Science on social media: a buffer or reinforcer of inequality?

Assessing the moderating effect of science on social media on the relationship between educational level and attending lectures or talks about science.

Ellen Möhlmann

7476310

Utrecht University

Sociology: Contemporary Social Problems

Supervisor: Matthias Kern

Second reader: Vardan Barsegyan

Word count: 7659

Date: 24-06-2022

Abstract

In order to provide the public with more scientific knowledge, lectures and talks about science are organized that people can go to voluntarily. In this research, the socio-demographic composition of the people who attend these lectures is investigated. According to the theory, higher educated people are more likely to attend these lectures. Reasons for this are not just lack of understanding and lack of interest among lower educated people, but also habitus plays a role. This concept, developed by Bourdieu (1990), defines why people feel (un)comfortable in a place or situation depending on the environment that they grew up in. Furthermore, this research investigates a moderating relationship of seeing science on social media on the relationship between educational level and attending the lectures or talks about science. We expect a negative moderating relationship, because we theorize that seeing science on social media could work as a buffer on the direct relationship. For this research, an existing dataset by PewResearch was used with a sample size of 2731 respondents. Logistic regression analysis was used in order to test the hypotheses. In line with what was expected, the results show a positive relationship between educational level and attending the lectures and talks about science. The moderating effect, however, was found to be not significant. In the conclusion and discussion section, these findings are explained. Furthermore, limitations, suggestions for future research and policy advice are discussed.

This research received ethical approval from the Ethical Review Board of the Faculty of Social and Behavioural Sciences of Utrecht University on the 31st of March 2022, and was filed under number 22-0835.

Table of contents

1. Introduction

In today's society, people often get confronted with complex and conflicting information, of which they are themselves expected to judge the credibility. Scientific research is hereby often doubted and scientific facts are being denied. With the outbreak of the COVID-19 pandemic, conspiracy theories and 'alternative facts' were being developed and spread. A lot of people did not trust the scientific evidence regarding the virus, which led to them not following the rules that were in place to limit the spread of the virus (Kartono et al., 2020). In this case, believing in conspiracy theories turned into a serious global health hazard. This is just one example that shows the importance of the public having some scientific knowledge. Furthermore, this knowledge is not only relevant in the context of a pandemic. Nowadays, the general public is expected to keep learning and developing themselves (Field, 2006). This additional knowledge and development already starts when children go to school. Extracurricular activities, where children engage in outside of their school curriculum, are thought to be important for both their school career as well as their professional career. Among alumni, extracurricular activities are reflected as key to developing self-identity, social networks and career prospects or career pathways (Stuart et al., 2011). Among employers, extracurricular activities are seen as a means to 'distinguish' candidates, provide evidence of cultural fit, leadership, commitment, and 'selling' original activities (Stuart et al., 2011). After graduating, people are still expected to develop themselves and gain more knowledge (Field, 2006). In this research, we will talk about attending lectures or talks about science specifically.

This research will investigate the socio-demographic composition of the people who attend these lectures or talks about science. In general, higher educated people are more likely to attend these lectures and talks about science (Hunt, 2007; Von Stumm, 2017). There are a few possible reasons for this relationship. First, it is possible that lower educated people are just not interested in the scientific topics that are being discussed during these events (Ho & Devi, 2020). Furthermore, it could be that they do not possess the needed knowledge or language that is required in order to understand what is said during these lectures and talks. A third possible reason for this relationship is the habitus. This concept, developed by Bourdieu (1990), explains why people feel (un)comfortable in a place or situation depending on the environment that they grew up in. In this research, we will look at the relationship between educational level and attending these lectures or talks about science.

Nowadays, social media are an important way of communicating. As social media grew, so did the science communication of social media (Davies et al., 2019). Research shows that a diverse range of factors influence the engagement of specific audiences. This depends on the platform selected (Twitter, Facebook, Youtube), the type of actor doing the communication (science journalists, universities, scientists, companies) and the nature of the content (text-only or multimedia) (Davies et al., 2021). Social media use does have an effect on civic and political participation (Boulianne, 2015). In this research, we focus on how much science people see on social media, so how many posts they see that are science related. Seeing science on social media could affect the relationship between educational level and attending lectures or talks about science. Science on social media could have a positive effect on this relationship, because it speaks more to higher educated people which makes them more likely to attend. On the other hand, seeing science on social media could have a negative moderating effect, and act as a buffer in this relationship. A reason for this is that social media makes science more accessible, which could lower the threshold for lower educated people to attend the lectures or talks about science. This research, therefor, investigates the moderating relationship that seeing science on social media has on the relationship between educational level and attending lectures or talks about science.

Although a lot of research has been done on the topic of extracurricular activities, most of this research uses vague terms and examples to define extracurricular activities. Multiple different types of activities are here considered under one definition (Bartkus et al., 2012). This research, therefor, adds scientific relevance by defining the extracurricular activity that the research is about in a more specific way. Instead of combining different activities, this research only investigates one type of extracurricular activity, being voluntarily attending lectures or talks about science. Furthermore, this research measures how much science people see on social media instead of only measuring how often they use social media in general. This research therefore contributes to the body of knowledge about science on social media and the influence this has on the relationship between educational level and attending lectures or talks about science.

Extracurricular activities are the topic of societal debate. To what extent are these activities accessible to people from all kinds of different societal groups? While people with low SES could get more advantages out of extracurricular activities (Eccles et al., 2003), it is often the case that they are less likely to participate (Hunt, 2007; Stuart et al., 2011). It thus seems that these activities possibly only widen the gap between the majority and minority, higher and lower educated people, and people with high SES and low SES. This poses the question whether extracurricular activities should be stimulated, to make sure that the people who participate are able to bring out the best in themselves, or if these activities in the form that they exist now should not be stimulated, to prevent widening the gap between different socio-economic groups. To be able to answer this question, it is important to investigate the effects of extracurricular activities and the factors that contribute to this effect.

The following questions will be answered in this research:

1. What is the socio-demographic composition of people who attend voluntary lectures?
2. To what extent does educational level have an effect on attending voluntary lectures, and to what extent is this effect moderated by seeing science on social media?
3. What can be improved by organizations who organize lectures and talks about science to benefit more from science on social media?

First, a theoretical framework will be provided to address the context of this subject. Second, the methodology section will describe the methods and data that have been used in this research to answer the research questions stated above. This will be followed by a results section, which will give an overview of the most important findings. Finally, the conclusion and discussion will present the implications of those findings and offer advice for future research as well as policy advice.

2. Theoretical framework

Previous research has shown that extracurricular activities have a positive effect on student outcomes, for example on grades, social contacts, and future career (Clegg, Stevenson, & Willott, 2008; Seow & Pan, 2014; Stuart et al., 2011). However, because the definition is often unclear, it is also unclear what part of the extracurricular activities actually causes this effect. There are also multiple theories that propose that not the extracurricular activities, but correlating factors are the cause of the positive effects. For example, Hunt (2007) proposes that the effect works in the opposite direction. According to them, it is not the case that students participating in extracurricular activities leads them to perform better in school. Instead, their research indicates that students who have higher academic outcomes are more likely to engage in extracurricular activities (Hunt, 2007). In this research, we just focus on attendance of lectures and talks about science. This is not just a type of extracurricular activity, but also an event that people can go to who are not students anymore.

In this chapter, the relationship between educational level and attending lectures about science will be discussed using the theory on habitus by Bourdieu. After this, two possible effects that seeing science on social media could have on the relationship between educational level and attending lectures will be discussed. First, a possible positive moderating relationship on the basis of trust in science will be explained. After this, a possible negative moderating relationship will be presented on the basis of social media theories.

2.1 The effect of educational level

A positive relationship is expected to exist between educational level and attending voluntary lectures or talks about science. There are a few possible reasons for this. It could be argued, for example, that lower educated people are not interested in the scientific topics that are discussed during these lectures and talks. To measure long-term interest in science, research is often done by questioning students. Dierks et al. (2016) found that higher performing students have more interest in science in general. People who are more interested in science are not only more likely to attend these lectures and talks, they are also more likely to learn something from it. Interest in a topic facilitates learning (Lamb et al., 2011). Another reason for why lower educated people could be less likely to attend these lectures and talks could be because they do not understand the contents. On higher educational levels, much effort is put in learning skills that have to do with complex reasoning (King & Kitchener, 2004). Furthermore, people who have done a study in a similar scientific field as the topic of the lecture, are more likely to be able to understand the contents than someone who has studied to have a more practical job.

Another reason for the relationship between educational level and attending the lectures and talks lies in a concept developed by Bourdieu (1990): the habitus. The habitus is a way in which social systems are kept in practice. The habitus consists of “systems of durable, transposable dispositions, structured structures predisposed to function as structuring structures” (Bourdieu, 1990, p. 53). The habitus is based on the past, because it depends on the environment in which you were born. It is inscribed in the present, because it influences the things you do or not do and things you say or do not say. Lastly, the habitus leads the future, because it will have an effect on what your future is going to look like, and even has its impact on the future of your children. The habitus, thus, is a product of history, that produces more history in accordance with the schemes generated by history. Every person unconsciously has schemes of perception, thought and action that are led by their habitus. These schemes, then, make sure that practices are ‘correct’ and constant over time (Bourdieu, 1990).

Someone’s educational level is one of the consequences as well as one of the causes of one’s habitus. On the one hand, educational level is a consequence of the habitus of a person because people start developing their identity and their habitus from the moment that they are born. The socio-economic status of their parents influences the educational level, cultural capital and social capital of the children (Loury, 1977). Independent of intelligence, SES influences the educational attainment of children (Von Stumm, 2017). On the other hand, the school is also an environment where children further develop their habitus. Educational institutions facilitate the intergenerational transfer of cultural capital (Bourdieu & Passeron, 1977). Because the habitus influences the things that people will and will not do, it will also influence whether people attend lectures or talks about science. Whether people participate in science after their compulsory science classes, depends a lot on their identity and whether they see themselves as a ‘science person’ (DeWitt, Archer, & Mau, 2016). Because people with a higher educational level already have chosen to continue with a scientific study, they will also be more likely to voluntarily attend lectures or talks about science. For lower educated people, their habitus will lead them to think that the lectures or talks about science are not meant for them. They feel like they do not fit in this environment, independent of their initial interest in science (DeWitt et al., 2016). From this body of theory, the first hypothesis can be derived:

H1: Educational level has a positive effect on attending lectures or talks about science.

2.2 The effect of seeing science on social media

The moderating relationship of seeing science on social media on the relationship between educational level and attending lectures about science, could be argued to be positive as well as negative. A positive moderating relationship would mean that seeing science on social media strengthens the positive direct relationship for higher educated people. A reason for this could be that higher educated people were already more likely to attend lectures or talks about science, and when they see science on social media, they get even more likely to attend the lectures or talks. The information that you consciously see on social media, namely, is not random (Sohn, 2014). Only a tiny fraction of the information that is available for you to see is actually processed in your brain (Anderson, Van Essen, & Olshausen, 2005). Posts that people are interested in are more likely to attract their attention. The specific post about science, subsequently, will only have an impact on the people who actually saw it, which will for the most part be people who were already interested in science.

However, it is also possible that a negative moderating relationship exists. Seeing science on social media, then, acts as a buffer in the relationship between educational level and attending voluntary lectures. A possible reason for this is that science, through social media, becomes more accessible for people who would normally be less likely to come into contact with science. In order for people to attend events about science, it is important that they trust science. The generally lower levels of trust in science among lower educated people could therefore be an important factor in why they are less likely to attend the lectures or talks. Research shows that online media use increases science knowledge (Su et al., 2015) and positive attitudes toward science (Dudo et al., 2011), and social media news use increases trust in science (Huber, Barnidge, Gil de Zúñiga, & Liu, 2019). This relationship might be stronger for lower educated people, because according to the reflexive-modernization theory, higher educated people tend to be more critical of the science that they see. Thus, higher educated people are more likely to have an anti-institutional inclination. They are more likely to see the bad things and therefore contest and debate science (Nisbet & Markowitz, 2014). This could lead to less trust in science among higher educated people when they see science on social media, while the trust of lower educated people increases when they see science on social media.

Huber et al. (2019) listed two explanations for the relationship between science on social media and trust in science that are relevant for this research. First, social media diversify and expand information networks. People who are active on social media will encounter science news through incidental exposure (Huber et al., 2019). In this case, although we focus on social media in general instead of social media news, people will still see posts about science incidentally. Because social media companies work with algorithms, people who are active on social media will get more exposed to a greater volume and broader range of science posts (Huber et al., 2019). Second, scientists and universities increasingly rely on social media to interact with users. The research concluded that people prefer scientific information from scientists instead of journalists, because they are seen as more trustworthy, precise, and objective (Huber et al., 2019). The trust that lower educated people have in science might thus improve when they see science on social media. Based on the theory about science and social media, the second hypothesis is as follows:

H2: Seeing science on social media has a negative moderating effect on the relationship between educational level and attending lectures or talks about science.

2.3 Challenges in science communication on social media

The use of social media in the research cycle is argued to be leading to greater transparency of the scientific process and increased accuracy of the science. Posting science on social media is thought to provide access to a broader audience, and support conversations across different disciplines and beyond academia (Ke, Ahn, & Sugimoto, 2017; Pavlov et al., 2018). However, there are still some difficulties with science communication via social media. According to Sugimoto et al. (2017), social media is still being used predominantly for communication between scholars. Furthermore, science organizations are primarily using Facebook and Twitter for one-way information dissemination (Lee, VanDyke, & Cummins, 2017; Su et al., 2017). This method of communication is based on the 'deficit model', which assumes that people make decisions or have specific opinions based on a lack of knowledge. The deficit model assumes that by making more information available, the public will become more "informed", which will change their behavior and opinions (National Academies of Sciences, Engineering, and Medicine, 2017).

However, science communication research has shown that this model is ineffective (George, 2019). According to Lee et al. (2017), engagement can be encouraged by posting questions to the audience and interacting with the audience's questions and comments. Scientists are in the position to answer people's questions about the research, and should also do this on social media (Lee et al., 2017). Furthermore, social media could be incorporated more into the research cycle, so that the public is involved in the whole process instead of only finding out about it at the end of the research (George, 2019). When social media would be used more for two-way science communication and dialogue, it could encourage engagement and deepen trust (Su et al., 2017). The tools to broaden the scope of scientific research are there, but science communication poses challenges in terms of audience-appropriate messaging (Van Eperen & Marincola, 2011). Literature therefore suggests that increased training and social media policies are needed in order to create a better understanding of how to use the tools (Pavlov et al., 2018).

In figure 1, the two formulated hypotheses are illustrated in a conceptual model.

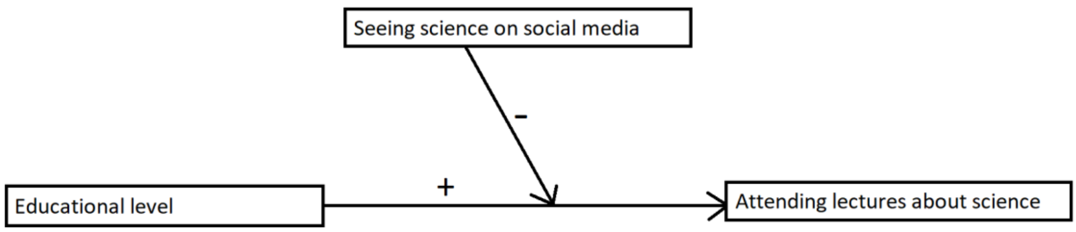

Figure 1 Conceptual model of the relationship between educational level and attending lectures about science, with seeing science on social media as a moderator.

3. Data and methodology

3.1 Dataset and sample

In order to formulate an answer to the research question, existing data from PewResearch KnowledgePanel in the USA has been used. This data was collected in 2017 and has 4024 respondents of 18 years and older. The dataset is representative for the American society, with a margin of error of 1.6 percentage points. A combination of random digit dialing and address-based sampling have been used to recruit respondents. The content of the data includes questions about visiting cultural places and events (museums, sports, live music), reading news, including science, feelings about science and the way it is reported, and science-related hobbies. While the total dataset has 4024 respondents, only the data will be analyzed of the respondents who answered the questions about educational level, attending voluntary lectures or talks, and seeing science on social media. After filtering out all the people who did not answer the questions on one of these topics or the control variables, 2731 respondents remain in the sample that will be analyzed.

3.2 Variables and operationalization

Whether people attend lectures or talks about science, the dependent variable in this research, has been measured by the question "Which, if any, of the following have you done within the past 12 months?". People could choose one or multiple things out of a list of 9 activities, 'none of these', and 'refuse'. These activities are cultural activities like going to an art museum or gallery, going to a public library, and attending an event with live music. The activity that is analyzed in this research is framed as 'attended a lecture or talk about science'. Respondents either selected this activity (coded as 1) or did not select this activity (coded as 0).

The independent variable, educational level, has been measured by four categories: 1) less than high school, 2) high school, 3) some college and 4) bachelor's degree or higher. Because there are only four answer categories and they are quite broad, it is not suitable to change this into a scale. Therefore, the decision was made to combine some of the categories so that only two categories remained, for which a dummy variable was made. In this study, 'less than high school', 'high school' and 'some college' will be considered as lower educated, while 'bachelor's degree or higher' will be considered as higher educated.

The moderator, seeing science on social media, was measured using a combination of two questions. The first question was: "Of the posts you see on social media, how many are about science?". The answering categories are 1) a lot, 2) some, 3) not many, 4) none. The answer categories have been reversed so that 1) becomes the lowest value. The second question was: "Do you use social media…", where the answer categories were 1) several times a day, 2) about once a day, 3) a few times a week, 4) every few weeks, and 5) less often. This variable has also been recoded so that 1) becomes the lowest value. This will make the reasoning and argumentation more logical, because then the ones who see the least science on social media also have the lowest value on the scale that was made. Subsequently, these two questions have been multiplied so that they form one scale that will be used as a measure of how many science people encounter on social media. Although there was also a question in the data about following science accounts on social media, the decision was made to focus on seeing science on social media. The reason for this is that people have to deliberately choose to follow science on social media, which would create a selection effect. Seeing science on social media reduces this effect, because people can also get to see science because of algorithms and not because they chose to follow it themselves. Following science on social media was later incorporated as a control variable.

3.3 Control variables

In this research, three variables were included as control variables. The control variables are age, following science on social media, and household income. Age was reported in whole years in the survey. However, because the age groups that attend these lectures at Studium Generale Utrecht University are often either young people or older people, age was recoded. 'Young' became the reference category, ranging from 18 to 30 years of age. A dummy was created for 'middle' age, being 31 – 55. Another dummy was created for the ages of 56 and older, which was called 'old' age. Age could have an influence on seeing science on social media, because older people are less likely to be on social media. Age could also have an influence on attending voluntary lectures.

Following science on social media was measured by the question: “On social media, do you follow any organizations, people or pages that are focused on science?”. The answer categories to this question were 1) yes, at least one, and 2) no, none. This was recoded into 0) no, none, and 1) yes, at least one. Before this variable was incorporated as a moderator, the VIF was tested. The VIF turned out to be 1.004 which, presuming a threshold of 5, shows that this variable does not have too much overlap with the moderating variable. Following science on social media could have an effect on seeing science on social media and attending voluntary lectures. First, following science on social media could influence seeing science on social media because of the algorithms that social media work with. When it becomes clear to the algorithm that you are interested in something, it will get more likely that you get to see posts about this topic. Following science on social media could also influence whether people attend voluntary lectures. When people follow science on social media, this shows that they are interested in science. Consequently, people who are interested in science, will be more likely to voluntarily attend lectures and talks about science.

Household income was measured by 21 answer categories, with the lowest being “less than $5000” and the highest being “$250,000 or more”. This was considered a scale variable. Household income could influence whether people attend voluntary lectures, where people with higher income levels are more likely to attend these kinds of events. There are multiple different reasons for this, for example because people with higher income have more resources to be able to travel to the events. Furthermore, whether people attend these lectures has to do with their leisure time (Veal, 2015). On the one hand, increased leisure time can be seen as an indicator for increased well-being. People with higher income then have more free time, and do not have to work all the time in order to be able to provide for themselves. On the other hand, Veal (2015) found that people with higher income levels are often working a lot of hours and thus have less leisure time, but in the free time they have, they are more likely to attend cultural activities.

3.4 Analysis

Because the dependent variable in this study is measured as a binary variable, logistic regression analysis is suitable. IBM SPSS software version 27 was used to carry out the analysis. After filtering out the people who had missing values on the dependent, independent, moderating, or control variables, there are 2731 respondents left in the dataset. To be able to test the moderation effect, the regression analysis will consist of multiple models. First, seeing science posts on social media is multiplied by how often people use social media. This variable is then mean-centred. After this, an interaction variable can be made between this variable and educational level. In regression model 1, the direct effect of educational level on attending voluntary lectures will be tested. The confounders will be added in model 2. In model 3, the variable of seeing science on social media will be added. Model 4, lastly, will include the interaction variable to be able to test the moderating effect of seeing science posts on social media.

4. Results

4.1 Frequencies

Table 1 shows the descriptive statistics of the variables used in the analysis.

Table 1 frequencies, N = 2731

	Minimum	**Maximum**	**Mean**	**SD**
Attended a lecture/talk	0	1	.11	.312
High education	0	1	.362	.481
Seeing science on social media (c)	-10.89	8.11	.093	4.242
Follow science on social media	0	1	.260	.439
Middle age	0	1	.435	.496
Old age	0	1	.364	.481
Income (c)	-11.95	8.05	-.002	4.606

This table shows that 11% of the respondents said that they attended a lecture or talk about science in the past 12 months. The table also shows that about 36% of the sample is high educated, which means that they have a bachelor's degree or higher (M= .362, SD= .481). This can be compared to the average amount of people who have this degree in the US, which was 37.9% in 2021 (United States Census Bureau, 2022). There is a lot of variety in the mean centered variable ‘seeing science on social media’ (min= -10.89, max= 8.11, SD= 4.242). The mean centered variable income also has a big variance (min= -11.95, max= 8.05, SD= 4.606).

The data also show that 43.5% of the respondents are middle aged, so between 30 and 55 years old, and 36.4% are older than 55. This means that the remaining 20.1% of the respondents falls into the young age category, between 18 and 29 years old.

4.2 Correlations

Table 2 shows the correlations between the variables.

Table 2 Correlations

	Attended a lecture/ talk	High education	Seeing science on social media (c)	Followingscience on social media	Middle age	Old age	Income (c)
Attended a lecture/talk	1	.224**	-.142**	.196**	-.041*	-.027	.158**
High education		1	-.149**	.101**	.053**	-.037	.383**
Seeing science on social media (c)			1	-.184**	.022	-.060**	-.079**
Following science on social media				1	.062**	-.150**	.036
Middle age					1	-.665**	.069**
Old age						1	.008
Income (c)							1

Note: ** $p < .001$

When the correlation exceeds .90, there is a strong correlation between the two variables. This shows that the variables overlap too much, or are too similar to each other. In this case, the highest correlation can be identified between middle age and old age ($r = -.665$, $p < .001$). These variables are negatively correlated, because if someone falls into the middle aged category, they cannot fall into the old aged category. The next highest correlation that could be relevant is between high education and income ($r = .383$, $p < .001$). This correlation is understandable, because people with a higher education generally have a higher income (Tinbergen, 1972).

4.3 Logistic regression

Tables 4 and 5 show the results of the logistic regression analysis that have been conducted.

Table 3 Logistic regression

	Model 1			Model 2		
	Exp(B)	**95% CI**	**P value**	**Exp(B)**	**95% CI**	**P value**
Constant	.060		<.001	.070		<.001
High education	4.207	(3.259, 5.431)	<.001	3.136	(2.370, 4.150)	<.001
Seeing science on social media (c)						
High education * seeing science on social media						
Middle age				.450	(.326, .622)	<.001
Old age				.618	(.443, .863)	.005
Income (c)				1.087	(1.051, 1.124)	<.001
Following science on social media				3.111	(2.400, 4.034)	<.001
Nagelkerke R^2	.094			.175		

Table 4 Logistic regression

	Model 3			Model 4		
	Exp(B)	**95% CI**	**P value**	**Exp(B)**	**95% CI**	**P value**
Constant	.072		<.001	.072		<.001
High education	2.967	(2.238, 3.933)	<.001	3.008	(2.237, 4.043)	<.001
Seeing science on social media (c)	.915	(.884, .946)	<.001	.909	(.864, .957)	<.001
High education * seeing science on social media				1.011	(.944, 1.081)	.761
Middle age	.437	(.316, .605)	<.001	.437	(.316, .605)	<.001
Old age	.578	(.413, .810)	.001	.578	(.413, .809)	.001
Income (c)	1.087	(1.051, 1.124)	<.001	1.087	(1.051, 1.124)	<.001
Following science on social media	2.818	(2.167, 3.664)	<.001	2.812	(2.162, 3.657)	<.001
Nagelkerke R^2	.193			.193		

In model 1, the direct relationship between being high educated and attending lectures or talks about science has been tested. This shows that being high educated increases the odds of attending a lecture or talk about science by about 321% (Exp(B)= 4.207, p<.001, [3.259, 5.431]). The Nagelkerke R^2 of this model is .094, which means that 9.4% of the variance in attending a lecture or talk can be explained by this model. In model 2, the confounders have been added to this relationship. When the confounders are taken into account, being high educated increases the odds of attending a lecture or talk about science by about 214% (Exp(B)= 3.136, p< .001, [2.370, 4.150]). This result is in line with the first hypothesis: 'Educational level has a positive effect on attending lectures or talks about science'. While all the control variables have significant effects, the effect of following science on social media is especially big. When someone follows science on social media, the odds of them attending a lecture or talk about science increase with 211% (Exp(B)= 3.111, p< .001, [2.400, 4.034]). The Nagelkerke R^2 of this model is higher than that of the previous model, which means that a bigger part of the variance can be explained when the control variables are taken into consideration. The Nagelkerke R^2 has now increased to .175, which means that 17.5% of the variance in attending a lecture or talk about science can be explained by this model. Model 3 includes the effect of seeing science on social media. An interesting finding is that seeing science on social media decreases the odds of attending a lecture or talk about science by 8.5%. This is the direct effect that seeing science on social media would have on attending these lectures or talks. The last model, model 4, includes the interaction effect between high education and seeing science on social media. The moderating effect of seeing science on social media is found to be not significant. This thus does not line up with the expectation that was formulated in the second hypothesis: 'Seeing science on social media has a negative moderating effect on the relationship between educational level and attending lectures or talks about science.'

5. Conclusion and discussion

5.1 Conclusion

Extracurricular activities are often thought to be an important way for students to develop extra skills and improve their academic achievement (Clegg et al., 2008; Seow & Pan, 2014; Stuart et al., 2011). However, previous research has shown that higher educated people participate in extracurricular activities more often (Clegg et al., 2008; Hunt, 2007; Stuart et al., 2011; White & Gager, 2007). This research therefore further investigated the relationship between educational level and attending lectures or talks about science. Nowadays, social media is seen as an important way of communicating. This research therefore also investigated the possibility of a moderating effect of seeing science on social media on the relationship between educational level and attending lectures or talks about science.

The most important conclusion of this thesis is that educational level has a big influence on whether people attend a lecture or talk about science. The choice for this specific kind of activity could have caused an even greater effect to be found, because it is one of the activities that especially high educated people take part in (Stuart et al., 2011). Principles of cultural capital and human capital can provide possible explanations for why high educated people are more likely to attend lectures or talks about science. For example, according to the literature, parental SES appears to be an important factor (Bennett, Lutz, & Jayaram, 2012). Because these kinds of capital are passed on from parents to their children (Bourdieu & Passeron, 1977), the finding that lower educated people are less likely to attend these lectures comes from processes of intergenerational inequalities. The intergenerationally transmission of inequalities causes adults to often have a similar SES as the one that their parents had and that they grew up in (Erikson & Goldthorpe, 2002). Children from parents with low SES will, therefore, generally have low SES themselves as well. They are less likely to attend university when they grow up, because their parents also did not attend university.

In this study, we found that educational level as well as household income have positive effects on the likelihood of someone attending a lecture or talk about science. There are a few possible explanations for the existence of this effect. It could be that lower educated people have less interested in science, and therefore are less likely to attend the events. Furthermore, a lack of understanding of the scientific topics that are discussed during these lectures and talks could lead lower educated people to not attend them. A third possible explanation for why lower educated people do not attend is because of their habitus. This concept, developed by Bourdieu (1970), theorizes that people with a lower education are less likely to attend when they feel like they are out of place, or in an environment where they are not supposed to be, they do not feel comfortable. This process can possibly cause a cycle: higher educated people are more likely to attend lectures or talks about science. Then, when lower educated people know this is the case, they will become even less likely to attend these lectures because of their habitus.

Apart from the direct relationship between educational level and attending lectures or talks about science, a moderating effect of seeing science on social media has also been investigated. This relationship turns out to be not significant. A possible explanation for this is that the positive effect and the negative effect counterbalance each other. A positive effect could be that higher educated people get more likely to attend a lecture or talk about science because they are already more interested in science, and seeing it on social media makes them even more likely to attend. Lower educated people could get even less likely to attend the event because they are more likely to distrust the science that they see in general (Bak, 2001), which is potentially also the case for the science they see on social media. On the other hand, a possible negative moderating relationship might exist that balances out this positive effect. Lower educated people might feel as though the barrier for attending these lectures or talks is lower when they see the advertisement on social media, thus they would be more likely to attend the event. That is, however, when the type of communication is appropriate for the specific audience (Van Eperen & Marincola, 2011). However, research from Su et al (2017) shows that when science is promoted on social media, it is done through one-way communication. Thus it is possible that people, and especially lower educated people, are not engaged with science through social media because the science is delivered to them in a linear deficit way. This deficit model assumes that people’s opinions and behaviors are based on a lack of knowledge, and that this knowledge can be provided by giving them the information that is needed, which will change their behavior and opinions (National Academies of Sciences, Engineering, and Medicine, 2017). However, science communication research has shown that this model is ineffective (George, 2019). This shows that there are still chances within public engagement to move away from this type of one-way communication and towards a more interactive way of science communication.

Following science on social media is positively associated with attending lectures or talks about science. This shows that posting these events on social media could have an effect for the people that actually follow the page. Universities could thus have an influence on how many people attend their lectures and talks by promoting themselves on social media. If they would gain more followers, the chances increase of more people attending the lectures as well. Furthermore, we found that the direct effect of seeing science on social media on attending lectures or talks about science is negative. This is interesting, because previous research shows that people who are engaged with science on social media are also more likely to participate in science-related activities (Pew Research Center, 2017). It could be that the positive effect in this research was explained by the people who followed science on social media. We controlled for this factor, which could have lead the positive effect to disappear. The reason for why we found a negative effect, however, remains unclear. We could theorize that people see the science on social media as some kind of alternative for the lectures. They could reason that they read or watch videos about scientific topics on social media, and therefore feel like they already know enough about science. This feeling of having enough scientific knowledge already could then possibly withhold them from attending the lectures and talks about science. However, further research should be done to identify whether this effect exists.

Furthermore, we did not measure the type of science that people saw on social media. For example, this science could be something that they disagree with or they distrust, which could lead to people being less likely to attend lectures and talks about science. Additionally, the results show that people of middle age and old age actually are more likely to attend a lecture or talk about science than young people. This is against the expectation that young and old people would be the most likely to attend the lectures. A possible explanation for this is that this dataset measured attendance for all different kinds of lectures, while the age categories where made on the basis of experience of Studium Generale Utrecht University. Therefore, the age of the attendants of these events could differ from the age of the people who generally attend Studium Generale events.

5.2 Discussion

This study has multiple limitations that could explain why incorrect results have been found. A possible explanation for finding a relationship between following science on social media and attending lectures or talks about science, could be that the effect does not really come from social media, but from another correlating factor. For example, it could be the case that people who are interested in science are more likely to attend the events. Following science on social media then does not have anything specific to do with attending the events, it is just that people who are interested in science follow it on social media and people who are interested in science also are more likely to attend the events. For the relationship between age and attending lectures, an alternative explanation could be that the age brackets were chosen incorrectly. The hypothesis was that young people were more likely to attend the events than middle aged people. The cause of finding the opposite result could be that the wrong ages were chosen to make up the categories. Because these categories were made out of the experience that Studium Generale has, and the ages of the people attending the events are guessed, this could be the case.

Additionally, while there was no significant effect found for the moderating effect of seeing science on social media, it is possible that this effect does exist in reality. In this research, seeing science on social media was measured. However, we did not measure what kind of science people saw and what their opinion was about this science, for example whether they trusted it or not. As a consequence, it is possible that part of the science people saw was seen in a negative way. Their distrust or negative perception on the science they saw on social media could have possibly reduced the possibility of them attending a lecture or talk about science. Whether people see this science in a positive or negative way, could also differ for people with a higher and lower educational level. The possibility of science on social media being seen in a negative way was not taken into account in neither the theory nor in the dataset. When this would have been taken into consideration, the effects of seeing science in a positive way and seeing science in a negative way could have been separated, which could have lead to other conclusions about the effects of seeing science on social media.

The findings of this research lead us to some recommendations for future research. Eye tracking research could be done for example, with which could be measured how long people look at different posts on social media. This method could also discover exactly what kinds of posts people see, so you would also know how many of these posts are about science. In addition to this method, a questionnaire could be developed where people can assess what there feelings were about different posts. In this way, whether people think positively or negatively about the science they see on social media can be taken into account. This method could also be used independently of the eye tracking method. This research could discover if and in what way the science posts that high educated people see is different from the science posts that low educated people see. Subsequently, this could also address the ways in which people feel about the science posts they see. Second, before putting the ages in categories, future researchers should go to different kinds of science events and ask people their age. Other questions could also be asked that could help the researchers assess the influence of social media. For example, a question could be included about how people knew about the existence of this event. Now that we know that lower educated people are less likely to attend lectures or talks, and other extracurricular activities, more research should be done into how lower educated people can become more engaged in these activities.

5.3 Policy advice

Because this research does not show clear positive moderating effects of seeing science posts on social media for the relationship between educational level and attending lectures or talks about science, this advice has to be nuanced. Because we concluded that seeing science on social media does not always have positive effects for the amount of people who attend a lecture or talk about science, organizations should start with doing research into the effects that spreading research on social media has or could have for them. A consultant or researcher who has expertise on the topic of social media use within organizations could give them this advice. On the basis of this advice, the organization can assess whether and how they will invest more in social media and what their specific focus will be. However, we did find a strong positive association between following science on social media and attending lectures or talks about science. We therefore advice organizations to focus on the amount of followers they have. The communications manager within the organization will be responsible for this job. A higher amount of followers would increase the chances that the people who follow their social media, and thus are interested in their scientific content, also attend the lectures or talks about science. A possible way in which the organization could do this is to incorporate two-way communication on social media. This gives them more opportunities to interact with their followers, which could lead to more engagement and deepened trust among their followers (Su et al., 2017). Studium Generale at Utrecht University is specifically trying to get more lower educated people to attend their lectures and talks. In order to accomplish this, they should think about focusing their lectures and talks less on academic scientists. Instead, they could try to invite people with more practical jobs sometimes, like a policeman or a nurse. Their talks might be more interesting, understandable and relatable for lower educated people, which could lead them to be more likely to attend.

Reference list

Anderson, C. H., van Essen, D. C., & Olshausen, B. A. (2005). Directed visual attention and the dynamic control of information flow. In L. Itti, G. Rees, & J. K. Tsotsos (Eds.), *Neurobiology of Attention* (pp. 11–17). Elsevier Gezondheidszorg.

Bak, H. J. (2001). Education and Public Attitudes toward Science: Implications for the "Deficit Model" of Education and Support for Science and Technology. *Social Science Quarterly*, *82*(4), 779–795. https://doi.org/10.1111/0038-4941.00059

Bartkus, K. R., Nemelka, B., Nemelka, M., & Gardner, P. (2012). Clarifying The Meaning Of Extracurricular Activity: A Literature Review Of Definitions. *American Journal of Business Education (AJBE)*, *5*(6), 693–704. https://doi.org/10.19030/ajbe.v5i6.7391

Bennett, P. R., Lutz, A. C., & Jayaram, L. (2012). Beyond the Schoolyard. *Sociology of Education*, *85*(2), 131–157. https://doi.org/10.1177/0038040711431585

Boulianne, S. (2015). Social media use and participation: a meta-analysis of current research. *Information, Communication & Society*, *18*(5), 524–538. https://doi.org/10.1080/1369118x.2015.1008542

Bourdieu, P. (1990). *The Logic of Practice*. Amsterdam University Press.

Bourdieu, P., & Passeron, J. C. (1990). *Reproduction in Education, Society and Culture* (2nd Revised edition). SAGE Publications.

Clegg, S., Stevenson, J., & Willott, J. (2009). *Extending Conceptualisations of the Diversity and Value of Extracurricular Activities: A Cultural Capital Approach to Graduate Outcomes*. https://eprints.leedsbeckett.ac.uk/id/eprint/850/1/Extending%20conceptualisations%20of%20the%20diversity%20and%20value%20of%20extracurricular%20activities.pdf

Davies, S. R., Franks, S., Jensen, A. M., Mannino, I., Roche, J., Schmidt, A. L., Wells, R., Woods, R., & Zollo, F. (2019). *Summary report: European science communication* *today* (D1.1 EU H2020-funded 824634 QUEST Project). https://ec.europa.eu/research/participants/documents/downloadPublic?documentIds=080166e5c8de6cb9&appId=PPGMS

Davies, S. R., Franks, S., Roche, J., Schmidt, A. L., Wells, R., & Zollo, F. (2021). The landscape of European science communication. *Journal of Science Communication*, *20*(03), A01. https://doi.org/10.22323/2.20030201

DeWitt, J., Archer, L., & Mau, A. (2016). Dimensions of science capital: exploring its potential for understanding students' science participation. *International Journal of Science Education*, *38*(16), 2431–2449. https://doi.org/10.1080/09500693.2016.1248520

Dierks, P. O., Höffler, T. N., Blankenburg, J. S., Peters, H., & Parchmann, I. (2016). Interest in science: a RIASEC-based analysis of students' interests. *International Journal of Science Education*, *38*(2), 238–258. https://doi.org/10.1080/09500693.2016.1138337

Dudo, A., Brossard, D., Shanahan, J., Scheufele, D. A., Morgan, M., & Signorielli, N. (2010). Science on Television in the 21st Century. *Communication Research*, *38*(6), 754–777. https://doi.org/10.1177/0093650210384988

Eccles, J. S., Barber, B. L., Stone, M., & Hunt, J. (2003). Extracurricular Activities and Adolescent Development. *Journal of Social Issues*, *59*(4), 865–889. https://doi.org/10.1046/j.0022-4537.2003.00095.x

Erikson, R., & Goldthorpe, J. H. (2002). Intergenerational Inequality: A Sociological Perspective. *Journal of Economic Perspectives*, *16*(3), 31–44. https://doi.org/10.1257/089533002760278695

Field, J. (2006). *Lifelong Learning and the New Educational Order*. Adfo Books.

George, E. M. (2019). *Cisco Coregonus Artedi Restoration in Lake Ontario: Ecology, genetics, and science communication* (PhD Thesis).

https://www.researchgate.net/publication/333582288_Cisco_Coregonus_artedi_Restoration_in_Lake_Ontario_Ecology_Genetics_and_Science_Communication

Ho, L., & Devi, I. P. (2020). Students' Understanding of Interest in Learning Science. *Integrated Science Education Journal*, *2020 (1)*(2), 60–64. https://doi.org/10.37251/isej.v1i2.72

Huber, B., Barnidge, M., Gil De Zúñiga, H., & Liu, J. (2019). Fostering public trust in science: The role of social media. *Public Understanding of Science*, *28*(7), 759–777. https://doi.org/10.1177/0963662519869097

Hunt, H. D. (2007). The Effect of Extracurricular Activities in the Educational Process: Influence on Academic Outcomes? *Sociological Spectrum*, *25*(4), 417–445. https://doi.org/10.1080/027321790947171

Kartono, D. T., Soemanto, R. B., Zuber, A., Akbar, R. D., & Suryadinata, T. A. (2020). Civil Disobedience for the Covid-19 Policy. *EasyChair*, 1–17. https://wvvw.easychair.org/publications/preprint_download/8fPp

Ke, Q., Ahn, Y. Y., & Sugimoto, C. R. (2017). A systematic identification and analysis of scientists on Twitter. *PLOS ONE*, *12*(4), e0175368. https://doi.org/10.1371/journal.pone.0175368

King, P. M., & Kitchener, K. S. (2004). Reflective Judgment: Theory and Research on the Development of Epistemic Assumptions Through Adulthood. *Educational Psychologist*, *39*(1), 5–18. https://doi.org/10.1207/s15326985ep3901_2

Lamb, R. L., Annetta, L., Meldrum, J., & Vallett, D. (2011). Measuring Science Interest: Rasch Validation of the Science Interest Survey. *International Journal of Science and Mathematics Education*, *10*(3), 643–668. https://doi.org/10.1007/s10763-011-9314-z

Lee, N. M., VanDyke, M. S., & Cummins, R. G. (2017). A Missed Opportunity?: NOAA's Use of Social Media to Communicate Climate Science. *Environmental Communication*, *12*(2), 274–283. https://doi.org/10.1080/17524032.2016.1269825

Loury, G. C. (1977). A dynamic theory of racial income differences. In P. Wallace & A. LaMond (Eds.), *Women, Minorities, and Employment Discrimination* (pp. 153–188). Michigan: Lexington Books. https://www.kellogg.northwestern.edu/research/math/papers/225.pdf

National Academies of Sciences, Engineering, and Medicine, Education, D. O. B. A. S. S. A., & Committee on the Science of Science Communication: A Research Agenda. (2017). *Communicating Science Effectively: A Research Agenda*. National Academies Press.

Nisbet, M., & Markowitz, E. M. (2014). Understanding Public Opinion in Debates over Biomedical Research: Looking beyond Political Partisanship to Focus on Beliefs about Science and Society. *PLoS ONE*, *9*(2), e88473. https://doi.org/10.1371/journal.pone.0088473

Ocobock, C., & Hawley, P. (2020). Science on tap: effective public engagement or preaching to the choir? *Journal of Science Communication*, *19*(01), A04. https://doi.org/10.22323/2.19010204

Pavlov, A. K., Meyer, A., Rösel, A., Cohen, L., King, J., Itkin, P., Negrel, J., Gerland, S., Hudson, S. R., Dodd, P. A., de Steur, L., Mathisen, S., Cobbing, N., & Granskog, M. A. (2018). Does Your Lab Use Social Media?: Sharing Three Years of Experience in Science Communication. *Bulletin of the American Meteorological Society*, *99*(6), 1135–1146. https://doi.org/10.1175/bams-d-17-0195.1

Pew Research Center (2017). Science News and Information Today. https://www.pewresearch.org/journalism/2017/09/20/science-news-and-information-today/

Seow, P. S., & Pan, G. (2014). A Literature Review of the Impact of Extracurricular Activities Participation on Students' Academic Performance. *Journal of Education for Business*, *89*(7), 361–366. https://doi.org/10.1080/08832323.2014.912195

Sohn, D. (2014). Coping with information in social media: The effects of network structure and knowledge on perception of information value. *Computers in Human Behavior*, *32*, 145–151. https://doi.org/10.1016/j.chb.2013.12.006

Stuart, M., Lido, C., Morgan, J., Solomon, L., & May, S. (2011). The impact of engagement with extracurricular activities on the student experience and graduate outcomes for widening participation populations. *Active Learning in Higher Education*, *12*(3), 203–215. https://doi.org/10.1177/1469787411415081

Su, L. Y. F., Akin, H., Brossard, D., Scheufele, D. A., & Xenos, M. A. (2015). Science News Consumption Patterns and Their Implications for Public Understanding of Science. *Journalism & Mass Communication Quarterly*, *92*(3), 597–616. https://doi.org/10.1177/1077699015586415

Su, L. Y. F., Scheufele, D. A., Bell, L., Brossard, D., & Xenos, M. A. (2017). Information-Sharing and Community-Building: Exploring the Use of Twitter in Science Public Relations. *Science Communication*, *39*(5), 569–597. https://doi.org/10.1177/1075547017734226

Sugimoto, C. R., Work, S., Larivière, V., & Haustein, S. (2017). Scholarly use of social media and altmetrics: A review of the literature. *Journal of the Association for Information Science and Technology*, *68*(9), 2037–2062. https://doi.org/10.1002/asi.23833

Tinbergen, J. (1972). THE IMPACT OF EDUCATION ON INCOME DISTRIBUTION. *Review of Income and Wealth*, *18*(3), 255–265. https://doi.org/10.1111/j.1475-4991.1972.tb00865.x

United States Census Bureau. (2022, February 24). *Educational Attainment in the United States: 2021*. Census.gov. Retrieved June 1, 2022, from https://www.census.gov/data/tables/2021/demo/educational-attainment/cps-detailed-tables.html

van Eperen, L., & Marincola, F. M. (2011). How scientists use social media to communicate their research. *Journal of Translational Medicine*, *9*(1). https://doi.org/10.1186/1479-5876-9-199

Veal, A. (2015). Leisure, income inequality and the Veblen effect: cross-national analysis of leisure time and sport and cultural activity. *Leisure Studies*, *35*(2), 215–240. https://doi.org/10.1080/02614367.2015.1036104

von Stumm, S. (2017). Socioeconomic status amplifies the achievement gap throughout compulsory education independent of intelligence. *Intelligence*, *60*, 57–62. https://doi.org/10.1016/j.intell.2016.11.006

White, A. M., & Gager, C. T. (2007). Idle Hands and Empty Pockets? Youth Involvement in Extracurricular Activities, Social Capital, and Economic Status. *Youth & Society*, *39*(1), 75–111. https://doi.org/10.1177/0044118x06296906

Appendix: syntax

```
RECODE seeingscience (1=4) (2=3) (3=2) (4=1).

EXECUTE.


RECODE usesocialmedia (1=5) (2=4) (3=3) (4=2) (5=1).

EXECUTE.


COMPUTE sciencesocialmedia=usesocialmedia * seeingscience.

EXECUTE.


RECODE FOLLOW (1=1) (2=0) INTO followsocialmedia.

EXECUTE.


USE ALL.

COMPUTE filter_$=(attendlectures >= 0 AND usesocialmedia >= 0 AND seeingscience >= 0
AND followsocialmedia >=

   0 AND education >= 0 AND income >= 0 AND age >= 18).

VARIABLE LABELS filter_$ 'attendlectures >= 0 AND usesocialmedia >= 0 AND
seeingscience >= 0 AND '+

   'FOLLOW >= 0 AND education >= 0 AND income >= 0 AND age >= 18 (FILTER)'.

VALUE LABELS filter_$ 0 'Not Selected' 1 'Selected'.

FORMATS filter_$ (f1.0).

FILTER BY filter_$.

EXECUTE.
```

```
FREQUENCIES VARIABLES=sciencesocialmedia
  /STATISTICS=STDDEV MINIMUM MAXIMUM SEMEAN MEAN
  /ORDER=ANALYSIS.

COMPUTE c_sciencesocialmedia=sciencesocialmedia - 11.8853.
EXECUTE.

FREQUENCIES VARIABLES=c_sciencesocialmedia
  /STATISTICS=STDDEV MINIMUM MAXIMUM SEMEAN MEAN
  /ORDER=ANALYSIS.

RECODE education (1=0) (2=0) (3=0) (4=1) INTO educ_high.
EXECUTE.

FREQUENCIES VARIABLES=educ_high
  /STATISTICS=MEAN
  /ORDER=ANALYSIS.

FREQUENCIES VARIABLES=age
  /ORDER=ANALYSIS.

RECODE age (31 thru 55=1) (ELSE=0) INTO age_middle.
EXECUTE.
```

```
RECODE age (56 thru 99=1) (ELSE=0) INTO age_old.
EXECUTE.

FREQUENCIES VARIABLES=age_middle age_old
  /STATISTICS=MEAN
  /ORDER=ANALYSIS.

REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS R ANOVA
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT attendlectures
  /METHOD=ENTER educ_high.

LOGISTIC REGRESSION VARIABLES attendlectures
  /METHOD=ENTER educ_high
  /CRITERIA=PIN(.05) POUT(.10) ITERATE(20) CUT(.5).

COMPUTE higheduc_sciencesocialmedia=educ_high * c_sciencesocialmedia.
EXECUTE.

FREQUENCIES VARIABLES=attendlectures c_sciencesocialmedia followsocialmedia
educ_high
    age_middle age_old income
```

```
  /ORDER=ANALYSIS.

FREQUENCIES VARIABLES=income
  /STATISTICS=MEAN
  /ORDER=ANALYSIS.

COMPUTE c_income=income - 12.95.
EXECUTE.

FREQUENCIES VARIABLES=c_income
  /STATISTICS=MEAN
  /ORDER=ANALYSIS.

FREQUENCIES VARIABLES=attendlectures c_sciencesocialmedia educ_high age_middle
age_old
    followsocialmedia c_income
  /STATISTICS=STDDEV MINIMUM MAXIMUM MEAN
  /ORDER=ANALYSIS.

EXAMINE VARIABLES=MUSEUM_g BY followsocialmedia sciencesocialmedia age
income education
  /PLOT BOXPLOT NPPLOT
  /COMPARE GROUPS
  /STATISTICS DESCRIPTIVES
  /CINTERVAL 95
```

```
  /MISSING LISTWISE
  /NOTOTAL.

CORRELATIONS
  /VARIABLES=attendlectures educ_high c_sciencesocialmedia followsocialmedia
age_middle age_old
    c_income
  /PRINT=TWOTAIL NOSIG FULL
  /MISSING=PAIRWISE.

REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS R ANOVA COLLIN TOL
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT attendlectures
  /METHOD=ENTER c_sciencesocialmedia followsocialmedia.

LOGISTIC REGRESSION VARIABLES attendlectures
  /METHOD=ENTER educ_high
  /PRINT=CI(95)
  /CRITERIA=PIN(0.05) POUT(0.10) ITERATE(20) CUT(0.5).

LOGISTIC REGRESSION VARIABLES attendlectures
  /METHOD=ENTER educ_high age_middle age_old followsocialmedia c_income
```

```
  /PRINT=CI(95)
  /CRITERIA=PIN(0.05) POUT(0.10) ITERATE(20) CUT(0.5).

LOGISTIC REGRESSION VARIABLES attendlectures
  /METHOD=ENTER c_sciencesocialmedia educ_high age_middle age_old
followsocialmedia c_income
  /PRINT=CI(95)
  /CRITERIA=PIN(0.05) POUT(0.10) ITERATE(20) CUT(0.5).

LOGISTIC REGRESSION VARIABLES attendlectures
  /METHOD=ENTER higheduc_sciencesocialmedia c_sciencesocialmedia educ_high
age_middle age_old
    followsocialmedia c_income
  /PRINT=CI(95)
  /CRITERIA=PIN(0.05) POUT(0.10) ITERATE(20) CUT(0.5).
```