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„ TikTok Videos and Indeterminacy: The Influence of Autonomy, Sensation Seeking, and System-Justification on the Preference and Liking of Algorithmic Selected Content."

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Abstract

Social media platforms, like TikTok, use algorithms to predict the perfectly suited content for each user and determine what they will see. But do users always want determinate perfection? Indeed, research assumes that people prefer imperfect indeterminate processes. In this study, I assume that the possibility of interrupting determinate processes attenuates the preference for indeterminate processes. The possible interruption could create autonomy, which is according to the self determination theory an essential psychological need. I examined if there is a higher preference for determinate algorithmic selected TikTok videos when they are combined with indeterminate random selected TikTok videos compared to only algorithmic selected TikTok videos. It is suspected that this preference is greater when people cannot autonomously swipe through the videos compared to when they can autonomously swipe. To test this effect a platform was created where an algorithm was trained to show each participant suited TikTok videos. First participants saw only algorithmic selected videos and then they saw algorithmic selected videos combined with random selected video. Results revealed no higher preference for algorithmic selected videos combined with random selected videos when users cannot swipe. Other than expected participants that could swipe showed a higher liking in the algorithmic selected videos combined with random selected videos than participants that could not swipe. Further, the connection of the preference for the algorithmic selected videos combined with random selected videos and individual differences in the personality was looked closer at.

Keywords: algorithm, autonomy, indeterminate process, determinate process, indeterminacy, sensation seeking, system justification

It talks to you, responds to your question, and recognizes your voice and face. On top of it, it often knows exactly what you want. Who might it be? No, it is not a close friend. It is not even a person. Just made by persons to copy human beings: It is artificial intelligence (AI) (Kersting, 2018).

AI is very present online; it is making personalized decisions for every user. However, this presence also means that humans have less influence on the decision-making process. The question however is, if people want these easy decisions by AI or do they want to decide for themselves? In this study, I will look closer if autonomy influences the liking and preference for algorithmic decisions. Moreover, also the effect of the personality traits sensation seeking, and system justification on the preference and liking of algorithmic decisions will be looked closer at.

Buiten (2019) states that AI is becoming increasingly important in many scientific fields and in daily life. AI is used to detect cancerous cells (Al-shamasneh & Binti Obaidellah, 2017), to predict earthquakes (Fuller & Metz, 2018), and to construct social robots for the care-taking system (Ray, 2022). On the other hand, it also made some terrible decisions, i.e., the chater bot Tay had to be switched off because of racist, inflammatory, and political statements (Hunt, 2019). Buiten (2019) says that algorithms consist of a set of rules or instructions to whom a computer follows. Solving a problem can be done by prioritizing, classifying, associating and/or filtering items. Systems with machine learning algorithms can learn (Jarrahi, 2018). The program not just applies the rules but finds patterns in the data and implements them in the instructions (Buiten, 2019). Koen (2019) states that by reviewing and statistically analyzing the data sets, algorithms come to a decision. This algorithmic decision making is a revolution, given that the decision-making processes till now was exclusive to humans. While people have a holistic and intuitive approach to decision making (Jarrahi, 2018), AI is more analytical, dependable, easier, time-efficient, and less costly (Kwan, 2021). Further, Jarrahi (2018) states that complex situations require to consider many variables. Managing this mass of information at a high speed is not possible for even the smartest person. In complex tasks, AI shows more quantitative, mathematical, and analytical skills than humans.

Thus, machine learning algorithms can provide the perfect solutions when they are not based on biased data. Given that machine learning algorithms calculate a solution based on pre known data sets their final decision is determinate. However, a study by Vosgerau et al. (2006) shows that people prefer indeterminacy in situations where the process rather than the results matters. Indeterminacy means that it is not pre known what will happen. It is not planned and thus not always perfect. People show a preference for imperfection. They prefer to see a concert live rather than taped and edited to perfection. I assume that the preference for indeterminate processes mitigates when people can interrupt a determinate process. This possibility to interrupt a process gives people the possibility to decide for themselves and therefore could create autonomy, which leads to positive emotions. The self determination theory (SDT) states that autonomy is a basic psychological need for well-being (Ryan & Deci, 2017). Does autonomy influence the preference for indeterminate processes?

In this present thesis I will look closer at the influence of possible autonomous decisions on the preference of indeterminacy. The investigation uses videos from the social media platform TikTok. In this study two sequences of Tik Tok videos were shown to the participants. The first sequence consists of determinate videos, that are selected by an algorithm. The second sequence consists of indeterminate videos, that are a combination of algorithm selected and random selected videos. Some users will be able to interrupt the videos by swiping autonomously through the sequence, others will not be able to swipe forward autonomously. Further, also the relationship of the preference for indeterminate processes with the personality traits sensation seeking and system justification will be looked closer at. Till now the relationship of autonomy, sensation seeking, and system justification with algorithms, as they are on social media, has never been investigated. Thanks to this study it is possible to gain greater knowledge about these relationships and so bring the following advantages for users: It can help to get the best predictions from the use of algorithms and thus supply an even better experience. Further, it can also be a help for politicians to protect users from negative consequences of algorithms. And finally, it can help to understand how people react to algorithmic decisions and thus built a future where humans understand and know how to manage algorithms more to their advantage.

Theoretical Background

Algorithms and Social Media

In everyday life algorithms are used on apps and on social media, where they predict suited content for every user, as stated by Jewiss (2021). They calculate what users will like based on data a person previously interacted, trends and sponsored posts. Beyond that it can also include posts liked by users' friends, the search history of a person and how long they looked at posts. The selected content by algorithms is so good that the consequences of them are noticeable through data mining, filter bubbles, and social media addiction.

Data Mining

An algorithm can only work well when it has some data about the user. However, collecting personal information of people can have negative effects if it gets misused. According to Van Wel and Royakkers (2004) the personal data mining by the algorithm is a risk. Data mining refers to the technique to automatically collect information about a user. This technique can then be misused for companies to have greater knowledge of their possible costumer and so misuse data for a greater success. Therefore, data mining threatens privacy on the internet and on social media.

Filter Bubbles

Further, the target of algorithm is to show consumers only what suits them. This is how they filter information, and thus filter bubbles emerge. The term filter bubble is used to describe the phenomenon of polarization on social media platforms (Pariser, 2011). According to Spohr (2017), algorithms are causing filter bubbles and thus make some information more accessible than others. More and more people use social media to read news and get information. However, filter bubbles on social media increase ideological polarization and are often connected with fake news. This effect of one-sided information could be avoided if people would not get limited information due to filter bubbles (Spohr, 2017). While algorithmic selected information may restrict people's autonomy (Zuiderveen Borgesius et al., 2016), self-selected information may enhance this autonomy. Another study by Nikolov et al. (2015) found evidence that the information reachable through social media is significantly lower in heterogeneity than through a search baseline and thus reinforces collective filter bubbles. Besides ideological polarization also addictive behavior might be a result of filter bubbles and content that suits user.

Social Media Addiction

Further, as explained previously algorithms are trained continuously – meaning they adapt each time a user interacts with them (Jarrahi, 2018). Depending on how much a user interacts the algorithm gets more adapted to the individual preferences. Further, well adapted algorithms also mean a greater risk for an addiction on the platform (Yampolskiy, 2018). Social media addiction refers to the phenomena of maladaptive social media use, according to Sun and Zhang (2021). Its symptoms are addiction-like behaviour and/or lower self-regulation. It is associated with low work performance, less healthy social relationships, sleep problems, low life satisfaction and feelings of anxiety, depression, and jealousy.

All in all, algorithms build a suited online world for every user. The user must interact with an online platform and the algorithm then searches the suited content (Jewiss, 2021). Given that the algorithm decides the user's content on preselected data, it is determinate. Determinacy means that what will happen next is already decided in advance, while it does not necessarily mean that consumers know what will happen next (Vosgerau et al., 2006).

Do People Want Determinate Content on Social Media?

On one hand users seem to enjoy their suited content with all its negative consequences such as data mining, filter bubbles, and social media addiction. On the other hand, there is evidence that people do prefer imperfection and indeterminacy (Vosgerau et al., 2006).

Seeking Imperfection and Indeterminacy

Determinate algorithmic selected content is suited for users because it is specifically selected based on what users like (Jewiss, 2021). However, people might prefer indeterminate content, meaning random content that is not based on previously selected data. In some situations, people prefer imperfect indeterminacy over perfect determinacy, as found by Vosgerau et al. (2006). The preference for imperfection and indeterminacy is given when the focus is on an event's process. However, the preference for indeterminacy does not show when watching an outcome-oriented event, such as lottery. A soccer game is per se indeterminate when watching it live. However, when consumers watch it taped than it is not indeterminate anymore given that the event already took place, and a decision has been made.

Indeterminate content might be more thrilling for consumers than determinate content because indeterminate content is not predefined. When possible unsuited content is shown, users might feel the urge to be ready to swipe the content away if it is not a fit. Vosgerau et al. (2006) stated that indeterminate events are associated with excitement, cued by the unknown of how an event will unfold. Excitement is entailed by action readiness. Frijda et al. (1989) states that action readiness links the experience and the emotion together and is the actual state of the behavioral readiness. There exist different states of action readiness which depends on the readiness or unreadiness of the individual to intervene in its environment. Also, the feeling of being in control has an influence on excitement. The excitement is low when people feel helpless and not in control (Vosgerau et al., 2006).

Uncertainty Effects

Predicted content is determinate, although only the algorithm knows the calculation and the future results. As claimed by Vosgerau et al. (2006), an event must be internal and external uncertain to be defined as indeterminate. Thus, algorithmic selected content is determinate and therefore less exciting. An explanation for it could be the missing uncertainty of what will happen next. Further, predicted content could also bring up rather negative emotions given that the algorithm knows what will happen, while the user does not. As explained by Brun and Teigen (1990) predictions are found more exciting than post-dictions. Also, wrong predictions cause less discomfort than wrong post-dictions. The preference of predictions is caused by the internal and external uncertainty an event has: internal uncertainty is more accepted when dealing with an external uncertainty rather than an external fact which brings up negative emotions.

However, sticking to algorithmic selected content should be always a winning situation because it shows what the user likes. Instead, a random content might be risky, there could appear a lot of not suited content. Moreover, people usually have a risk-aversion in a domain of gain and uncertainty can be seen as such a risk (Shen et al., 2018). However there exist exceptions where the risk aversion does not happen. When dealing with uncertain incentives, as stated by Goldsmith and Amir (2010), people can have the same positive attitude as for the best possible outcome of this uncertain incentive when they are absent of thoughtful consideration. When doing more consideration or when being in a context that evokes more consideration this effect can be negated.

People can use social media in two ways. They can either search for something specific or just get entertained. When they do specific research the outcome matters. But when people use social media for entertainment not the outcome but the process of entertainment matters. Here uncertainty plays a bigger role because for people it is uncertain what they are going to see. Shen et al. (2015) found that people spend more money, time, and effort for an uncertain reward than for a certain reward where the value is also expected to be higher. However, the effect can only be observed when the focus is on the process instead of the outcome. This motivational-uncertainty effect underlines the preference for uncertainty when being process-oriented. Shen et al. (2015) underlines that when being outcome-oriented, people get negative feelings (aversion) towards uncertainty when an uncertain prospect can be valued less. But, when being process-oriented people get positive feelings (excitement, interest) towards uncertainty when uncertain prospect can be valued more than its best outcome. When people are working towards an uncertain goal, this unresolved uncertainty stimulates extra positive energy (Shen et al., 2018). So, as found by Shen et al. (2015) before an auction bidders valued a bag higher when they knew what was in the bag. During the auction they found the unrevealed bag more motivating. So, the certain reward was valued higher before the auction, where the outcome mattered. However, during the process of the auction the uncertain reward was valued higher. These finding underlines that the focus on the process is crucial for the preference for uncertainty.

The question is if repeating such a process influences the preference for indeterminacy? This question is crucial to clarify whether social media users still prefer indeterminacy after repeated use. Shen et al. (2018) found a reinforcing-uncertainty effect when dealing with repetitions. After each repeated shot comes the opportunity of resolving the uncertainty. Thus, repeating the procedure is additionally to the material reward, also a mental reward. That is why people prefer repeating an uncertain incentive with its lower material, but also mental reward, instead of a certain incentive with just a higher material reward.

So, researchers have shown that humans get excited when they feel in control of an uncertain process and need to be ready to act (Vosgerau et al., 2006; Shen et al., 2015; Shen et al., 2018). This action readiness is why they prefer an imperfect indeterminate process over a determinate process (Vosgerau et al., 2006). Further, when focusing on the process uncertainty can push the motivation to invest more money, time, and effort (Shen et al., 2015), and additionally reinforce the repetition of an action (Shen et al, 2018). I assume that this feeling of being in control and the action readiness is in line with acting autonomously, meaning not letting an algorithm decide for oneself but being ready to decide on one's own.

Autonomy in the World of Algorithms

On one hand, algorithms challenge the autonomy of users by deciding for them (Dogruel et al. 2020). On the other hand, an algorithm may also be useful by showing what users want to see or also just by helping them to find what they want to see. Autonomy describes the need to self-regulate one's experiences and actions, according to Ryan and Deci (2017). It is based on voluntary, congruence and integration.

Awareness of Algorithmic Decision-Making

According to Dogruel et al. (2020) algorithms can support the users` autonomy when helping with the decision-making process by offering information about alternatives and acting as an automated and efficient long arm of users. However, in this case algorithms can also be controlling when offering alternatives based on a third-party interest and not on the users' desire. The lack of control and opaque workings of algorithms are critical for the autonomy of the users. The algorithmic procedures and underlying criteria are invisible and remain largely unknown for the users. According to Dogruel et al. (2020), users can be divided into three groups when asking about their definition of algorithms. The first group realizes that their online behavior is being tracked to personalize content and recommendation, but they miss the technical understanding of the algorithm. The second group has a technical approach and describe algorithms as computer- based mathematical programs, or operations to analyze data and process data automatically. Lastly, uninformed participants were often aware of algorithms, but they could not explain the term. Depending on the context more transparency and explanation on how algorithms are working can help to enhance the users' autonomy.

Self-Determination Theory

Even though the content provided by algorithms is determinate, the feeling of acting autonomously is to a certain extent given on social media. Users need to swipe and like to feed the algorithm with data (Jewiss, 2020). There is evidence that when users feel in control of interacting, they do not notice of how much the algorithm guides their experience (Dogruel et al., 2020). Thus, they might feel more autonomous than they really are.

Further, the possibility for autonomous interaction might stimulate positive emotions in users. According to the self-determination theory by Ryan and Deci (2017) autonomy is a basic psychological need. The theory describes human motivation, and personality in social contexts. Its focus is on intrinsic factors for individual development and within social contexts that enhance vitality, motivation, social integration, and well-being and on its counterparts which provoke antisocial behavior and unhappiness. These factors are autonomy, competence, and relatedness. All these basic psychological needs need to be satisfied for well-being.

Autonomy is given on a certain degree on social media because people can interact. However, the question is how would users enjoy their social media when they were not able to interact anymore? The reactance theory by Brehm (1966) states that if people's behavioural freedom is being reduced people will try to get it back. This motivation to restore one's freedom puts people in an unpleasant state of anger and negative cognitions (Dillard & Shen, 2005).

The Importance of Swiping and the Preference of Random Selected Videos

People can swipe through their TikTok content. Thus, they can decide whether they want to watch a video or whether they want to go on. By swiping they can easily interrupt the determinate video and jump to the next determinate video. Through this interaction they are still free to decide what they see and thus have some degree of autonomy in their choice – even though the next video is also determinate by the algorithm. If the possibility to swipe is taken away from people, according to the reactance theory (Brehm, 1966) it should put people in an unpleasant state, and they should want it back. I assume that the possibility to swipe, and therefore being autonomous, can influence the preference for indeterminate processes.

A simple example of indeterminately selected videos would be completely random videos. However, I assume that only random selected videos might not be so entertaining and exciting. Therefor as an indeterminate process I chose for this study to take TikTok videos selected by the algorithm combined with random selected videos. This way there is still some fitting content chosen by the algorithm, but also some random content in it which makes the process indeterminate. Further, it is not clear if the next video is selected by the algorithm or randomly. Given that people prefer indeterminate processes, as stated by Vosgerau et al. (2006), I assume that people prefer algorithmic selected TikTok videos combined with random TikTok videos over only algorithmic selected TikTok videos.

I hypothesize that the feeling of autonomy influences the preference for indeterminate processes. More clearly: the possibility to swipe influences the preference of algorithmic selected videos combined with random selected videos. When people cannot autonomously swipe, they should prefer the algorithmic selected videos combined with random selected videos more than people who can autonomously swipe. People that cannot intervene must watch what the algorithm shows them, and they have no influence on it. However, if they can intervene, the algorithm is more in the role of suggesting a video and users can swipe further if they do not like it. Thus, they get to see good, fitted videos and can also decide what to watch. This effect of autonomy should be visible as the preference and liking of algorithmic selected videos combined with random selected videos over only algorithmic selected videos. Based on these assumptions I deduce the following hypotheses.

H_1: The preference for algorithmic selected videos combined with random selected videos over only algorithmic selected videos is greater when users cannot swipe, as opposed to when users can swipe.

H_2: Algorithmic selected videos combined with random selected videos are more liked over an only algorithmic selected videos when users cannot swipe compared to when users can swipe.

It is important to mention that not every person reacts the same way to a threat of freedom, some might react stronger to not being able to swipe any more than others. Therefore, personality traits might also be important to be looked closer at. The reactance depends on the importance of the freedom and the how big the threat is (Steindl et al., 2015). Research has observed that high psychological reactant people have problems to accept obligations, other's beliefs, and rules (Dowd et al., 1994). Further, for high psychological reactant people such as for high sensation seeker a dogmatic language style is already perceived as a threat (Quick & Stephenson, 2008). Further, there was found a positive correlation of autonomy and sensation seeking (Zuckerman & Link, 1968). Having the freedom to swipe or not to swipe might be more important to people who are high autonomous and seek different stimuli and sensations. Therefore, the effect of sensation seeking in the context of the influence of autonomy on the preference of indeterminate processes should be looked closer at.

Sensation Seeking

While some people might not mind watching the same or similar videos, there might also be people that find it boring and want to see different videos, even though they might not be all entertaining. I assume that depending on the personality the preference for indeterminate algorithmic selected TikTok videos over only selected TikTok videos varies. The best levels of stimulation differ from person to person and is a basic personality trait, as stated by Zuckerman et al. (1972). Sensation seeking describes a person that needs a varied, complex, and novel sensations and experiences to keep an optimal level of arousal. It is also connected with the willingness to take physical and social risk for such a high arousal stimulation (Zuckerman, 1994). As Zuckerman (1990) stated, high sensation seekers show stronger physiological orienting response to novel stimuli with moderate intensity and especially when of specific interest than low sensation seekers. Low sensation seekers tend to show defensive response when dealing with novel stimuli. Further, high sensation seekers and low sensation seekers have different biological strategies on how to process new or strong stimuli. Intense stimuli rise high sensation seekers' cortical reaction and reduces those of low sensation seekers. As explained by Norbury and Husain (2015), high sensation seekers show high tonic dopamine levels and a hyper-reactive midbrain dopaminergic response when they get signals that soon a reward will be received. This diverse neurological response by low and high sensation seekers may cause a different approach-avoidance reaction to the same intense stimuli and it explains the preference for intense stimuli for high sensation seekers. Additionally, Tapia León et al. (2019) found that highly stimulating task that require risky behaviour provoke a higher neural activity in high sensation seekers. On the other side moderate stimuli show the optimal stimulation for low sensation seekers. According to Blum et al. (2020) high sensation seekers show a reward deficiency, meaning that their brain shows a dopamine resistance and so a deprivation of the brain's reward and or pleasure mechanism. This syndrome manifests when people are not able to derive reward from everyday activity. Therefore, high sensation seekers might search for higher stimulating situations (Tapia León et al., 2019).

When an algorithm is trained to show what people like, it will find out that some people like varied content with higher stimulation, while others prefer to watch the same videos of the same category repeatedly. However, in this case high sensation seekers might still not be satisfied because the algorithm still decides for them. The findings by Zuckerman and Link (1968) show that sensation seeking also correlates significantly with field independency. High sensation seekers have a generalized sceptical attitude towards authority and are not likely to follow dominance of a given visual field. They want to be independent of their field and make their own autonomous decisions. Given that algorithms restrict the users' autonomy by taking the control and not being transparent (Dogruel et al., 2020), high sensation seekers should not be in favour of using algorithmic decisions. Low sensation seekers on the other hand might be more in favour of algorithm-made decisions: they prefer to make save decisions (Tapia León et al., 2019) and show a better acceptance of authorities (Zuckerman & Link, 1968). A person who scores high on the sensation seeking scale is enterprising and takes risks in physical, social, legal, and financial contexts to feel exciting (Zuckerman, 1979). High sensation seeker should prefer the algorithmic selected videos combined with random selected videos over only algorithmic selected videos because the random selected videos bring more various stimuli in, and it is riskier. Also, here the effect should be visible on the preference of which selected videos users would like to see and on the liking of how much users enjoyed seeing the algorithmic selected videos combined with random selected videos. Based on this theory about sensation seeking I propose the following hypotheses.

H_3: The higher sensation seeking, the greater the preference for algorithmic selected videos combined with random selected videos.

H_4: The higher sensation seeking, the greater the liking for algorithmic selected videos combined with random selected videos.

However, while some people might have a problem with algorithms because their freedom to choose is threatened and they get less variations in their content, others might be in favor of it. In the following it will be looked closer at when people might prefer determinate processes and when they prefer only algorithmic selected videos.

System Justification Theory

Users might prefer algorithmic selected videos over algorithmic selected videos combined with random ones because they are just used to see algorithmic selected videos on their TikTok. It is not because they prefer less variation and lower sensation, but more because they are used to be living in a world where algorithms decide for them what they see on social media. The system justification theory, as stated by Jost et al. (2004), is about a favorable attituded people have towards the system they live in. The attitude can be seen in ideological motives that justify the system. These ideological motives cause by degrees that low status people develop an outgroup favoritism meaning internalize themselves as being inferior. Thus, low status people are in favor of the status quo. The justification happens implicitly and unconsciously and is mostly seen in disadvantaged groups of a social order.

There are advantages for a user to go for algorithm-made decisions (Jarrahi, 2018; Kwan, 2021; Jewiss, 2021; Cunningham & Craig, 2019). However, there are also disadvantages to go for algorithm-made decisions, such as data mining (Van Wel & Royakkers, 2004), social media addiction (Sun and Zhang, 2021) and filter bubbles (Spohr, 2017). These disadvantages are likely to be ignored by users (Jost et al., 2004). They might implicitly and unconsciously come up with a justification to use the algorithm-made decision, because it is the status quo to use it. Therefore, to use TikTok without algorithmic selected videos might be threatful to system justifiers. By justifying the system people percept their current social, economic, and political arrangements as fair and legitimate (Jost & Hunyady, 2005). According to social psychology, people engaging in system justification can be divided into advantage and disadvantage groups (Jost & Hunyady, 2002). The consequences of system justification for advantaged and disadvantaged groups are increased positive affect and decreased negative affect, increased perception of legitimacy, and decreased support for social changes, as stated by Jost and Hunyady (2005). However, while advantaged groups get a higher self-esteem and subjective well-being and have further a high in-group favoritism, disadvantaged groups get a lower self-esteem and subjective well-being and show a decreased in-group, but high out-group favoritism for the advantaged group. Forerunner of system justification are a high need for order, structure, and closure, seeing the world as dangerous, fearing death and being afraid of an instable system. Mostly uncertainty and threat are a cause of developing justifications for the system and conservatism. While on the other hand, cognitive complexity and openness to new experience are not in favor of it. An explanation for this need to avoid uncertainty and threat and to justify the system is that by protecting the status quo, uncertain consequences of social change can be avoided, and people can stick to their familiarities. Disadvantaged groups prefer a known enemy, instead of a possible unknown one. It is important to mention that the need of system justification various from person to person (Jost et al., 2004).

System justifiers should prefer the determinate process with algorithmic selected videos because it is the status quo and brings no uncertainty. They would feel lost when no algorithm would help them guiding through the massive online information. Therefore, I assume that system justifiers prefer and like only algorithmic selected videos more than algorithmic selected videos combined with random selected videos. Based on these assumptions the following hypotheses are deduced.

H_5: The higher system justification, the smaller the preference for algorithmic selected videos combined with random selected videos.

H6: The higher system justification, the smaller the liking of indeterminate processes. algorithmic selected videos combined with random selected videos.

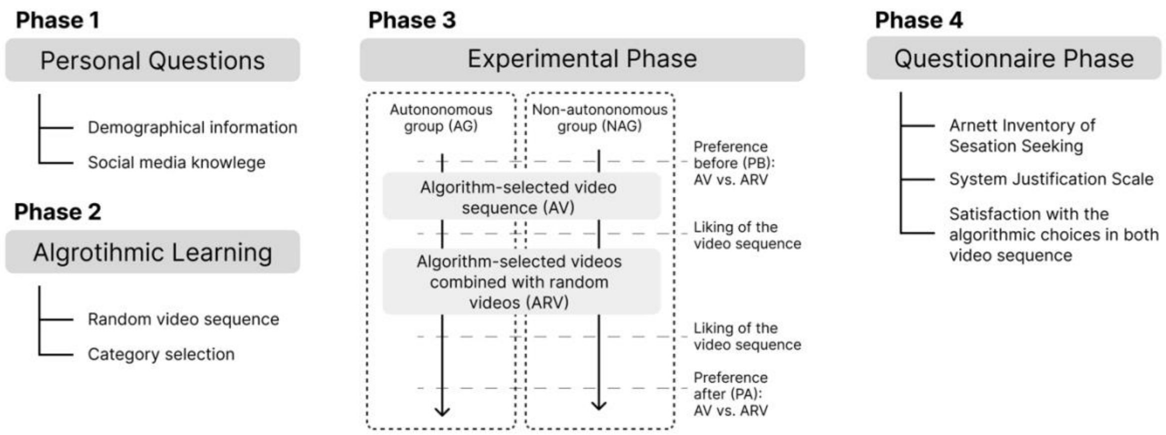
In sum, I hypothesize that not being able to autonomously swipe through TikTok videos will influence the preference for algorithmic selected videos combined with random selected videos over only algorithmic selected videos. Further, I believe that sensation seeking will show a positive relationship with the preference and liking for algorithmic selected videos combined with random selected videos, while system justification will show a negative relationship with it.

The Present Study

The present study was designed to test the preference of indeterminate processes by Vosgerau et al. (2006) and its relationship with autonomy, sensation seeking and system justification on the preference and liking of indeterminate processes. More precisely this was tested in the context of algorithms on social media. To test this an online platform was programmed that included a simple algorithm and a selection of TikTok videos. The study can be divided in four sections: demographical questions, algorithmic learning phase, experimental part, and questionnaire phase. The four phases of the study can be seen in Figure 1. First the demographical questions were asked, followed by the algorithmic learning phase. Here participants had to like and swipe through a sequence of TikTok videos to train the algorithm. Then the experimental part begun. First the general preference between algorithmic selected videos combined with random selected videos and only algorithmic selected videos was asked. Then autonomy was manipulated by the possibility to swipe through the videos: one group could swipe, the other could not. The determinate process started: it was represented by only algorithmic selected videos, that were ranked in a certain order. The ranking was calculated a priori in the algorithmic learning phase. Then the overall liking of this determinate videos was asked. Afterwards, the indeterminate process started: it was represented by algorithmic selected videos combined with random selected videos. Here still some algorithmic selected videos were part of the process, so that participants had still the possibility to see what suits them. But it can still be seen as an indeterminate process because it was not clear if the next video was random or selected by the algorithm, and some videos were totally random. Then the liking of these indeterminate videos was asked. After having experienced this, once again participants had to tell the general preference between algorithmic selected videos combined with random selected videos and only algorithmic selected videos. This experimental part was followed by questionnaires for sensation seeking and system justification. Finally, participants were asked how much they were satisfied with the selected TikTok videos in general.

Figure 1

The study design was based on four phases: personal questions, algorithmic learning, experimental phase, and questionnaire phase.



Method

Participants and Design

Participants were recruited via Facebook and WhatsApp by using the snowball technique. The software *G*Power 3* was used to calculate the needed sample size (Faul et al., 2009). For a medium effect size (Cohen's *d* of 0.5 (Bakker et al, 2019)), the sample size needed was 128. A platform was designed for the study (see appendix C) and participants could conduct the study online on any mobile device. At the end 152 participants were recruited. Out of the 152 participants 150 (91 women, 57 men, 2 diverse; age: 57.33% 18-25 years, 18.67% 26-30 years, 10% 31-50 years, and 14% over 50 years) completed the survey. Even though 60.67% never use TikTok, only 19.33% did not know the concept of TikTok videos. While 11.33% never use Instagram, similar 20 % were not familiar with Instagram Reels. Many participants had very good to excellent English (74.67%) and German (96.67%) skills.

The experiment had a 2 (video sequences) x 2 (swipe-modes) design. The video sequences, as a within-subject factor, were first only algorithmic selected videos and then algorithmic selected videos combined with random selected videos. The swipe-modes, as between-subject factor, were the autonomous swipe group and the no-swipe group. In the swipe group participants were able to swipe or click forward and backward between the videos. In the no-swipe group, participants were not able to do so. They had to watch the videos, without deciding how long/often they wanted to watch a video. The duration of each experimental part was three minutes in both video sequences. Participants got randomly assigned to one of the swipe-modes ($n_{\text{swipe group}} = 75$; $n_{\text{no-swipe group}} = 75$). Predictor variables were the video sequences, the swipe-modes (H_1 and H_2), sensation seeking (H_3 and H_4), and system justification (H_5 and H_6). The outcome variables were the general preference (asked before and after the video sequences) and the liking (asked after each video sequence).

TikTok Videos

When people make a TikTok account they can choose between categories they like. These categories where the basis for the research for TikTok videos. 305 videos were found for the study from the following 13 categories: do-it-yourself (34 videos), dance (30 videos), art (28 videos), beauty and fashion (28 videos), (domestic-) animals (28 videos), cars and more (26 videos), science (26 videos), sport (23 videos), games (20 videos), travel (18 videos), comedy (17 videos), music (17 videos), ASMR (10 videos). The most liked and viewed videos were taken. All videos beside being assigned to a category were also tagged based on features the video had. Overall, there were 47 tags, they can be found in the appendix A.

Measurements

Sensation Seeking

In this study the *Arnett Inventory of Sensation Seeking* (*AISS*) by Arnett (1944) was used to measure sensation seeking. The *AISS* consists of 20 items and is a four-point Likert scale (1 = *describes me very well* to 4 = *does not describe me at all*). The *AISS* does not contain any items that are per se age-correlating, social norm-breaking, or illegal.

Roth (2006) tested the psychometric characteristics of the German *AISS*' version on 228 students. Research showed with reliability analyses that some items should be excluded for higher internal consistency (Ferrando & Chico, 2001; Haynes et al., 2000; Roth, 2006). Roth (2006) recommends excluding the items 03, 13, and 15 (novelty), such as 02, 10, and 14 (intensity) due to not significant factor load. These items were removed in this present study. By removing the items Roth (2006) mentions that the internal consistency of the scale raises (α = .66 (total)). However, it is to notice that the reliability is still rather low. A Cronbach's alpha of around 0.7 is usually desirable, but a Cronbach's alpha of .64 – .85 can be interpreted as adequate (Taber, 2017). In this study the Cronbach's alpha of the total scale (α = .69) was a bit higher than reported by Roth (2006).

System Justification

To measure system justification, I used the *System Justification Scale* by Kay and Jost (2003). It consists of eight items. The scale is originally used with a seven-point Likert scale from 1 (*I completely disagree*) to 7 (*I completely agree*). However, a Rasch analyses by Roccato et al. (2014) shows that the seven-point Likert scale leads to inclusion of non-discriminant categories. So, the best length suggested by Roccato et al. (2014) is a four-point Likert scale (1 = *completely disagree* to 4 = *I completely agree*) to exclude non-discriminant categories. Additionally, the research showed that the *System Justification Scale* is unidimensional and shows good psychometric qualities. In this present study the items were translated into German and adapted to the topic of big data companies. A four-point Likert scale was used (1 = *I completely disagree* to 4 = *I completely agree*). In this study Cronbach's alpha of the scale was good, α = .73.

Liking

To measure liking of the presented video sequences I used as an orientation some items of a questionnaire of a study that measured a mobile gamification system by Su and Cheng (2014). A 5-point Likert scale (1 = *strongly disagree* to 5 = *strongly agree*) was used. The questionnaire was used because it showed good psychometric qualities in the study by Su and Cheng (2014), with high Cronbach's alpha of α =.95. The item S1 was the basis for question one and two of the present study, item A3 with was used as question three, and item A4 was used as question four. The translation is displayed in Table 1. The chosen items for this present study contained elements of attention and satisfaction. Attention means that participants easily concentrated on the videos. Satisfaction means that participants enjoyed watching the videos. I considered these elements essential to calculate an overall liking of the watched videos. The questions were adapted and translated into German for this study. The used liking scale showed good reliability (liking of the only algorithmic selected video sequence a = .91; liking of the algorithmic selected videos combined with random selected videos sequence a = .89).

Preference

To measure the preference between algorithmic selected videos combined with random selected videos and only algorithmic selected videos I used the same items from the questionnaire by Su and Cheng (2014) as were utilized to measure the liking of the video sequences. But, instead of a Likert scale a slider control with 7 gradations from -3 to +3 was used. On one side of the slide control there was the option for *only algorithmic selected videos*

(-3) and on the other side the option for *algorithmic selected videos combined with random selected videos* (+3). The questions were asked twice: before the only algorithmic selected videos (preference before the video sequences) and after the liking questions for the algorithmic selected videos combined with random selected videos (preference after the video sequences). Thus, they were asked at the beginning and the end of the experimental part. The preference before the video sequences and after were the equal questions. They showed good psychometric characteristics. The preference before the video sequences had a Cronbach's alpha of α =.86, while the preference after the video sequences showed a Cronbach's alpha of α =.87.

Table 1

Original items by Su and Cheng (2014) and their adapted translation.

Original item	Adapted and translated item preference/liking
S1: I enjoyed the 'Understanding of Insects' learning activities	1. Ich möchte zukünftig lieber sehen. / Ich habe die Videos gerne gesehen.
S1: I enjoyed the 'Understanding of Insects' learning activities	2. Mir würde besser gefallen zu sehen. / Mir haben die Videos gut gefallen.
A3: I can concentrate on the learning activities.	3. Reverse code: Mich würde eher langweilen zu sehen. / Mich haben die Videos gelangweilt.
A4: The learning activities aroused my curiosity.	4. Mich würde neugierig machen zu sehen. / Die Videos haben meine Aufmerksamkeit angezogen.

Procedure

At the beginning of the survey the background of the study and the duration (approx. 13 min.) were explained. Also, it was mentioned that good internet connection quality is needed, and that the collected data is anonymous and will only be used for this study. With clicking forward collecting the given data of the person was accepted.

Then demographical questions were asked: age, sex, country, German, and English skills, and if participants know TikTok and Instagram and the concept of TikTok videos and Instagram reels. Further, a sound check was made to guarantee that participants had their audio activated.

Afterwards there was the algorithmic learning phase: The algorithm was calculated for every person individually. It was based on a points system. The more points a video received, the more suitable it was for the person. The points were based on the way people watched the first videos and the liked categories. The first videos were random and were at least 60 sec long or included minimum 10 videos. Based on the watching behavior a score for each participant was calculated. If a video was liked the tags and the category of the video got +1 point. A dislike meant -1 point. The duration of how long a video was watched also brought points relatively to the whole duration of the video. However, if the value was under 0.3 than -0.5 points were given. If participants swiped backwards to rewatch a video +1 point was given. Further, participants had do choose at least three of the 13 TikTok video categories. Every chosen category got +2 points. This way each of the 305 videos got points depending on the watching behavior and the favorite categories. The algorithm calculated the points for each video by measuring the watching behavior and the favorite categories and then ranked all 305 TikTok for each user individually.

The next phase was the experimental phase. Participants answered the first questions to their preference before seeing a video sequences. After that they were randomly assigned to the swipe group or the no-swipe group. They saw only algorithmic selected videos, followed by the liking questions to the video sequences. Then the algorithmic selected videos combined with random selected videos sequence started. Afterwards they got again the liking questions and the preference questions.

Afterwards the questionnaire phase started. First participants answered the *AISS* questionnaire and then the *System Justification Scale*. At the end it was asked how much participants were satisfied with the chosen videos in the first and in the second video sequence. All questionnaires can be found in the appendix B.

Results

In H_1 I expected that a preference for algorithmic selected videos combined with random selected videos could be found and that this preference was stronger in the no-swipe group than in the swipe group. To evaluate this hypothesis, I used two *t*-tests for independent samples. For the first *t*-test the dependent variable was the total preference before the video sequences, and for the second *t*-test the dependent variable was the the total preference after the video sequences. The preference before the video sequences met all requirements to calculate a *t*-test, the preference after the video sequences was not normally distributed (Shapiro-Wilk test: $p_{\text{swipe group}}$ = .011.; $p_{\text{no-swipe group}}$ = .002). However, the *t*-test is robust against the violation of normal distribution (Rasch & Guiard, 2004). The difference between the swipe-mode and the preference before the video sequences was not significant ($t(148) = 0.087$, p = .931, d = .014). Similar was the difference between the swipe-mode and the preference after the video sequences not significant ($t(148) = 0.251$, p = .802, d = .041), as displayed in Table 2. The mean of the preference before the video sequences showed that there was little more preference for algorithmic selected videos combined with random selected videos in both swipe-modes ($M_{\text{swipe group}}$ = 0. 407, $M_{\text{no-swipe group}}$ = 0. 387; 95% *CI* [-0.436, 0.476]). This preference for algorithmic selected videos combined with random selected videos in both groups was even a bit higher for the preference after the video sequences (($M_{\text{swipe group}}$ = 0.65, $M_{\text{no-swipe group}}$ = 0. 59; 95% *CI* [-0.412, 0.532).

Table 2

Preference of algorithmic selected videos combined with random selected videos over only algorithmic selected videos in the preference before the video sequences and preference after the video sequences of the swipe-modes

Preference	$t(148)$	p*	Cohen`s d	$M_{\text{swipe group}}$	$M_{\text{no-swipe group}}$
Before	0.087	.931	.014	0.407	0.387
After	0.251	.802	.041	0.65	0.59

*$p < .05$, two-tailed.

In H_2 I stated that there is a higher liking for indeterminate processes in the no-swipe group than in the swipe group. To analyse the effect of autonomy on the liking of indeterminate processes, I used a mixed model ANOVA, displayed in Table 3. The independent variables were the swipe-modes, while the dependent variable was the liking of the video sequences. First, a Shapiro-Wilk test showed that the normal distribution was missed in the no-swipe group in only algorithmic selected videos (p = .0455), and in the swipe group with the algorithmic selected videos combined with random selected videos (p = .0477). Further, the algorithmic selected videos combined with random selected videos showed heteroscedasticity (Levene test: p =.006). However, given that the group sizes in the swipe-modes were equal the ANOVA is still robust (Weiner, 2003). There was a statistically significant interaction between the swipe-modes and the video sequences in explaining the liking score, $F(1, 148) = 6.235$, p = .014. This means that the difference in the means of the liking between the swiping modes was not the same across the video sequences. Considering the Bonferroni adjusted p-value (p.adj), the simple main effect of the swipe-mode was significant for the algorithmic selected videos combined with random selected videos (p = .048) but not for the only algorithmic selected videos (p = .886). Pairwise comparisons show that the mean liking of the video sequence score was significantly different in the two swipe-modes for the algorithmic selected videos combined with random selected videos (p = .024), but not for the only algorithmic selected videos (p = .443). There was a statistically significant effect of the video sequence on the liking score for the swipe group (p = .004). The boxplot in Figure 2 shows, that the swipe group showed a higher liking in the algorithmic selected videos combined with random selected videos than the no-swipe group. A pairwise paired *t*-test comparisons showed that for the swipe group the mean liking score was statistically significantly different between the two video sequences (p = .002).

Table 3

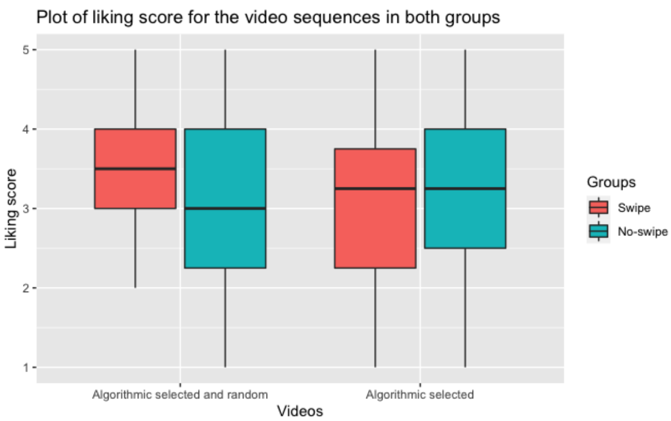
Comparison of the liking score in the video sequences and the swipe-modes

Effect	*DFn*	*DFd*	*F*	*p*	η^2
Swipe-mode	1	148	0.746	0.389	0.003
Video sequence	1	148	3.017	0.084	0.007
Swipe-mode*video sequence	1	148	6.235	0.014*	0.015

*p < .05, two-tailed.

Figure 2

Comparison of the mean liking score in the two swipe-modes and video sequences.



Note. The graph visualizes that the swipe group showed a greater liking of the algorithmic selected videos combined with random selected videos than the no-swipe group.

For H_3 I analysed the relationship of sensation seeking on the preference for algorithmic selected videos combined with random selected videos. Two Pearson correlations were calculated for the *AISS* scores and the two measured preferences. Neither the preference before the video sequences ($r(148) = -.07$, $p = .367$), nor the preference after the video sequences ($r(148) = -.05$, $p = .558$) showed a linear correlation with the *AISS* scores. In Table 4 all correlations are displayed.

For H_4 I tested the relationship of sensation seeking and the liking of indeterminacy. Here, I found with a Pearson correlation that there is a small positive but not significant correlation of the *AISS* scores with the algorithmic selected videos combined with random selected videos ($r(148) = .14$, $p = .09$), illustrated in Figure 3. A correlation of 0.1 to 0.3 can be interpreted as weak (Dancey & Reidy, 2007) Additional analysis showed that the only algorithmic selected videos had no linear correlation with sensation seeking ($r(148) = .04$, $p = .596$).

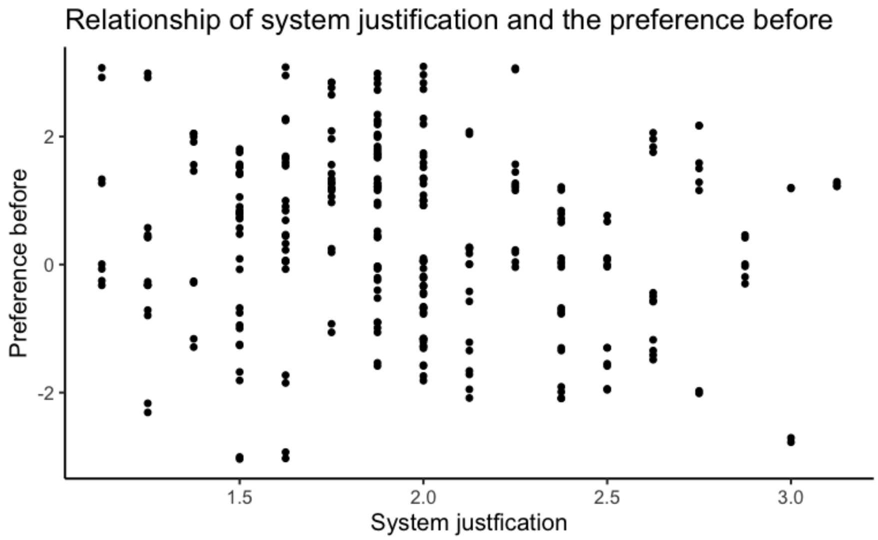
Figure 3

Weak positive but not significant relationship of sensation seeking and the liking of algorithmic selected videos combined with random selected videos.

For H_5 I looked whether there is a relationship of system justification on the preference for indeterminacy with a Pearson correlation. The results showed a weak negative but not significant correlation with the preference before the video sequences ($r(148) = -.13$, $p = .126$), illustrated in Figure 4. This relationship was not found after the experimental phase with the preference after the video sequences and system justification ($r(148) = -.04$, $p = .654$).

Figure 4

Weak negative but not significant relationship of system justification and the preference before the video sequences.



Note. High values of the preference before the video sequences stand for a preferred algorithmic selected videos combined with random selected videos, while low values stand for a preferred the only algorithmic selected videos.

For H_6 I tested if there is a relationship of system justification and the liking of algorithmic selected videos combined with random selected videos. The Pearson correlation found no linear relationship for the algorithmic selected videos combined with random selected videos with system justification (*r*(148) = .03, *p* = .682). Additional analyses showed no correlation between the liking of the only algorithmic selected videos and system justification (*r*(148) = -.05, *p* = .558).

Table 4

Correlation of the preference (before and after the video sequences) / liking (of the only algorithmic selected videos and algorithmic selected videos combined with random selected videos) with sensation seeking and system justification

	Preference of the video sequence		Liking of selected videos	
Score	before	after	only algorithmic	algorithmic and random
AISS	-.07	-.05	.04	.14
System Justification Scale	-.13	-.04	.05	.03

At the end participants answered the questions for the satisfaction with the algorithm-selected videos in the video sequences. 43.33% of the participants said they were dissatisfied by the videos only selected by the algorithm. Less people were dissatisfied with the videos selected by the algorithm combined with random selected videos, where just 24.67% stated to be dissatisfied.

Discussion

The aim of this study was to evaluate the influence of autonomy on the preference and the liking of indeterminate algorithmic selected videos combined with random selected videos compared to determinate only algorithmic selected videos. Moreover, the relationship with sensation seeking and system justification was analysed. Thus, a new step in research on the coexistence of algorithms and consumers has been achieved. Since to my knowledge it is the first time that TikTok videos and autonomy, such as sensation seeking, and system justification are combined into one study.

Autonomy and Indeterminacy

In everyday life algorithms predict suited content for every user on social media platforms (2021). On one hand, users get well entertained because of personalized content, on the other hand, this algorithm selected content also brings some downsides, such as data mining (Van Wel & Royakkers, 2004), social media addiction (Sun and Zhang, 2021) and filter bubbles (Spohr, 2017). Algorithm selected content means, that the algorithm computes a priori what users are going to see. However, there is evidence by Vosgerau et al. (2006) that people prefer indeterminate processes that are not calculated a priori but happen unplanned. In such indeterminate processes people feel more excited because they feel in control of the situation and need to be ready to act. People like the uncertainty when focusing on processes that are indeterminate (Shen et al., 2015) and would also rather repeat an uncertain lower reward than a certain higher reward when focusing on the process (Shen et al., 2018). In this study the uncertain indeterminate process was the algorithmic selected videos combined with random selected videos, while the determinate process was the only algorithmic selected videos. When algorithms are deciding a priori what people are going to see, it should be less exciting given that users should not feel autonomously in control of the situation. Moreover, the SDT states that autonomy is a basic psychological need for wellbeing (Ryan & Deci, 2017). It is important to mention that people have still the possibility to swipe through the content. Swiping gives them the possibility to interrupt the determinate algorithmic selected content, so users can still to some degree autonomously decide what they want to see. The question is if people do prefer indeterminate content on social media and if not being able to swipe influences this preference?

The present study found a little increase in the preference for algorithmic selected videos combined with random selected videos when confronting the preference before the video sequences regarding only algorithmic selected videos or algorithmic selected videos combined with random selected videos. This tendency was even higher when looking at the algorithmic selected videos combined with random selected videos. This finding is in line with the preferred indeterminate process (Vosgerau et al., 2006), the preferred uncertainty (Shen et al., 2006), and the reinforcing-uncertainty effect, that says that an uncertain reward is rather repeated than a certain one (Shen et al., 2018). This finding might also show that users had higher hopes in the choices of the algorithm before seeing the video sequences. After seeing the video sequences, they noticed that the algorithm was not so sophisticated as the ones from social media and therefor they preferred not only algorithm selected videos.

Additionally, an influence of autonomy on indeterminacy could not be found, meaning whether participants could swipe or not had the same effect on the preference regarding only algorithmic selected videos or algorithmic selected videos combined with random selected videos. The reason why no effect of the swiping was found might be that the algorithm was not so sophisticated as people are used on their social media. Thus, it was equal if people could swipe or not, because the videos were per se not so well suited for the participant.

Further, I hypothesized a higher liking of the algorithmic selected videos combined with random selected videos in the no-swipe group. An effect of the swiping-modes and the video sequences on the liking score was found. But contrary than expected the swipe group liked the algorithmic selected videos combined with random selected videos more than the no-swipe group. Further, the swipe group also liked the algorithmic selected videos combined with random selected videos more than the only algorithmic selected videos. Also, here the not so sophisticated algorithm as they are on social media might have caused this effect. Participants in the swipe group might not have liked the algorithmic selected content and were therefore more in favour of the video sequence with combined random selected videos. However, they might have been just in favour of it because they could swipe the not fitted videos away. Given that the no-swipe group had to watch all the videos there was no difference in the liking for the video sequences. They were not able to swipe the not suited algorithmic selected videos away which was present in both video sequences. Further, it might be that the participants did not attentive watch the videos in the no-swipe group because no interaction was possible. They just waited till the video sequences were over.

Sensation Seeking

Further, I tested whether sensation seeking is in a positive relationship with the preference and liking of algorithmic selected videos. There was no relationship of high sensation seekers and the preference for algorithmic selected videos neither before nor after the video sequences. Also, the influence of autonomy on the preference of indeterminate processes was not found in this study. This is in line with research that showed a positive correlation of autonomy with sensation seeking (Zuckerman & Link, 1968). Apart from this, as expected, there is a weak relationship between high sensation seekers and the liking of indetermined algorithmic selected videos combined with random selected videos. Further analyses showed that there was no relationship of high sensation seekers and the liking of the determinate only algorithmic selected videos. Watching random selected videos is risky because participants do not know what awaits them, or if they will like it. While theoretically the algorithm selected videos should suit them. Research about sensation seekers states that sensation seeking relates to the need of a varied, complex, and novel sensations and experiences to keep an optimal level of arousal (Zuckerman et al., 1972). Besides, sensation seeking relates to the willingness to take risks (Zuckerman, 1994). The uncertainty of random selected videos could be seen as such a risk and is preferred when being process-orientated (Shen et al., 2018). However, why the relationship between high sensation seekers and the liking of indetermined algorithmic selected videos combined with random selected videos was rather weak might be because the random selected videos were too little suited for the participants and simply not liked. Further, the German *AISS* shows only adequate reliability.

System Justification

Lastly, it was hypothesized that system justification is in a negative relationship with the preference and liking of algorithmic selected videos. As expected, a weak negative relationship was found for the preference before the video sequences and system justifiers. This means that a high value of system justification relates to a lower preference for indeterminate algorithmic selected videos combined with random selected videos, and a higher preference for only algorithmic selected videos. However, this relationship was not found for the preference after the video sequences. An explanation for finding this relationship just before, but not after watching the video sequences, might be that a weakly designed algorithm was not so good as the status quo algorithms on social media and influenced participants in their preference after seeing the video sequences.

Further, as expected, a negative relationship between the preference for algorithmic selected videos combined with random selected videos before the video sequences and system justification was found. System justification means going with the familiarities, avoid uncertainty, and being in favor of the status quo (Jost & Hunyady, 2005). Against the expectations, there was no linear correlation between system justification and the liking of algorithmic selected videos combined with random selected videos – this might be explained by the algorithm of this study that was not so sophisticated as known social media algorithms.

Limitations, Strengths, and Further Research

The study was conducted in a current important context: social media. The currency gives the study high importance. However, one of the main limitations could be the weakly designed algorithm. This is one of the main limitations of this study. The algorithm calculated the individually fit of videos in a quite simple way. Compared to algorithms used by social media platforms the algorithm used in this study is not that sophisticated. As explained by Jewiss (2021) the social media algorithms are highly complex. It is known that algorithms use personal data for selecting the suited content, but it is unknown how exactly the algorithms work. Further, on social media not a simple algorithm as in this study, but machine learning algorithms are used. However, the algorithm can also be seen as a strength of the study because the study has high external validity. Further, it was a field experiment with a real algorithm. Participants were in their familiar surroundings, and autonomy was manipulated. Further, many participants were recruited.

The study provided real TikTok videos which once again adds to the high external validity. But the selection and tagging of the videos was not done automatically and therefore a subjective bias might have occurred. Besides, the variability of the videos is greater on social media platform – for the study 305 videos were collected; however, these videos are only a fraction of the videos that are available on TikTok. Further, while many participants had known TikTok, they reported to not use it. On the other hand, a lot more participants use Instagram. It might have been better to use videos from Instagram for this study. The study had also high external validity because participants were able to conduct the study on any mobile device. So, the context was like when users would consume social media content as usually. However, it could be that participants might have shown a different watching behavior as normally on social media because they knew that they were part of a survey.

Further, the internal validity of the study is rather low. While there was a sound check, there was no control of the attention of the participants during watching the video sequences. The context in which participants did the study is unknown. It might have been that participants did not fully read the instructions and did not understand the difference between the two video sequences. Further, the internet connection had to be good to see the videos without loading bar, but this was not controlled in the study.

Further studies could check for even higher external validity where it is controlled that participants really act like when using social media. Additionally, a study with high internal validity would be interesting to exclude disturbance variables. Also, the knowledge about algorithms of users in the online and social media context can bring some more understanding of the results. The questionnaires should be selected carefully, and their psychometric qualities should be considered. And most importantly, the algorithm is a crucial part and should therefore be very sophisticated. It is recommended to invest enough time into building a good algorithm. If the algorithm took videos directly from a social media platform and tagged them automatically, subjective bias could be decreased. Such a sophisticated algorithm would need technical advanced expertise, but it would make it possible to examine the influence of autonomy on algorithms more precisely.

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Appendix A: Tags of the TikTok Videos

Tag	Number of videos
Baby	7
Ball sport	4
Crafting	11
Car	16
Cats	14
Cute	14
Decoration	9
Dogs	9
Experiments	18
Yarn	5
Family	7
Photos	2
Gaming Station	2
Groups	15
Gymnastic	5
Hair	8

House	11
History	5
Impressive drawin	17
Simple drawing	11
Instrument	11
Clothing	15
Magic	6
Make-up	4
Manga	3
Men	96
Minecraft	3
Motorcycle	10
Nails	3
Narrator	22
Old-school	3
Animals	8
Outside	13
Places	10

Accessories	8
School	5
Shooting game	2
Singing	9
Speaking	60
Stunts	15
Summer sports	7
Text	93
Trendy	37
Tutorial	67
Virtual reality	5
Winter sports	5
Women	98

Appendix B: Questionnaires

Demographic Questions

Instructions: Algorithmen haben zum Ziel jeder Person das passendste Video zu zeigen. Damit Sie dies machen können, sammeln Sie im Vorfeld viele Daten, wie z.B. auch demografische Daten. Auch in dieser Studie soll ein Algorithmus für Sie erstellt werden. Daher folgen nun ein paar Fragen zu Ihrer Person.

1. Wie alt sind Sie? <18/18-25/26-30/31-35/36-40/41-45/50+
2. Welches Geschlecht haben Sie? weiblich/männlich/divers
3. Wo wohnen Sie? Österreich/Deutschland/Italien/Anderes Land
4. Verwenden Sie TikTok? Nie/Selten/Manchmal/Häufig/Sehr häufig
5. Kennen Sie das Konzept von TikTok Videos? Ja/Nein
6. Verwenden Sie Instagram? Nie/Selten/Manchmal/Häufig/Sehr häufig
7. Kennen Sie das Konzept von Instagram Reels? Ja/Nein
8. Wie gut sind Ihre Englischkenntnisse von 1(=überhaupt nicht gut) bis 5 (=ausgezeichnet)? 1/2/3/4/5
9. Wie gut sind Ihre Deutschkenntnisse von 1(=überhaupt nicht gut) bis 5 (=ausgezeichnet)? 1/2/3/4/5

Preference Questions

Instruction: Bitte geben Sie anhand des Schiebereglers an, was Sie lieber möchten.

Slider control: A= only algorithmic selected videos vs. B= algorithmic selected videos combined with random selected videos

1. Ich möchte zukünftig lieber sehen.

2. Mir würde besser gefallen zu sehen.

3. Mich würde eher langweilen zu sehen. (Reverse code)

4. Mich würde neugierig machen zu sehen.

Liking Questions

Instruction: Bewerten Sie bitte, inwiefern folgende Aussagen auf einer Skala von 1 bis 5 auf Sie zutreffen. 1= stimme überhaupt nicht zu; 5= stimme völlig zu

1. Ich habe die Videos gerne gesehen.

2. Mir haben die Videos gut gefallen.

3. Mich haben die Videos gelangweilt. (Reverse code)

4. Die Videos haben meine Aufmerksamkeit angezogen.

AISS

Instruction: Im Folgenden finden Sie vierzehn Aussagen zur Beschreibung der eigenen Person, bitte geben Sie bei jeder Aussage an, wie sehr diese auf Sie persönlich zutrifft. Hierfür stehen Ihnen folgende Antworten zur Verfügung:

1=trifft gar nicht auf mich zu; 2=trifft kaum auf mich zu; 3=trifft etwas auf mich zu; 4= trifft stark auch mich zu

1. Ich fände es interessant, jemanden aus dem Ausland zu heiraten.
2. Wenn ich Musik höre, sollte sie laut sein.
3. Wenn ich verreise, denke ich, dass es am besten ist, so wenige Pläne wie möglich zu machen und es so zu nehmen, wie es kommt.
4. Ich gehe nicht in Kinofilme, die ängstigend oder "nervenaufreibend" sind.
5. Es würde mir Spaß machen, und ich fände es aufregend, vor einer Gruppe aufzutreten oder zu sprechen.
6. Wenn ich auf einen Rummel gehe, würde ich die Achterbahn oder andere schnelle Bahnen bevorzugen.

7. Ich würde gerne an fremde und entfernte Orte reisen.
8. Mir hätte es gefallen, eine:r der ersten Entdecker:innen eines unbekannten Landes gewesen zu sein.
9. Ich mag Filme, in denen eine Menge Explosionen und Verfolgungsjagden vorkommen.
10. Es wäre interessant, einen Autounfall zu beobachten.
11. Ich denke, wenn man im Restaurant isst, ist es am besten, sich etwas Bekanntes zu bestellen.
12. Ich mag das Gefühl, am Rande eines Abgrundes oder in großer Höhe zu stehen und herunterzuschauen.
13. Wenn es möglich wäre, umsonst auf den Mond oder einen anderen Planeten zu fliegen, wäre ich unter den ersten, die sich dafür melden würden.
14. Ich kann mir vorstellen, dass es aufregend sein muss, während eines Krieges in einem Kampf zu sein.

System Justification Scale

Instruction: Bewerten Sie bitte, inwiefern folgende Aussagen auf einer Skala von 1 bis 4 auf Sie persönlich zutreffen. 1 = Ich stimme überhaupt nicht zu; 4 = Ich stimme völlig zu

1. Im Allgemeinen finde ich unsere Gesellschaft als gerecht.
2. Im Allgemeinen finde ich, unser politisches System garantiert, dass Big Data Unternehmen und deren Algorithmen den Verbrauchern gegnüber fair sind.
3. Die Datenschutzpolitik in unserem Land muss radikal umstrukturiert werden.
4. Für Verbraucher:innen ist unser digitales System das Beste der Welt.
5. Die meisten konsum- und wirtschaftspolitischen Maßnahmen in der digitalen Welt dienen dem Allgemeinwohl.

6. Alle Verbaucher:innen haben eine faire Chance online transparente Informationen über Produkte zu erhalten, um eine fundierte Entscheidung treffen zu können.
7. Die Ausbeutung der Verbraucher:innen durch die Big Data Unternehmen und deren Algorithmen wird von Jahr zu jahr schlimmer.
8. Das Verhältnis zwischen Big Data Unternehmen und Verbraucher:innen ist so gestaltet, dass die Verbraucher:innen in der Regel bekommen, was sie verdienen.

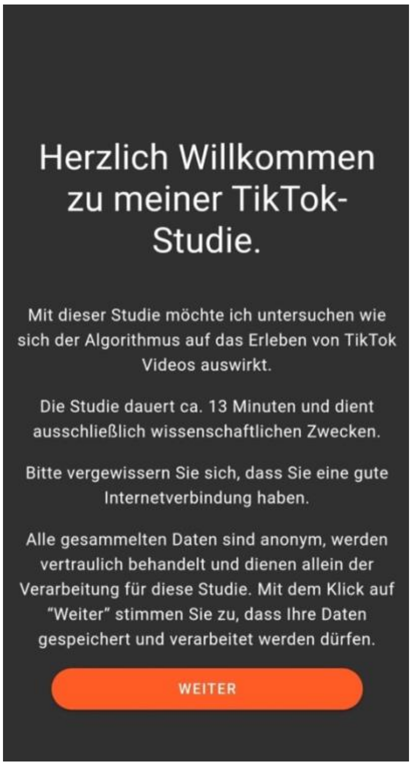
Satisfaction with Algorithmic Choices in the Video Sequences

Instruction: Bewerten Sie bitte, inwiefern folgende Aussagen auf einer Skala von 1-5 auf Sie persönlich zutreffen. 1= überhaupt nicht zufrieden / 2 =eher nicht zufrieden / 3= teilweise zufrieden / 4= eher zufrieden / 5= sehr zufrieden

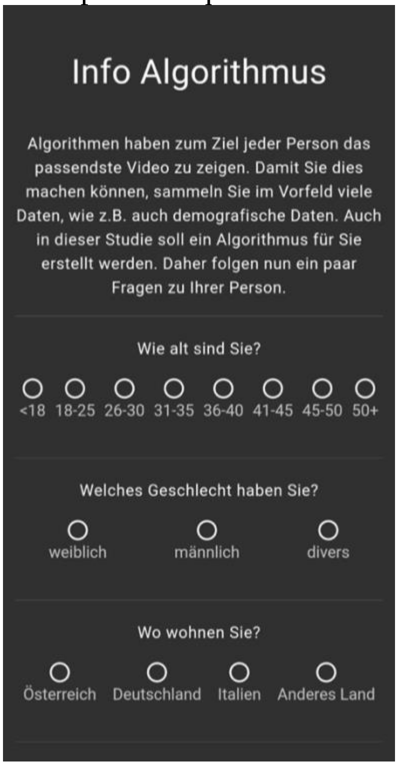
1. Wie zufrieden sind Sie mit der Auswahl des Algorithmus im ersten Teil der Studie?
2. Wie zufrieden sind Sie mit der Auswahl des Algorithmus im zweiten Teil der Studie?

Appendix C: Screenshots of the Experiment

1. Welcome text and data collecting acceptance

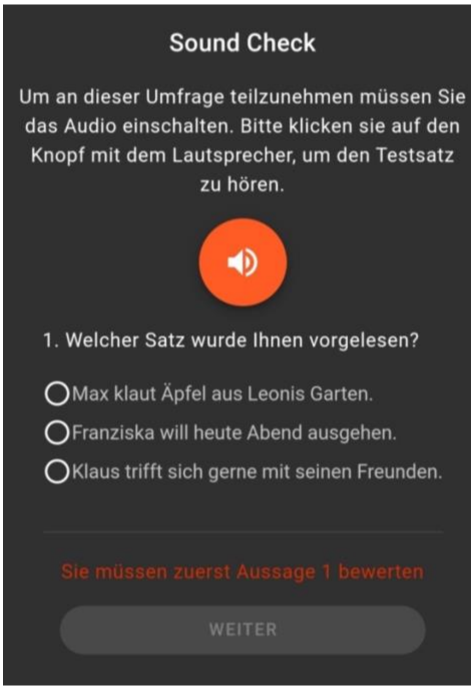


2. General information about algorithm and personal questions



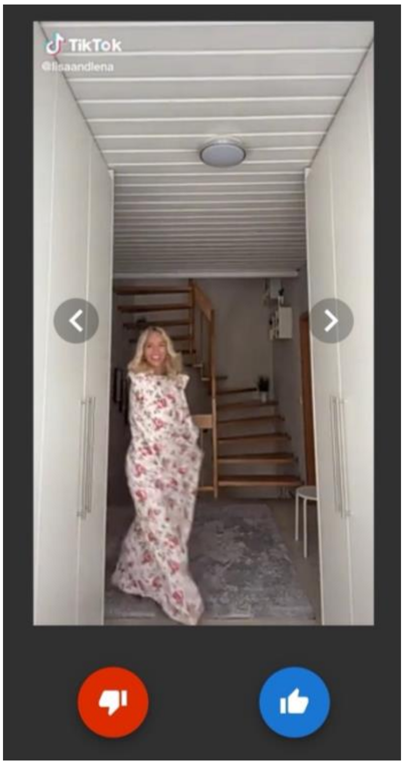
* For full questionnaire see Appendix B

3. Sound check

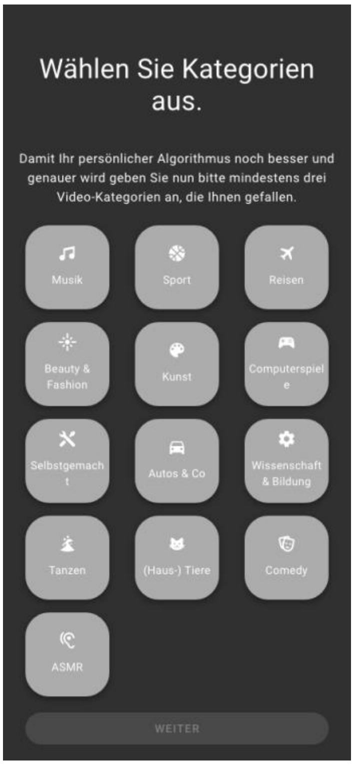


4. Algorithmic learning phase: Introduction

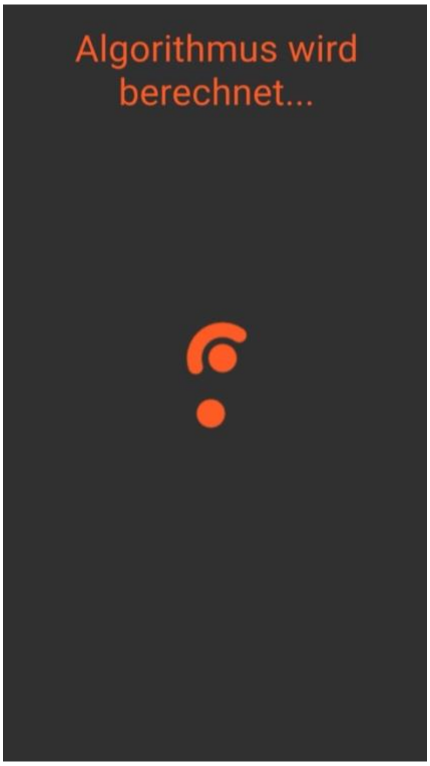
5. Algorithmic learning phase: Videos



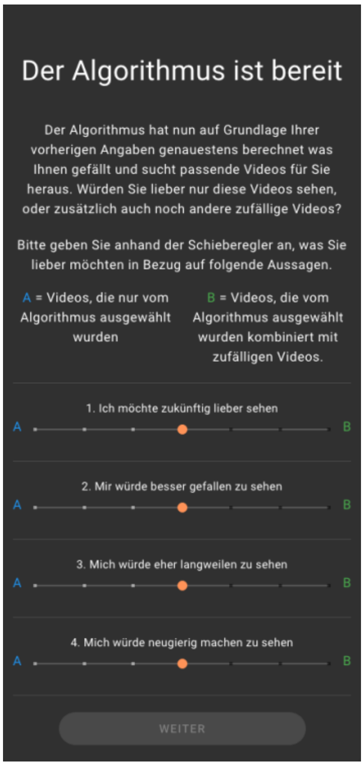
6. Algorithmic learning phase: Categories



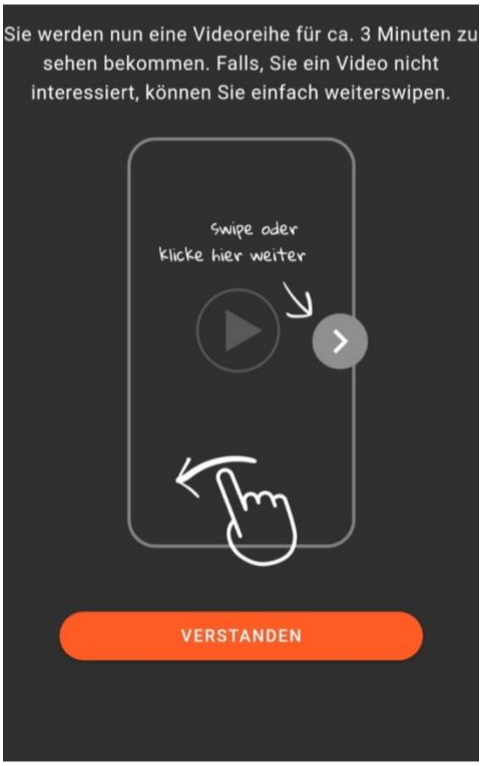
7. Algorithmic learning phase: Calculating



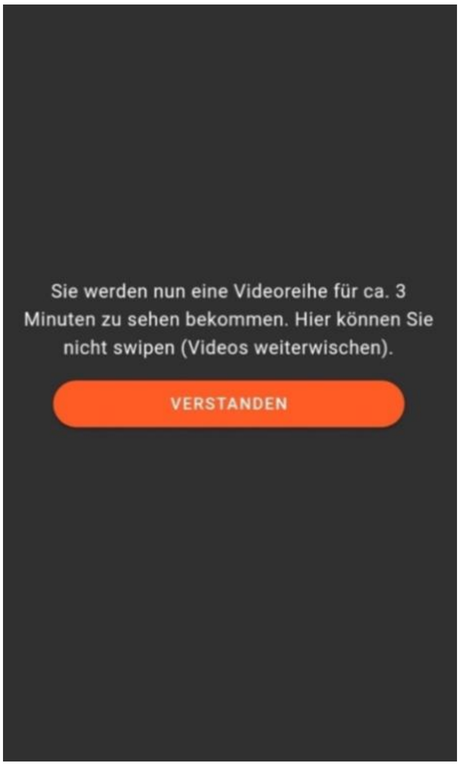
8. Experimental phase: preference before the video sequences



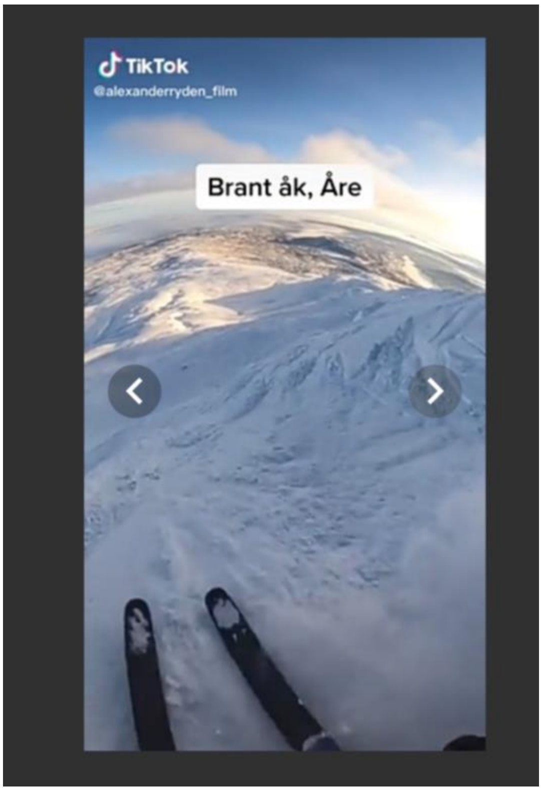
9a. Experimental phase: Instruction the swipe group



9b. Experimental phase: Instruction in the no-swipe group



10a. Experimental phase: only algorithmic selected videos in the swipe group

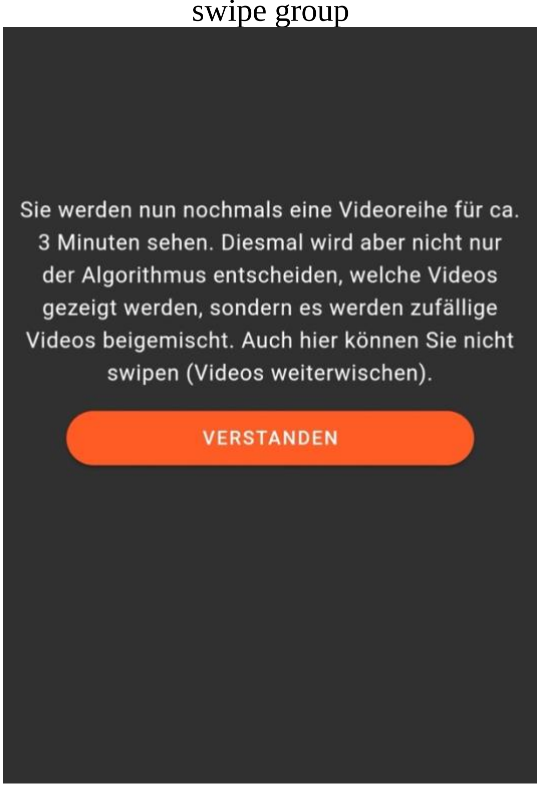


10b. Experimental phase: only algorithmic selected videos in the no-swipe group

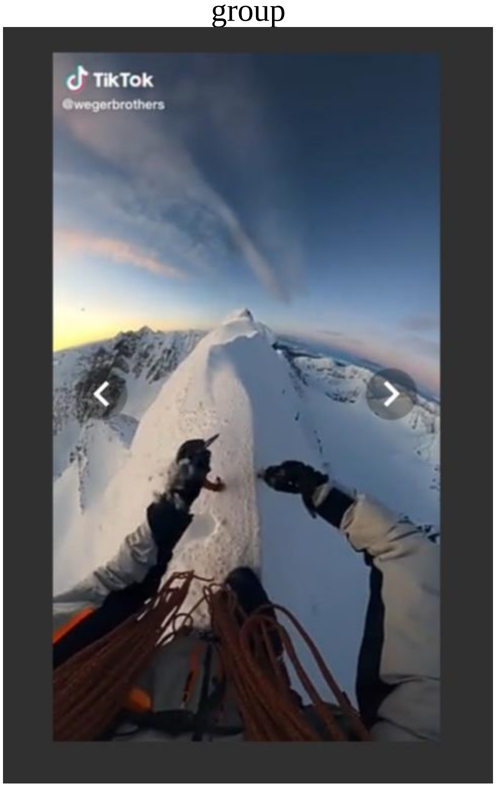
11. Experimental phase: Liking of onlyalgorithmic selected videos

12a. Experimental phase: Instruction the swipe group

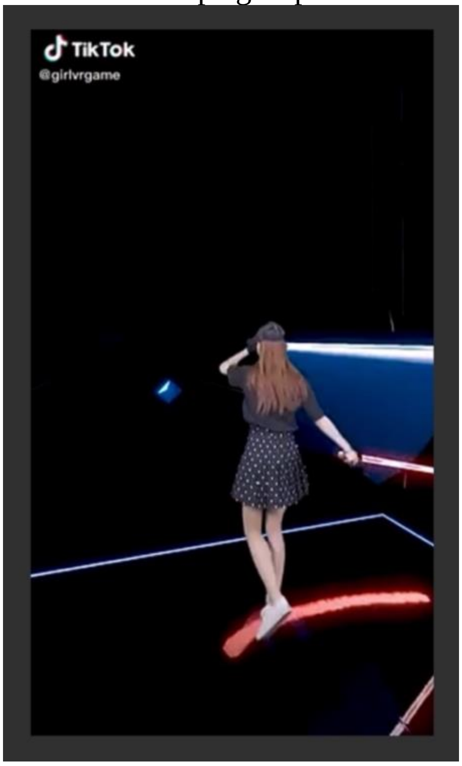
12b. Experimental phase: Instruction the no-swipe group



13a. Experimental phase: AVR in the swipe group

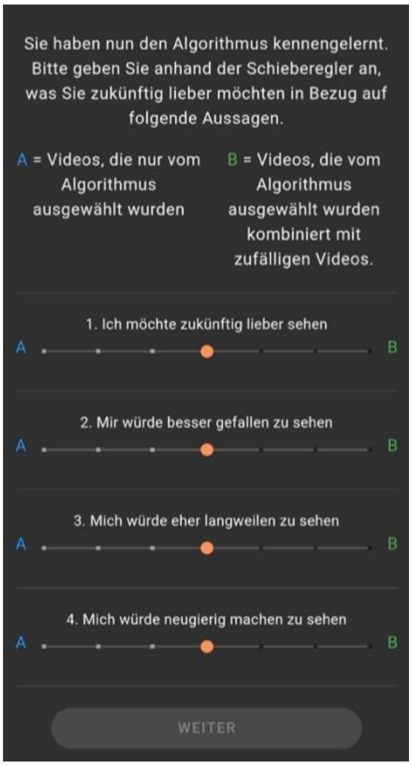


13b. Experimental phase: AVR in the no-swipe group

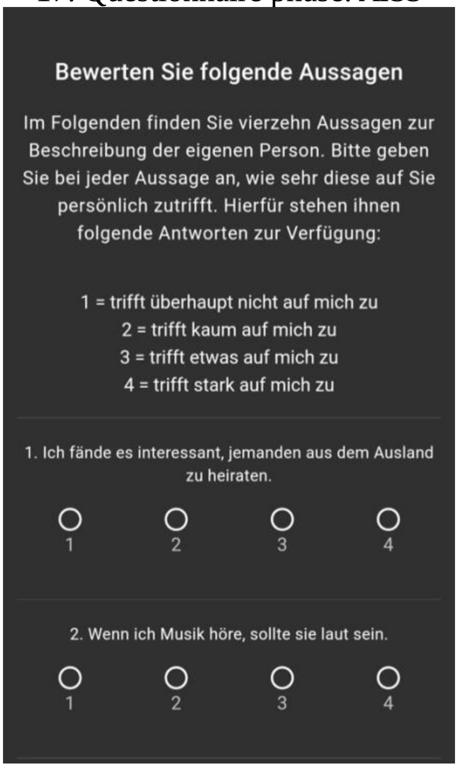


15. Experimental phase: Liking of the AVR

16. Experimental phase: preference after the video sequences

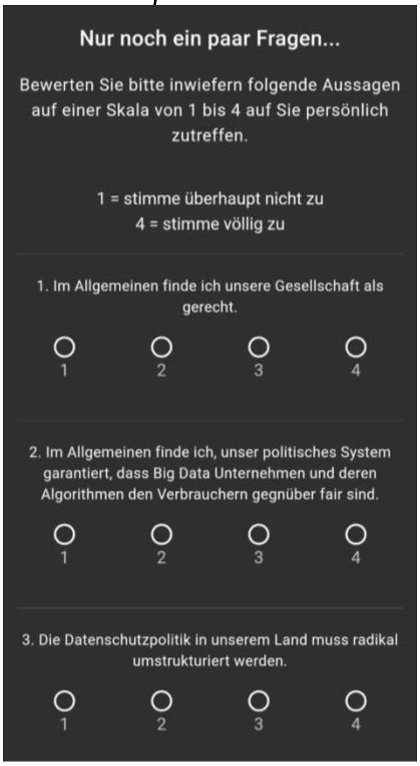


17. Questionnaire phase: *AISS*



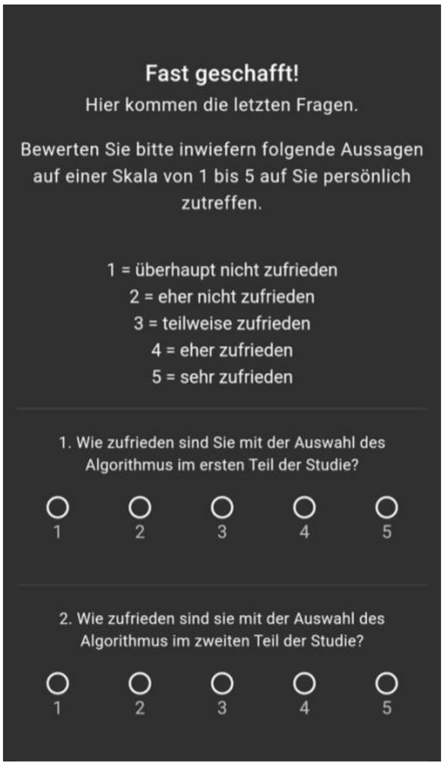
*For full questionnaire see Appendix B

18. Questionnaire phase: *System Justification Scale*



* For full questionnaire see Appendix B

19. Questionnaire phase: Satisfaction with the algorithmic choices in both video sequences



20. Final page

Appendix D: Deutsche Zusammenfassung

Social-Media-Plattformen wie TikTok verwenden Algorithmen, um die perfekt passenden Inhalte für jede*n Nutzer*in zu bestimmen. Aber wollen die Nutzer*innen diese determinierte Perfektion? Die Forschung legt nahe, dass Menschen unvollkommene, indeterminierte Prozesse bevorzugen. In dieser Studie gehe ich davon aus, dass die Möglichkeit, determinierte Prozesse zu unterbrechen, die Präferenz für indeterminierte Prozesse abschwächt. Die mögliche Unterbrechung könnte Autonomie schaffen, die nach der Self Determination Theorie ein wesentliches psychologisches Bedürfnis ist. Ich habe untersucht, ob eine höhere Präferenz für determinierte, algorithmisch ausgewählte TikTok-Videos besteht, wenn sie mit indeterminierten, zufälligen TikTok-Videos kombiniert werden, als ohne Zufallsvideos. Es wird vermutet, dass diese Vorliebe größer ist, wenn Personen nicht autonom durch die Videos wischen können, als wenn sie autonom wischen können. Um diesen Effekt zu testen, wurde eine Plattform geschaffen, auf der ein Algorithmus trainierte, jeder Versuchsperson die passenden Videos zu zeigen. Die Ergebnisse zeigten keine höhere Vorliebe für algorithmisch ausgewählte Videos in Kombination mit Zufallsvideos, wenn die Person nicht Videos wischen können. Allerdings zeigte Personen, die wischen konnten, eine höhere Vorliebe für algorithmisch ausgewählte Videos in Kombination mit Zufallsvideos als die Personen, welche nicht wischen konnten. Außerdem wurde der Zusammenhang zwischen der Vorliebe für algorithmisch ausgewählte Videos in Kombination mit Zufallsvideos und individuellen Unterschieden in der Persönlichkeit näher untersucht.