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"In the Shoes of an Algorithm": A Media Education Game to Address Issues Related to Recommendation Algorithms*

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ABSTRACT

Recommendation algorithms play an important role in the current media landscape by fostering interactions between users of digital media platforms and media content. The growing concern with recommendation algorithms raises important questions for media educators who emphasize critical analysis of media content and creative production and are required to develop media education initiatives focused on a critical understanding of digital platforms and their underlying technical infrastructures. What are teenagers' current perception and experiences of recommendation algorithms? What should be the key issues these initiatives should address, and how should they be addressed? The "In the Shoes of an Algorithm" project approached these questions through design-based research (DBR). This project led to the creation of a series of pen-and-paper games designed to (1) help teenagers share their daily experiences of recommendation algorithms to identify core issues that should be addressed by media educators and (2) to foster a better understanding of key issues related to recommendation algorithms used by digital media platforms. The project was initiated in Belgium and expanded as an international program, in collaboration with South-Korean researchers and practitioners.

Keywords: recommendation algorithm, media education, design-based research, data literacy, media literacy.

Ⅰ. Introduction

Recommendation algorithms are embedded in many digital media platforms. They are designed to foster interactions between the platforms’ users and content. To do so, they collect and use data to suggest contents that the users might want to interact with. This key role of recommendation algorithms is becoming increasingly concerning, as the functioning and choices behind them have a strong cultural and economic impact. Tackling these issues is crucial for media educators who would like to empower users and help them become active and autonomous citizens by being creative, reflexive, and critical in their interactions with digital media that relies on recommendation algorithms.

In this context, media education initiatives should aim at developing a better understanding of the technical dimensions of digital media platforms to establish a deeper and more complex capacity for their users to question and understand the social impacts of these platforms. This paper presents the "In the Shoes of an Algorithm" project that attempts to address recommendation algorithms within the field of media education and to connect the understanding of technology with societal issues. Two mains goals motivate this project:

1) understanding and documenting teenagers’ current experiences and representations of recommendation algorithms to envision media education initiatives connected to teenagers’ actual practices and understanding of digital media platforms, and
2) developing educational responses focused on recommendation algorithms to foster a greater capacity for teenagers to understand the algorithms’ technical functioning as well as the societal challenges they raise.

The first section of the paper details the theoretical connections between the fields of media education and science and technology studies (STS) as the theoretical framework of this project. Following sections discuss the methodology and the different pen-and-paper games developed in Belgium and South Korea. The paper concludes with a discussion of the implications and lessons learned for researchers and media educators.

Ⅱ. Theoretical Framework

1. Data Literacy and Recommendation Algorithms

The first challenge for media educators is to establish a basic understanding of recommendations algorithms.

Data literacy has recently emerged as an area of media education in response to growing concerns for "datafication." The term was coined by Mayer-Schoenberger and Cukier (2013). It means the conversion of social actions and phenomena, which have not been previously quantified, into data points, in a manner that often enables tracking and surveillance (Halegoua, 2020). The increasing datafication raises critical concerns such as the dominance of data-driven epistemologies, the loss of individual agency, and the inequality and injustice in decision-making processes and governance in society. In the context of today's "datafied" society, data literacy refers to a set of skills to understand and reflect on how data is created, collected, and (re)constituted; and to eventually resist the negative effects of datafication (Pangrazio & Sefton-Green, 2019).

A recommendation algorithm transforms data on peoples' norms, tastes, values, interests, and relationships into a series of mathematical rules; it is a key example of datafication of our lives. Since the late 1980s, engineers have been engaged in designing recommendation algorithms, with the hope of addressing "information overload" or increasing "commercial revenue." The recommendation algorithms, seeking to foster interactions between users and items (Ricci et al., 2011), now constitute a cornerstone of most digital infrastructures. Thus, engineers hope to achieve two main aims. First, recommendation algorithms enable them to automatically *filter* among the mass of available content that is continuously uploaded by billions of users and displayed by a limited number of platforms. Second, recommendation algorithms enable them to produce personal *recommendations*, associating specific items to specific users whose personal data may now be continuously collected and stored by the platforms. These take place in an overall commercial system where digital platforms essentially depend on advertisement revenues.

The recommendation algorithms mediate most of our interactions with digital infrastructures, which often finding ourselves invested with hopes and fears. We hope to assist ourselves in selecting items that might best suit ourselves, e.g., our revenues; and we fear that we might produce an environment significantly shaped by digital empires, e.g., bubble filters, swinging elections, and propaganda. These seemingly opposite concerns, hopes and fears, both stem from the difficulty of understanding what recommendation algorithms are and how they shape our digital environments.

Therefore, educational responses must be developed to address this issue. To that end, this project used two complementary perspectives: media education and STS.

2. The Media Education Perspective

Media education has a long tradition of valuing young people's lived media experiences (e.g., Buckingham, 2000; Niesyto, Buckingham, & Fisherkeller, 2003; Dezuanni, 2010). To strengthen media education’s theoretical ground, it is argued that young people’s media culture should be thoroughly examined and studied and become the basis of media education topics and concepts (Livingstone, 2004). Simultaneously, literacy scholars emphasize the importance of the lived culture of education participants. Specifically, researchers who focus on the changing nature of literacy practices with a socio-critical perspective emphasize the need to closely reflect upon what the official school curriculum considers valid knowledge and literacy practice (Gutiérrez, 2008). As such, media education research must examine what young people do in and with the media.

In the constantly evolving media environment, media education should not only deal with traditional key concepts but also expand the scope of themes and topics of education to include young people’s up-to-date media culture and experiences. As the mass media environment turned into a digitalized, individualized, mobilized, and socially connected media environment, questions have been raised about the validity of traditional core concepts of media education. Attempts to expand and transform the core concepts’ content or focus to the changing media environment are initiated and applied in the field of media education (e.g., Parry & Powell, 2011).

In the digital and mobile media environments, young people’s media experiences can vary not only according to the media contents they access but also the media platforms and the tools (e.g., personal computer or mobile phone) they use. The differences are mainly due to the different algorithms that a platform or a tool enables and offers to users. Therefore, media educators must deal with the underlying structure of media platform, i.e., the algorithm and flow of data caused by a specific medium.

Livingstone and colleagues point out that media literacy of media users is not simply determined by personal knowledge and skills related to media but by the transparency and complexity of the media interface itself (Livingstone, Lunt, & Miller, 2007). As such, media education should expand its realm, and support young people, so that they look into the media interfaces with which they interact. “Data literacy” is increasingly used as a conceptual tool to address the need for critical intervention in the “datafication” of contemporary society (Pangrazio & Sefton-Green, 2019).

However, when putting the media interface and algorithm into the picture, it is also critical not to consider media technology as value-neutral. Media technology clearly affects the media user's culture; however, its development is determined through the active intervention of media users within the social context. Therefore, it is necessary to encompass STS to fully incorporate the complexity of young people’s media experiences into media education.

3. The Science and Technology Studies Perspective

The STS literature offers valuable accounts of engineering practices, disclosing the processes through which technical constraints and social objectives mesh into large socio-technical systems (Akrich, 1987; Star, 1991). The design of "serious games" has significantly relied on works about computing practices (Grier, 2005; Jaton, 2017), data practices (Edwards et al., 2011, Leonelli, 2014), and recommender systems (Seavers, 2019; Parks et al., 2017), with the aim of facilitating a realistic and yet intuitive understanding of these complex and actual processes. Consequently, media education initiatives have focused on the following three concepts.

1) Algorithms have been considered as stabilized and formalized computational techniques that engineers recognize and manipulate as a technical object, through a variety of disparate inscriptions (e.g., formalized expressions, diagrammatic representations, and traces of executions) and actions (e.g., intuitive manipulations, material implementations, and concrete experimentations). Examples of such algorithms are the k-nearest neighbors or the matrix factorization algorithms, or recurrent neural networks.
2) Data has been considered as traces of a past situation or process that can be subjected to different expectations or actions: as something to be missed, as something to be evaluated, or as something to be computed (Hoffmann, 2016). Examples of such data would be, demographic data about the population watching a video, statistical data about that video's success, or historical data about the interactions between users and items.
3) Metrics have been considered as conventional procedures, articulating both social objectives and technical processes, enabling engineers to attribute numerical scores to algorithms behaviors. The recommender systems, although they may consist of different combinations of algorithms and data, may be evaluated in a similar fashion, through similar metrics. Examples of such metrics are user engagement, advertisement revenues, or recommendation diversities (e.g., Netflix).

The perspective adopted on engineering practices and objects provided invaluable insights for addressing the second challenge encountered by media educators: coming up with a way to communicate a robust enough understanding of the social and technical activities involved in creating recommender systems so as to enable participants to collectively reflect on and discuss the ways recommender systems shape digital platforms and affect their media practices (Grosman et al, 2018). The emphasis was put on the stable and intuitive definition of the recommendation *problem* (i.e., the *data* characterizing the recommendation and the *metrics* qualifying the engineered solutions), rather than the unstable and tedious variety of recommendation algorithms (i.e., the *structures* and *operations* characterizing nearest neighbors, matrix factorization, or neural techniques).

Hence, in our envisioned educational activity, participants confront, as engineers would, one aspect of the recommendation problem (i.e., how to move from an unordered set of data about videos to an ordered set of videos ready to be recommended) and are expected to reinvent a technical scheme, rather than copy one that is already presented (i.e., a calculation rule that would enable them to rank videos, according to the data about the videos to recommend and about the user to be recommended). Furthermore, the educational activity leaves the recommender systems’ aims undefined, making participants realize that such aims are technically needed and socially debatable.

Ⅲ. Case Studies

1. A Design-Based Research

The two case studies of this project adopted a Design-Based Research (DBR) approach (Cobb et al., 2003; The Design-Based Research Collective, 2003; Barab & Squire, 2004; Wang & Hannafin, 2005; Anderson & Shattuck, 2012; McKenney & Reeves, 2013). The core idea of DBR is to “depart from a problem and then pursue both knowledge and interventions that address it” (McKenney & Reeves, 2013, p. 4). The method consists of several iterative steps, comprising several cycles of inventions and revisions (Cobb et al., 2003), and could be described as “research through mistakes” (Anderson & Shattuck, 2012). The different steps taken and the first results of the two case studies are described below.

To anchor the results in the field, the approach recommends classroom experiments, close collaboration between researchers and practitioners, and a team combining different areas of expertise depending on the theme and the nature of the educational activity (Cobb et al., 2003). The Belgian research team integrates researchers from complementary fields of expertise (Digital and Media Literacy Education, Information Literacy, and STS), as well as media educators from the association *Action Média Jeunes*. The Korean research team integrates researchers from similar fields of expertise, including Educational Studies and Computer Sciences.

2. The First Case Study: Dans la Peau d'un Algorithme

The educational and research project started in Belgium as an initiative of the researchers of the University of Namur and practitioners from Action Médias Jeunes, a media education association working with children and teenagers. The project comprised three main stages, spanning over two years. During the first stage, from November 2016 to March 2017, an activity was designed to facilitate research and education about digital issues (see Section 1) escription of the Game). During the second stage, from November 2017 to November 2018, the designed activity was tested in the classrooms to determine necessary adjustments, and the empirical material was collected and analyzed to develop key issues (see Section 2) First Results). During the third stage, from November 2018 to November 2019, the activity was improved to better address the key issues identified in the second stage.

The educational objective was to develop an activity that would empower participants, enabling them to critically discuss and reflect on the consequences that recommendation algorithms have on their use of digital media. The activity, bridging reflections from media education and STS, sought not to turn participants into computer scientists or software engineers but rather to provide them with an intuitive understanding of data and algorithms. The activity let participants become engineers and algorithms, hoping that their lived experience would enable them to address some of the key issues at stake regarding these digital platforms.

The research objective was to identify the issues experienced by teenagers using digital media. The interpretative stance taken sought to put participants in a situation that would enable them to express and discuss, among themselves and with educators, during the activity and the debriefing, what they thought constituted an important issue raised by the activity just carried out as well as their daily media practices. This research project was inspired by previous work in the field of media education mentioned above and by the necessity to adopt an interpretive approach to develop media education initiatives anchored in lived experiences of users, which require a careful documentation of their practices (e.g., their goals, motivations, and problems) and their representations (Jacques & Fastrez, 2018; Ligurgo et al., 2019).

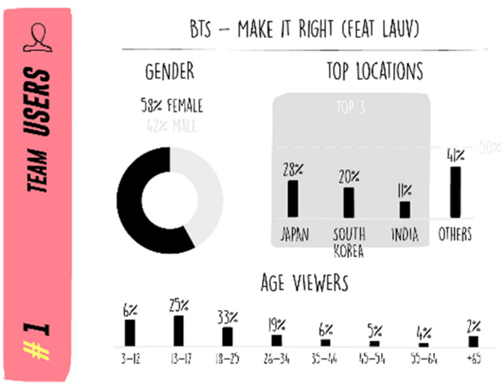
The activity was deployed in several classrooms to test the game in a real-world context and to collect data on the issues that the participants raised in relation to recommendation algorithms. Thus, the game was used as a playful focus-group technique to collect discourses about representations and problems encountered by the players and connected to their daily interactions with recommendation algorithms. Feedback collected during play was incorporated to improve the game and to note teenagers' concerns, reflections, perceptions, and questions about their media experiences.

1) escription of the Game

"In the Shoes of an Algorithm" (*Dans la peau d'un algorithme*, in French) is a two-hour long pen-and-paper activity that can be played by people aged 14 and over. The objectives are to develop a recommendation algorithm, to rank videos, and to evaluate the different recommendation algorithms. During the first phase, participants are divided into three groups. They are expected to act as engineers designing a recommendation algorithm, and as computers executing the designed algorithm. During the second phase, participants are grouped together. They are expected to present and argue about the merits of their respective algorithms and to more generally discuss and reflect on their media practices.

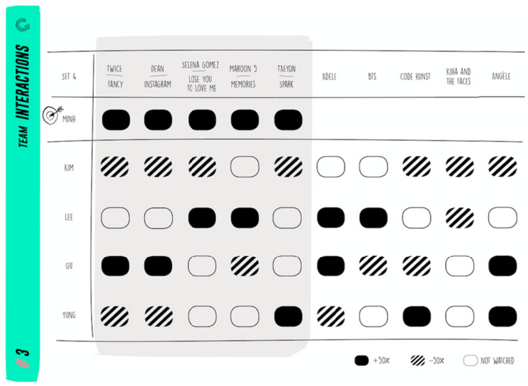
During the first phase, each group receives different kinds of data. The first step requires participants to act as engineers. Each group receives a data sample about the videos to recommend, and they need to devise a calculation rule general enough to enable them to rank the videos (and others received). The second step requires participants to act as computers. Each group receives, at regular intervals, new data that needs to be quickly processed, following the devised calculation rule, to produce actual recommendations. The participants are given little instruction on how to proceed and are encouraged to collectively address possibilities and obstacles.

- The “Users” team receives data about the population having viewed the videos (gender, age balance, and origins) and data about the user to whom videos are to be recommended.



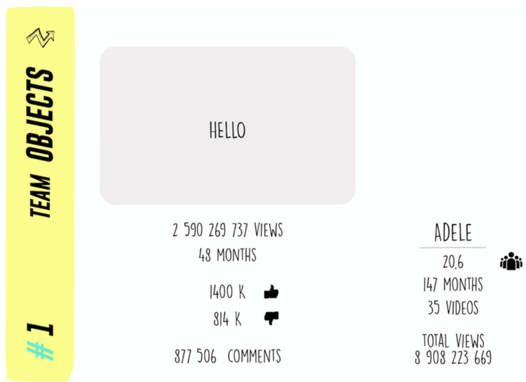
[Figure 1] Data received by the team "Users"

- The “Interactions” team receives data about the people that have similar viewing histories to the user to whom videos are to be recommended.



[Figure 2] Data received by the team "Interactions"

- The “Objects” team only receives data about the music videos (dates, views, subscriptions, etc.). The recommendations are general rather than personalized.



[Figure 3] Data received by the team "Objects"

The first phase typically leads to a series of discussions about the ways of interpreting the data received, formalizing the ranking rule, and handling computational tasks. The data discussion focuses on the meaning and the relevance of the kinds of data received. The rule discussion focuses on the aspects that should matter most when recommending as well as the possible formalizations. The computational discussion focuses on the rules’ efficiency and ability to handle tedious and specific calculations.

By the end of the first hour, each group needs to have computed a score for each video, ranked the list of videos, and be ready to present their algorithm and results to the other groups.

During the second phase, the three teams discuss and evaluate their algorithms. The first step requires participants to present their own algorithm, to discuss their respective calculation rules and, eventually, to vote to evaluate the most convincing recommendation algorithm. The second step requires the media educator to step in, acting as a Chief Technology Officer, and propose participants to evaluate, for them, their respective algorithms as most digital platforms would. In the third step, the participants more broadly discuss the challenges encountered in the course of the educational activity, the experience they have of digital platforms, and the importance of recommendation in forming cultural habits.

The educational activity has considerably evolved over the past three years, before reaching the form presented in this paper. The second phase, especially, has gone through significant changes. As long as the game was used as a research device, the discussion remained rather unstructured (second stage of the project), leaving open space for participants to voice *all* and *any* issues that mattered to them (e.g., deceptions with recommendations, monetization of videos, and idle watching leisure). As soon as the game started to be used as an educational device (third stage of the project), the discussion was structured and enriched around the concerns previously raised by the students, to guide media educators in leading the final discussion.

1) First Results

The preliminary research comprised four sessions with teenagers from different secondary schools, engaged in different programs (two majoring in mathematics, one majoring in computer science, and one pursuing vocational training) to collect a variety of data. The four sessions were animated by two media educators, with the punctual assistance of one or more researchers. The four sessions were all video-recorded, while the researchers took note of the educators and participants' discourses and interactions (e.g., within the group or in the class, and through language or materials) to develop an understanding of the learning ecology thus staged (Cobb et al., 2003). The researchers also voiced the media educators' experiences (e.g., obstacles, challenges, and suggestions) through semi-directed interviews.

The data collected enabled us to identify the concerns participants expressed when they were put in a position to collectively reflect upon their media practices, with the hope to define the issues media education should focus on when dealing with recommendation algorithms. The data analysis thus adopted a grounded theory approach (Glaser & Strauss, 1967; Lejeune, 2019) and combined inductive and deductive approaches (Ligurgo et al., 2018), leading to the identification of three clusters of issues: (1) data and computational issues, (2) personal tastes and recommendation issues, and (3) recommendation algorithms and digital platforms issues. These issues were used to structure the final version of the educational activity.

Cluster 1: Data and Computational Issues

The participants repeatedly faced difficulties in interpreting the data and formalizing computations. The main data issue has to do with the conflicting ways of interpreting the displayed numbers. The participants argued over the meaning of various data entries: "How should a specific data entry be understood?" They disputed the relative usefulness of different kinds of data: "How relevant is this kind of data for recommending videos?" They sometimes discussed the kinds of information they experienced as missing: "How would we recommend if we had this or that kind of data?" The participants also considered ways of displaying the data to enable more intuitive or easier computations.

The participants faced three computational issues. The first concerns the formulation of abstract calculation rules: "How to design a rule independent of the data at hand so that it is applicable to other videos or profiles?" The second concern has to do with the definition of an efficient computational rule: "How to design a sensible and yet manageable rule in terms of resources, to produce rankings within a reasonable time period?" The third concern is related to the difficulty in anticipating computational results: "How to make sure the rule is stable and robust enough to produce the expected effect in all circumstances?"

This first cluster of issues draws the contour of a first media education goal: understanding how data collection and algorithm designs are far from being neutral or objective and that they depend on human decisions. The activity provided participants with a unique opportunity (1) to interrogate the various kinds of data that are being collected about them and the various meanings that can be attributed to these bits of information, and (2) to interrogate the social norms and values that are embedded in the calculational rules devised by engineers and the companies employing them. The educational activity enabled participants to experience these situations, essentially leaving the explicit articulation of such teaching to media educators.

Cluster 2: Personal Tastes and Recommendations

The participants often encountered difficulties when discussing personal tastes and recommendations. The main point of contention in discussing personal tastes has to do with the difficulty of defining and explicitly stating them. When designing or evaluating recommender systems, the participants often mobilized their personal tastes or common *clichés,* simultaneously acknowledging how little relevance these might have for them; and when discussing the possibility to partially capture one’s tastes through computational rules, they often insisted on the ever-evolving character of personal tastes. More generally, the participants, when reflecting on the difficulties to provide a coherent account of their personal tastes, repeatedly noted their “illogical” character.

The second cluster of issues draws the contour of a second media education goal: personal tastes should be thought of as dynamic constructs which emerge from interactions between humans and environments, and they constantly evolve and are reconfigured. The activity offers the media educators with the opportunity (1) to equip participants with subtler concepts for discussing the formation of personal tastes or opinions, and (2) to nuance the capacities of recommendation algorithms to satisfyingly deal with the complexity of human tastes. The educational activity brought all these tensions to surface, leaving their resolution open to the participants and the media educators.

Cluster 3: Digital Platforms and Recommendations

The participants often voiced concerns about how recommendation algorithms affected their media practices.

The first set of issues concerns the computational rules designed during the game sessions. The participants were often led to vivid arguments about the variety and importance of criteria that could and should be used for recommending items to people. Interestingly enough, the participants gradually made sense of the available descriptive data (e.g., about the videos or the profiles subjected to recommendation) in the light of normative objectives (e.g., please the user, make money, and be fair).

The second set of issues specifically concerns YouTube’s recommender system. The first issue, invariably expressed, concerns the dissatisfaction they experienced regarding YouTube’s recommendations. The second issue was commonly mentioned and showed a clear awareness of YouTube’s commercial objectives and policies (e.g., changes in the monetization of content). The third issue was less commonly brought up and had to do with users being unable to escape the capture of attention.

The third cluster of issues draws the contour of one more media education goal: recommendation processes, inasmuch as they are both social and technical constructs, need to be understood with regard to the audiences they address and the objectives they serve. The activity provides media educators with a unique opportunity (1) to foster reflection on the main objectives that the recommendation algorithms of digital platform serve, and (2) to broaden participants’ perspectives on the place of recommendation algorithms amidst more traditional recommendation processes ranging from radio broadcasting to critical reviews.

3. Second Case Study: Let's Make YouTube Algorithms!

1) Description of the Different Versions of the Game

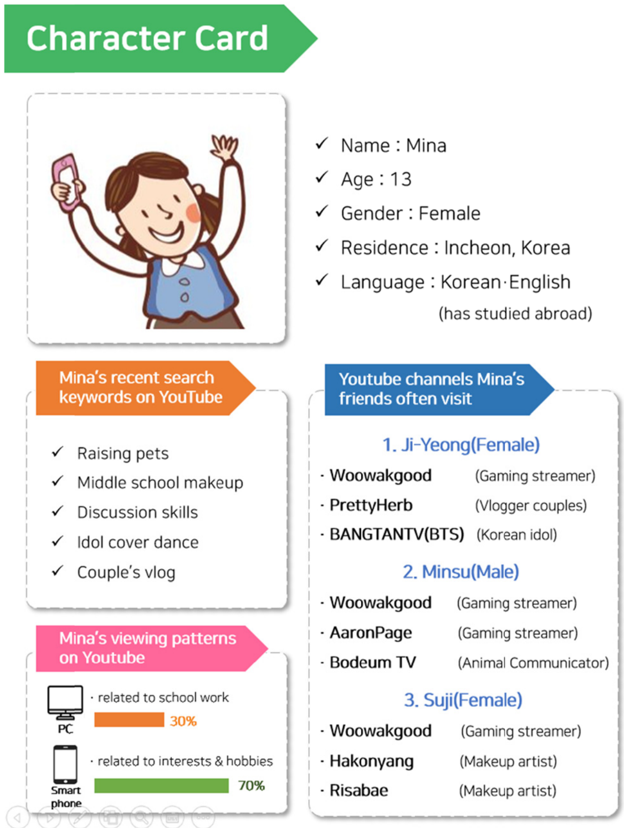
The development of the South Korean version of the game began after the Belgian researchers translated the original French-written game into English to help the Korean partners understand the overall aim, structure, components, procedures, rules, and the datasets of the game. By sharing a Google document and holding a video conference with the Belgian team, the Korean researchers and educators understood the goals and the core principles of the game. While the Korean version of the game shares the pedagogic purpose with the Belgian one, it had to be recontextualized to reflect the Korean youth culture's use of YouTube and to simplify the activities of the game so that it can be accommodated in Korean classroom environments.

There are two main differences in the Korean version of the game. First, while the genre of the videos to recommend is limited to music in the Belgian game, the Korean version includes more diverse genres such as game, music, and know-how/style, reflecting the actual use of YouTube content by the South Korean youth. The report of the Korea Press Foundation shows that South Korean tweens and teens mostly interact with games, music/dance, television drama/entertainment, food/cooking, movies, and sports content (Kim & Lee, 2019). Considering these characteristics, the list of recommended videos was prepared by reflecting various YouTube genres that interest Korean teenagers.

Second, while each student group is required to create a recommendation algorithm based on a different kind of dataset in the Belgian version, students are asked to play the game with the same dataset, albeit in different groups, in the Korean version. To be precise, the students are divided into small groups and requested to create recommendation algorithms based on the same dataset and present the results to the whole class. In Korean classrooms, teachers and students are familiar with working in small groups for discussions and presentations. The Korean version of the game was designed to help students understand that even with the same dataset, the processes and outcomes of the algorithm development could vary depending on the value judgments of the algorithm developers.

In the Korean version of the game, students are asked to make a calculation to recommend video clips to a fictional student named "Mina," by using information on the character as well as video clips. Contained in a box as if it were a board game, three game materials are provided for the participants. The first material is the Game Guide which describes the mission and the procedures of the game. The mission of the game is for participant-groups to write recommendation algorithms to suggest videos that Mina would like to watch on YouTube. The participants are asked to analyze Mina’s viewing patterns, preferences on YouTube content based on the information provided on the character card, to establish a set of criteria for deciding the order of the videos for Mina to watch, to assign a relative weight to each video’s score, to rank the ten video clips in order of the score calculated, and post the videos with the individual participant’s thoughts on sticky notes on a big-sized paper to share with the whole group.

The second is Mina's character card, which includes Mina's brief personal information (age, gender, residence, and language of use), recently used search keywords on YouTube, main purposes of YouTube use and corresponding devices, and the YouTube channels frequented by Mina’s friends. The information on Mina’s character card was derived from in-depth interviews with four middle school students in the Seoul metropolitan area, which was conducted in November 2019 to reflect real adolescent persons’ YouTube culture, similarly as the Belgian version constructed the dataset based on the experiences of real teenagers. The purpose of using YouTube is largely divided into academic and personal ones, reflecting the results of the interviews with the Korean teenagers. Interestingly, main devices used also tended to be divided into PCs and mobile devices depending on the purpose, as shown on Mina’s viewing patterns on YouTube on the character card. As peer interactions are important among adolescents, the character card was designed to show the YouTube channels that her friends often visited. While the Belgian version of the game provides the information on individual users and the one on the interaction of each user with other users in separate datasets, the Korean version shows the information of these two categories in a rather simpler way on the character card. Compared with the Belgian version, the Korean game also provides a range of additional information on the character card: two different main purposes of YouTube use, corresponding devices according to the purposes, the languages of the user, and the user’s “real” friends' interests.



[Figure 4] Character Card

Thirdly, it provides 10 video cards with information on thumbnail, duration, title, number of views, upload date, number of likes and dislikes, and channel names. The video cards are based on the aforementioned in-depth interviews, with three detailed selection criteria: interviewees' interests, their friends' interests, and topics that adolescents are likely to be interested in. The title of the final 10 videos also reflects the languages that can be used by Mina, the character. The examples of the selected clips are *BTS "IDOL" Dance Practice*; *The Most Popular Videos Funny Tik Tok US MEMES COMPILATION*; and *Picked Out My Girlfriend by Just Looking at Her School Uniform (Pretty Girls' School Uniform Styling)*.

The Korean version of the game was applied to a class at a girls' high school located in Incheon. After introducing the game method at the beginning of the class, the participating students played the game in groups of four to five. By exploring the information presented on character cards and video cards, the students came up with a calculation formula by setting the recommendation criteria and weight for each. Then, they ranked the 10 videos according to the calculation formula. The class ended by explaining the logic behind the calculation and the ranking as well as sharing the lessons learned through the game.

2) First results

The Korean version of the game was designed for the small groups to present their results to the whole class. Therefore, students shared their thoughts by writing them down on sticky notes, considering that it was difficult for all participating students to discuss due to time constraints. The common themes that have emerged from the students' impressions are summarized below.

I had never concretely thought about YouTube before

The students reported their biggest achievement from the activities as being able to understand how videos on YouTube might be recommended to them. Such comments were most frequently cited by both students who wrote that they were curious about YouTube's recommendation algorithm and those who said that they had not been particularly interested. Two students mentioned a popular comment meme on YouTube: "YouTube's unknown algorithm brought me here." This meme is used when users click on a YouTube-recommended video that meets their tastes, even though the recommended video does not match the users’ interests. The participants of the game expressed that they found the processes of disassembling and reassembling unknown algorithms “wonderful” and “interesting.”

This positive assessment of the game contrasts with the view that girls generally have low levels of interest and achievement in programming education (Margolis & Fisher, 2002). There seems to be three main reasons why the participants had positive experiences, unlike the existing assumptions. First, the game is based on YouTube, which is used repeatedly in adolescents’ real lives. Therefore, the participants might have been interested in the game that required them to make a YouTube recommendation algorithm. Second, the game requires students to analyze Mina, who is a fictional character but still someone that the participants could relate to. Lastly, students produce a simple calculation formula, which can be immediately applied to generate tangible results. Margolis and Fisher (2002), who conducted research to increase the proportion of female students majoring in Computer Science at the Carnegie Mellon University, argue that girls conceptualize programming as a way of solving problems that are close to real life and not as an abstract activity far from realities. While this game was not developed as a means of learning programming, it could be an effective approach for students who recognize programming as a solution to specific problems, if it could include the aspects of learning about programming.

The more deeply I think, the more diverse algorithms I create

Some students found that the orders of videos they intuitively ranked at the beginning of the classes were similar to those decided by a group decision. On the contrary, some students found that their criteria and others' were different, which led to "feeling embarrassed" or "leaving strong impressions."

While some students went beyond the fragmentary responses to the experience of differences and recognized that the results could be different, even if the algorithm was developed for the same purpose, due to the difference in value and complexity of the criteria for ranking. One student said, "I was impressed that the deeper I thought, the more diverse YouTube algorithms I could create. I learned that algorithms are complicated, because there are more things to consider than I thought."

As described before, the Korean version of the game requires all small groups to use the same kind of datasets to help learners understand the significance of value judgements by algorithm developers. Some students' reflections of the game suggest that the game can help them take a critical stance on taking a given algorithm for granted and recognize the human values playing a role in its selection and construction.

Link to the critical understanding of an algorithmic world

There was a relatively small number of students who have extended their thinking to critical evaluation of the algorithmic world, beyond contemplating the development process of algorithms and the values of developers laden in them. One student wrote, "While it is convenient to find videos of my interests through algorithms, I also get a little bit of fear thinking algorithms seem to know me better than I do." Although this is a personal concern, it seems to show that the game might have led to discussions on user-related issues in a data-driven society, such as the collection and profiling of personal information for the development of algorithms.

Another student wrote, "When I looked at recommended videos based on algorithms, I came to think about whether I am taking disinformation as it is, and whether it would become social distrust as the disinformation spreads in groups." This game was developed not as a one-time game of two hours but with the consideration of adding briefing and debriefing sessions before and after the game. It has wide scalability with small variations on game descriptions, virtual characters' information, and small video cards. For example, the current game description instructs students to rank videos in the order Mina would like to watch; however, students' experiences can change by asking them to rank videos in the order that they would like to watch. The ultimate goal of the Korean version of the game is to go beyond critical thinking about algorithms and help students understand the algorithmic media environment and its impacts on human life by incorporating political and economic perspectives. The critical perception of the algorithmic society mentioned in the students' reflection notes shows that this game can extend to literacy education on digital platforms, beyond algorithm literacy education.

Ⅳ. Discussion

The two case studies presented in this paper illustrate how an international collaboration may fruitfully address some of the contemporary issues raised by an increasingly globalized digital media landscape. The results of our research and the educational project presented here, insofar as they were produced by researchers and practitioners from different disciplines and countries, call for opening a preliminary discussion, contrasting the educational activities developed as well as, and perhaps more tentatively, the media experience these latter revealed, i.e., how youngsters might use and represent recommendation algorithms.

The early results show that core elements are shared across borders. The recommendation algorithms appear to be invariably experienced by participants as particularly influential in media consumption and particularly difficult to apprehend. In that regard, the educational activities seem to have succeeded, as spontaneously expressed by several participants, in fostering an intuitive understanding of recommendation algorithms and in facilitating discussion on alternative forms of algorithmic recommendations. This can be considered as an achievement of the core educational principles implemented in both the Belgian and the Korean educational versions.

However, the early results also show that the different contexts and activities displayed and produced significant differences. The main difference concerns participant engagement. The Korean students, although most were puzzled by the importance of engineering decisions and their deep entanglement with social issues, more rarely critically assessed the digital landscape they inhabit. The Belgian students would, by contrast, frequently argue, rather vividly, over the choices that were made or could be made by the digital platforms designing recommender systems.

These differences in kinds of engagement can largely be explained as differences in *classroom cultures*, in *media education* and in *game versions*.

First, the difference in classroom cultures may, to a certain extent, be understood as a contrast between the place of students’ debates within educational activities. The more debate-oriented Belgian classroom culture, on the one hand, gave rise to an activity leaving considerable time for discussions, providing participants with little instructions (and minimal support from the educators) to encourage them to collectively face and address all questions regarding recommendation algorithms that mattered to them. The less debate-oriented Korean culture, on the other hand, called for a more structured and guided educational activity where participants would receive a relatively detailed description (as well as results from the previous piloted sessions) of the game to suggest how they could design, fairly concretely, their recommendation algorithm.

Second, the difference in media education can be approached, in part at least, as a contrast between the institutionalization levels of media education.

The advanced institutionalization of media education in Korea (i.e., the significance of government funds and of media centers) (Yoon, Jeong & Kim, 2019) propelled the Korean team to develop an educational activity that could be passed over to a large number of educators and whose outcomes could be readily measured. Thus, as overt instruction gains importance as a pedagogical approach to multiliteracies—along with situated practice, critical framing, and transformed practice—more interventions were made through the Game Guide to scaffold students' learning activities. The less strongly institutionalized media education initiatives in Belgium made it less urgent to develop an off-the-shelf activity, encouraging educators to focus instead on unleashing the participants' critical abilities.

The differences in institutional contexts equally led to differences in the games' unfolding. The Korean version would typically seek to guide the students' reading of the data, by making easier the linkage between the videos selected and the terms searched or by categorizing the videos by topics and formats (e.g., preventing students from pondering nuanced qualities such as artistic tastes). The Belgian version, by contrast, would seek to expose participants to frictions by deliberately choosing videos with strong emotional investments to stimulate discussion amongst them (e.g., confronting subtle and sharp taste judgments with rigid and flat formal calculations).

Third, the difference in the games' versions can largely be understood as achieving a different balance between two main objectives: accessibility for the younger public and adequacy of recommender systems. While the Belgian version of the game privileged an educational activity closer to recommendation practices, restricting the age of participants to 16 years old or above, the Korean version of the game, relaxing the adequacy objective, could easily be adapted for younger ages. Thus, for instance, the data staged in the respective versions of the game would significantly differ. The Belgian version would expose participants to a broader variety of data, e.g., often numerical data about videos, channels, and users. Instead, the Korean version offered basic and descriptive information, intuitively duplicating the actual first page of YouTube.

The discussion showed how a debate-based classroom culture, variously institutionalized media education initiatives, and slight variations in the concrete aims of the game versions inflected the development of the educational activities in different contexts. In a nutshell, the Belgian version sought to engage students in active discussions and appeared to be closer to engineering practices; however, it was much harder for participants to approach or for educators to use. The Korean version, sought to provide students with a sense of achievement through the completion of tasks and was more structured; thus, it was easier for students to approach and simpler for educators to use. However, both appear equally successful in enabling participants to acquire an intuitive understanding of recommendation algorithms and reflecting upon digital platforms.

Ⅴ. Conclusion

Limits

This exploratory educational and research project paves the way for further research and inevitably had several limitations.

First, an unerasable gap persists between the kinds of recommendation algorithms developed by the digital platforms and the kinds of recommendation algorithms developed in the course of the educational game. The recommendation algorithms are inaccessible, because they constantly evolve; are tuned all the time by the platforms' engineers; particularly valuable and may be subjected to trade secrets; and unavoidably complex, mobilizing hundreds of engineers. Furthermore, the educational activity leaves out a central aspect of recommendation algorithms; most belong to a range of techniques thought to belong to “machine learning” or “artificial intelligence.” However, the focus on the actual definition of the recommendation problem rather than on the actual techniques aimed to address it does its part in achieving a meaningful balance between overly complex and overly simplified versions of recommendation practices.

Second, the “development, implementation and re-searching” of the design-based “pedagogical approach” raise an important methodological “challenge” (Barab & Squire, 2004, p.10). The core difficulty has to do with the researchers' practical involvement in the process, which provides researchers an intimate knowledge of the educational dynamics (Anderson & Shattuck, 2012) and mitigates researchers' theoretical commitment to its evaluation. Extensive empirical analyses and evaluations of the educational activities are expected to be carried out in the context of another publication. However, the presentation and comparison of the Belgian and Korean case studies offer a rudimentary opportunity for more thoroughly reflecting upon the design decisions made and contrasting the differences that might be attributed to classroom cultures, media education traditions, versions of the game, or the common framing of the educational activity.

Lessons learned

Despite its limited scope, the project revealed valuable insights in terms of expanding media education to include a critical understanding of recommendation algorithms. Educators should keep in mind that addressing such a complex issue might, at first glance, discourage some teenagers who find this subject too complex to deal with. This was especially the case for participants with lower levels in mathematics or computer science. Despite these difficulties, in all case-study participants managed to design a recommendation algorithm, although very simple, with the proper support from the educators.

Our game sessions showed that youngsters tend to focus on economic problems, leaving out others such as cultural or political concerns, which are raised as quite serious issues regarding YouTube’s recommendation algorithms (Oh & Song, 2019). Some also tended to use simplistic judgments ("it's good," "it's bad") to express their opinions, which show a room for an opportunity to develop a more nuanced understanding of this issue. Educators should help teenagers to create more complex and informed representations of the technical dimension of recommendation algorithms as well as their impact on individuals and societies. To do so, it is crucial to consider that youngsters already know and have an experience of recommendation algorithms. These representations and experiences can be used to anchor such activities in their daily lives. On that basis, educators may want to help teenagers to gain more solid and focused knowledge on the issue of recommendation algorithms in digital platforms as well as to take a step back to see the "big picture" of algorithms and the societal challenges they raise. In this process, helping them to think about alternative forms of recommendations, algorithms designs, data or objectives, seems particularly meaningful.

Perspectives on Future Research

This project will be further refined by adding instruction and class activities that overcome the aforementioned limitations. In particular, the main consideration in the future endeavor for improvement is a critical understanding of the historical and socio-cultural contexts of YouTube’s recommendation algorithms. The basis of YouTube recommendation algorithms has changed from traditional data mining to deep learning, and it will continue to evolve. The follow-up research needs to be designed to encourage students to explore the historical trajectory of algorithm development and recognize the human and technological forces driving those changes.

Furthermore, future research should include debriefing and discussion activities that delve into how the YouTube recommendation algorithms that students have made affect individuals (e.g., information bias and confirmation bias) and societies (e.g., social inclusion and growth of democracy). The current version of the program is well suited to understand that algorithms are social constructions rather than inevitable answers to given problems. With this basic understanding that algorithms are contingent to changes, students can exercise agency to change the algorithms in positive directions. Ultimately, future research should examine the ways in which students, as citizens living in the age of digital platforms, can take actions to produce such positive outcomes.

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