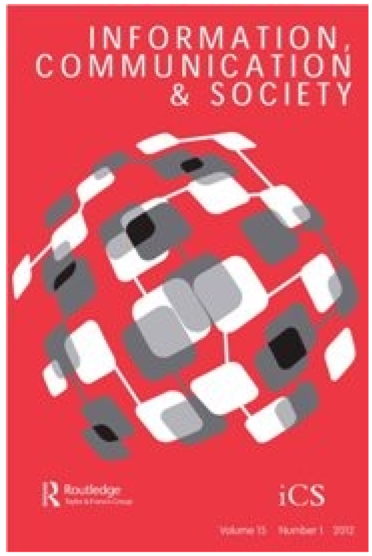

Making curation algorithms apparent: a case study of AwarenessTool as a means to heighten awareness and understanding of Instagram's algorithm

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Making curation algorithms apparent: a case study of AwarenessTool as a means to heighten awareness and understanding of Instagram's algorithm

Despite the increasing prevalence of curation algorithms on everyday social network sites (SNSs) they often are imperceptible and difficult to become knowledgeable about since little insight in the actual working of these algorithms is given. To address this, we developed an online interface as a visual feedback tool to decrease the ignorance about the Instagram curation algorithm (hereafter referred to as 'AwarenessTool' to ensure an anonymous review process). As such, the goal of this article is to validate the actual effectiveness of awarenessTool and to demonstrate how people can be made aware of the Instagram curation algorithm using a quasi-experiment. Validating the actual effectiveness of AwarenessTool allowed us to connect additional findings about the influence of awareness and understanding of Instagram's curation algorithm to our primary validated findings about achieving such awareness. These show that it is not cognitive understanding about Instagram's algorithms but solely awareness about them that appears to be sufficient for people to indicate increased critical concerns towards SNSs. Furthermore, our visual feedback AwarenessTool proved to be efficient in increasing cognitive media literacy (CML) and in indirectly stimulating critical concerns towards SNSs.

Keywords: Algorithm Awareness, Media Literacy, Social Network Sites, Instagram

1. Introduction

Curation algorithms arrange content by prioritising, classifying and filtering information. As a means for gatekeeping, they are shaped by many actors (i.e. developers, engineers, end users, regulation, industry) as well as by the datasets they curate such as the digital traces left behind from the everyday use of a social network site (SNS) (Bucher, 2012). Similar to pre-digital gatekeeping, algorithms can raise problems in terms of distortion of reality, for example through the creation of a filter bubble.

However, this filter bubble, where users are presented mostly with content that interests them and that fits their discourse or way of thinking (Pariser, 2011), has already been challenged by a number of studies, especially regarding news (e.g., Zuiderveen et al., 2016; Fletcher & Nielsen, 2018). Nevertheless, there are also other reasons for why algorithm awareness is important, for example, that algorithmic systems are neither perfect nor neutral and bear the potential for discrimination (e.g., Eubanks, 2018; Matzat et al., 2019; Noble, 2018; O'Neil, 2016). Also, algorithm awareness is a first step in understanding the algorithm and serves as a precursor for the 'right to explanation' (or right to an explanation); a right to receive an explanation about an algorithm's output (Goodman et al., 2017; Edwards et al., 2017).

Instagram uses algorithms to personalise the news feed of each user based on data resulting from one's online activities, thereby 'showing the moments one cares about the most' (Cotter, 2019). Six factors are currently used by Instagram to algorithmically determine the ranking of posts shown in the news feed each time the feed is loaded: (1) interest, (2) recency, (3) relationship, (4) frequency, (5) following and (6) usage (Constine, 2018). Although these factors were officially communicated by the Instagram product team, there is still little understanding on how these six factors get computed.

Studies have argued that users' literacy about curation algorithms and their experiences with them, might affect their attitudes towards how the platform should be used (Beer, 2017). Despite the common deployment of curation algorithms on SNSs, only few SNSs offer insights in their algorithms' outcomes. With no feedback mechanism available, it can be difficult for users to become knowledgeable about these curation algorithms, to assess their personal news feed from a critical angle and to change attitudes accordingly. Yet, it is this feedback mechanism that might ultimately be required to prevent the potential negative effects of algorithmic selection and curation, such as growing concerns over the Filter Bubble effect (Hannák et al., 2017) or threats to the realisation of important public policy goals, such as media diversity, public debate and competition on the marketplace of ideas (Zuiderveen et al., 2016).

To address these shortcomings, this article discusses 'AwarenessTool'; an online interface that functions as a visual feedback tool to decrease the ignorance about Instagram's curation algorithms. Our aim is to assess if and how AwarenessTool, a self-developed visual feedback tool, increases awareness and media literacy about Instagram's curation algorithms. AwarenessTool lets people log in with their personal Instagram account where after it extracts information from their Instagram news feed in order to reveal the mechanisms behind the curation algorithm. By means of AwarenessTool, people are offered a side-by-side comparison of their news feed with and without curation algorithm, as well as other insights such as highest or lowest ranked friends and 'hidden' posts.

This article continues by outlining the relevant literature, the central research question and the hypotheses in section 2. In section 3, the study design is explained. Next, results are discussed in section 4. Conclusions as well as debating points and the limitations of our research are presented in section 5.

2. Literature

In this section we first delineate the conceptualization of algorithms using the taxonomy of analytics from Delen and Demirkan (2013) and discuss studies on users' awareness of curation algorithms (section 2.1). Next, we focus on media literacy and operationalize the concepts of technical and cognitive social media literacy as these are important to understand and explain the AwarenessTool (section 2.2). Lastly, we look at how people claim to be bothered by algorithmic curation while not acting accordingly (e.g. by actively altering the effects of the algorithm and critically assessing online information). We propose the concept of the ‘Algorithm Paradox’ to address the assumption of this contradictory relationship and posit one research question and three research hypotheses (section 2.3).

Cotter (2019) utilizes a combined approach of co-evolutionary and instrumentality in her work on ‘playing the visibility game on Instagram’. Therein, the adopted perspective on ‘playing the game’ acknowledges the authority of SNSs’ owners to set constraints on how the SNS could be used, although not neglecting the autonomy of SNS users to interpret these limitations, and act upon them. In line with this, the perspective throughout this paper is one where algorithms are more structural and instrumental elements to which users can adapt even if they do not know, nor understand, the complete ‘rulebook’. People tend to play a visibility game on everyday platforms to avoid ‘the threat of invisibility’ (Bucher, 2012), thereby consciously engaging with, interpreting and acting upon the rules set by the SNSs.

2.1 Algorithms

These rules that are set by the SNSs materialise in the form algorithms. Algorithms on SNSs have been discussed in a variety of ways. Research ranges from gatekeeping (Bozdag, 2013; Bucher, 2012; Tandoc Jr, 2014) to ways of auditing (black box) algorithms (Bucher, 2016; Sandvig, Hamilton, Karahalios & Langbort, 2014) or to research focused on the perception, understanding and awareness of algorithms on SNSs (Bucher, 2017; Eslami et al., 2016; Eslami, Rickman et al., 2015; Eslami, Vaccaro, Karahalios & Hamilton, 2017; Hamilton, Karahalios, Sandvig & Eslami, 2014; Rader & Gray, 2015; Verdegem, Haspeslagh & Vanwynsberghe, 2014).

While the exact definition of ‘algorithm’ is hard to provide, it can be described as a finite set of precisely defined rules and processes to achieve a certain outcome.

Algorithms take input and transform this through their computational rules (throughput) into output (Cormen, Leiserson, Rivest & Stein, 2009). Subsequently, 'algorithmic curation' (also labelled as algorithmic selection) is considered as the process where relevance is assigned to information elements of a data set by a computational assessment of its input, i.e. generated data signals (Latzer et al., 2016).

To further delineate the conceptualization of algorithms, we use the taxonomy of analytics from Delen and Demirkan (2013). This taxonomy has three categories based on algorithms' capabilities: (1) descriptive analytics, used to describe data, identify opportunity or outcome; (2) predictive analytics, used to discover patterns which might explain input-output relationships; and (3) prescriptive analytics, used to determine a set of best course of actions for a given situation. Curation algorithms are considered as prescriptive algorithms throughout this article.

An important study on users' awareness of curation algorithms is the work of Eslami, Rickman et al. (2015) who developed 'FeedVis', a visual feedback tool which allowed them to present their 40 participants a side-by-side comparison of one's curated vs. uncurated (i.e. all possible content in reverse chronological order) Facebook news feed. Major findings were that 62.5% of participants were unaware of the curation algorithm and initially developed negative attitudes with consequences such as feelings of betrayal or doubts about real life relationships because of missed posts. Over time, some participants started to manipulate the algorithm with newly developed habits including an increasing use of the 'most recent' view, setting goals as to who appears in their feed, liking friends' posts and more. They also developed more positive feelings as they became more knowledgeable about the algorithm.

In contrast with these results, Rader and Gray (2015) found that only 22% of their total sample (n=464) was unaware of the Facebook curation algorithm. These contradictory findings are likely due to the recruitment approach of Rader and Gray, as they aimed for a generally more aware population who had thought about curation before. More interestingly is the wide range of users' beliefs on curation and the effect on their attitudes and habits. For example, there was the trend of passive and uncritical consumption during which users did not reflect all too often about why they see the posts they do. Moreover, more than half of these respondents were aware of Facebook's news feed algorithm while exerting this uncritical behavior, indicating one might not have thought about possible issues and side-effects such as filter bubbles. Other common beliefs were that: (1) the curation helped them by displaying what they wanted to see; (2) they are missing posts because of the curation and; (3) data on personal behavior is used in combination with factors such as popularity to prioritize posts. Our study will contribute to these existing works on awareness and understanding of algorithms by demonstrating how people can be made aware of curation algorithms by means of our visual feedback AwarenessTool. As such, it addresses the call for research (e.g., Eslami, Rickman et al., 2015) that quantitatively confirms previous findings about the effects and effectiveness of exposing hidden algorithmic processes to users with the help of visual feedback tools.

2.2 Media Literacy

These beliefs on how e.g. algorithms use personal data to prioritize posts can be considered as components of media literacy. 'Media literacy' is used to address how knowledgeable one is about different aspects of his or her media consumption and describes both technical and cognitive competencies (Livingstone, Van Couvering and Thumin, 2008). With regards to this distinction, Helsper and Eynon (2013) defined four broad skill categories: operational competencies including technical and creative skills and strategic competencies including social and critical skills. A series of studies in the

Netherlands suggested and validated four similar types of skills: (1) operational, (2) formal, (3) information and (4) strategic (van Deursen, Courtois & van Dijk, 2014; van Deursen & van Dijk, 2015; van Deursen, van Dijk & Peters, 2012). Operational and formal skills account for technical or medium-related aspects whereas information and strategic skills account for cognitive or content-related aspects of media consumption. Two additional skills, (5) content creation and (6) communication, were later added and validated which resulted in a six fold typology (van Deursen, Helsper & Eynon, 2016; van Dijk & van Deursen, 2014). These skills are interdependent and show some overlap. For example, technical media literacy (TML) is found to be required for performances on cognitive media literacy (CML) (van Deursen & van Dijk, 2015).

Research on 'social media literacy' argues that more traditional definitions of media literacy (e.g., the aforementioned typology) are only partly applicable to social media, due to the higher degree of participation required on SNSs (Vanwynsberghe, Boudry and Verdegem, 2015). Thus, social media literacy is defined as including the competencies to actively participate online (requiring skills such as communicating and content creation), as well as the more traditional technical and cognitive competencies. This twofold definition is adopted in this article, using the first four skill types of the six fold typology of van Dijk and van Deursen to operationalise the concepts of technical and cognitive media literacy (Table 1). Since the latter part of our twofold definition (i.e. competencies to actively participate online) is no subject of this paper's research questions and analysis, the operationalisation of these skills was omitted from Table 1.

<< INSERT TABLE 1 HERE>>

2.3 Knowledge versus attitudes: the 'Algorithm Paradox'

Based on cognitive dissonance theory, we expect people to adapt their attitudes or expectations according to their knowledge in order to reduce dissonance. Still, this is not always the case. The information privacy paradox, for instance, is a phenomenon where users claim to value their personal information while their actual behavior in terms of personal information management and disclosure is contradictory (Norberg, Horne & Horne, 2007). Moreover, this inconsistency has also been found between people's attitudes towards information transparency features while using personalized online services (Awad & Krishnan, 2006). The discrepancy between privacy attitudes and privacy behavior should not be regarded as a paradox however, given that continued research provided several explanations, such as the fact that perceived benefits of participation on SNSs seem to outweigh observed risks (Kokolakis, 2017).

Not only privacy but also algorithmic curation appears to have such discrepancy. Based on the study of Verdergem et al. (2014), only 30% of the questioned were aware of the curation algorithm behind Facebook although many of them (83% - 56%) claim they would in fact mind if SNSs carried out curative activities. Put differently, users have a vague understanding of what curation algorithms are and hence of their existence. They claim to be bothered by algorithmic curation while not acting accordingly, that is, actively altering the effects of the algorithm and critically assessing online information. This article proposes the concept of the 'Algorithm Paradox' to address the assumption of this contradictory relationship.

Building upon the concluding remarks of Kokolakis (2017), this 'Algorithm Paradox' might similarly be a complex phenomenon rather than a paradox. One explanation might be that cognitive skills, to understand what algorithms are able to do, are a required asset to properly take subsequent actions, such as a more critical assessment of what content is presented on SNSs. In fact, when people understand what effect algorithms have on their news feed, they act upon this accordingly. This was the case in several studies where curation on Facebook was thoroughly explained to participants, resulting in them acting upon this accordingly by altering settings, changing interaction patterns or visiting different profiles (Eslami, Rickman et al., 2015; Eslami et al., 2016). As such, the cognitive development of curation algorithms' actual working in relation towards attitudes is the subject matter of this article.

Based on the aforementioned literature we posit one research question and three research hypotheses:

RQ What is the relation between TML and CML of Instagram's curation algorithm and what are the attitudes towards Instagram for Flemish adults?

H1 Average CML is significantly higher for people using AwarenessTool compared to those who did not.

H2 Average general feelings are significantly higher for people using AwarenessTool compared to those who did not.

H3 Average critical concern is significantly higher for people using AwarenessTool compared to those who did not.

3. Study design

In order to examine these hypotheses, a twofold approach was taken. First, the visual feedback AwarenessTool was developed by the first author. This website requires people to log in with their personal Instagram account and subsequently reveals the mechanisms behind the Instagram algorithm (for more information see [deleted to maintain the integrity of the review process]). Second, a pre-post mixed design quasi-experiment consisting of three phases was conducted to answer the research question and hypotheses. In the first phase, the level of technical media literacy (TML), cognitive media literacy (CML) and attitudes (ATT) were measured for each participant using an online questionnaire (see Annex 1). Next, participants were randomly selected for phase two and asked to use AwarenessTool, preferably a few times per week. After two to three weeks, phase 3 began in which participants were asked to retake the online questionnaire (see Annex 2) which again measured their levels of media literacy and attitudes. Finally, these two collected datasets were combined and used for further data analysis (see Table 2 for study design overview).

<< INSERT TABLE 2 HERE>>

3.1 Pre-assessment

The quasi-experiment started with an initial measurement of three latent concepts which addressed participants' familiarity with Instagram, as well as their attitudes towards Instagram. To ensure participants could answer these questions in a meaningful way, a weekly use of Instagram was set as a prerequisite to partake in the experiment. Participants were on average 43 minutes (SD = 20.16, n = 52) active on Instagram on a daily basis.

First, TML was measured using (1) frequency and (2) familiarity. Frequency encompasses the number of performed online activities and how frequently these are done. Items used in the questionnaire were adopted from Vanwynsberghe and Haspeslagh (2014) and included questions about the frequency of practices such as 'creating a story', 'using hashtags', 'tagging people' and more. Familiarity, on the other hand, encompasses the understanding of various digital related terms and has been found to be an even stronger predictor for TML than frequency or self-efficacy (Hargittai, 2005). This scale, also adopted from Vanwynsberghe and Haspeslagh (2014), included items about the familiarity with 'tagging', 'search function', 'unfollowing' and more. Overall, both frequency and familiarity scale were found to have a good internal validity (Cronbach's Alpha of respectively .79 and .85).

Second, CML was measured by looking at (1) knowledge and (2) critical thinking. The latter differentiates itself from (critical) attitudes by measuring respondents' awareness — or rather ignorance — instead of concerns, general feelings and habits (Vanwynsberghe & Haspeslagh, 2014). Vanwynsberghe and Haspeslagh (2014) scale to measure CML was adopted for this article. The scale includes items focused on filtering mechanisms and was found to have good internal validity (Cronbach's Alpha of .74).

Third, attitudes (ATT) was measured by looking at: (1) critical concern, (2) general feelings and (3) critical habits. Respondents were asked about the extent to which they critically reflect upon and have concerns about actions the Instagram algorithm performs such as 'altering your feed based on your usage data', 'keeping deleted data' and more. Attitudinal items (e.g. happy/annoyed or positive/negative) as well as cognitive attitudinal items (e.g. opaque/transparent or beneficial/ harmful) from Yang and Yoo (2004) were used to measure general feelings towards Instagram. Since no validated scale for critical habits in this contexts exits, the scale of Vanwynsberghe & Haspeslagh (2014) and van Deursen & van Dijk (2009) on knowledge, critical thinking and informational skills was used to determine what could be a "critical habit". Critical habits were measured by asking respondents if they had performed or will perform actions such as 'changing interaction with friends', 'attributing their recently received number of likes partly to an algorithm' and more. The scales for critical concern and general feelings had a good internal validity (Cronbach's Alpha of respectively .88 and .81), the critical habits scale however had too low internal validity to be used as a continuous scale and was therefore further used as ordinal statements.

At the end of the questionnaire, participants answered socio-demographic questions and were randomly divided into two groups: (1) group A received no placebo effect and acted as the control group; (2) group B was prompted to use and play with AwarenessTool which, unknowingly to the participants, served as the manipulation in the quasi-experiment. Some dropout occurred in group B which was accounted for by stratifying the random assignments for equal group sizes. In total, AwarenessTool had 72 unique page views over the course from pre to post-test. The views varied from 1 to 5 times (Median = 2 times) for each participant of group B before they started the post-assessment.

3.2 Intervention: using AwarenessTool

We developed AwarenessTool to personalize the explanation of curation algorithms' capabilities. To start, participants were asked to log in on AwarenessTool by copying their cookies from Instagram's website so that their personal Instagram data could be fetched. This data was then analysed in order to visually reveal the effects of Instagram's curation algorithm on participants' personal news feed with the help of a guided tour through AwarenessTool. This initial step was nonetheless not straightforward, especially for participants with low ICT-literacy. To ensure low drop-out, a step-by-step guide was provided on AwarenessTool and participants were guided on how to copy their cookies in one click using the *EditThisCookie* browser extension and paste them in AwarenessTool to continue. In total we experienced a drop-out of 36 out of 100 recruited participants.

After log in, the tool fetched the first 50 posts as ranked by the curation algorithm to be shown in the news feed (hereafter 'curated posts'). This first set, the curated posts, is thus equal to the first 50 posts one can scroll through when opening their Instagram app. The least recent post from this curated posts set was then determined and further used as cut-off value. Note that this least recent post (i.e. the oldest post in the set) is almost never the last or 50^{th} post of the curated posts, due to Instagram's ranking algorithm.

Next, the AwarenessTool created a second set of posts. This set (hereafter 'uncurated posts') included the curated posts and all posts that were more recent than the previously calculated cut-off value of the least recent post. Thus, the extra included posts would all appear in a user's feed before the least recent post if the feed were shown in reverse chronological order instead of Instagram's ranking algorithm's order. In other words, users now miss out on all these extra included posts due to Instagram's ranking algorithm. In order to visualize this to participants, the uncurated posts were reversed chronically sorted and compared to their uncurated feed. Hence, the main difference between the curated and uncurated posts set is (1) the size of the set and (2) the sequence in which the posts appear; for the curated posts, this is a smaller set and the sequencing in which they appear is determined by Instagram's ranking algorithm and personalised for each user (see – URL not disclosed to ensure an anonymous review process – for a more detailed explanation and live example).

We computed the Kendall Tau coefficient and amount of 'hidden' posts for each user of AwarenessTool in order to gain and share insights about the algorithm's dynamics. The average Kendall Tau (T_b) was 0.48 and ranged from -0.19 to 0.98. This shows that most users' news feeds are significantly reordered while largely still in line with the posts' recency (i.e. the positive correlation between the curated and uncurated reverse chronological posts lists). Also, the amount of posts that were filtered out of the curated posts as a consequence of their lower ranking (i.e. hidden posts) again show how substantially posts get reordered. This varied greatly between participants and ranged from zero hidden posts for some, to a few dozen for most, up to hundreds of hidden posts for others ($M_{hiddenPosts}$ = 119.36, SD = 151.15, Median = 43, n = 83), see Figure 1.

<< INSERT FIGURE 1 HERE>>

The different views offered by AwarenessTool to the participants in the quasi experiment, resulting from the calculations described above, are discussed next.

3.2.1 View one: disclosing personalised rankings

The first view's purpose was to disclose the main effect of the Instagram curation algorithm, that is, ranking posts differently based on one's prior behavior. This view was set up with two columns, allowing users to compare the list of uncurated posts with the list of curated posts (Figure 2). Additional information was provided for enhanced comparison of the algorithm-free (uncurated posts) and curated feed (curated posts). This view also featured a step by step guided tour for the participants in group B. For example, one of the steps covered the highest ranked post and asked participants to reflect upon questions such as 'Did this post indeed deserve the highest spot in the curated posts?'. This type of critical questions, as well as other critical questions in any subsequent views (see infra), were used to stimulate reflection on the consequences of Instagram's algorithm. Similar to Baumer et al. (2014) we use a broad, general conceptualization of 'reflection' and consider 'reflection' in this context as an individual, largely mental or cognitive activity of reviewing a series of previous Instagram posts and putting them together in such a way as to come to a better understanding. Reflection on the consequences of Instagram's algorithm thus involves synthesizing different Instagram posts to arrive at some greater understanding of Instagram's algorithm.

<< INSERT FIGURE 2 HERE>>

3.3.2 View two: disclosing estimated affinity

The second view's purpose was to disclose the patterns of the Instagram curation algorithm by showing Instagram followings divided into three categories (Figure 3), coupled with their cumulative rank. Similar to view one, critical questions were posed in the guided tour concerning the algorithm's working. For example, when explaining the category 'higher ranked', questions such as 'Do you really want to see [name following] more frequently in your news feed?' were asked.

<< INSERT FIGURE 3 HERE>>

3.2.3 View three: disclosing hidden posts

The third view's purpose was to disclose how one could overlook some of their Instagram followings and to show the absence of certain followings in the curated posts. In order to facilitate this, a side-by-side comparison of the uncurated posts list on the left and the curated posts lists on the right was presented (Figure 4). The differences with view one, however, are that this view presents (1) a full-length uncurated posts list that is not shortened to the same size as the curated posts list and that (2) posts are in reverse chronological order for both lists, which allowed for easier comparison. Next to each post that appeared in the uncurated posts list but not in the curated posts list, the label 'hidden' was added. In the guided tour participants were informed that Instagram deploys a ranking algorithm and therefore does not hide any posts if one keeps scrolling far enough. However, posts can be overlooked if one only peeks at the first posts in his or her news feed. Similarly to view one and two, critical questions were asked, for example 'Do you feel that you frequently miss out on important posts?', to further raise awareness about Instagram's algorithm.

<< INSERT FIGURE 4 HERE>>

3.3 Post-assessment

In order to understand how CML and the attitudes of participants evolved after using AwarenessTool, as well as to understand the effectiveness of using a visual feedback tool to raise these competencies, participants were assessed in a post-test. Two to three weeks after the pre-test, participants were invited to fill out the same questionnaire as described in section 3.1, which was slightly altered for group B by adding 'After the use of AwarenessTool, [...]' before each question. After this, responses were linked to the participant's pre-test responses. Although group A could be influenced by learning effects from reading and answering the questions in the pre-test, no significant differences ($p >$ .05) were found for this group between pre- and post-test, which allowed us to use them for between-subject comparisons.

3.4 Participants

Participants were recruited using the snowball sampling method on social media through the personal network of the authors. 93 respondents started the pre-test of which 70 completed the entire questionnaire. Ultimately, 64 respondents (=n) completed all three phases. No incentive was granted to participate. 64% women and 36% men constituted the sample, ranging between 18 and 35 years ($M_{age} = 23.97$, $SD = 2.81$). Participants were mainly (86%) highly educated with 31% having obtained a bachelor's degree while an additional 55% had obtained a master's degree.

3.5 Data analysis

Data analysis was done with R (R Core Team, 2018) and the PROCESS v3 macro for SPSS from Hayes (2017). First, summation scales were calculated for each measured concept. Second, a simple mediation analysis was conducted using ordinary least squares path analysis to interpret the mediation model (Hayes, 2017, model 4) which helped to partly answer the RQ. Post-test scores were used to analyze this model (Hayes, 2017). Next, a one-way analysis of covariance (ANCOVA) was conducted using pretest scores as covariates to analyze differences in CML, general feelings and critical concern between group A and B for H_1, H_2 and H_3. Subsequently, Spearman correlation tests were used to detect covariates (e.g., TML) but this yielded no positive results. In some cases, we followed up with a two-way mixed analysis of variance (MANOVA). Last, each of the three analyses were preceded by testing their underlying assumption confirming the data's model fit for every used test.

Even though a MANOVA could also be used to initially test H_1, H_2 and H_3, a one-way ANCOVA analysis allows for detecting and comparing (post-test) differences rather than analyzing the amount of gain for each group (Wright, 2006). Overall, a one-way ANCOVA is the preferred method for randomized pre- post-test designs as it allows for a higher degree of external validity thanks to reduced error variance (Dimitrov & Rumrill, 2003). Thus, a one-way ANCOVA appeared to be the most appropriate test to answer H_1, H_2 and H_3 while a MANOVA allowed for appropriate follow-up testing when the ANCOVA results were inconclusive.

4. Results

4.1 H1: AwarenessTool' effectiveness in raising algorithm awareness

Hypothesis one tests if people gained some understanding of the actual working of Instagram's algorithm after using AwarenessTool. After adjusting for the pre-test CML scores, positive differences with a large effect size in the post-test CML scores are found for those who used AwarenessTool, $F(1, 61) = 8.93$, $p = .004$, $\eta^2_p = .13$. Participants in group B thus gained significant better understanding about algorithms and their capabilities (Figure 5 and Table 1).

<< INSERT FIGURE 5 HERE>>

In short, CML is found to be 2.36 points (=M_{diff}, 95% CI [0.81, 3.91]) higher after the intervention on a 0 to 20 scale for group B (M_b = 13.18, 95% CI [12.06, 14.30]) compared to control group A (M_a = 10.82, 95% CI [9.70, 11.94]). Furthermore, a paired sample t-test shows that the gain score in mean difference from pre- to post-test is significant for solely group B with an increase of 2.69, $t(31) = 3.56$, $p = .001$, and not for group A, which had a gain score in mean difference of 0.53, $p = .28$. This paired sample t-test additionally supports the already indicated effectiveness of AwarenessTool, as only group B gained a significant increase over time

<< INSERT TABLE 3 HERE>>

4.2 H2: AwarenessTool' effect on general feelings towards Instagram

Hypothesis two tests if people who used AwarenessTool had more positive general feelings towards Instagram than those who did not use AwarenessTool. After adjusting for the pre-test general feelings scores, those who used AwarenessTool appear to have more or less the same feelings towards Instagram than those who did not use the tool, $F(1, 60) = 1.18$, $p = .28$, $\eta^2_p = .02$. Manipulation group B had a mean score on general feelings of 13.59 for the post-test, which is a small increase of 0.53 points (= Mdiff, 95% CI [−0.42, 1.48]) on a scale of 0 to 24 compared to the mean general feelings score of 13.06 for control group A during the post-test.

More importantly, however, is the observed overall decrease in general feelings towards Instagram from pre- to post-test as indicated by a follow-up MANOVA. Even though we confirmed a slight increase for the post-test general feelings scores for group B compared to group A, both groups do actually have less positive feelings towards Instagram in the post-test. As mentioned above, people who did fill in the posttest questionnaire after using AwarenessTool (group B) postulate less negative feelings (Mdiff = 0.53) compared to those who only filled in the post-test questionnaire and did not use AwarenessTool (group A). The mean general feelings score for control group A decreased pre to post from 13.75 to 12.81 (Mdiff = −0.94) and for group B from 13.84 to 13.66 (Mdiff = −0.19) (Figure 6). This decrease in general feelings is not significant for the interaction effect between intervention and time ($F(1, 62) = 1.40$, $p = .24$, $\eta^2_p = .02$), nor for the simple main effect of time ($F(1, 61) = 3.15$, $p = .08$, $\eta^2_p = .05$).

<< INSERT FIGURE 6 HERE>>

4.3 H3: AwarenessTool' effect on critical concern towards Instagram's curation algorithms

In hypothesis three, we ask if people who used AwarenessTool have increased critical concerns towards Instagram compared to those who did not use AwarenessTool. After adjusting for pre-test scores of critical concerns, users of AwarenessTool do not significantly pose increased critical concerns towards Instagram compared to participants who did not use AwarenessTool, $F(1, 61) = 1.63$, $p = .21$, $\eta^2_p = .03$. The post-test mean critical concern score is 27.89 for group B and higher by 1.56 points (= Mdiff, 95% CI [−0.83, 3.94]) on a scale from 0 to 40 compared to the mean critical concern score of 26.33 for group A.

Even though no significant increase in critical concerns can be attributed to solely the use of AwarenessTool, we do nevertheless provide proof that our experiment impacts participant's critical concerns towards Instagram. The simple main effect of time in both groups, that is, either completing the questionnaires or completing the questionnaires using AwarenessTool in between, stimulated our participants to significantly pose increased critical concerns, $F(1, 62) = 8.52$, $p = .005$, $\eta^2_p = .12$

<< INSERT FIGURE 7 HERE>>

Figure 7 shows an increase in mean critical concerns from pre- to post-test for control group A from 15.38 to 16.44 ($M_{diff} = 1.06$) while there is a slightly bigger increase in mean critical concerns score for group B from 15.09 to 17.78 ($M_{diff} = 2.69$). The interaction effect between time and intervention appears to be insignificant, $F(1, 62) = 1.60$, $p = .21$, $\eta^2_p = .03$. This suggests that becoming aware (i.e. through learning effects from the questionnaire) is sufficient to pose increased critical concerns towards Instagram while becoming knowledgeable about curation algorithms' capabilities (i.e. increased CML next to becoming aware by the use of AwarenessTool) does not further increase critical concerns significantly.

Overall, this confirms previous studies as well as the first stage of the proposed 'Algorithm Paradox', that is, that people who know about the existence of curation algorithms claim to be bothered by it. Even though people who used AwarenessTool did not mind activities such as feed curation significantly more than others who solely became aware of this, the overall findings are still insightful in evaluating the relationship between media literacy and attitudes as posed in our main research question.

4.4 Overview hypotheses testing

<< INSERT TABLE 4 HERE>>

4.5 RQ: What is the relation between TML and CML of Instagram's curation algorithm and what are the attitudes towards Instagram for Flemish adults?

<< INSERT FIGURE 8 HERE>>

Users' cognitive understanding and competencies in consuming and evaluating Instagrams' content and mechanisms has both a (1) direct and (2) indirect influence on their critical concerns towards activities Instagram carries out, such as content filtering or selling and using personal behavioral data. First, the direct effect is seen in participants having higher cognitive understanding also indicating to have raised critical concerns (*c'* = 0.50). Second, the indirect influence arises through CML's effect on users' technical understanding and competencies in using Instagram (Figure 8 and Table 5).

<< INSERT TABLE 5 HERE>>

The relationships in the mediation model (i.e. a, b, c', Figure 8) show a sensible causal process. First, since technical understanding is considered to be required for the development of cognitive understanding (section 2.3), it is reasonable for CML to be an indicator of TML (a). Second, users' cognitive understanding can develop through frequent use or oppositely diminish when users lack the ability to make appropriate use of their technical understanding. In this way, we believe that TML affects critical concern (b). Third, earlier studies indicated attitudinal and habit changes as a result of change in cognitive understanding, making it reasonable to believe that this will equally affect users' critical concerns (c').

Nearly all participants (95%) are aware of at least one activity that encompasses some form of algorithmic curation at the start of the experiment and the vast majority (80%) knows at least 3 (out of 7) of curation algorithms' features. This contrasts studies that indicate far lower awareness of filtering and curation mechanisms. One explanation might be that participants had to indicate the activities thought to be present on Instagram, instead of answering questions directly probing about some 'algorithm'. Moreover, more than half of the participants (63%) indicated to have the feeling they sometimes miss posts and nearly all (98%) indicated to have the feeling of missing posts 'due to some filtering of Instagram itself'.

Furthermore, this high level of participants' awareness seems in line with their TML level. The majority indicates to be highly familiar with Instagram (Mfamiliarity = 30.66, SD = 7.57, scale = 0 − 45) even while stating to use features such as 'posting a story' or 'commenting on a post' monthly or less frequently on average (Mfrequency = 9.42, SD = 4.77, scale = 0−28). Participants' above average operational and formal skills are reflected in their ability to find, evaluate and utilise the presented content as seen in their fair to high CML level (Mcml = 10.39, SD = 3.95, scale = 0 − 20). We argue this is a fair to high CML level because participants had no prior formal education in this and existing knowledge was gained through (experimental) usage.

H_1 and H_3 confirmed the significant gain in participants' level of CML and concerns by making them aware, supporting the fact that our participants do adapt their attitudes and expectations accordingly to their knowledge. However, no change in habits to act accordingly to their increased concerns was identified as examined by McNemar's test for neither group A nor B from pre to post. Likewise, no correlation was found between participants level of concerns and their habits as examined by a point-biserial correlation, except for fear of missing out (FOMO), r(62) = .36, p = .004, and blaming the algorithm when having fewer likes, r(62) = .32, p = .01.

As such, these findings support our positioning of the Algorithm Paradox: when people know the existence of curation algorithms, they claim to be bothered by them while not acting accordingly (e.g. by altering settings, changing interaction modes or visiting other profiles).

5. Conclusion and discussion

This article addressed the influential yet subtle and often hidden side effects of Instagram's algorithmic curation. One such side effect is a potential filter bubble, where prescriptive algorithms personalize content based on estimates about what fits people's beliefs and likings. The filter bubble effect is exacerbated and especially difficult to tackle due to people's ignorance about these personalization mechanisms and high faith in the veracity of its results. People appear to be unable to escape their filter bubble because of their ignorance of personalization mechanisms and their side effects, which in turn impedes the - required - change in critical attitudes, what we called the 'Algorithm Paradox'.

This aligns with the information privacy paradox, where users claim to value their personal information while their actual behavior is contradictory (Norberg, Horne & Horne, 2007) or with people's attitudes towards information transparency features while using personalized online services (Awad & Krishnan, 2006). As such, although AwarenessTool heightened how knowledgeable one is about different aspects of his or her media consumption, described by both technical and cognitive competencies (Livingstone, Van Couvering and Thumin, 2008), these higher critical concerns and claims about being bothered by algorithms' mechanisms did not change habits in using Instagram accordingly. Yet, it is this change in habits, such as checking different sources, following a diversity of profiles or acknowledging greater prevalence of like-minded opinions, that is ultimately required to overcome the potential negative side effects of filter bubbles. For this reason, further research on the existence and explanation of the algorithm paradox similar to the continued research about the privacy paradox (e.g. that the perceived advantages outweigh the perceived disadvantages to such an extent that habits are not changed)[1] is promoted.

Our findings also revealed unexpected differences in conceptualising TML. In short, the effect of frequency of use stimulates critical concerns, whereas the effect of self-reported familiarity on critical concerns seems to be completely absent.

Our approach contributes to increasing algorithmic awareness, CML and critical attitudes and quantitatively confirms findings about the effects and effectiveness of exposing hidden algorithmic processes to users with the help of visual feedback tools (Eslami, Rickman et al., 2015). AwarenessTool showed to be effective in exposing and explaining the working of invisible curation algorithms thereby directly increasing CML. Also, solely making participants aware of the curation algorithms' existence (e.g., through a questionnaire) appeared to be already sufficient to raise people's critical concerns.

6. Limitations of the study

Some limitations in our research approach should be noted however. With regards to development of AwarenessTool, we had to limit the amount of fetched curated posts to a total of 50 posts. However, this limited list of 50 curated posts as the base for further calculations was found to still reveal quality information while not too often reaching the API's limits. Also, due to the unavailability of an official API to fetch one's news feed, the Instagram website endpoints had to be used to implement the retrieval of one's news feed. During this process no personal data was saved except for (1) the rankings produced by the curation algorithm and (2) the amount of hidden posts. Data was also processed

[1] We would like to thank the anonymous reviewer for this suggestion.

anonymously and transferred with encryption. With regards to the data and data analysis we should point out that, due to the convenience sample we gathered, we cannot claim to have reached a representative sample of Instagram users; participants were a non-randomized, homogeneous (young, well-educated, mainly female) group of just 64 respondents. Also the mediation analysis could have been optimised if the pre-test scores were used as covariates when interpreting the model (Hayes, 2017, p. 544) using structural equation modelling. Other limitations such as reliability issues in online surveys and a possible self-selection bias need to be also taken into account (Gosling et al. 2004).

Nevertheless, the following benefits that come with using a visual feedback tool make this the preferred approach. First, AwarenessTool enables users to become far more knowledgeable about the consequences of personalization. Second, AwarenessTool can positively impact users' self-development by enabling their capabilities to better assess the impact on their self-presentation. Third, AwarenessTool educates users about the 'rulebook' they can adapt to and informs them on how to play the 'visibility game' accordingly. Taking these benefits into account we are happy to note the increasing availability of other visual feedback tools (e.g. https://algorithms.exposed or https://algotransparency.org/) and encourage and welcome other software contributions that help to increase algorithmic awareness.

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Table 1. Conceptual definitions and operationalisation of the media literacy competencies typology as proposed by van Dijk and van Deursen (source and complete definitions: van Deursen, van Dijk & Peeters, 2012; van Deursen, Courtois & van Dijk, 2014 and van Deursen & van Dijk, 2015).

Technical media literacy *Medium related*		*Cognitive media literacy* *Content related*	
Operational	Formal	Informational	Strategic
Skills to operate digital media, 'button knowledge'	Skills to orient oneself within nonlinear medium specific structures	Skills to find, select and evaluate sources of digital information	Skills to use digital sources to reach a personal or professional goal
Download files Open files Using shortcuts Using bookmarks Connect to Wi-Fi	Navigate between menus Following hyperlinks No disorientation when navigating Understanding the design flow	Deciding keywords Evaluating information sources Check correctness of sources Examine not only top results Understanding filter mechanisms	Orientation towards a particular goal Taking the right actions to reach this goal Making the right decisions to reach this goal Gaining benefits resulting from this goal

Table 2. Study design overview

Phase	Group A (n=32)	Group B (n=32)	Union (*A* + *B*)
Pre-test	Measure TML, CML and ATT		—
Intervention	Control group without placebo Follow-up: 14-18 days	Group using AwarenessTool Follow-up: 14-21 days	—
Post-test	Measure TML, CML and ATT		RQ (N=64)
Mixed-design	H1, H2, H3		—

Table 3. Adjusted and unadjusted means and variability for post-test CML with pre-test CML as covariates, split by control group A and group B that used AwarenessTool.

		Unadjusted		*Adjusted*	
	n	*M*	*SD*	*M*	*SE*
Control (A)	32	10.69	3.65	10.82	0.55
AwarenessTool (B)	32	13.31	4.04	13.18	0.55

Control = Control group A that received no treatment, AwarenessTool = Group B that used AwarenessTool. Range CML: 0 – 20

Table 4. Overview of the hypotheses testing results

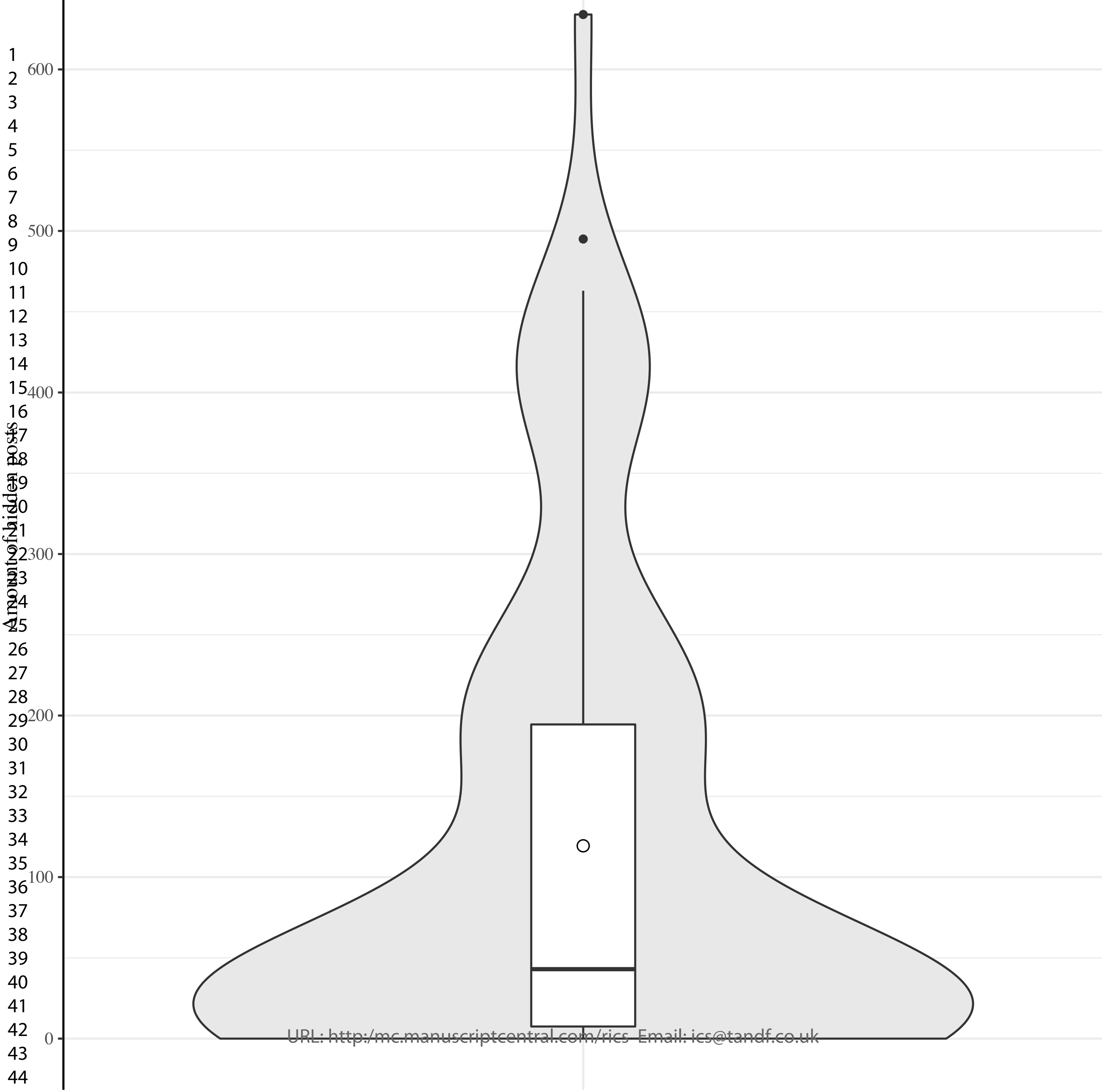
Alternative hypothesis	*Result*	*Interpretation*
H_1	accepted**	Using AwarenessTool significantly increases cognitive media literacy.
H_2	rejected	Using AwarenessTool reduces the decrease in general feelings towards SNS. The reduction and decrease in general feelings is, however, not significant.
H_3	rejected	The effect of using of AwarenessTool is insufficient to significantly increase critical concerns towards certain activities SNSs carry out, although becoming aware of solely algorithms' presence is sufficient to pose increased critical concerns.

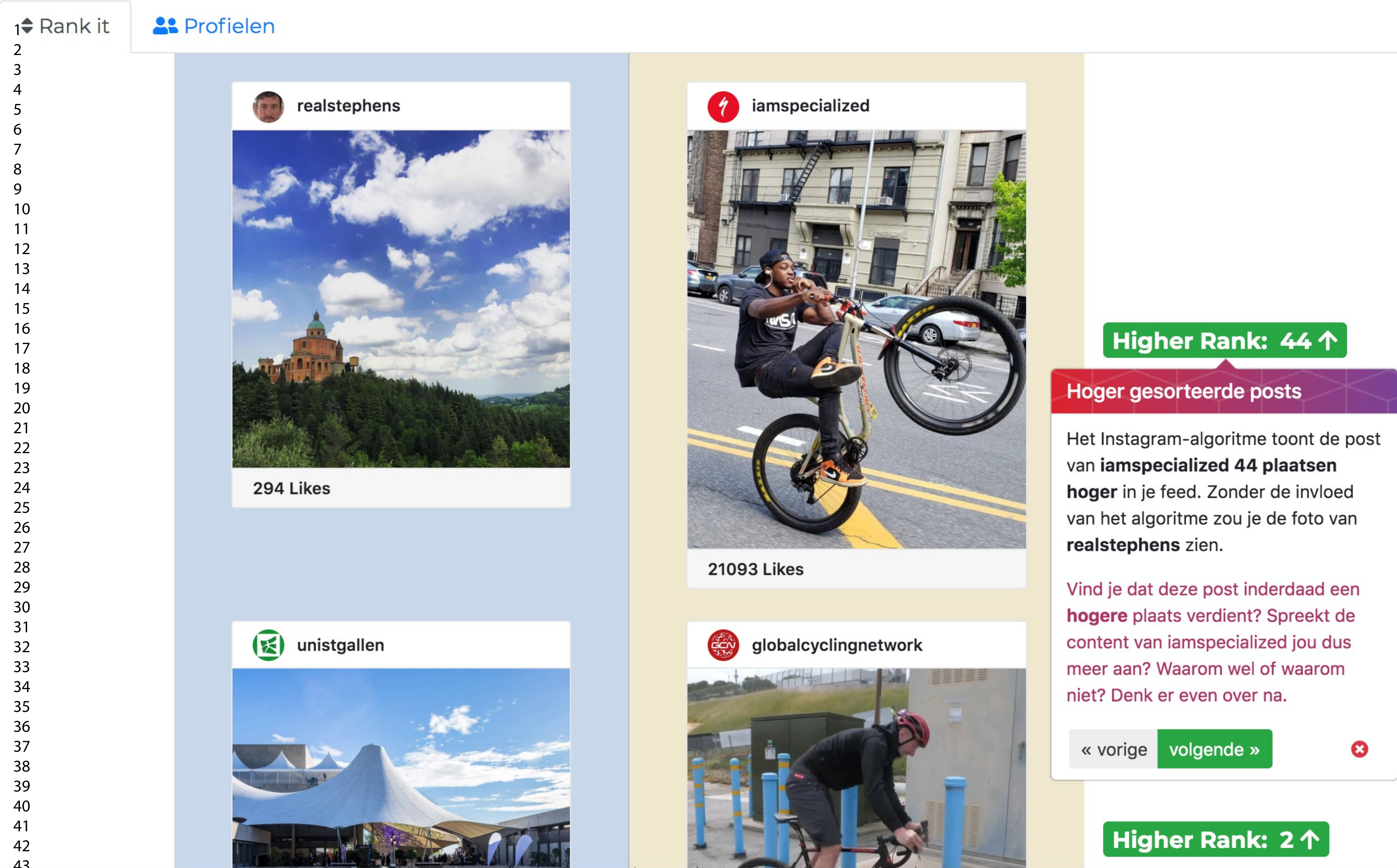
$* = p < .05, ** = p < .01$, only the alternative hypotheses are listed as was done in section 2.

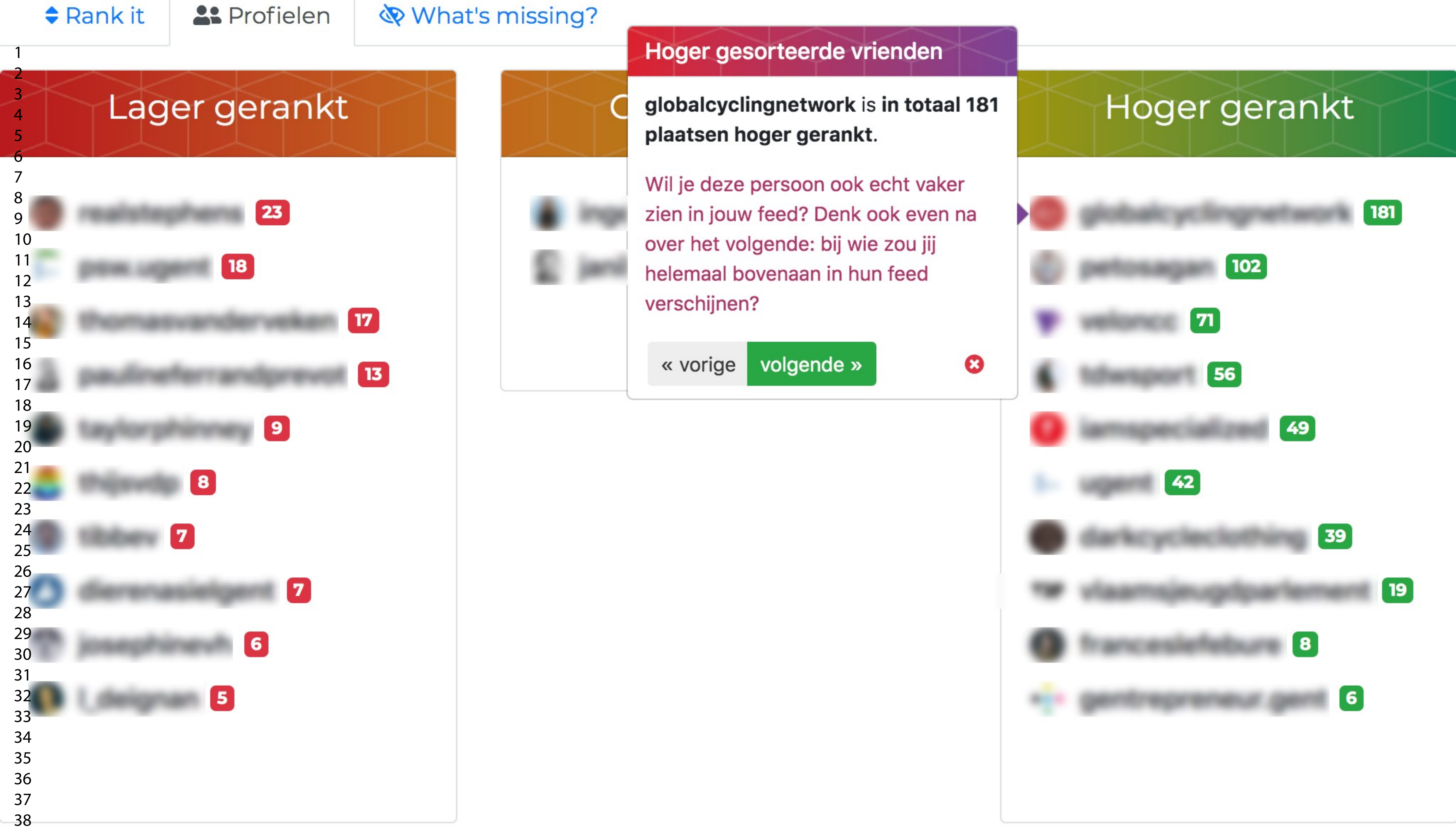
Table 5. Overview mediation model

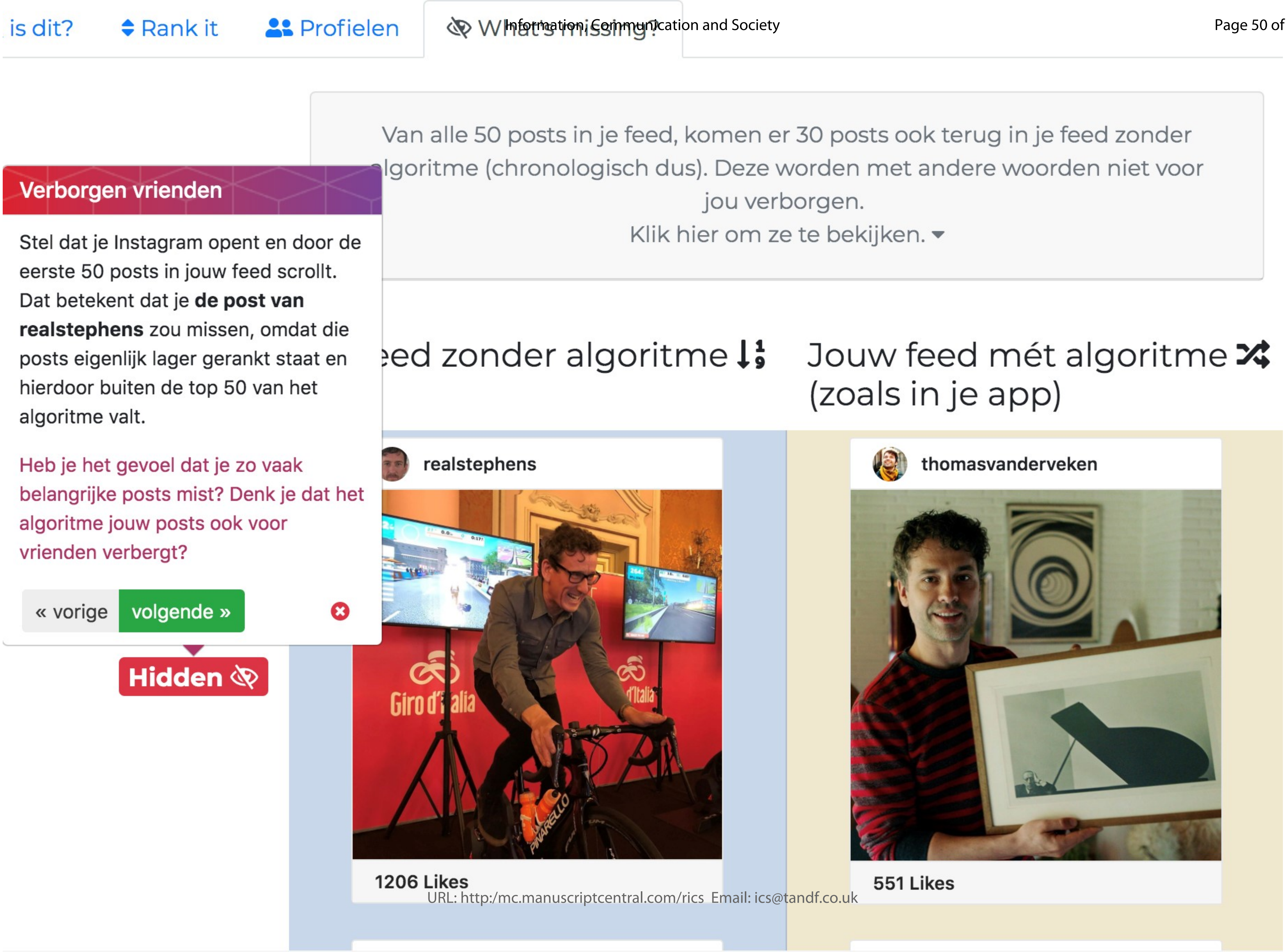
		Consequent						
		M(TML[a])				*Y* (CRITICAL CONCERNS)		
Antecedent		Coeff.	*SE*	*p*		Coeff.	*SE*	*p*
X(CML)	*a*	0.29	0.15	.06	*c'*	0.50	0.19	.009
M(TML[a])		—	—	—	*b*	0.61	0.15	< .001
constant	i_M	13.10	1.91	< .001	i_Y	1.27	3.04	.68
		$R^2 = .06$				$R^2 = .33$		
		$F(1,61) = 3.78, p = .06$				$F(1,61) = 14.96, p < .001$		

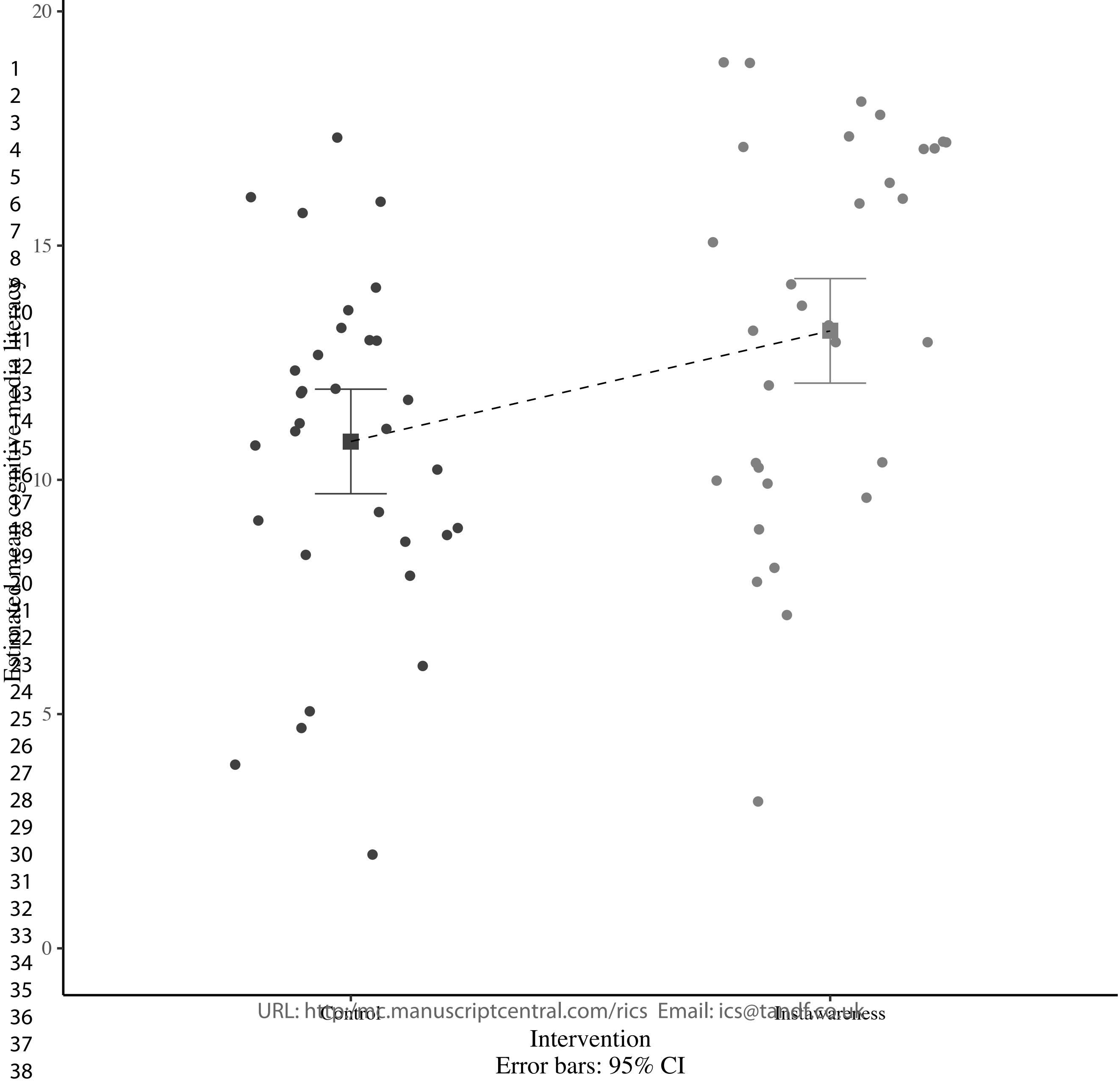
[a]Frequency was used as a proxy. The analysis was conducted with a one-tailed α of .05 as we expected a positive correlation, which is equal to running the mediation analysis at two-tailed α of .1. Unstandardised coefficients have been reported.

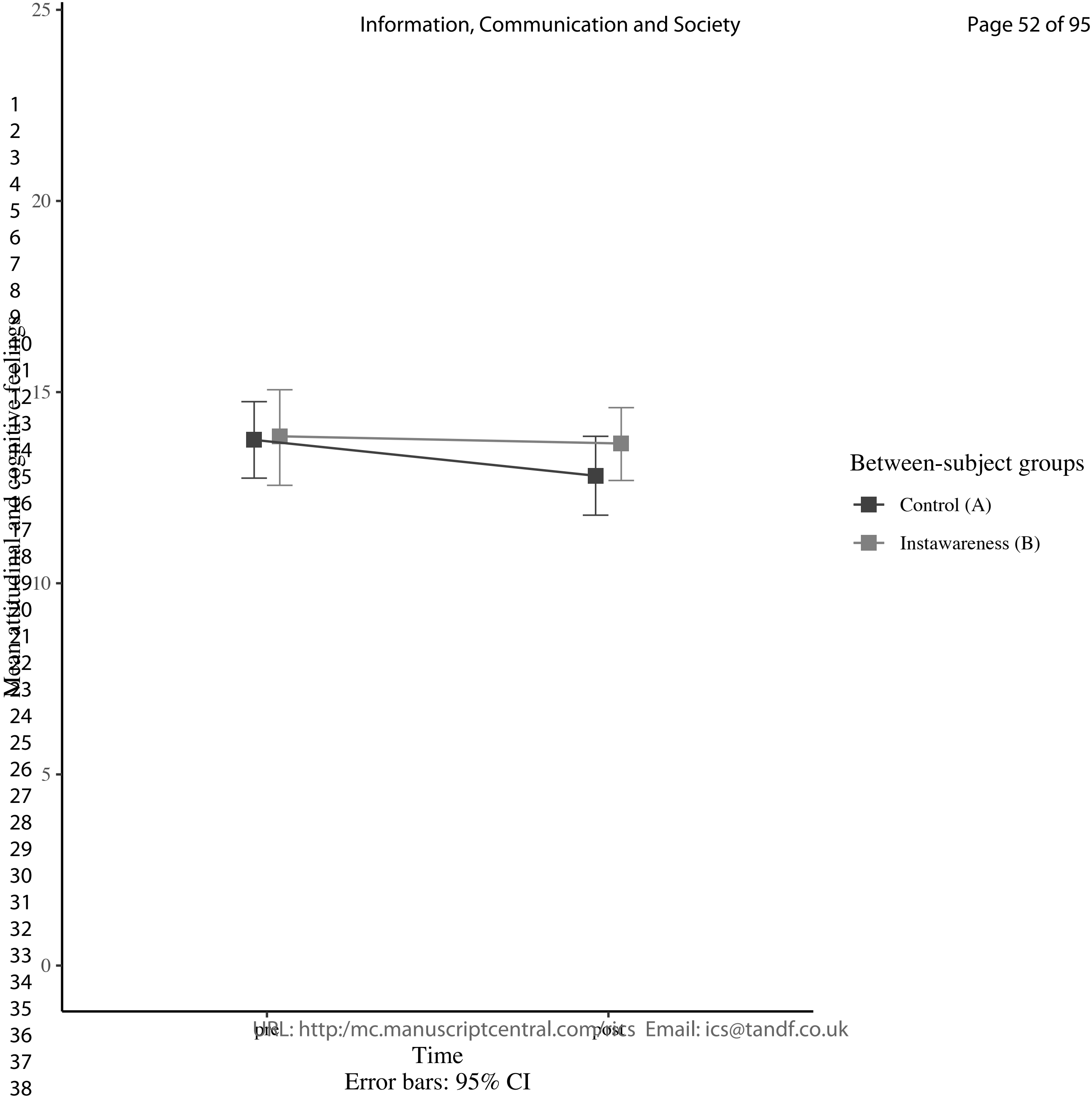

Amount of hidden posts
600
500
400
300
200
100
0

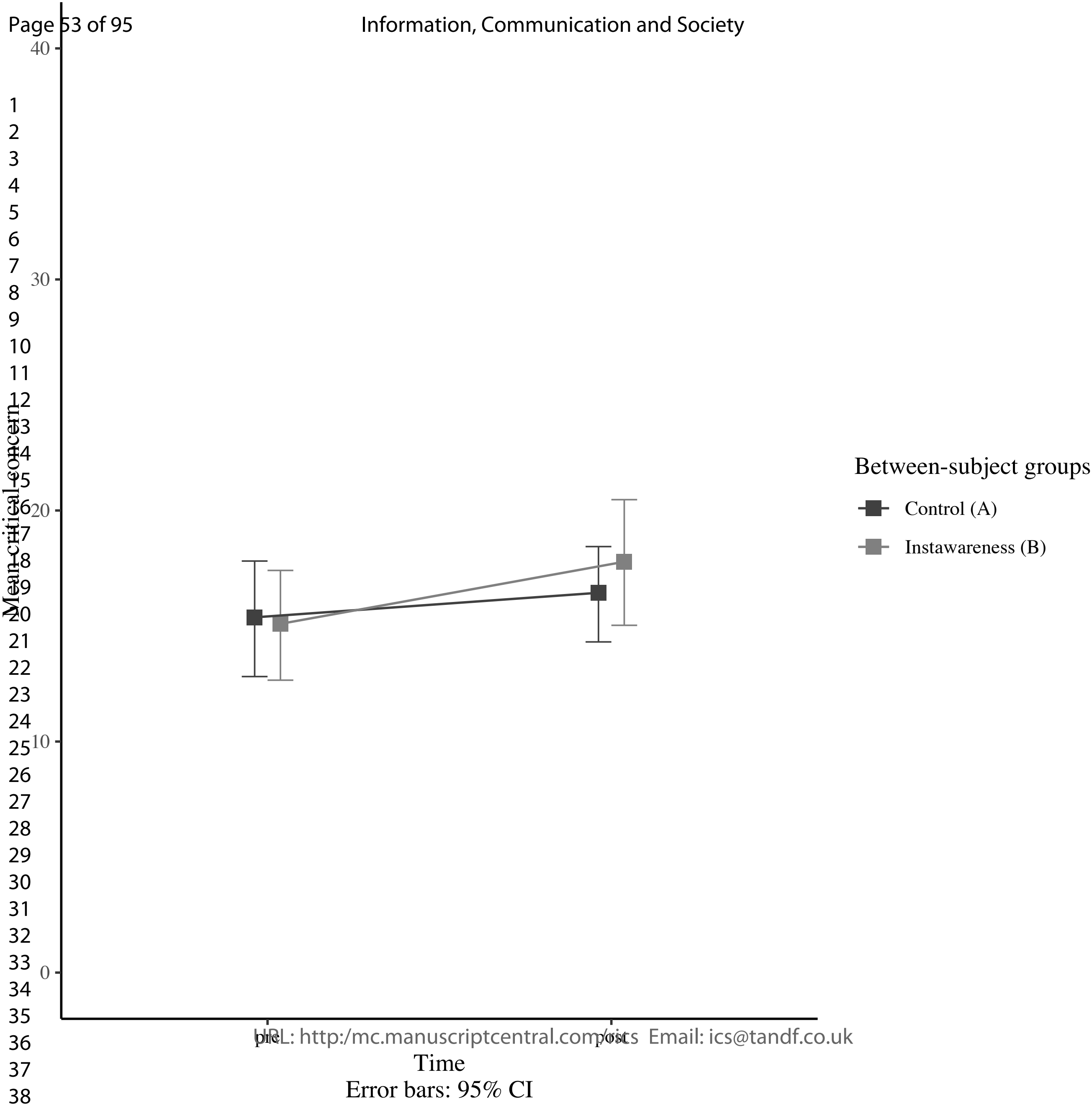

Rank it
Profielen
realstephens
294 Likes
iamspecialized
21093 Likes
unistgallen
globalcyclingnetwork
Higher Rank: 44
Hoger gesorteerde posts
Het Instagram-algoritme toont de post van iamspecialized 44 plaatsen hoger in je feed. Zonder de invloed van het algoritme zou je de foto van realstephens zien.
Vind je dat deze post inderdaad een hogere plaats verdient? Spreekt de content van iamspecialized jou dus meer aan? Waarom wel of waarom niet? Denk er even over na.
« vorige
volgende »
Higher Rank: 2

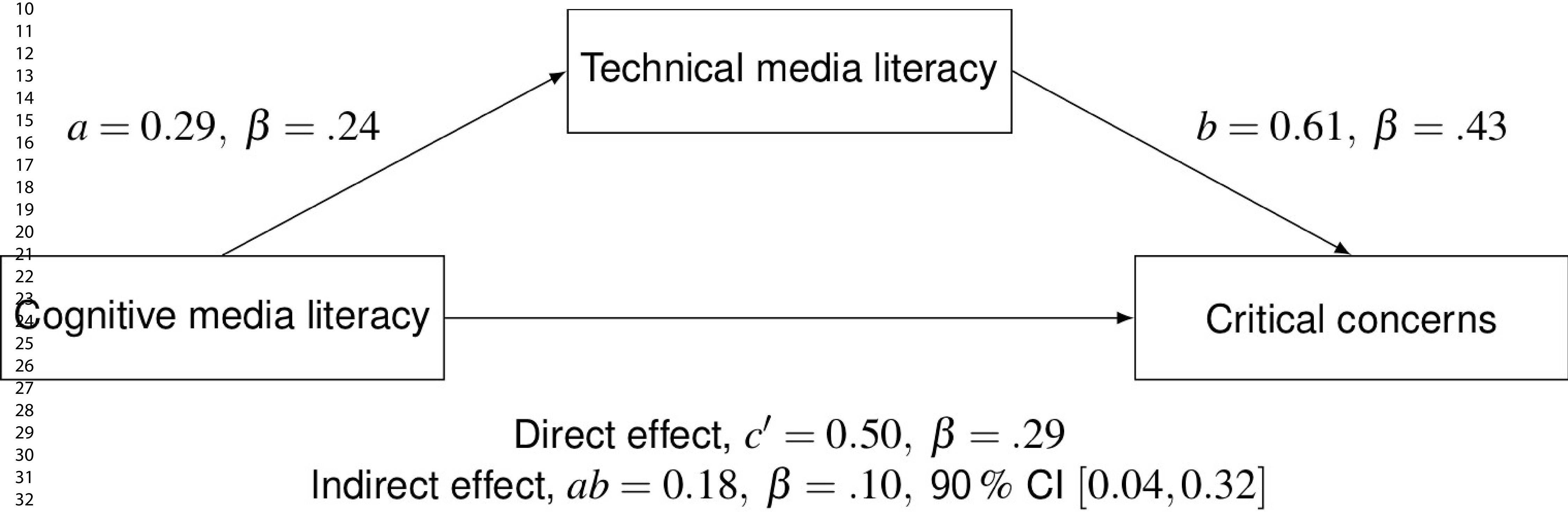

Rank it
Profielen
What's missing?
Lager gerankt
23
18
17
13
9
8
7
7
6
5
Hoger gesorteerde vrienden
globalcyclingnetwork is in totaal 181 plaatsen hoger gerankt.
Wil je deze persoon ook echt vaker zien in jouw feed? Denk ook even na over het volgende: bij wie zou jij helemaal bovenaan in hun feed verschijnen?
« vorige
volgende »
Hoger gerankt
181
102
71
56
49
42
39
19
8
6


is dit?
Rank it
Profielen
What's missing?
Van alle 50 posts in je feed, komen er 30 posts ook terug in je feed zonder algoritme (chronologisch dus). Deze worden met andere woorden niet voor jou verborgen.
Klik hier om ze te bekijken.
Verborgen vrienden
Stel dat je Instagram opent en door de eerste 50 posts in jouw feed scrollt. Dat betekent dat je de post van realstephens zou missen, omdat die posts eigenlijk lager gerankt staat en hierdoor buiten de top 50 van het algoritme valt.
Heb je het gevoel dat je zo vaak belangrijke posts mist? Denk je dat het algoritme jouw posts ook voor vrienden verbergt?
« vorige
volgende »
Hidden
eed zonder algoritme
Jouw feed mét algoritme (zoals in je app)
realstephens
1206 Likes
thomasvanderveken
551 Likes


Estimated mean cognitive media literacy
20
15
10
5
0
Control
Instawareness
Intervention
Error bars: 95% CI


25
20
15
10
5
0
Mean attitudinal and cognitive feelings
pre
post
Time
Error bars: 95% CI
Between-subject groups
Control (A)
Instawareness (B)


40
30
20
10
0
Mean critical concern
pre
post
Time
Error bars: 95% CI
Between-subject groups
Control (A)
Instawareness (B)


Technical media literacy
$a = 0.29,\ \beta = .24$
$b = 0.61,\ \beta = .43$
Cognitive media literacy
Critical concerns
Direct effect, $c' = 0.50,\ \beta = .29$
Indirect effect, $ab = 0.18,\ \beta = .10,\ 90\,\%$ CI $[0.04, 0.32]$