiring new information in their free time. In addition, participants used social media apps the least to "develop knowledge and skills". In the post-study questionnaire, around 80% of the experiment group stated they would like to see more informative videos in the original YouTube application, resulting in a significant difference in the pre and post-study results for the experiment group. Furthermore, approximately 70% percent are in favor of an application that helps them balance the time spent watching pure entertaining vs informative content. This observation was not found for the control group. Finally, most of the experiment group participants plan to spend more time watching informative videos (mean of around 4.1) with a significant difference from the control group that did not agree with this statement.

C. Limitations

We conducted our experiment with a small sample of 37 participants. In addition, we limited our study time to one week and could not observe longer-term effects.

VI. Implications and Future Research

In this work, we set out to investigate the impact of injecting micro-informative units into video streaming platforms on users' perceived satisfaction and behavior.

Our results show that consuming micro-informative content in addition to general non-micro-informative units on video streaming platforms positively impacts the perceived users' satisfaction with how they spend their time online, enables them to learn new information on the go, and acts as a possible motivator to increase users' interest in informative content. The conducted online experiment sheds light on the potential of our micro-informative driven recommendation strategy on improving online user experience and motivating informal learning. If an algorithm learns the right policy (frequency, personalized content, timing) by combining purely entertaining with micro-informative content, social media can also serve as an entry point for continuous informal learning. This experiment signifies the importance of social media apps in influencing user behavior, especially among students and young people. While micro-informative content was well received by our experiment participants, it is important to provide it within an adaptive recommendation approach that learns the right recommendation frequency and topics for a target user profile for the intervention to yield a positive user experience.

This study opens the door to research studying the properties of informative and specifically micro-informative content that interests users. We could not notice the same effect for the control group even though some of the general videos recommended were informative in nature. This sheds the light on the properties of micro-informative videos which are brief, animated and focused on a single topic. Further studies could consider and vary the format (video, text, images, games, questionnaires), length and complexity of micro-informative units. In addition, future research could explore whether such recommendations could be applied to other social media platforms and try to incorporate them into existing social media feeds.

VII. Conclusion

In this paper, we presented MStream, a video streaming application that recommends micro-informative content to users according to user preferences and history while blending them with other content. Testing the app with 37 participants showed that injecting micro-informative content can act as a catalyst to improve the perceived satisfaction of users, enable them to learn something new, and act as a motivator to increase users' interest in informative content.

References

[1] Pew. (2021) Social media use in 2021. [Online]. Available: https://www.pewresearch.org/internet/2021/04/07/social-media-use-in-2021

[2] B. Auxier and M. Anderson, "Social media use in 2021," *Pew Research Center*, 2021.

[3] M. O'Reilly, N. Dogra, N. Whiteman, J. Hughes, S. Eruyar, and P. Reilly, "Is social media bad for mental health and wellbeing? exploring the perspectives of adolescents," *Clinical child psychology and psychiatry*, vol. 23, no. 4, pp. 601–613, 2018.

[4] S. B. Lee, S. C. Lee, and Y. H. Suh, "Technostress from mobile communication and its impact on quality of life and productivity," *Total Quality Management & Business Excellence*, vol. 27, no. 7-8, pp. 775–790, 2016.

[5] Google. (2021) Digital Wellbeing through technology | Google. Google. [Online]. Available: https://wellbeing.google/

[6] E. I. Collins, A. L. Cox, J. Bird, and D. Harrison, "Social networking use and rescuetime: the issue of engagement," in *Proceedings of the 2014 ACM International Joint Conference on Pervasive and Ubiquitous Computing: Adjunct Publication*, 2014, pp. 687–690.

[7] M. Sleeper, A. Acquisti, L. F. Cranor, P. G. Kelley, S. A. Munson, and N. Sadeh, "I would like to..., i shouldn't..., i wish i... exploring behavior-change goals for social networking sites," in *Proceedings of the 18th ACM Conference on Computer Supported Cooperative Work & Social Computing*, 2015, pp. 1058–1069.

[8] J. Aked, N. Marks, C. Cordon, and S. Thompson, "A report presented to the foresight project on communicating the evidence base for improving people's well-being," *London: New Economics Foundation*, 2008.

[9] M. Narushima, J. Liu, and N. Diestelkamp, "Lifelong learning in active ageing discourse: Its conserving effect on wellbeing, health and vulnerability," *Ageing & Society*, vol. 38, no. 4, pp. 651–675, 2018.

[10] C. Hammond*, "Impacts of lifelong learning upon emotional resilience, psychological and mental health: Fieldwork evidence," *Oxford Review of Education*, vol. 30, no. 4, pp. 551–568, 2004.

[11] S. Serrano-Iglesias, E. Gómez-Sánchez, M. L. Bote-Lorenzo, G. Vega-Gorgojo, A. Ruiz-Calleja, and J. I. Asensio-Pérez, "From informal to formal: connecting learning experiences in smart learning environments," in *2021 International Conference on Advanced Learning Technologies (ICALT)*. IEEE, 2021, pp. 363–364.

[12] G. Kovacs, "Feedlearn: Using facebook feeds for microlearning," in *Proceedings of the 33rd annual ACM Conference extended abstracts on human factors in computing systems*, 2015, pp. 1461–1466.

[13] Ö. Özgöbek, J. A. Gulla, and R. C. Erdur, "A survey on challenges and methods in news recommendation." in *WEBIST (2)*, 2014, pp. 278–285.

[14] L. Li, D. Wang, T. Li, D. Knox, and B. Padmanabhan, "Scene: a scalable two-stage personalized news recommendation system," in *Proceedings of the 34th international ACM SIGIR conference on Research and development in Information Retrieval*, 2011, pp. 125–134.

[15] A. Monge Roffarello and L. De Russis, "Coping with digital wellbeing in a multi-device world," in *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems*, 2021, pp. 1–14.

[16] TED-Ed. (2021) TED-Ed - YouTube. TED-Ed. [Online]. Available: https://www.youtube.com/teded

[17] X. Zhao, L. Xia, L. Zhang, Z. Ding, D. Yin, and J. Tang, "Deep reinforcement learning for page-wise recommendations," in *Proceedings of the 12th ACM Conference on Recommender Systems*, 2018, pp. 95–103.

[18] R. Islambouli, S. Ingram, and D. Gillet, "Is your time well spent online?: Focusing on quality experiences through a user-centered recommendation algorithm and simulation model," in *2021 20th IEEE International Conference on Machine Learning and Applications (ICMLA)*. IEEE, 2021, pp. 1043–1048.