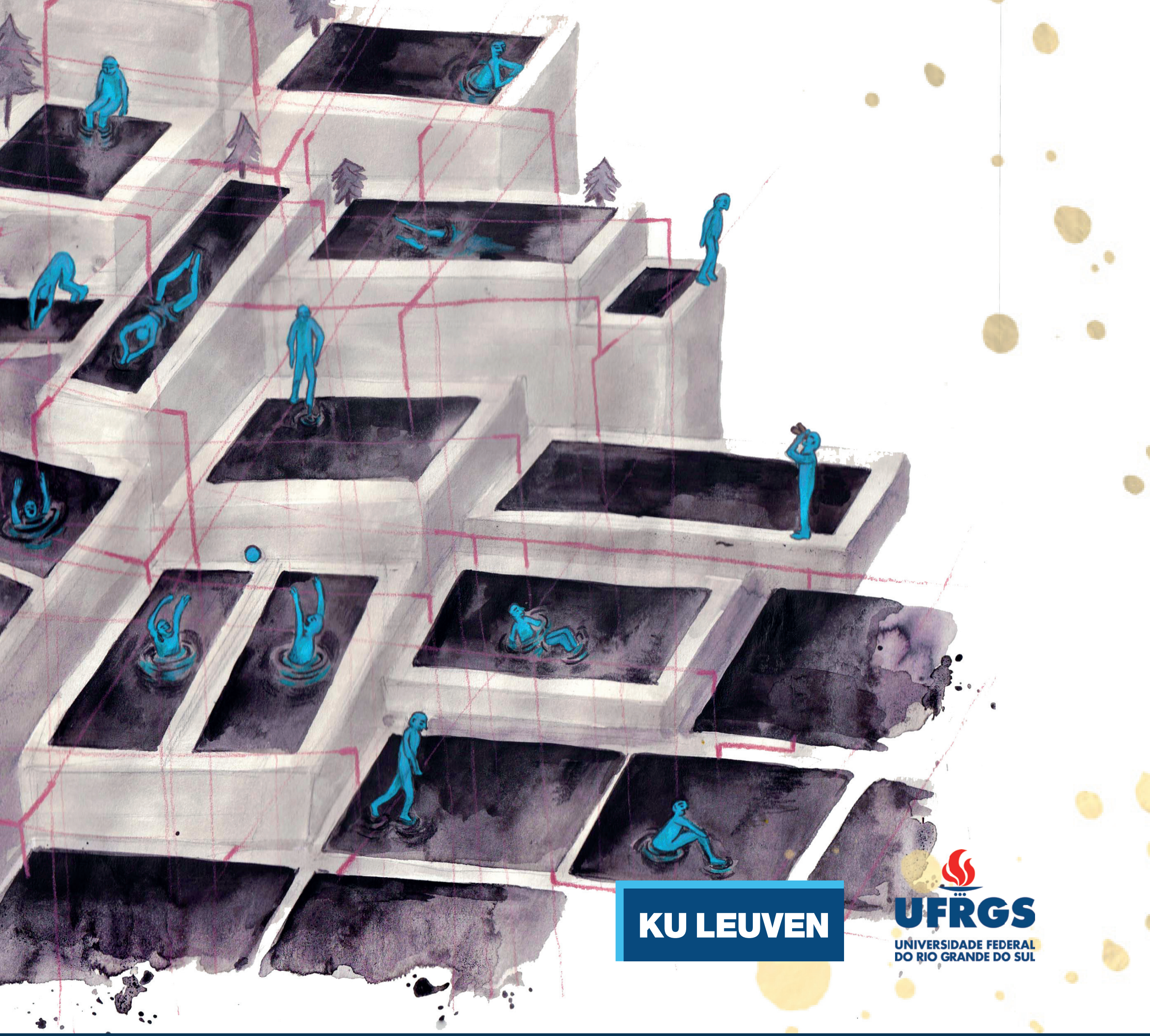
Recommendations in Academic Social Media: the shaping of scholarly communication through algorithmic mediation

Luciana MONTEIRO-KREBS



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And to those of you reading this book, thank you for taking an interest in my research. Without you, the hard work of many years is stored on a shelf. And I don't want that because I'm allergic to dust. I hope that reading it brings you something good, arouses some interest, demonstrates that you were right in your intuition or that makes you want to contradict me. In science everything is fleeting. That's why I want this research to travel, be transformed, evolve, just as I - with the help of all these people above - evolved to be able to write it.

Abstract (English)

Scholarly communication is increasingly being mediated by Academic Social Media (ASM) platforms, which combine the functions of a scientific repository with social media features such as personal profiles, followers and comments. In ASM, algorithmic mediation is responsible for filtering the content and distributing it in personalised individual feeds and recommendations according to inferred relevance to users. However, if communication among researchers is intertwined with these platforms, in what ways may the recommendation algorithms in ASM shape scholarly communication? Scientific literature has been investigating how content is mediated in data-driven environments ranging from social media platforms to specific apps, whereas algorithmic mediation in scientific environments remains neglected. This thesis starts from the premise that ASM platforms are sociocultural artefacts embedded in a mutually shaping relationship with research practices and economic, political and social arrangements. Therefore, implications of algorithmic mediation can be studied through the artefact itself, peoples' practices and the social/political/economic arrangements that affect and are affected by such interactions. Most studies on ASM focus on one of these elements at a time, either examining design elements or the users' behaviour on and perceptions about such platforms. In this thesis, a multifaceted approach is taken to analyse the artefact as well as the practices and arrangements traversed by algorithmic mediation. Chapter 1 reviews the literature about ASM platforms, and explains the history of algorithmic recommendations, starting from the first Information Retrieval systems to current Recommender Systems, highlighting the use of different data sources and techniques. The chapter also presents the mediation framework and how it applies to ASM platforms, before outlining the thesis. The rest of the thesis is divided in two parts. Part I focuses on how recommender systems in ASM shape what

users can see and how users interact with and through the platform. Part II investigates how, in turn, researchers make sense of their online interactions within ASM. The end of Chapter 1 shows the methodological choices for each following chapter.

Part I presents a case study of one of the most popular ASM platforms in which a walkthrough method was conducted in four steps (interface analysis, web code inspection, patent analysis and company inquiry using the General Data Protection Regulation (GDPR)). In Chapter 2 it is shown that almost all the content in ASM platforms are algorithmically mediated through mechanisms of profiling, information selection and commodification. It is also discussed how the company avoids explaining the workings of recommender systems and the mutually shaping characteristic of ASM platforms. Chapter 3 explores the distortions and biases that ASM platforms can uphold. Results show how profiling, datafication and prioritization have the potential to foster homogeneity bias, discrimination, the Matthew effect of cumulative advantage in science and other distortions.

Part II consists of two empirical studies involving participants from different countries in interviews (n=11) and a research game (n=13). Chapter 4 presents the interviews combined with the show and tell technique. The results show the participant's perceptions on ASM affordances, that revolve around six main themes: (1) getting access to relevant content; (2) reaching out to other scholars; (3) algorithmic impact on exposure to content; (4) to see and to be seen; (5) blurred boundaries of potential ethical or legal infringements, and (6) the more I give, the more I get. We argue that algorithmic mediation not only constructs a narration of the self, but also a narration of the relevant other in ASM platforms, configuring an image of the relevant other that is both participatory and productive. Chapter 5 presents the design process of a research game and the results of the empirical sessions, where participants were observed while playing the game. There are two outcomes for the study. First, the human values researchers relate to algorithmic features in ASM, the most prominent being stimulation, universalism and self-direction. Second, the role of the researcher's approach (collaborative, competitive or ambivalent) in academic tasks, showing the consequential choices people make regarding algo-

rithmic features and the motivations behind those choices. The results led to four archetypal profiles: (1) the collaborative reader; (2) the competitive writer; (3) the collaborative disseminator; and (4) the ambivalent evaluator.

The final chapter summarises the ways in which ASM platforms forges people's perceptions and the strategies people employ to use the systems in benefit of their careers, answering each research question. Chapter 6 discusses the implications of algorithmic mediation for scholarly communication and science in general. The dissertation ends with reflections on human agency in data-driven environments, the role of algorithmic inferences in science and the challenge of reconciling individual user's needs with broader goals of the scientific community. By doing so, the contribution of this thesis is twofold, (1) providing in-depth knowledge about the ASM artefact, and (2) unfolding different aspects of the human perspective in dealing with algorithmic mediation in ASM. Both perspectives are discussed in light of social arrangements that are mutually shaped by artefact and practices.

Keywords

algorithmic mediation, recommender systems, academic social media, algorithmic biases, scholarly communication.

Resumo (Português)

A comunicação acadêmica é cada vez mais mediada por plataformas de Mídia Social Acadêmica (MSA), que combinam as funções de um repositório científico com recursos de mídia social, como perfis pessoais, seguidores e comentários. Nas MSA, a mediação algorítmica é responsável por filtrar o conteúdo e distribuí-lo em feeds e recomendações individuais personalizados de acordo com a relevância inferida para os usuários. No entanto, se a comunicação entre pesquisadores está entrelaçada com essas plataformas, de que forma os algoritmos de recomendação nas MSA podem moldar a comunicação acadêmica? A literatura científica vem investigando como o conteúdo é mediado em ambientes orientados por dados, desde plataformas de mídia social até aplicativos específicos, enquanto a mediação algorítmica em ambientes científicos permanece negligenciada. Esta tese parte da premissa de que as plataformas de MSA são artefatos socioculturais inseridos em uma relação mutuamente modeladora com práticas de pesquisa e arranjos econômicos, políticos e sociais. Portanto, as implicações da mediação algorítmica podem ser estudadas através do próprio artefato, das práticas humanas e dos arranjos sociais/políticos/econômicos que afetam e são afetados por tais interações. A maioria dos estudos sobre MSA se concentra em um desses elementos de cada vez, seja examinando elementos de design ou o comportamento e percepções dos usuários sobre essas plataformas. Nesta tese, uma abordagem multifacetada é feita para analisar o artefato, bem como as práticas e arranjos atravessados pela mediação algorítmica. O Capítulo 1 revisa a literatura sobre plataformas de MSA e explica a história das recomendações algorítmicas, desde os primeiros sistemas de Recuperação de Informação até os atuais Sistemas de Recomendação, destacando o uso de diferentes fontes de dados e técnicas. O capítulo também apresenta o quadro teórico (mediation framework) e como ele se aplica às plataformas MSA, antes de delinear a

estrutura da tese. O restante da tese está dividido em duas partes. A Parte I se concentra em como os sistemas de recomendação nas MSA moldam o que os usuários podem ver e como os usuários interagem com e na plataforma. A Parte II, por sua vez, investiga como os pesquisadores dão sentido às suas interações online dentro das MSA. O final do Capítulo 1 mostra as opções metodológicas para cada capítulo seguinte.

A Parte I apresenta um estudo de caso de uma das plataformas de MSA mais populares em que o walkthrough method foi realizado em quatro etapas (análise de interface, inspeção de código web, análise de patente e consulta à empresa usando o General Data Protection Regulation (GDPR)). No Capítulo 2 é mostrado que quase todo o conteúdo das plataformas ASM é mediado por algoritmos por meio de mecanismos de perfilamento, seleção de informações e mercantilização. Também é discutido como a empresa evita explicar o funcionamento dos sistemas de recomendação e a característica de modelagem mútua das plataformas de MSA. O Capítulo 3 explora as distorções e vieses que as plataformas de MSA podem sustentar. Os resultados mostram como o perfilamento, a datificação e a priorização de conteúdo têm o potencial de promover viés de homogeneidade, discriminação, o efeito Mateus de vantagem cumulativa na ciência e outras distorções.

A Parte II consiste em dois estudos empíricos envolvendo participantes de diferentes países em entrevistas (n=11) e um jogo de pesquisa (n=13). O capítulo 4 apresenta as entrevistas combinadas com a técnica show and tell. Os resultados mostram as percepções dos participantes sobre as affordances das MSA, que giram em torno de seis temas principais: (1) ter acesso a conteúdos relevantes; (2) acesso a outros pesquisadores; (3) impacto algorítmico na exposição ao conteúdo; (4) ver e ser visto; (5) limites difusos de potenciais infrações éticas ou legais e (6) quanto mais eu dou, mais eu recebo. Argumentamos que a mediação algorítmica não apenas constrói uma narração do eu, mas também uma narração do outro nas plataformas de MSA, configurando uma imagem do outro ao mesmo tempo participativa e produtiva. O capítulo 5 apresenta o processo de design de um jogo de pesquisa e os resultados das sessões empíricas, onde os participantes foram observados enquanto jogavam o jogo. Há dois resultados para o estudo. Primeiro, quais valores humanos os pesquisadores relacionam com recursos algorítmicos nas MSA, sendo os mais proeminentes o estímulo, o universalismo e o autodirecionamento. Em segundo lugar, o papel da abordagem do pesquisador (colaborativa, competitiva ou ambivalente) em tarefas acadêmicas, mostrando as escolhas consequentes que as pessoas fazem em relação aos recursos algorítmicos e as motivações por trás dessas escolhas. Os resultados levaram a quatro perfis arquetípicos: (1) o leitor colaborativo; (2) o escritor competitivo; (3) o divulgador colaborativo; e (4) o avaliador ambivalente.

O capítulo final (Capítulo 6) resume as maneiras pelas quais as plataformas de MSA forjam as percepções das pessoas e as estratégias que as pessoas empregam para usar os sistemas em benefício de suas carreiras, respondendo a cada questão de pesquisa. O capítulo discute ainda as implicações da mediação algorítmica para a comunicação acadêmica e a ciência em geral. A dissertação termina com reflexões sobre a agência humana em ambientes orientados por dados, o papel das inferências algorítmicas na ciência e o desafio de conciliar as necessidades individuais do usuário com os objetivos mais amplos da comunidade científica. Ao fazê-lo, a contribuição desta tese é dupla, (1) fornecendo conhecimento aprofundado sobre o artefato plataformas de MSA, e (2) desdobrando diferentes aspectos da perspectiva humana ao lidar com mediação algorítmica em ASM. Ambas as perspectivas são discutidas à luz de arranjos sociais que são mutuamente moldados por artefatos e práticas.

Palavras-chave

mediação algorítmica, sistemas de recomendação, redes sociais acadêmicas, vieses algorítmicos, comunicação científica.

Abstract (Dutch)

Wetenschappelijke communicatie wordt in toenemende mate bemiddeld door Academic Social Media (ASM)-platforms, die de functies van een wetenschappelijk archief combineren met sociale-mediafuncties zoals persoonlijke profielen, volgers en commentaren. In ASM is algoritmische bemiddeling verantwoordelijk voor het filteren van de inhoud en het distribueren ervan in gepersonaliseerde individuele feeds en aanbevelingen op basis van afgeleide relevantie voor gebruikers. Als communicatie tussen onderzoekers echter verweven is met deze platforms, op welke manieren geven de aanbevelingsalgoritmen in ASM dan vorm aan wetenschappelijke communicatie? Wetenschappelijke literatuur heeft onderzocht hoe inhoud wordt gemedieerd in datagestuurde omgevingen, variërend van sociale-mediaplatforms tot specifieke apps, terwijl algoritmische bemiddeling in wetenschappelijke omgevingen verwaarloosd blijft. Dit proefschrift vertrekt van het uitgangspunt dat ASM-platforms sociaal-culturele artefacten zijn die zijn ingebed in een wederzijds vormende relatie met onderzoekspraktijken en economische, politieke en sociale arrangementen. Daarom kunnen implicaties van algoritmische bemiddeling worden bestudeerd via het artefact zelf, de praktijken van mensen en de sociale/politieke/economische regelingen die dergelijke interacties beïnvloeden en erdoor worden beïnvloed. De meeste onderzoeken naar ASM richten zich op één van deze elementen tegelijk, waarbij ofwel ontwerpelementen ofwel het gedrag van gebruikers op en percepties over dergelijke platforms worden onderzocht. In dit proefschrift wordt een veelzijdige benadering gevolgd om zowel het artefact als de praktijken en arrangementen te analyseren die door algoritmische bemiddeling worden doorlopen. Hoofdstuk 1 geeft een overzicht van de literatuur over ASM-platforms en legt de geschiedenis van algoritmische aanbevelingen uit, beginnend bij de eerste Information Retrieval-systemen tot de huidige

Recommender-systemen, waarbij het gebruik van verschillende gegevens en technieken wordt benadrukt. Het hoofdstuk presenteert ook het bemiddelingskader en hoe het van toepassing is op ASM-platforms, voordat het proefschrift uiteen wordt gezet. De rest van het proefschrift is verdeeld in twee delen. Deel I richt zich op hoe aanbevelingssystemen in ASM bepalen wat gebruikers kunnen zien en hoe gebruikers omgaan met het platform. Deel II onderzoekt hoe onderzoekers op hun beurt betekenis geven aan hun online interacties binnen ASM. Het slot van hoofdstuk 1 toont de methodologische keuzes voor elk volgend hoofdstuk.

Deel I presenteert een case study van een van de meest populaire ASM-platforms waarin een walkthrough-methode werd uitgevoerd in vier stappen (interface-analyse, webcode-inspectie, octrooianalyse en bedrijfsonderzoek met behulp van de Algemene Verordening Gegevensbescherming (AVG)). In hoofdstuk 2 wordt aangetoond dat bijna alle inhoud in ASM-platforms algoritmisch wordt gemedieerd via mechanismen van profilering, informatieselectie en commodificatie. Ook wordt besproken hoe het bedrijf vermijdt om de werking van aanbevelingssystemen en het wederzijds vormende kenmerk van ASM-platforms uit te leggen. Hoofdstuk 3 onderzoekt de vervormingen en vooroordelen die ASM-platforms kunnen handhaven. De resultaten laten zien hoe profilering, dataficatie en prioritering het potentieel hebben om homogeniteitsbias, discriminatie, het Matthew-effect van cumulatief voordeel in de wetenschap en andere verstoringen te bevorderen.

Deel II bestaat uit twee empirische onderzoeken met deelnemers uit verschillende landen in interviews (n=11) en een onderzoeksspel (n=13). Hoofdstuk 4 presenteert de interviews gecombineerd met de show and tell-techniek. De resultaten tonen de perceptie van de deelnemer over ASM-mogelijkheden, die draaien rond zes hoofdthema's: (1) toegang krijgen tot relevante inhoud; (2) het bereiken van andere onderzoekers; (3) algoritmische impact op blootstelling aan inhoud; (4) zien en gezien worden; (5) vervagende grenzen van mogelijke ethische of wettelijke inbreuken, en (6) hoe meer ik geef, hoe meer ik krijg. We stellen dat algoritmische bemiddeling niet alleen een vertelling van het zelf construeert, maar ook een vertelling van de relevante ander in ASM-platforms, waarbij een beeld van de relevante ander wordt gevormd dat zowel participatief als productief is. Hoofdstuk 5 presenteert het ontwerpproces van een onderzoeksspel en de resultaten van de empirische sessies, waarbij deelnemers werden geobserveerd tijdens het spelen van het spel. Er zijn twee uitkomsten voor het onderzoek. Ten eerste, de menselijke waarden die onderzoekers hebben met betrekking tot algoritmische kenmerken in ASM, de meest prominente zijnde stimulatie, universalisme en zelfsturing. Ten tweede, de rol van de benadering van de onderzoeker (samenwerkend, competitief of ambivalent) in academische taken, die de consequente keuzes laat zien die mensen maken met betrekking tot algoritmische kenmerken en de motivaties achter die keuzes. De resultaten leidden tot vier archetypische profielen: (1) de samenwerkende lezer; (2) de concurrerende schrijver; (3) de samenwerkende verspreider; en (4) de ambivalente beoordelaar.

Het laatste hoofdstuk vat de manieren samen waarop ASM-platforms de percepties van mensen vormen en de strategieën die mensen gebruiken om de systemen te gebruiken ten behoeve van hun loopbaan, waarbij elke onderzoeksvraag wordt beantwoord. Hoofdstuk 6 bespreekt de implicaties van algoritmische bemiddeling voor wetenschappelijke communicatie en wetenschap in het algemeen. Het proefschrift eindigt met reflecties over menselijk handelen in datagestuurde omgevingen, de rol van algoritmische gevolgtrekkingen in de wetenschap en de uitdaging om de behoeften van individuele gebruikers te verzoenen met bredere doelen van de wetenschappelijke gemeenschap. Door dit te doen, is de bijdrage van dit proefschrift tweeledig, (1) het verschaffen van diepgaande kennis over het ASM-artefact, en (2) het blootleggen van verschillende aspecten van het menselijk perspectief bij het omgaan met algoritmische bemiddeling in ASM. Beide perspectieven worden besproken in het licht van sociale arrangementen die onderling worden gevormd door artefacten en praktijken.

Trefwoorden

algoritmische bemiddeling, recommender-systemen, Academic Social Media, algoritmische vooringenomenheid, wetenschappelijke communicatie.

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PART II

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PREFACE

The most profound technologies are those that disappear. They weave themselves into the fabric of everyday life until they are indistinguishable from it.

Mark Weiser, The Computer of the 21st Century (1991)

"We think you will like this research." When interacting with non-human actors that are making this kind of recommendation, it is important to reflect on what this sentence actually tells us. Who are "we"? What exactly is "liking"? And why is "this" particular research found to be so interesting that it is popping-up right at the top of my feed? While getting more and more dependent on algorithmic mediation, we might tend to disregard such questions. After all, technologies are increasingly becoming entangled in our daily lives.

Artificial Intelligence (AI) took over many routine activities for us humans, which is quite convenient, of course. AI-based applications assist humans in finding the cheapest flight to vacations, taking the fastest route to work or automating financial investment. Using AI apps to make the calculations that lead to these decisions was enthusiastically embraced by most societies from all around the globe. Meanwhile, the technological devices became cheap, small and "accessible" to people from varied social layers. However, AI applications are also increasingly penetrating other kinds of decisions we deal with hundreds of times a day. We are delegating to AI systems questions with no single answer, but that are rather subjective, open-ended, and embedded with values (Tufekci, 2016). For example, what kind of videos should my son watch on Youtube? Who are the people I will interact with on social media today? What is the most important news I should read this morning? Who will be a good match for a casual date tonight? The automated decisions that culminate in suggestions to answer these questions are heavily based on past behaviour, comparisons with "similar" profiles, inferred preferences and many other factors that are collected imperceptibly throughout our lives, whether we like it or not, whether we are aware of it or not, whether we agree with these criteria or not.

The awareness about the logic of such systems, though, is becoming less optional as technologies become increasingly ubiquitous. Many events in the last decades dragged us back to the - sometimes inconvenient but nevertheless crucial - debate on the societal implications of automated decision-making. Threats to democracy such as the manipulation of the presidential elections, personal data leaks, and the systemic negligence to mental health issues caused by platforms, which have been denounced by whistleblowers, are just a few examples. Social media platforms are being pointed out by specialists and the very own designers and ex-employees of big tech companies as the root of disinformation and fake news spreading, polarisation, radicalization, addiction, vanitification and mental health harm (Orlowski, 2020). The documentaries The Social Dilemma (Orlowski, 2020) and Coded Bias (Kantayya, 2020) are examples of the challenges and the exhaustion that the algorithmic dynamic imposes upon us. It seems that we can no longer delay the conversation about how these algorithmic predictions are being made and what are the implications of them in different public spheres. In designing platforms' affordances, those who make the design decisions also decide what we can and cannot do. It is necessary to increase transparency by design and hold accountable those in power of making the design decisions. And for that to happen, we first need to dive into understanding the mechanisms involved in algorithmic mediation and how they affect us.

Surprisingly, the ongoing debate about the repercussions of general social media (such as Facebook, Instagram and WhatsApp) does not seem to include the Academic Social Media (ASM) platforms. Particularly for the academic community, it is still unclear what is the role of algorithmic mediation in the way scholars conduct research, as well as how they communicate with each other and with the broader public. Except from the recent work of Polonioli (Polonioli, 2020) on the ethics of scientific recommender systems, and Oliveira's study on the mediatization of science (T. M. Oliveira, 2018), very little has been published about recommender systems in academia. In other words, we don't know enough about the recommendation algorithms or what are the potential impacts of content personalisation on science practices.

This thesis fills this gap by deeply exploring the algorithmic recommendations in ASM to shed light on the very same mechanisms that exist in general social media to better understand and critically reflect on their implications for scholarly communication. In order to pursue this goal, this thesis will focus on three elements: ASM platforms as artefacts, the human interactions with and through these artefacts[1], and the social arrangements that surround the interactions, shaping and being shaped by them. By doing so, this study is not limited to an artefact perspective, because I renounce the neutrality of digital technologies, as if they were inanimate tools with no agency (Matos, 2020, p. 73). Yet I also disbelieve the idea that the media channels have the inherent power to influence audiences on their own, which is defended by technological determinism. I consider digital technologies as complex, interactive, situated and value-entangled platforms, a view that allows me to critically reflect on their role in shaping the access to information and in being shaped by people's beliefs and practices.

I acknowledge the several advantages ASM platforms have brought to scholarly communication, such as democratising access to scientific literature, facilitating networking, bringing researchers from around the globe closer to each other, allowing early-career researchers to build their own reputation and be part of the conversations previously restricted to very specific arenas. They also have the potential to facilitate data sharing and promote scientific collaboration (Orduña-Malea et al., 2017). At the same time, I also recognize that some very specific human traits are being cleverly engendered in social media design with the sole purpose of making users stay longer on these platforms, exchanging their attention and personal data for free services (Goldhaber, 1997; Orlowski, 2020). We should be able to ask ourselves the real cost of such transactions.

1 The online interactions to which we refer in this thesis are both the interactions of the user with the system, and the interactions among users mediated by the system. These two types of interactions are intertwined because of the visibility afforded in social media platforms. For instance, when a person shares content, it can be considered an interaction of that person with the system. However, even when a person shares content via the system (and thus interacts with the system), they do so with an audience of other people in mind (and sometimes even with the workings of the systems in mind, in order to increase their RG score, for instance). Also, from the moment that a follower "likes" or comments on that content, even though the interaction occurs with the platform (clicking on a button), the author of the content typically receives a notification, characterising an interaction occurring between the user and its audience **through** the platform. Therefore, in the scope of this thesis, online interactions among people within the platform or online interactions with the platform itself, are indissociable.

To give an example of how human traits are used to increase the time people spend on platforms, let me take the sense of belonging. Mankind learned throughout our evolutionary history that being part of a community makes us live longer and better. Then, our brain created a mechanism to reinforce the basic biological imperative for connecting with other people. This reinforcement happens through the release of dopamine in the reward pathway whenever we feel embraced by a community (Lembke, 2021). Thus, the sense of belonging is really important to us, and social acceptance and approval are actually a signal that our vital urge to live together, form groups and perpetuate the species is on the right track. This is one of the reasons why academic social media are so appealing: because it optimises the connection between people (Lembke, 2021; Orlowski, 2020).

The same goes for recommendations. Providing and accepting suggestions is not new, it actually goes back to evolutionary habits, hard-wired to survival impulses. Sharing acquired knowledge has enabled mankind to evolve and dominate the planet, because we save effort when we learn from the experience of others, without necessarily having to go through it. Our choices are therefore guided by what others have done before, since these choices have already been tested and mean security. If someone else has succeeded, that is the right way to go. "Following recommendations, solicited or not, is as striking a trait of the social individual as walking upright" (Abel, 2004, p. 13).

It becomes clear that, to truly understand the impact of algorithmic recommendations in ASM, we need to embrace its complexity and embeddedness in the fabric of everyday life. It is not a matter of scrutinising the features of the systems as neutral tools, nor advocating for the drop-out of the platforms. Rather, we should understand the interplay between human and non-human actors in the digital environments to critically reflect on these interactions, understand how they relate to our human values and how we want to shape the platforms that, in turn, will shape us. My aspiration for this thesis is that it can explain and critique the elements in this dynamic that have the most relevant implications for scholarly communication. As a result, I start from a comprehensive yet deep analysis on recommendation algorithms in ASM and I deliver such analysis by examining at the deepest possible level the artefact (platform), the practices (use) and the social / political / economic arrangements involved in the phenomena of recommendations mediated by algorithms in ASM.

It is important to clarify what this thesis is not. I do not perform reverse engineering nor scrutinise the code of the algorithms. This would not be possible due to commercial secrecy and does not meet my research interests. Although I used code analysis as one of the methodological steps in order to better understand the workings of recommender algorithms in ASM, this thesis is inserted in the larger context of Social Sciences, and people's sense-making is still the focal point. It is neither a manifesto against recommender systems or an attempt to demonise them. As I said in the previous paragraphs, I recognize how crucial these filters are in the digital era. On the contrary, I believe we need to improve them and better align what they can do for us with our human values. I also do not deliver detailed guidelines of potential solutions for the threats that were found in the empirical research, due to time constraints. But throughout each chapter and conclusion I discuss some paths that, as a researcher, I believe would be beneficial for both the platforms and also to my fellow ASM users. From the platforms, I would like to see more emphasis on serendipity and transparency. As for the researchers, it would be nice to witness some growing digital literacy and the always welcomed inquisitive minds.

At this point I would like to offer a reflexivity stance to this thesis. I grew up in many different places, having lived in 5 different states in Brazil before I was 10 years old. I changed schools many times, went to different neighbourhoods, made friends in distant places, with whom I corresponded by letter during my childhood and adolescence. In Brazil, some states are the size of entire countries in Europe, and therefore the distance between one and the other is reflected in cultural differences, social norms, habits, accents, temperatures, aromas. As an adult, I continued to pursue this restless journey, and perhaps this is why I had the ambition to study different disciplines and do research abroad. My formal education so far included Information Science, Linguistics, Terminology and Human-computer Interaction. Additionally, Computer Sciences, Marketing, Psychology and Economy are among my areas of interest. I believe that this variety of experiences gave me "code-switching" skills -

or the ability to change language, dialect, or other communication resources from one environment to the next, while learning to navigate the culture of spaces so far away from each other. Code-switching is an underestimated skill and one that I have used to bring the perspectives of people from various backgrounds to my research. See for example, my previous work on terminological variation and the inclusion of lay users in information retrieval systems[2, 3, 4].

I can see connections between many seemingly diverse ways of thinking, which I think is a positive thing. In my work, this is reflected in the way I try to find similarities in people's productions of meaning, rather than distinctions. Thus, I bring together groups of participants from different countries, ages, genders, years of experience, and areas of knowledge, and still manage to find converging paths between their research practices. On the other hand, this approach may lack distinctive comparisons, cultural or infrastructural aspects that can have an effect on scientific practices in different places. A statistical consultancy informed me that it would not be possible to draw significant differences between demographic subgroups for such small groups of participants. However, even though the participants do not represent the entirety of researchers using ASM, we were able to observe predominant informative categories of people's perceptions, sense-making and human values associated with recommender systems in ASM through the qualitative studies that were part of my PhD journey. An alternative approach would be to highlight points of divergence between people of different levels of seniority, or from different locations, for example, which would help identify cultural differences.

2 http://aleph20.letras.up.pt/index.php/prismacom/article/view/3926

3 http://www.repositorio.jesuita.org.br/handle/UNISINOS/5053

4 https://www.editorainterciencia.com.br/index.asp?pg=prodDetalhado.asp&idprod=532&token=

I also acknowledge my personal profile shaped my vision of the world, which ultimately frames my research. I am a white, cisgender woman, which put me in a position of priviledge. On the other hand, I come from a humble family, living in a developing country, with access to fairly poor elementary school education. I was the first person in my extended family to complete a master's degree and to this day I am the only one. Even so, my family always valued education and respect for educational institutions, because education proved to be one of the few means of social upward mobility for people like us. When I finally got my degree as a scholarship student, it became very evident that, although my classmates were attending the same spaces, we didn't have the same family structures and safety nets. While some classmates had their expenses paid by their parents, others, like myself, had to work 6 or even 8-hour jobs to support themselves and their families. While some had English classes since elementary school, others learned on their own, without pedagogical support or adequate materials, such as myself. Yet, the same competence and dedication time was expected of all students, in order to meet the minimal requirements of higher education. I believe that this experience made me very aware of the arrangements and structures surrounding the subject that directly affect people's academic performance. It seems to me that to analyse a phenomenon broadly, one needs to understand people's behaviour in performing their role (how), what drives them to do what they do (why), and how much of this is encouraged by the materiality of the artefacts they use as well as the arrangements.

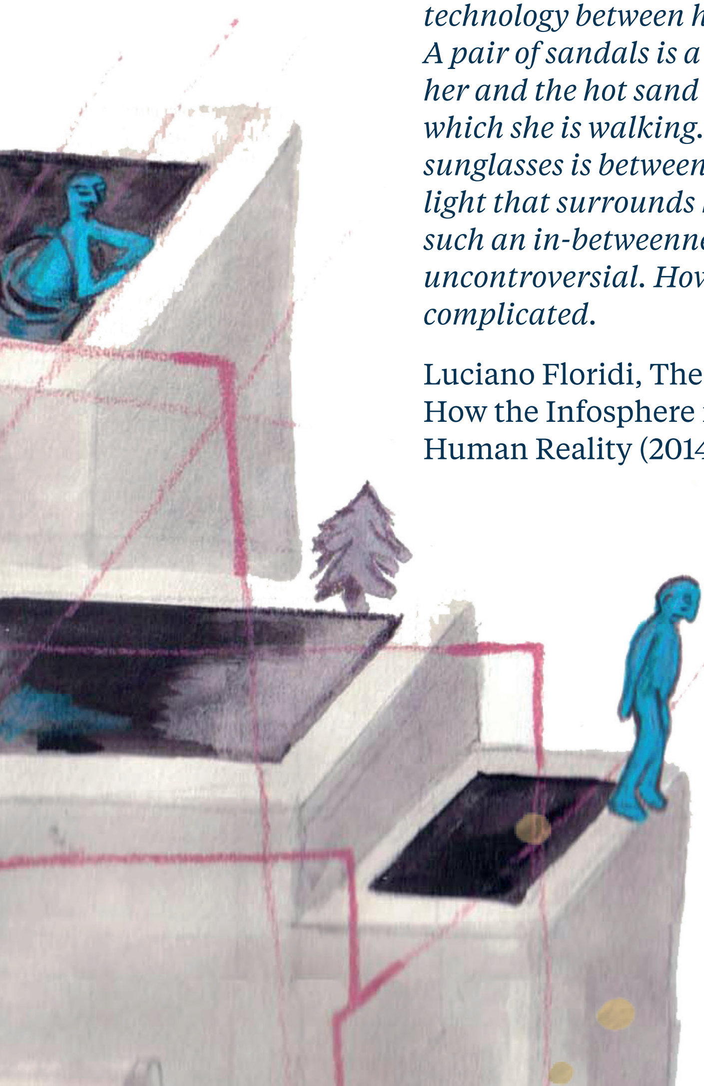
In this sense, the chosen theoretical framework is a coherent choice because it considers the research topic broadly, holistically, with mutually shaping elements. And to examine things as different as a technological artefact, people's practices towards the artefact, and the political and social structures in which this dynamic is embedded, I combined different methodological and epistemological approaches. In doing so, I followed a pragmatic approach to decide which methods would be part of the research design, focusing on the complexity of the research problem and judging the appropriateness in terms of its potential to give an answer to the research questions. My research is therefore framed as partly post-humanistic and partly interpretative. Our approach can also be characterised as being interdisciplinary in nature, at the intersection of various fields, expanding the breadth of the literature review as it is reflected in the References list. Finally, I enthusiastically encourage future research on this topic, as many more questions emerged while I was crafting this thesis than I could ever possibly handle throughout my PhD. However, I hope this thesis provides enough contribution to help the scientific community in building “a solid path towards a positive digital future” (KU Leuven Digital Society Institute, 2021) involving algorithmic mediation in academia.

chapter 1

INTRODUCTION

One of the most obvious features that characterizes any technology is its in-betweenness. Suppose Alice lives in Rio de Janeiro, not in Oxford. A hat is a technology between her and the sunshine. A pair of sandals is a technology between her and the hot sand of the beach on which she is walking. And a pair of sunglasses is between her and the bright light that surrounds her. The idea of such an in-betweenness seems clear and uncontroversial. However, it soon gets complicated.

Luciano Floridi, The Fourth Revolution: How the Infosphere is Reshaping Human Reality (2014, p. 25)



Seeing online platforms as entities that not only do things **for** us, but also do things **to** us, while we interact with them, is a broad notion that can be observed in several theories across different domains. Some examples are the Actor-Network Theory (Latour, 2007), and concepts such as the platform Selection[5] (van Dijck, 2013), the filter bubble (Pariser, 2011) and the Infosphere (Floridi, 2014). Aligned with this idea, in my thesis I see platforms as automated mediators, that collect information that is produced by people, and store it, label it, organise it, cluster it, shuffle it and distribute it back to people following a predefined coded logic. To make that happen, online platforms systematically **collect** information about people (by tracking and counting our footprints), about content (metadata that describes the theme, when the content was produced, who wrote it, etc.) and about institutions (where the content was produced, affiliations, etc.). The platforms also autonomously **produce** information, by inferring contextual data, for example. These data are used in the organising processes (e.g. classification, ranking, etc.) and also in reward systems (such as altmetrics and all sorts of quantifiers that are used to create scores within the platforms), mostly to keep the user active and engaged within the platform. This process is called algorithmic mediation.

1.1 Problem statement, Objective and Research Questions

Algorithmic mediation has become an essential feature of online platforms to mitigate information overload, becoming popular across a variety of web-based services, including shopping, entertainment and social networking platforms. Recommender systems, one method used to filter

5 Platform Selection is defined as "[...] the ability of platforms to trigger and filter user activity through interfaces and algorithms, while users, through their interaction with these coded environments, influence the online visibility and availability of particular content, services, and people" (van Dijck et al., 2018, p. 40).

content, has also increased in academia through Academic Social Media (ASM) such as ResearchGate.net, Academia.edu and Mendeley. Such platforms facilitate scientific dissemination and information retrieval, while also enabling networking practices, by suggesting papers to read, researchers to follow, and jobs to apply for. These applications mediate the information used to make decisions, from the most trivial to the most relevant ones. Willson argues that the systems to which we delegate routine activities represent an important category of recommender algorithms because the daily practices are the ones that constitute "[...] the background upon which people operate" (Willson 2017).

Paradoxically, while recommender systems expand the access to content, people and opportunities (when compared to databases behind paywalls or distributed academic directories), they also narrow the content according to predefined parameters. By definition, recommender systems reduce the amount of information a platform displays to a user by predicting what that user may want to find. However, how the content is selected by the algorithm is often protected by commercial secrecy, it varies across platforms and changes constantly. Therefore, the algorithm often appears to users as a *black box* (Barassi, 2017; Bozdag, 2013; Tufekci, 2017).

The research project **Algorithmic Mediation in Academic Social Systems (AMASS)**[6] originated from the premise that the systems that exert algorithmic mediation shape and are shaped by the interactions happening within ASM. Such platforms present to its users a certain vision of the world, influencing how researchers see themselves, the others, the work environment and the relationships between different actors. The platforms' users, in turn, produce and interact with content, which impacts information flows in the digital environments. Content created by users and also users' navigation history are collected and indexed by the platform to be distributed in users' feeds (which determines what the users connections will see) and to tailor their own profiles (which determines new recommendations for themselves).

6 The research project is a collaboration between the research group Comunicação Científica (UFRGS, Porto Alegre – Brazil) and the Meaningful Interactions Lab (Mintlab – KU Leuven – Belgium). More information available at: https://soc.kuleuven.be/mintlab/blog/project/amass/. This research is partially funded by Higher Education Improvement Coordination – Brazil (CAPES) – Financing Code 001; and partially funded by KU Leuven.

Even though users have the agency whether or not to access the platform, choose what to read and decide who to connect with, the platform itself also has agency. It does so by selecting the content that will appear to each user, choosing the order and the moment in which they will be shown, and nudging the user to connect through notifications. Thus, users and platforms are constantly negotiating agency in such interactions, and there is much to investigate when such automated decision-making is determining the subsets of information to which we are (or are not) exposed to and with which we are (or are not) allowed to interact with. This can influence what people understand as worthy of attention, popular, valuable or trustworthy. Ultimately, it can determine even what researchers will work on next. I also believe that this dynamic is forged by novel, subtle and silent mechanisms, which makes it challenging to apprehend from a single disciplinary point of view. For this reason, I applied different methods from various disciplines (Librarianship, Information Science and Human-computer Interaction). These methods will be explained in more detail in each empirical chapter of the thesis.

Studying algorithmic mediation in ASM platforms, the contribution of this thesis twofold. On the one hand, the thesis provides in-depth knowledge about the ASM artefact, unravelling how the platforms communicate with its users about algorithmic mediation, the main entities involved in the recommendations, the mechanisms embedded in them and the potential biases they may uphold. On the other hand, the thesis unfolds different aspects of the human perspective in dealing with algorithmic mediation in ASM. It does so by exploring how people make sense of recommendations in ASM and by describing the strategies and values that people put in motion depending on the academic role they are playing and the situation they find themselves in. In both perspectives, we discuss the implications of the artefacts and practices in the broader scientific arrangements. Combined, this dissertation provides an overarching overview of algorithmic mediation in ASM by equally emphasising both sides of the sociotechnical duality: the system's materiality (what the systems are doing and how) and the social/cultural facet (what people are doing and why). We demonstrate the mutually shaping characteristic of the algorithmic mediation phenomena, showing the ways the system forges people's perceptions and the strategies people employ to use the systems to benefit their careers.

This thesis will add to existing knowledge on recommender systems in ASM by addressing several issues that are not (sufficiently) covered in previous research. Previous work on the topic of recommender systems has focused on improving their efficiency (Lops et al., 2011; Lorenzi et al., 2011; Tsai & Brusilovsky, 2017; Zitouni et al., 2015) as well as on human factors such as trust, privacy, robustness and serendipity (Konstan & Riedl, 2012; Montaner et al., 2002; Pu et al., 2012; Ricci et al., 2011). However, none of these works reflect specifically on the role of recommendations on the academic environment.

As for the literature on the topic of ASM, most of the research can be clustered in two main lines. On the one hand, works focusing on the use of ASM by researchers, their practices and perceptions on the platforms. These works cover the motivations and perceptions towards the use of ASM (Elsayed, 2016; Lee et al., 2019; Nández & Borrego, 2013); the practices of scholars in knowledge sharing and exchanging resources through ASM (Jeng et al., 2017; Koranteng & Wiafe, 2019); and the implications of ASM for stakeholders in academic publishing (Laakso et al., 2017). Although insightful, these studies overlook the role of recommender systems in the ASM platforms.

On the other hand, research on ASM has interesting publications focusing on the platform rather than on the human's perspective. Such studies usually explore one or more of the many bibliometric or altmetric indicators available in ASM. Orduña-Malea, Martín-Martín, and Delgado-López-Cózar (Orduña-Malea et al., 2016) examined the advantages and risks offered by RG Score, a metric created by ResearchGate, when used for evaluating the impact of scientific publications. Delgado-López-Cózar and Orduña-Malea (Delgado-López-Cózar & Orduña-Malea, 2019) explore the Research Interest score, a bibliometric indicator designed to measure the influence of an author's publications on ResearchGate. In general, investigations regarding the functioning of recommendation algorithms remain neglected in the literature about ASM.

Against this backdrop – and echoing the broader call for algorithmic transparency and accountability in social media platforms (Kleanthous et al., 2019; Koene et al., 2015; Milano et al., 2019), it is crucial to discuss the workings of and the implications of algorithmic mediation in ASM platforms. This is important because it is not clear yet to what extent the academic environment is influenced by recommender algorithms. Therefore, in this thesis I aim to investigate in what ways the recommendation algorithms in ASM may shape scholarly communication.

Grasping this problem implies a better understanding of the functioning of recommender systems in ASM, how the platform communicates with its users about algorithmic mediation, how this relates to the scientists' individual practices and, ultimately, which are the implications for scholarly communication. I explore two different angles that revolve around the interactions within ASM mediated by algorithms. One is focused on the platform and its technological affordances. The other focuses on the users' appropriation of algorithmic recommendations. From both angles I discuss the findings in relation to the broader context (scientific arrangements) in which the platform and the human practiceWs are embedded. These perspectives are expressed in the following research questions:

RQ1. How do recommender systems of academic social media shape what users can see and how users interact with the platform? The following questions will further guide our inquiry: *What are the main entities involved in the recommendations on ASM platforms? Which mechanisms can be identified in ASM platforms? How do ASM platforms communicate with their users about recommender algorithms? How may algorithmic mediation, through recommender systems in ASM platforms, uphold biases in scholarly communication?*

RQ2. How do researchers make sense of their interactions online within academic social media? *The following questions will further guide our inquiry: How do technological affordances shape perceptions and scholarly practices? How do researchers relate human values to algorithmic recommendation features in ASM platforms? How are collaboration and competitiveness reflected in people's choices in ASM platforms when performing different academic roles?*

In this thesis I took a pragmatic approach that oriented the methods utilised and the quality criteria applicable for the analysis made. More particularly, I adhered to two complementary epistemological angles in my thesis: post-humanistic and interpretative. I combine methods that are known to fit in these different paradigms, such as web page code inspection (post-humanistic) and interviews (interpretative). This decision aimed at employing different lenses in a complex, "blackboxed" and volatile phenomenon, as I flesh out in the following.

On the one hand, the reader will find in Part I a post-humanistic perspective, assuming the agency of non-human actors in the interactions mediated by ASM platforms. The methodological choice for Part I also reflects the post-humanistic angle: through the walkthrough method, I break down the mechanisms that I assume exert influence on how information is selected, distributed and presented in ASM platforms. The approach to account for the agency of artefacts is inspired by previous work (Evans et al., 2017; Floridi, 2014; Latour, 2007; Pariser, 2011; van Dijck, 2013). In the analysis, it becomes clear that algorithmic mediation has an active role in the scholarly communication processes within ASM platforms. For example, commodification, datafication, selection and prioritisation are mechanisms that shape the content displayed for users. These mechanisms also shape the possible interactions with the content of the platform (i.e., clicking on the "like" button, downloading a paper, saving a research project) as well as with other users (i.e., following or unfollowing a profile, sending private messages).

On the other hand, in Part II I adopt an interpretative perspective to understand people's sense-making of ASM platforms, rather than how the platform actually works. Such an epistemological approach starts from the premise that people's behaviour is shaped by their beliefs. For instance, what people do or do not do in a platform is traversed by what the users think the platform does, being motivated by the expected results the user aims to achieve. And this is true regardless of whether or not the platform functions the way imagined by the user. Within this paradigm, knowledge is socially constructed, as there are typically multiple realities. Thus, I am interested in the meaning-making of people, their perceptions, in listening to their voices, as these very interpretations of the workings of the artefact shape people's practices. By doing so, I assume that people might refrain or be motivated to behave in a certain way by what they know about the workings of ASM platforms - or what they think they know.

In the following sections of this chapter I first start by describing the existing body of literature on the role of ASM platforms in scholarly communication. I briefly introduce the idea that algorithmic mediation of information is changing the way researchers communicate among each other and disseminate their work. I will argue that platforms and users are mutually shaping through connectivity, a notion that will be deepened throughout the empirical chapters.

Second, I present a summary of Information Retrieval systems and Recommender Systems (RS). I explain the origins of these systems, and show the main recommendation techniques as well asd how different sets of data are collected and used to build the inferences.

Third, I introduce the Mediation Framework (Lievrouw, 2014) on which I rely theoretically in this thesis. The framework considers the *artefact*, the *practices* and the social/political/economic *arrangements* that interplay in the digital environments. Thus, I will show how these elements apply to ASM, explaining and providing examples of them in the scientific context.

Finally, closing the literature review, I will argue that in order to investigate in what ways recommendation algorithms in ASM may shape scholarly communication, we need to look at the artefact and the human practices, leading to an outline for how this thesis answers the research questions.

1.2 Academic Social Media (ASM) platforms

An Online platform, according to van Dijck, Poell and Waal, “is a programmable digital architecture designed to organise interactions between users - not just end users but also corporate entities and public bodies. It is geared toward the systematic collection, algorithmic processing, circulation, and monetization of user data” (van Dijck et al., 2018, p. 4). ASM, a particular type of social media platform, has attracted interest from researchers in many areas of knowledge and all around the world. In a paper published in the journal Nature, van Noorden (2014) stated that ResearchGate had 4.5 million users at the time of publication and that ResearchGate received about 10,000 new users every day (Van Noorden, 2014). In a survey carried out with 3,500 researchers from 95 different countries, van Noorden pointed out that 88% of the respondents claimed to know ResearchGate. A study by Jamali, Nicholas, and Herman (2016) on the use of social media ResearchGate among European researchers identified that 44% of respondents use the platform intensely, while 33% of respondents reported using it sparingly (Jamali et al., 2016).

The recommendation algorithms on ASM platforms help users to easily detect works by those authors who have been previously quoted by the user in their paper's references list, and all this at a gigantic gain of speed when compared to the life cycle of traditional academic publications. In this context, filtering mechanisms are undoubtedly necessary to avoid information overdose. However, this also comes at a cost, because by promoting recommendations from the users' most active connections, they also deprive the actions of the less active connections, and hence the platform controls both the researcher and those who they can reach.

José van Dijck and Thomas Poell have coined the notion of connectivity to understand the logic of social media. The authors critique the idea of neutrality in online social media, arguing that, although the recommendation culture precedes the advent of social media, the "mechanisms of deep personalisation and networked customization" are new in the context of online platforms (van Dijck & Poell, 2013, p. 9). Van Dijck and Poell further refer to the calibration of online content, that is shaped by inferences about the needs of the users. According to the authors, these predictions are based on user profiles and behaviour in combination with platform owners' or advertisers' interests, which ultimately is orchestrated by the recommender algorithms. "Connectivity should thus be seen as an advanced strategy of algorithmically connecting users to content, users to users, platforms to users, users to advertisers, and platforms to platforms" (van Dijck & Poell, 2013, p. 9).

The notion of connectivity highlights the mutual shaping of the different actors involved in and with online platforms: namely, the users, the platforms, the advertisers, and the online environment in general (van

Dijck & Poell, 2013, p. 8). It differs, therefore, from the idea of Spreadability (Jenkins et al., 2013) that characterises the role of social media platforms as simply 'amplifiers' of existing social connections among individuals. Under the notion of Connectivity, social media platforms allow people to form communities by their own initiative while, at the same time, "forges target audiences" through clustering automated strategies (van Dijck & Poell, 2013, p. 8). Examples include personalised recommendations of products, such as 'People who bought this item also bought...' (Amazon), and group recommendations such as 'groups you may be interested in' (Flickr) (van Dijck & Poell, 2013, p. 8).

Because of their mutually shaping nature, ASM platforms have the potential to impact other academic dynamics, beyond the dissemination of research outputs. For example, the reputation[7] and authority conferred upon researchers may also be undergoing profound changes. While platforms such as Google Citations or the Scopus Author Identifier measure the academic impact "through citation in traditional formats of scientific communication, such as the journal article", ASM platforms as Academia.edu, ResearchGate and Kudos offer a wide variety of alternatives for measuring the impact and scientific reputation of a researcher or institution (Corrêa and Vanz, 2017). Examples include counting 'followers', downloads and engagement on the platform.

The ways in which we measure impact and reputation of researchers, institutions and domains can have much broader implications, such as in university rankings and funding priorities. All these possibilities and new ways of measuring impact and reputation emerge from online data sources and metrics.

7 Reputation is understood here as "the perception constructed of someone by other actors which, therefore, implies three elements: the 'self', the 'other' and the relationship between them. The concept of reputation directly implies the fact that there is information about who we are and what we think, which helps others to build, in turn, their impressions of us." (Recuero, 2009, p. 109).

1.3 Where do recommendations come from? The history of Information Retrieval systems

Recommender systems are embedded in Information Retrieval (IR) systems, whose main goal is “to provide, to its user, access to information/documents” (Campos, 2001, p. 17). Libraries were trailblazers in adopting IR systems, most of which were developed by academic institutions at first and then by commercial enterprises. In its first generation, IR systems “consisted of an automation of existing processes such as card catalogues searching” (Baeza-Yates & Ribeiro-Neto, 2011, p. 3) and basically only allowed searching for the name of the author and title of the document.

In 1945, the Director of the Office of Research and Scientific Development for the US government during World War II, Vannevar Bush, published the famous article “As We May Think” (Bush, 1945). The text shed light on the problem of what he called a “growing mountain of research” (Bush, 1945, p. 112). With the war, Bush argued, research had its production accelerated considerably, which would require a new way of managing the knowledge recorded in scientific documents. Bush then reasoned that the cost for not thinking about new ways of managing knowledge archives would be the irremediable loss of research and development due to lack of access (Bush 1945, p. 112).

This growing body of knowledge being produced and in need of treatment and organisation was called “informational explosion” (M. de Oliveira, 2011, p. 11). Making the documents accessible to users motivated the emergence of automated IR systems. The term “Information Retrieval” was coined by Mooers in 1951, who defined it as such:

> It is the process of finding or discovering stored information. It is another more generic name for the production of a bibliography on demand. Information retrieval encompasses the intellectual aspects of the information description and its research specification, as well as any systems, techniques or machines that are employed to perform the operation. Information retrieval is crucial for documenting and organizing knowledge. (Mooers, 1951, p. 25).

Three basic questions involve Mooers' conception of information retrieval, which are: "How to intellectually describe information?"; "How to specify intellectually the search?"; and "What systems, techniques, or machines should be employed?". From the development of the topic of IR, studies in various different topics gain relevance, such as "theoretical and conceptual studies on the nature of information, the structure of knowledge and its records (including bibliometrics), Human-Computer Interaction, among others" (M. de Oliveira 2011, p. 12–13). Departing from studies on IR, numerous applications have been developed, such as products, automated information systems, networks and services, eventually also contributing to the emergence of Information Science as a domain. Even though nowadays Information Science encompasses much more than the topic of Information Retrieval, in the core of IS there are still present problems related to information recovery.

To solve the issue of informational explosion, Bush (Bush, 1945) recommended to use the (then incipient) information technologies. He proposed "a machine with the capacity to 'associate ideas', which would duplicate 'mental processes artificially'" (M. de Oliveira, 2011, p. 6). Consistent with this idea, in 1955 Clapp and Murra noted that the essential requirements for the information organisation were twofold: on the one hand, it was necessary the identification of the publications, but only this process was insufficient. On the other hand, it was also necessary to analyse the content within the publications, so that their elements could be related to other information of any kind in a desirable manner (Clapp & Murra, 1955; Edmund Stiles, 1958). Thus, the first generation of automated information retrieval systems were used for bibliographic control. However, these systems were gradually adjusted to be able to also index other types of "unity", not only the book or the report, but also what Stiles calls them other "units of thought" (Edmund Stiles, 1958, p. 42). The latter second generation of automated IR systems, therefore, the search feature was added and allowed us to search for topic headings, keywords and some more complex facilities, such as "query operators" (Baeza-Yates & Ribeiro-Neto, 2011, p. 3). As a consequence, the information contained in the documents became equally important for indexing than the document itself. In the third generation of RS, the focus turned to the improvement of "graphical interfaces, electronic forms, hypertext features, and open system architectures" (Baeza-Yates and Ribeiro-Neto 2011, p. 3).

Information Retrieval is a field of research that deals with the ways of representing, storing, and organising information items [documents] so that users have easy access to the items they are interested in (Baeza-Yates & Ribeiro-Neto, 2011, p. 1). Thus, IR systems are designed to meet the informational needs of users. According to Marquesuzaà et al., IR deals with "models, techniques, and procedures to extract information that has already been processed, organised and stored (such as databases, files, XML files, among others)." (Marquesuzaà et al., 2008, p. 2)

Baeza-Yates and Ribeiro-Neto claim that today's web search engines continue to use indexes very similar to those used by librarians more than a century ago. What changed, according to them, were three key points, stemming from the advances of modern technology and the web boom: (a) low cost of access to information on the web; (b) increased access to technological advances in digital media; and (c) freedom of publication (Baeza-Yates & Ribeiro-Neto, 1999).

Firstly, it has become relatively cheap to access various sources of information. This facilitates the access to information by a wider public than before (a phenomenon similar to the creation of the press). Secondly, digital communication has advanced in such a way that access to the network has also increased. "This implies that the source of information is available, even if it is remotely located, and that access can be made quickly (often in a few seconds)" (Baeza-Yates & Ribeiro-Neto, 1999, pp. 7–8). And thirdly, the popularity of the web is due, in large part, to the freedom to publish any information that someone deems useful or interesting. It is the first time in history that many people have free access to large-scale publishing media[8].

8 Even though it is a general trend, it is not the case everywhere in the world, as there are also countries where the freedom to publish is threatened. Also, there are still publishers who put publications after a pay wall, which deepens asymmetries between central and peripheral countries in relation to information access, production and scientific protagonism.

Therefore, low cost, greater access, and freedom of publishing allowed people to use the web and digital libraries as a highly interactive communication media. “High interactivity is the fundamental and current change in the paradigm of communication.” (Baeza-Yates & Ribeiro-Neto, 1999, p. 8).

Once people started to have access to IR systems, the relationship between them and these systems could be classified into two main activities: information search (*searching*) and navigation (*browsing*). Searching for information refers to a search action that has a clear purpose which requires a search expression (*query*). It assumes that the user is already able to define with some accuracy the terms of the query to retrieve the documents they want.

Browsing refers to those search actions for which the goals are not yet clear at the beginning of the search and whose purposes may change during the process. Actions to try to find something that we may know with some rigour that exists - but not so precisely. Whereas searching activities require a search expression from the user, browsing is more of a passive activity. During browsing the user scrolls through content preselected by the system (usually the the web pages or the feed, in case of social media platforms) and chooses during the navigation what they might want to read, see more, and interact with (by clicking or commenting, for example).

In the search for information, in addition to the search expression, the users can use filters and categories that determine the set of results that they want to obtain. So, for example, a user of a library catalogue can search for a title of a document or a topic and, additionally, filter the results by document type (book, newspaper article, etc.). After performing the search, the user will navigate through the results, selecting the works one wants to read or access more details. The user can decide upon various actions, like downloading, printing the document, forwarding it to an email address and a variety of other operations that are made available by the systems.

These interactions between the user and the system create records that are stored in the log files of the system and that serve as input for many design decisions. Some platforms use search queries to learn more about the users' interests and language. Logs can help the development of thesaurus and ontologies to improve search results (Laipelt & Monteiro-Krebs, 2021) and in implementing sections in the platforms' web pages so the user does not need to elaborate a search query (to anticipate the informational demand, through FAQ section, for example). More importantly, logs containing the register of the users' interactions are used in the similarity calculations between items, between users, or user-item connections. Search expressions, filters, which items from the results the user clicked, which documents were viewed and / or downloaded, and all other traces of behavioural actions with the system form data that can be used as input for the recommendation. We will explain these operations in more detail in section 1.3.1 Recommender systems.

In addition to retrieving all documents that are relevant to fulfil users' needs, IR systems should retrieve as few as possible of the non-relevant documents (Baeza-Yates & Ribeiro-Neto, 2011, p. 4). This is precisely where the filtering processes step in.

Contemporary IR systems are going beyond the simple response to a query and encompass more sophisticated technologies to satisfy users' information needs. Navigation behaviour, historical data, similarity between intrinsic attributes of two items, comparison between users of similar profiles, and many other features are used to increment systems, bringing relevant results amidst an increasingly dense and complex miscellany of available information. Hence, prediction models are then used to create recommendations, in what is called recommender systems. How the system decides automatically which information is shown or not to the user is the topic of the following section.

1.3.1 Recommender systems

To offer the most relevant results, many Information Retrieval systems use algorithms that try to predict (and rank accordingly) which items will be more likely to be useful and meaningful to the user based on similarity and/or co-occurrence calculations. The choice and combination of variables as well as the context of use determine the quality of the Recommender System (RS). For example, we can think of a list of recommended movies based on popularity. A platform can recommend movies that are the most popular ones in the last year; in this case, no matter what your profile is, the list will be the same for all users. Another option is to recommend to every particular user a list with the most watched or well evaluated movies by users with a similar profile. If we think of different types of recommender systems in a spectrum of levels of personalisation that goes from generic recommendations to very specific ones, the first example would be positioned towards the more generic side of the continuum, while the second choice would be at the other end of the spectrum (i.e. more personalised side). The most recent recommender systems are hybrid and combine different strategies to counter the downsides of one or the other technique (Ricci et al., 2011).

According to Burke (2007), what makes RS a separate category of systems within IR systems revolves around personalisation and agency on the one hand and semantics on the other. Regarding the semantics of its user interaction, the result from an IR system is interpreted as a match to the user's query, whereas a result from a RS is understood as a suggestion, "an offer worthy to be considered" (Burke, 2007, p. 377). As for personalisation and agency, a RS customises its responses to the particular user profile. Rather than simply offering responses to queries elaborated by the user, which is what IR systems do, a RS "is intended to serve as an information agent" (Burke, 2007, p. 377). This agentivity is expressed by predictions that the RS actively provides to users based on their characteristics and past behaviour. Using data about the users, RS try to anticipate how likely the users are to find a certain content useful or meaningful.

1.3.2 Where the data comes from

To profile users and make predictions, RS need big amounts of data about the users, the products or content that is being recommended and the rules that define how the recommendations should look like. RS depend on these data to perform mathematical operations such as correlation, similarity and calculate future trends. These data come from various places. Regarding the origin of data, authors from various domains present, for similar concepts, different terms that make sense for that particular field. Although the terms might be different, such as data sources and data types, they mean virtually the same. For example, Burke (2002) lists three data **sources** to feed RS:

> (i) Background information: information that the system has before the process of recommendation begins;
>
> (ii) Input data: information that the user must communicate to the system in order to generate a recommendation; and
>
> (iii) An algorithm that combines background and input data to arrive at its suggestions. (Burke, 2002, p. 332)

Simone van der Hof distinguished three different **types** of data used on the internet, as part of what is called the current "datafication" [9] tendency. She also refers to recommendations, but does not use RS as a term. She lists three data types:

> (i) 'Data given': the data provided by individuals (about themselves or about others), usually knowingly though not necessarily intentionally, during their participation online;
>
> (ii) 'Data traces': the data left, mostly unknowingly – by participation online and captured via data-tracking technologies such as cookies, web beacons or device/browser fingerprinting, location data and other metadata;
>
> (iii) 'Inferred data': the data derived from analysing data given and data traces, often by algorithms (also referred to as 'profiling'), possibly combined with other data sources. (van der Hof, 2017, pp. 104–106)

Considering the definitions of both authors, it is possible to draw a relation between the terminologies, as "Data given" from van der Hof is equivalent to Burke's "Input data", yet the agency of the user/individual, more prominent in van der Hof's term, might justify the new label. The same way, "Background information" (from Burke) is equivalent to "Data traces" from van der Hof, and "Inferred data" is a label that well defines the result of the algorithm that Burke's describes in his typology. These data are used by the system though different techniques, as we explain in the following subsection.

9 Datafication is a term coined by Mayer-Schönberger and Cukier (Mayer-Schönberger & Cukier, 2013) to whom "to datafy a phenomenon is to put it in a quantified format so it can be tabulated and analysed" (Mayer-Schönberger & Cukier, 2013, p. 78).

1.3.3 Recommendation techniques

The RS employ different techniques to filter the items that are considered for recommendations to the user. The techniques have been described and classified by different authors (Burke, 2002, 2007; Resnick & Varian, 1997; Ricci et al., 2011) and are continuously evolving. So far, the consensus in literature is that three main categories are sufficient to accommodate all the techniques used in RS: content-based filtering, collaborative filtering and hybrid approach (Adomavicius & Tuzhilin, 2005; Koene et al., 2015).

In the **content-based** recommendations, the suggested items received by the user are similar to items that the user showed interest in the past (Adomavicius & Tuzhilin, 2005). These recommendations consider the characteristics of the items to calculate similarity. For example, if the user has positively rated a movie that belongs to the comedy genre, the system can learn to recommend other movies from this genre" (Ricci et al. 2011, 11).

In **collaborative** recommendations, the user receives suggestions of items that other people with similar tastes have shown interest in or rated positively in the past (Adomavicius & Tuzhilin, 2005). Therefore, to calculate how similar the preferences of two users are, the system uses "the similarity in the rating history of the users" (Ricci et al. 2011, 11–12). This similarity is also called "neighborhood" (Burke, 2007, p. 378), in a metaphor for how close or distant an user is from the other in terms of taste.

Hybrid approaches combine both collaborative and content-based methods (Adomavicius & Tuzhilin, 2005). By using the advantages of certain techniques, the hybrid recommender systems overcome the disadvantages of other techniques. Ricci and colleagues explain a typical example of a collaborative filtering drawback: the *cold-start* situation. Because the collaborative approach relies on users' ratings, the system cannot recommend the items until it has enough ratings from users. It is, however, common to have insufficient ratings in very new applications with a few users or for new items in the catalogue. This disadvantage can be countered by a content-based approach, because the latter essentially needs a description (features) of the items to make a prediction. And the items' descriptions are normally easier to find than user's ratings (Ricci et al., 2011, p. 14).

Koene and colleagues have stated that the three categories (content-based filtering, collaborative filtering and hybrid approaches) represent the most used techniques in practice (Koene et al., 2015). Throughout the history of the RS domain, mixed definitions were attributed to the above mentioned techniques. When compared, some of these definitions can, at the first glance, appear as conceptual inconsistencies in terms of the types of data used in each approach. For example, Burke claims the ratings attributed by users to a certain item (product or content)[10] are placed in the content-based approach (Burke, 2007, p. 378). However, Ricci and colleagues link the rating history to the collaborative approach (Ricci et al. 2011, 11–12). What can be slightly difficult to grasp is that ratings are used in both approaches, but the important element here is *whose* ratings.

In the case of content-based filtering, the rating history of a user is used on the recommendations for him or herself. If John rated positively a paper indexed with the keyword "algorithms", other papers indexed with the keyword algorithms will be recommended to him. However, in the case of collaborative filtering, the similarity between two users accounts for the similarity calculation between items. For example, let us assume Kevin rated several papers positively, among which some have the keyword "algorithms". If Isa has a profile similar to Kevin's (e.g. sharing some characteristics or tastes), Isa might start receiving recommendations of papers about algorithms even though she never showed interest on this topic before. Therefore, what determines the recommendations in this case is the similarity between two "neighbours" (i.e. how many other interests Isa and Kevin share) and not how well Isa rated the topic "algorithms" in the past. This similarity is calculated regardless of the intentional connection between Isa and Kevin. In fact, they might have extremely similar tastes and share historical records, but they will probably never know of the existence of each other, because how similarity is calculated is often opaque to the

10 In the beginning, recommender systems were heavily used in e-commerce. So the definitions also contain terms linked to commercial products to refer to what the recommender system can offer. However, recommender systems are currently also used in the curation of information, as is the focus of this thesis, as well as movies, music, and many other different categories of items represented in information systems. Therefore, I chose to replace the word "products" for "items" in the definitions, so it could also include information, because I believe this is a more generic term.

user. The classical example is "People who bought this also bought that", where the subject is never clear. The user never knows who exactly (or how many) made the purchase. The recommendations we receive are influenced not only by those to which we are connected to on a certain platform. The recommendations also are feeded by people from outside our network that unknowingly share with us preferences and characteristics. Despite the conscient connections we made in the platforms (following and being followed), usually apparent on the interface, the algorithms create implicit networks, which tie us to other individuals based on each other's similar behaviour. These autonomous algorithmic connections happen behind the interface and usually the user does not have control over them.

In addition to the three main categories of recommendation techniques, namely content-based filtering, collaborative filtering and hybrid approaches, other less prominent recommendation techniques can be found in literature. For example, recommendations based on demographic data (Burke, 2007, p. 378; Ricci et al., 2011, pp. 12–13), knowledge-based recommendations (Burke, 2007, p. 378; Ricci et al., 2011, pp. 12–13), and community-based recommendations (Ricci et al., 2011, p. 13).

Recommendations are used on a large scale in ASM platforms. The personalisation in these platforms is a striking feature that filters content with several data sources. The network connections are fed by the user's profile and online behaviour, but not exclusively by this information. Information about current and past affiliation allows the RS to infer similarities between users interests and that of their present and former colleagues. Also peers can be inferred by the field of research, in addition to correlation between keywords in publications.

1.4 Mediation framework and ASM

The mediation framework by (Lievrouw, 2014) illuminates the **mutual shaping** of the different elements interplaying in the online performative environment. The framework has been created to elucidate the materiality of technology in communicative processes and to depict the three elements of online platforms' infrastructure: artefacts, practices and arrangements. Artefacts are material devices and objects; practices are the actions that people engage with; and arrangements are the "patterns of relations, organising, and institutional structures" (Lievrouw, 2014, p. 45). Applying this framework to the phenomenon of recommender algorithms on ASM, points to the relevance of studying not only the artefact but also the related practices and arrangements.

At the level of the artefact, the building blocks of recommender systems must be understood; the systems follow different techniques (similarity measures) to process the data of user and items (products and/or content), according to the logic determined by the company that created the system. Recommendation techniques include content-based filtering, collaborative filtering, and hybrid approaches (see details in section 1.3.3 Recommendation techniques). The exact variables used in the automatic filtering process, as well as how these variables are weighted and combined, are kept as a commercial secret by most companies. Therefore, observing coding techniques (programmed by design) in social media platforms is difficult, and only possible through inspecting the " visible user interfaces and application programming interfaces (APIs), and sometimes through their (open) source codes" (van Dijck and Poell, 2013, p. 6).

Recommendation techniques are used to process data about users and items that are represented by entities and attributes in the system. For example, a publication item is an entity in the ASM, which is described by many attributes, such as its title and keywords. The entities' intrinsic attributes are not the only data that matter to the recommender system; metadata extrinsic to the entity (i.e. describing the relationship between entities) are also valuable because they help to predict the relevance of that entity to the user. Some examples of metadata extrinsic to the entity include the name of a user who liked that publication and how many keywords it has in common with another publication. In this thesis, we use recommendation attributes and metadata as interchangeable synonyms to refer to the classes of data that are used by the algorithm to form a recommendation.

As for the logic of the recommender system at the level of the artefact, the processing of machine-readable data allows the recommendation algorithm to calculate the similarity of user-user, item-item and user-item. Users can be aggregated by their attributes and past behaviour and then the cluster of users is labelled with a certain profile (this process is called profiling). For example, a user can be profiled as a heavy-user, male, 36-50 years old, lecturer, interested in astrophysics and mathematics. Profiling is often completed by algorithms that employ data from within the platform, sometimes combined with other data sources, to find patterns and correlations (van der Hof, 2017).

At the level of ***practices***, ASM platforms provide an environment for users to expose to other researchers their publications, projects and topics of interest, and to connect users instantly with other scientists and research groups with whom they might wish to relate. Like other social media platforms, ASM platforms allow users to follow other people (i.e., academics), recommend content (e.g., scientific papers, research projects) and post messages (e.g., intellectual output). Users of ASM can discuss specific topics using the Q&A section (e.g., researchers may interact between different research groups, universities and countries through thematic affinity) which resembles the forums and groups on other social media platforms.

Regarding ***arrangements***, the recommendation algorithms on ASM are generally considered responsible for connecting researchers with common research interests, enabling collaboration and providing updates about the work in the field. However, the interests and motivations of the users are not the only ones to be considered, as the development of a platform is guided by the economic and political interests of the company (van Dijck et al., 2018). For example, ResearchGate positions itself under the paradigm of open science. Open science advocates for, among other things, providing free-of-charge access to data sets and publications, with the aim of promoting transparency and a communal culture. It is motivated by the belief that open science counters the asymmetry between developed and developing countries. In ResearchGate, a feature allows researchers to upload and share their own intellectual output, making this alignment tangible. Arguably, implications of this policy can reach individual, institutional and societal dimensions. Although researchers might use this feature altruistically and/or to boost their impact (by promoting their work to potentially increase the number of citations received), major publishers can engage in judicial disputes with the platform over copyright infringement. Investigating the role of the different actors is to understand the context in which a platform is embedded and the expected use of the platform (Light et al., 2018).

1.5 Research design and outline of the thesis

Previous work on ASM has presented a wide variety of methods, survey being the most common of them (Elsayed, 2016; Laakso et al., 2017; Nández & Borrego, 2013). Researchers have performed bibliometric analyses (Laakso et al., 2017), statistical analysis on posts collected from ASM (Jeng et al., 2017), and analysis of users profiles on Academia.edu (Nández & Borrego, 2013). Qualitative methods, such as semi-structured interviews (Laakso et al., 2017) and qualitative content analysis (Jeng et al., 2017) can also be found in the existing body of literature on ASM. Other scholars (Barassi, 2017; Light et al., 2018; van Dijck & Poell, 2013) have investigated how platforms guide users through activities through an in-depth inspection of both the platforms' design and platforms' communicative practices. Some examples of thorough analysis of platforms include information infrastructure studies (Bowker et al., 2010), digital ethnography (Pink et al., 2015) and the walkthrough method (Light et al., 2018).

We used a multi-method approach combining the walkthrough method, interviews and a research game. In the next paragraphs the goals of each chapter are explained, followed by a brief presentation of the methods chosen to answer the research questions. The detailed explanation of the methodological steps are described in each chapter.

The thesis is divided in two parts, each part dedicated to one Research Question. Part I is dedicated to RQ1, and Part II is dedicated to RQ2. Each chapter is focused on one or more sub-questions of the RQs, as shown below. Figure 1.1 is a visual representation summarising the research design above explained.

In Part I (Chapters 2 and 3) we investigate the *artefact* and discuss the results in light of the scientific *arrangements* (i.e. what specific ASM features mean in the broader scientific dynamic). This part is led by RQ1: ***How do recommender systems of academic social media shape what users can see and how users interact with the platform?*** Chapters 2 and 3 together form a platform analysis in which we look at the artefact and arrangements to answer RQ1. ResearchGate was chosen as a case study for this analysis[11]. We employ the walkthrough method (Light et al., 2018) to design the protocol for the platform analysis consisting of four steps: an interface analysis, a web code inspection, a patent analysis and a company inquiry. These steps are explained thoroughly at the beginning of both chapters. Both chapters are based on published papers, as expressed in the footnotes of their titles.

In Chapter 2, we address the sub-questions of RQ1 "***What are the main entities involved in the recommendations on ASM platforms?", "Which mechanisms can be identified in ASM platforms?***" and "***How do ASM platforms communicate with their users about recommender algorithms?***". We do so by inspecting the design of the platform and by placing a data request. We employ the walkthrough method in two steps: interface analysis and company inquiry using General Data Protection Regulation (GDPR). The results show evidence of the mechanisms of selection, commodification and profiling. We also demonstrate in practice the mutual shaping of the different elements interplaying within the platform (artefact, practices and arrangements). We close the chapter discussing how the company shy away from providing details on automated profiling.

In Chapter 3, we reflect on algorithmic mediation and biases in scholarly communication potentially afforded by recommender algorithms, addressing the sub-question of RQ1 "***How may algorithmic mediation, through recommender systems in ASM platforms, uphold biases in scholarly communication?***". The walkthrough method included a patent analysis, an interface analysis and an inspection of the web page code. The findings reveal how the audience influences the recommendations and how the mechanisms of selection, prioritisation, datafication and profiling can bias the information flows in ASM. We also substantiate how the algorithm reinforces the reputation of eminent researchers (a phenomenon called the Matthew effect). As part of defining a future agenda, we discuss the need for serendipity and algorithmic transparency.

11 We chose to work with ResearchGate as a case study due to its popularity and outreach among researchers. At the time of writing this PhD manuscript (November, 2021) ResearchGate claimed to have 20 million users in over 190 countries, from diverse sectors. More about this choice will be explained in Chapter 2.

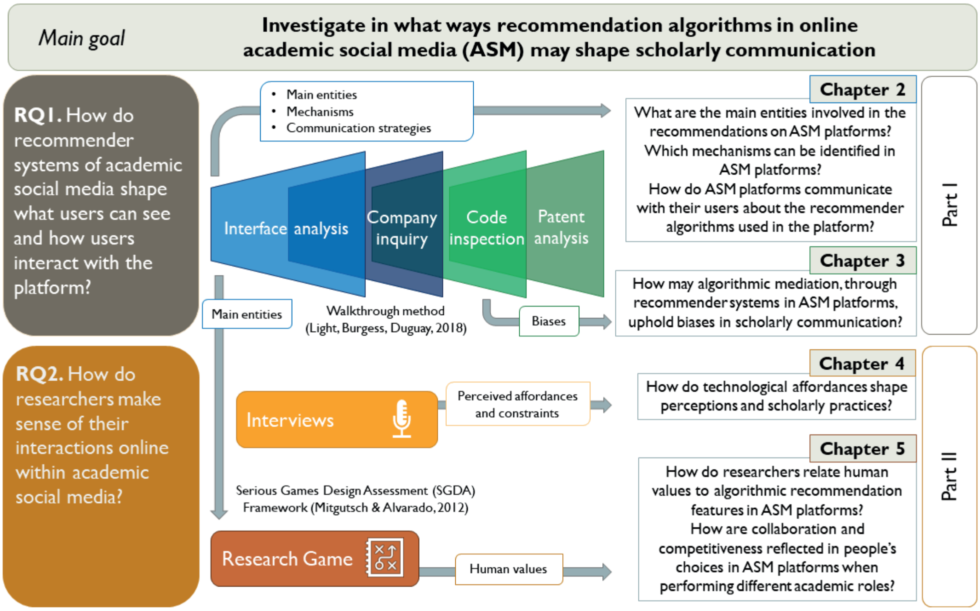


Figure 1.1 – Research design

The walkthrough method in Part I allowed us to focus on the digital artefact and arrangements that it affects and is affected by. As the workings of ASM platforms are protected by commercial secrecy, we had to combine data from various sources (interface, web page code, patent and a data set provided by the company itself) and in several formats (text, image, code, PDFs) to better understand how they function and what has been decided 'by design'. Notwithstanding our data triangulation, we acknowledge that we rely on one specific case study on Research Gate. While case studies allow for depth of investigation and it is thorough, they have the challenge of presenting results which are dependent on a single case (Savin-Baden & Major, 2013, p. 163-164). We tried to compensate for that in Part II of the thesis, where the participants are users of more than one ASM platform. Typically these were Academia.edu, ResearchGate and Mendeley, but also general social media that the participants use to scholarly communication, such as Twitter, Google Scholar, LinkedIn.

In Part II of the thesis (Chapters 4 and 5) we take the human perspective, analysing the research practices.The results are also discussed in the context of the scientific arrangements traversed by algorithmic mediation. This part is led by RQ2 "***How do researchers make sense of their interactions online within academic social media?***".

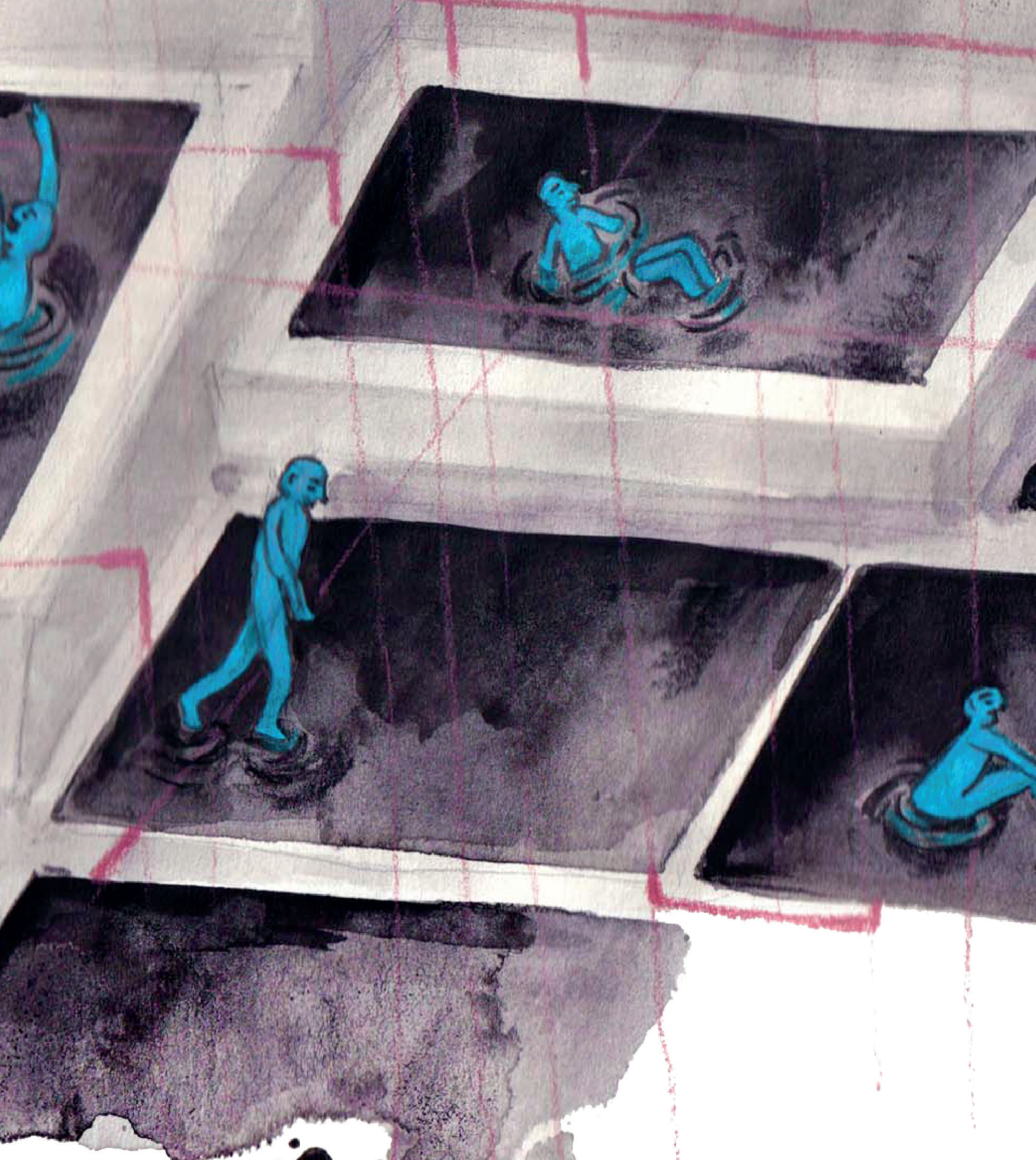
We inquired participants from Australia, Belgium, (different regions of) Brazil, Italy, Spain, The Netherlands and The United States of America. For each chapter we employed a different method, with the aim of, jointly, answering RQ2.

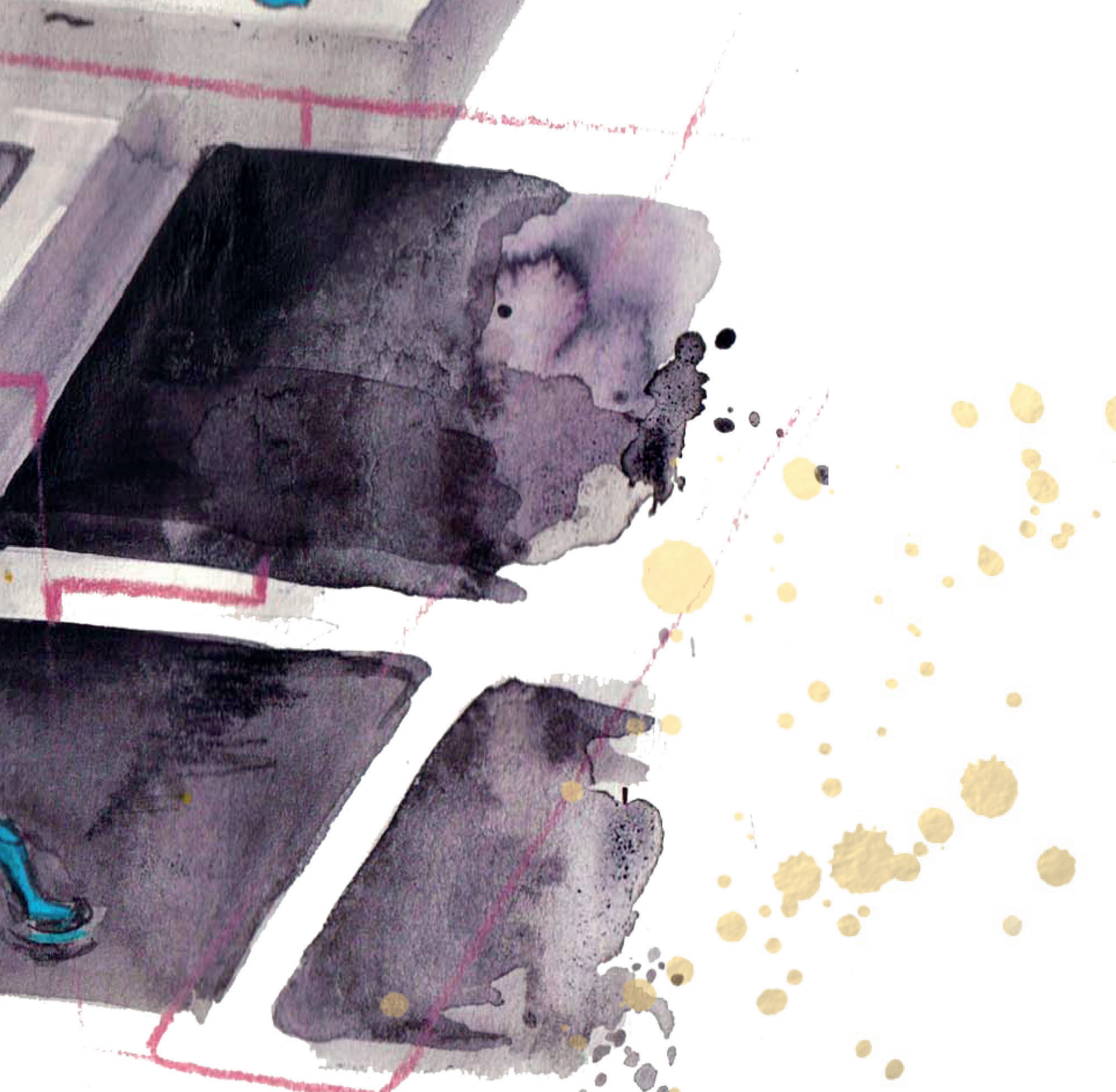
Chapter 4 presents a study aiming to address the following sub-question of RQ2: "***How do technological affordances shape perceptions and scholarly practices?***". We conducted online in-depth interviews with a show and tell technique. The participants were users of platforms such as Academia.edu, ResearchGate and Mendeley. The themes "Algorithmic impact on exposure to content", "To see and to be seen", "Blurred boundaries of potential ethical or legal infringements", and "The more I give, the more I get" are discussed, considering implications of datafication and visibility/findability in the scientific arrangements. In this chapter we show that algorithmic mediation not only constructs a narration of the self, but also a narration of the other in ASM, configuring the other as participatory and productive.

Interviews are an excellent method to understand the reasoning behind a participant's behaviour, yielding in-depth information gathering. However, this method is typically time consuming and resource intensive (Savin-Baden & Major, 2013, p. 371). They also are highly dependent on the honesty of the participants, who may provide information they think the researcher wants to hear or cast themselves in a favourable light, rather than provide accurate information (Yin, 2009; Savin-Baden & Major, 2013, p. 371). To make sure we would capture the most accurate possible results from the participants, we invited them to show and tell what they usually do on the platforms, while recording the screen. We did not identify any inconsistency between what participants were doing and what they were saying, which proved the "Think aloud" protocol (Genise, 2002), was efficient. According to Savin-Baden & Major, (2013, p. 371), "interviews also provide only the perspective of the interviewee, rather than the perspective of a group of individuals". Thus, the following study (chapter 5) includes a group dynamic, as explained next.

The focus of Chapter 5 is to answer the two following sub-questions of RQ2: "***How do researchers relate human values to algorithmic recommendation features in ASM platforms?***" and "***How are collaboration and competitiveness reflected in people's choices in ASM platforms when performing different academic roles?***". To provide insights on this matter, we crafted a research game aimed at collecting data. We built the game using the Serious Game Design Assessment (SGDA) framework (Mitgutsch & Alvarado, 2012). The game elements were built utilising literature on scholarly communication, recommender systems and empirical findings from the platform analysis. Chapter 5 is particularly dense because it brings the details of the game development and two sets of results. The first analysis uses the data of all participants showing the three most prominent associations people in our sample make between human values and recommendation strategies. The second analysis presents four data based archetypal profiles showing how people choose different approaches (collaborative, competitive or ambivalent) depending on the role they are performing academically. These archetypal profiles can be used in future research about the use of ASM and, by professionals in industry, to design new features or platforms.

The dissertation ends (Chapter 6) with a conclusion in which we concisely answer the research questions and reflect on the results of the studies and their broader meaning in terms of scientific practices and societal impact. I end the chapter indicating the limitations of this research and the need for further work in this area.





part I

Chapter 2
DEPICTING RECOMMENDATIONS IN ACADEMIA

Chapter 3
TRESPASSING THE GATES OF RESEARCH

chapter 2

DEPICTING RECOMMENDATIONS IN ACADEMIA: how ResearchGate communicates with its users (via design or upon request) about recommender algorithms[12]

“Quis custodiet ipsos custodes?”
or “Who watches the watchers?”

Juvenal (Roman poet), Satire VI,
lines 347–348, early 2nd century

12 This chapter is based on the following publication: Monteiro-Krebs L., Zaman B., Htun NN., Caregnato S.E., Geerts D. (2021) Depicting Recommendations in Academia: How ResearchGate Communicates with Its Users (via Design or upon Request) About Recommender Algorithms. In: Bisset Álvarez E. (eds) Data and Information in Online Environments. DIONE 2021. Lecture Notes of the Institute for Computer Sciences, Social Informatics and Telecommunications Engineering, vol 378. Springer, Cham. https://doi.org/10.1007/978-3-030-77417-2_1

2.1 Introduction

ASM are socio-technical artefacts that shape and are shaped by human practices and economic, political and social arrangements. These platforms are also increasingly using recommender systems to deliver relevant content to their users. While the recommender algorithms mediate the interactions happening within those platforms, the profound opacity of the algorithms that filter information makes it difficult to distinguish among the elements that may suffer and/or exert influence over the interactions within ASM. In fact, recommender systems remain neglected in literature about ASM and its mechanisms are referred to as black-boxes. Unfortunately, current research on ASM has yet to consider the agency of platforms in influencing users' decision-making. Although great attention has been directed at social media platforms, to the best of our knowledge, there is no prior research investigating the role of the automated mediation of information (i.e., with the help of recommender algorithms), specifically in ASM.

Against this backdrop, in the current chapter we focus both on the artefact and on communicative practices of an ASM platform chosen for case study. Our inquiry is led by the following research questions: ***What are the main entities involved in the recommendations on ASM platforms? Which mechanisms can be identified in ASM platforms? How do ASM platforms communicate with their users about recommender algorithms?***

The methodology used for this part of the thesis, as it will be shown, is quite detailed, technical and time-consuming, having several analytical steps. For this reason, and for the time constraints of a doctorate, it was unfeasible to include more than one platform in the analysis. We chose to work with ResearchGate due to its popularity and outreach among researchers. The platform has been growing through the years in number of users (Van Noorden, 2014), quantity of documents that it holds (Orduña-Malea et al., 2016) and the intensity of use (Jamali et al., 2016). At the time of writing this PhD manuscript (November, 2021) ResearchGate claimed to have 20 million users in over 190 countries, from diverse sectors.

2.2 Methods

In the walkthrough method (Light et al., 2018), we found a way to inspect the artefact while also expanding the analysis to arrangements, providing "a frame from which to identify embedded cultural values" (Light et al., 2018, p. 888). Combining a technical walkthrough on the artefact with the analysis of the communicative practices, we comprehensively delve into what is communicated via design (interface analysis - step i) and upon request (company inquiry - step ii) regarding the recommendations on ResearchGate. In the following subsections, we describe each step in detail.

2.2.1 (i) Interface analysis

This analytical procedure consisted of two phases. First, on the interface, we identified all communicative elements (content labels) that are in one way or the other linked to recommendations. For this phase, we looked for visual evidence of a recommendation in the interface, identifying content that was labelled as a suggestion or recommendation (e.g., when the word "suggested" appeared, or a button called "recommend" emerged). Through this search, we detected five content labels (header of a container) that we found were potentially showing recommended content. The labels are: "Suggested for you", "Who to follow", "Jobs you may be interested in", "Suggested projects" and "Questions we think you can answer". These content labels were above certain types of content, as can be seen in Figure 2.1. Every time we found one of those labels, we clicked on the label's link, which then led us to a new page. If the communicative element led us to an independent page with further information and the attributes found there were also connected to other entities, we inferred that it was an entity.

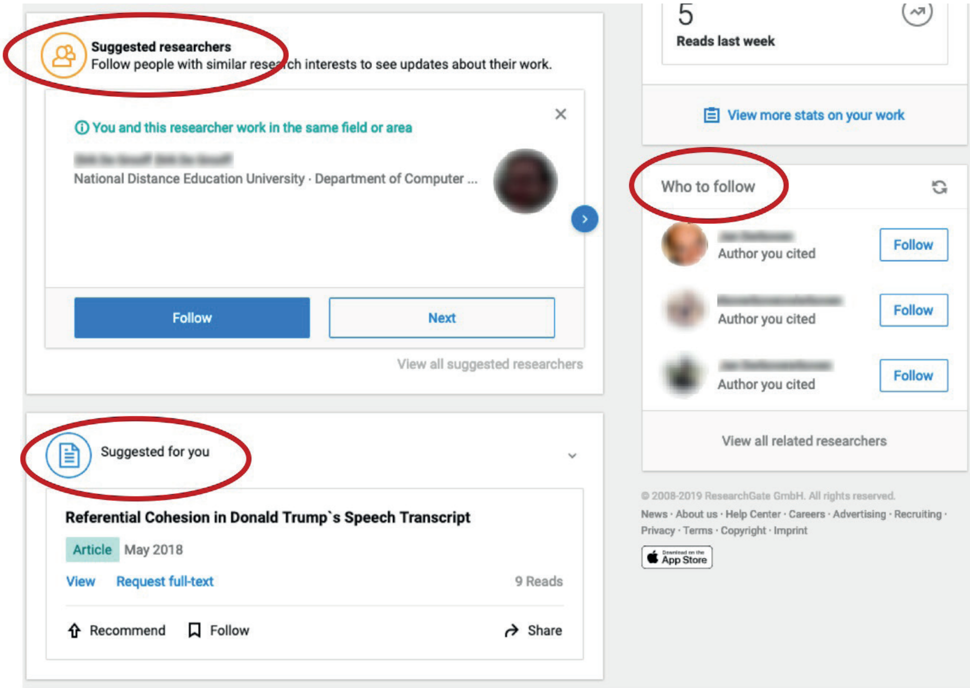


Figure 2.1 – Visual evidences of recommendation

The second phase of the interface analysis consisted of inspecting each of the entities in more depth and also describing their corresponding (visible) attributes. For example, the entity Researcher has an independent page and is detailed by several attributes, such as name, RG Score, degree and current affiliation. We did this until we reached the saturation point (when there was no new entity found anymore, only repeated ones). This process resulted in the mapping of six main entities that are involved in recommendations on ResearchGate: Researcher, Institution, Publication, Research Project, Job and Question.

We took screenshots and listed the entities that can be seen in the results section. For the interface analysis, we accessed ResearchGate with the login of the first author using Google Chrome Version 75.0.3770.100 (Official Build) (64-bit) as a web browser. The data collection occurred in February 2019.

2.2.2 (ii) Company Inquiry

For the company inquiry, the first author sent a data access request to Research- Gate via their contact form on 2 April 2019, asking for the data they have on the user and an explanation of how they create the recommendations (based on what data and criteria). The company replied on the 9th of April via email (sender support@researchgate.net), as follows: "*We consider metadata we may have about you such as the names of published articles plus your past interaction with the site in order to present content that we think might be relevant and interesting to you. We partly use cookies to do this. To view our cookie policy or to opt out visit our cookie policy: https://www.researchgate. net/cookie-consent-policy*".

The same day, on 9 April 2019, the first author wrote back with an extensive email citing the right to an explanation provided in GDPR (General Data Protection Regulation (GDPR), 2016) and specifying the exact information we wanted to receive. (see Appendix 4. Comprehensive company inquiry) Art. 15 GDPR grants individuals the right to know whether or not their personal data have been processed (by the company and/or third parties); it also grants access to personal data and information when it is collected. Our response was structured around 12 questions that were developed with the assistance of a team of legal researchers[13].

ResearchGate did not respond to our inquiry within a reasonable time. Hence, we reinforced the request with another email on the 23 April 2019. On the 24th of April, ResearchGate (sender support@researchgate.net) responded and thanked us for contacting them whilst also informing us they were "[...] in the process of responding to your request". On 13 May 2019, ResearchGate's Privacy department responded to our request. They sent us an introductory email with a seven-page plain explanatory text document as an attachment, and in the body text, they gave a reference to a URL to a set of 22 HTML files and 11 PDF files (see also the results section, below). The introductory email read as follows: "*Thank you for your data*

13 Questions originally designed for the research project Algorithmic Transparency and Accountability in Practice (ATAP), in which Luciana Monteiro-Krebs and David Geerts participated. See more in https://soc.kuleuven.be/mintlab/blog/news/re-thinking_recommenders/

subject access request dated 9 April 2019. Please find attached a document with more detailed answers to your questions and your data. If you wish to modify your privacy settings or update your personal data please access this page https://www.researchgate.net/profile.ProfilePrivacySettings.html. For more information please consult the Researchgate privacy policy at https://www.researchgate.net/privacy-policy. We remain available for any further information you may require."

As for the analysis of the company inquiry data set, we compared what was stated in the explanatory text with the data set. We describe the information found in the categories of data pointed out by the company in the results section. Additional findings are discussed further.

2.3 Results

In this section we present the results of the two methods explained above: interface analysis and company inquiry.

2.3.1 Interface analysis

After analysing the labels to containers on the home page, we found visual evidence of recommendations. In this subsection, we describe the technical walkthrough and how we went from the five initial labels on the interface to the six entities involved in recommendations and their respective attributes.

On ResearchGate's home page (see Figure 2.2), the recommendations under the label Suggested for you refer to publications, such as articles, chapters, books, technical reports, theses, conference papers, data and preprints. We have identified the following attributes: title of the publication, the type of publication (paper, report, chapter, etc.), whether there is a full document available, the date of publication, and the number of reads. The item container under the label Suggested for you also shows the but-

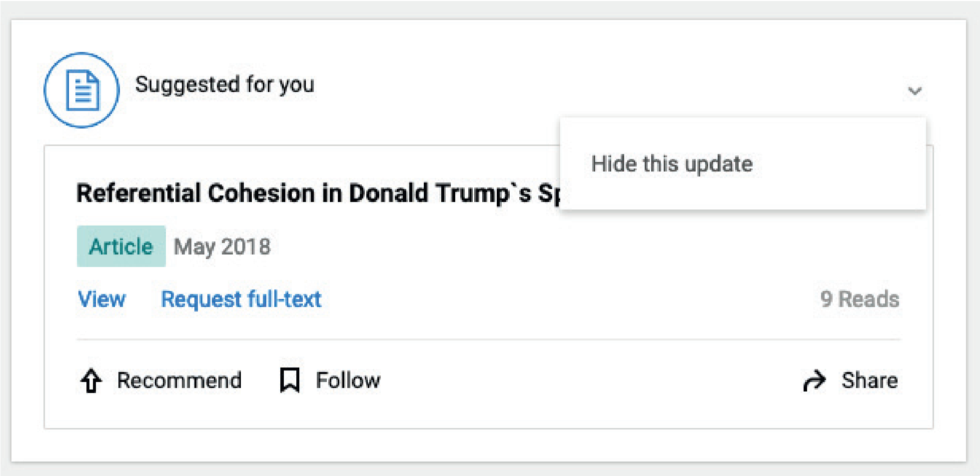


Figure 2.2 – Publication recommended in the feed

tons "View", "Download" (or "Request full text" in case the file is privately archived), "Recommend", "Follow" and "Share". At the bottom of the item container, the number of researchers who follow or recommend this particular publication is made visible. Our findings further show that by clicking on the "View" button, we are led to the complete page of the publication within the platform. On that page, we could find specific information about that publication, such as title, author(s), abstract, editor/journal and date. At the bottom of the publication's page, a container recommending more research items under the label "Similar research" appears. Because publications appear under two labels that indicate recommendations ("Suggested for you" and "Similar research"), we identified Publication as a recommended entity. Additionally, the entity publication has a specific page for it: each paper, book chapter or preprint registered on the platform has its own page with all the metadata regarding that publication that can be retrieved and recommended from that metadata. On the home page, many recommended publications are from authors related to the user, either as coauthors, colleagues, or people the user follows or cites.

As for the label "Who to follow", the interface analysis further showed that the main page gives concrete recommendations to follow other researchers. In the container under the label "Who to follow", there is a list of recommended researchers, showing a profile picture, name, the connection between the recommended researcher and the user (e.g., if he/she is someone the user cited previously, or is a coauthor, etc.) and a "Follow" button. Three researchers are shown in this container on the home page. At the bottom of that container, there is a link to "View all related researchers", which in turn leads to a new page with several options of researchers to follow. The recommended researchers to follow are introduced with short profiles that are ranked and separated by the following tabs: "Summary", "Your institution", "Your department", "Your coauthors", "Citations", "Similar interests", and "Your followers". The short profile features a picture, name, institution/company, the connection with the recommended researcher and the suggested researcher's RG Score. The RG Score is a metric created by ResearchGate to, according to the platform, "measure scientific reputation based on how your work is received by your peers" (ResearchGate, 2020). It is based on several aspects, including publications, citations and interactions within the platform. The RG Score is one of the few pieces of information that appears in the short summary of the researchers' profile on the interface. The interface also hints at the possibility of inspecting the connection in more detail, for example, by checking which publication the user and recommended researcher are co-authoring, the skills or expertise they share and the latest publication of the recommended researcher. Based on these attributes, we can infer two entities: Researcher and Institution. The Researcher has a specific page dedicated to it and is the entity that appears under the labels "Who to follow" and "View all related researchers". Institution appears to be relevant because it has its own specific page and because of two other reasons. First, in the list of recommended researchers, there are specific tabs for the people from "Your Institution" and "Your Department", to recommend colleagues for the user to follow. This suggests that it is because of the connection with the institution that other researchers are being recommended, and many suggestions on the homepage are from people working in the same institution as the user. Second, in the container with Job offers, it is the logo of the institution that appears next to the job position. The institution can be a university or faculty, a research institute or a company.

Regarding the label Jobs you may be interested in, on a list of five job offers, ResearchGate first shows the title of the position and information about the institution or company: the logo, name and location (city and country). Depending on how recent the vacancy is, a label appears: “New job” or “Expiring soon”. Two links appear at the bottom of this container on the home page in addition to the list of job positions: “Improve these suggestions” and “View more” (to visualise more suggestions). The link “Improve these suggestions”, activates a pop-up box that allows for updating the list of skills and expertise. Some suggested skills also appear in this box, showing the importance of the keywords used in job recommendation. Clicking “View more” leads to a page with job positions with the exact same metadata that the item container on the home page brings, but instead of showing five options on the side bar, a page with dynamic scrolling is shown, with job offers appearing in a long list that occupies the entire page.

When clicking on one of the job positions in the recommended list, a complete register of the vacancy is provided on a new page, including more information on the title of the position, the date on which it was published, the institution, the location, the logo, a job description, areas of research (what knowledge fields that position encompasses), a list of other positions at the bottom of the page (link called “Discover more”) and, on the right side of the screen, another list of recommendations: “Researchers also applied for”. In the list “Discover more”, which is at the bottom of the page, a list of 15 job positions is shown, but the only information on the link is the job title. In the list on the right side of the page, under the label “Researchers also applied for”, the format is the same as that of the home page (i.e., job title, logo, name of the institution and location). The latest list (“Researchers also applied for”) is shorter, with five positions only, and a link to “View more” appears at the bottom of this container. In this particular type of recommendation, we highlight the Job as an entity, because it appears under several recommendation labels (“Researchers also applied for”, “Discover more” and “View more”) and each job offer registered has a specific page. We confirmed the importance of the Institution because it appears prominently in job offers (logo and name of the institution). We also confirmed the importance of the entity Researcher through the label “Other researchers also applied for”.

The interface analysis with respect to the label Suggested projects further showed that this label is above an item container that provides information on the title of the project, a brief project description and the name(s) of (a selection of) the researcher(s) who are involved in the project. The latest are ranked in a way that researchers with a shared connection are shown first independently of who is the project lead, along with the number of other researchers in the project. Figure 2.3 shows an example recommendation of a project. Research project is then mapped as an entity, because it has a specific page to describe its attributes and is closely connected to other entities, namely Researcher and Publication.

On the home page, there is a link to a section with questions and answers, which is labelled "Questions". Clicking on this link, a new page appears with, among other content labels, one called Questions we think you can answer. By clicking on this label, we are led to a page with open questions posed by other researchers. The attributes on this page are the name of the researcher, date, main topic, title of the question, the first sentences of the question, some keywords, the number of replies, the number of reads and the buttons "Reply", "Recommend", "Follow" and "Share". We identified Question as an entity, not only because it also has a specific page but because its importance is reinforced by yet another container in the home page with the label "Do you have a research question?". In this item container on the interface, the user is invited to ask questions to get help from experts in their field. The link for "Questions" also appears on the home page (feed) accompanied by the following sentence: "[Researcher] asked a question in [keyword]". From that sentence, we infer that the recommended question is influenced by the keywords list. This influence is reinforced by the item container with the user's skills and expertise in the right column of the "Questions" page. The container shows the sentence: "*We use your skills and expertise to show you relevant questions. You can edit your skills and expertise at any time.*", which is followed by a list of keywords that represent the user's skills and expertise. The association between questions and keywords (in the home page) is made even if the keyword is not present in the user profile or in their list of skills and expertise. In other words, users see recommended questions with the indication of a topic (e.g., communication) based on their profile, even if the users

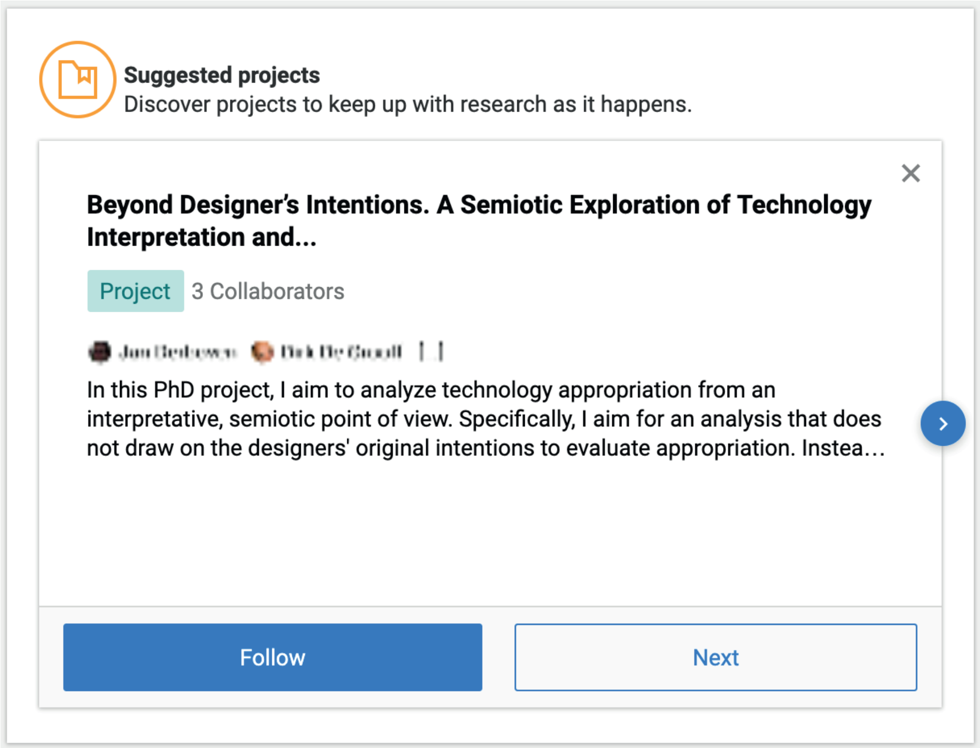


Figure 2.3 – Recommended projects

themselves did not list this specific keyword as a topic of interest. The inference made by the recommender algorithm might use co-occurrence as a similarity metric to suggest questions.

Summarising the findings from the interface analysis (step i), the main entities involved in recommendations on ResearchGate are Researcher, Publication, Research project, Institution, Job and Question. Because the vast majority of professional and institutional profiles, documents, and job offers shown within ResearchGate fit under these overarching categories of information mapped in our research, most of the interactions within the platform are somehow affected by the recommendation algorithm.

2.3.2 Company inquiry

In this section, we describe the aggregated classes of data (with the quantity of attributes for each class) contained on the data set (seven-page text document attached to the conversation email, 22 HTML files and 11 PDFs). We further highlight some key findings before the Discussion section.

The results of our company inquiry show that content on the ResearchGate platform is being recommended based on the processing of the following data:

- **Personal data**: According to the company, this information is used "to understand more about the users, visitors and viewers, and how they interact with our platform". We identified 105 attributes (on the files "Account", "Account emails", "Your Privacy Settings" and "Your Notification Settings" describing user's personal data (including name, address and email) and preferences (such as if other researchers can see certain interactions of the user). When asked about the company's personal data sharing practices with a possible data processor, ResearchGate replied that they do share personal data with a partner (Lotame.com), but did not inform which data they consider personal.
- **Bibliographical information**: This includes information about academic content from different sources, including databases (e.g., PubMed) or the website of a publisher. The information includes, for example, title of the article, name of the journal, date of publication and names of the various authors of the content. In the data set, we found three attributes that fit this category (distributed on the HTML files "Coauthors", "Your Projects", "Your Publications"). The data set also contained the full publications in PDF format, although no information was provided on how the PDFs were indexed.

- **Information pertaining to the user's work**: The HTML files "Project Collaborators" and "Profile information"[14] gather 29 attributes, including where and with whom the user works.
- **Historical data**: ResearchGate informed us that to recommend content, they process usage frequency, type of devices used, publications consulted, time spent on particular pages or parts of pages and number of clicks on a page of features. We identified 18 attributes on the HTML files "Login history", "Activity history"[15] and "Publication followings". These files contain the login data (when and from where the user logged in) and all sorts of interactions with different content (such as publications, researchers, advertisements, job offers and emails). The interactions include, but are not limited to, engage, view, react, update and open. For each interaction, the list shows the date, time, country, browser, operational system and (truncate) IP address[16] used in that activity. ResearchGate states that, for security reasons, it keeps the number of pages viewed by the user to prevent data harvesting by third parties. Indeed, in the data set, we could see the number of read publications, the number of read projects and the number of citations. However, ResearchGate not only keeps the number of visited pages to avoid security attacks, but also registers every page and which type of interaction (view, engage, react) the user has with that specific content (see Figure 2.4). This shows that the company not only keeps quantitative data about the accessed pages, but also keeps track, in great detail, of the users' interactions within the platform to observe their behaviour.

14 The file "Profile information" could also be considered personal data because it in-cludes email, phone and birthday.

15 The files "Login history" and "Activity history" also fit the category of personal data because of the type of attribute they register. They registered two years of interactions within the platform.

16 IP address is a numerical label assigned to each device connected to a computer network, used to identify it individually.

- **person:view:jobSuggestion** @ 2019-04-16 09:12:46 from Belgium, Chrome 72 on macOS (ip: 1
- **person:view:recommendation** @ 2019-04-16 09:12:46 from Belgium, Chrome 72 on macOS (ip
- **person:view:jobSuggestion** @ 2019-04-16 09:12:46 from Belgium, Chrome 72 on macOS (ip: 1
- **person:view:jobSuggestion** @ 2019-04-16 09:12:46 from Belgium, Chrome 72 on macOS (ip: 1
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- **person:view:jobSuggestion** @ 2019-04-16 09:12:46 from Belgium, Chrome 72 on macOS (ip: 1
- **person:view:activity** @ 2019-04-16 09:12:46 from Belgium, Chrome 72 on macOS (ip: 134.58.2
- **person:view:activity** @ 2019-04-16 09:12:46 from Belgium, Chrome 72 on macOS (ip: 134.58.2
- **person:view:activity** @ 2019-04-16 09:12:46 from Belgium, Chrome 72 on macOS (ip: 134.58.2
- **person:create:activity** @ 2019-04-16 09:12:46 from Belgium, Chrome 72 on macOS (ip: 134.58
- **person:update:device** @ 2019-04-16 09:12:45 from Belgium, Chrome 72 on macOS (ip: 134.58.
- **person:update:device** @ 2019-04-16 09:12:45 from Belgium, Chrome 72 on macOS (ip: 134.58.
- **person:update:device** @ 2019-04-15 14:52:08 from Belgium, Chrome 72 on macOS (ip: 134.58.
- **person:open:mail** @ 2019-04-15 14:52:08 from Belgium, Chrome 72 on macOS (ip: 134.58.253
- **person:receive:adslot** @ 2019-04-15 09:05:30 from Belgium, Chrome 72 on macOS (ip: 134.58.
- **person:view:adslot** @ 2019-04-15 09:05:23 from Belgium, Chrome 72 on macOS (ip: 134.58.25
- **person:receive:adslot** @ 2019-04-15 09:05:23 from Belgium, Chrome 72 on macOS (ip: 134.58.
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- **person:view:jobSuggestion** @ 2019-04-15 09:04:59 from Belgium, Chrome 72 on macOS (ip: 1
- **person:view:recommendation** @ 2019-04-15 09:04:55 from Belgium, Chrome 72 on macOS (ip
- **person:view:activity** @ 2019-04-15 09:04:55 from Belgium, Chrome 72 on macOS (ip: 134.58.2

Figure 2.4 – Part of HTML file with historical data

- **Authors the user may have chosen to follow**: The HTML files "Followers" and "Followings" (total six attributes) represent the network the user is in contact with.
- **The subject matter of articles the user may have authored**: As mentioned in the category bibliographical data, ResearchGate provided the PDF files of all publications registered in the platform by the user; however, it did not give information about the process of indexation of these content, that is, the extraction of the topics of the paper. We infer that there is a collection based on the PDF (and maybe that is why the platform is so insistent in asking the user to upload the full text). For example, there is no specific field on the interface to register the references of the papers. However, once the PDF is uploaded, metadata and links to the publications that are

cited appear on the publication page. This could also be the case for automatic extraction of topics, which leads us to the keywords.

- **Profiling keywords**: The data set also had a file called "Keywords and Skills", which contained a list of keywords, many of which were not added by the first author of the current paper. In total, the user profile in the platform had 22 keywords as skills and expertise at the time of the data gathering that were filled by the user and visible in the interface. The keywords HTML file of this same user had 67 keywords. Seventeen of them were classified as "Sciences" by the platform (e.g., Social Science, Semantics, Artificial Intelligence). As can be seen in step i (interface analysis), the section Questions normally uses skills and expertise to recommend questions to be answered by the user. Hence, if only 33% of the keywords (22 out of 67) in the user profile were actually provided by the user (data given), 67% of these recommendations are based solely on algorithmic inference (inferred data). It is not clear, however, how the match between keywords and content is made to recommend publications to the users. The company makes recommendations based on "The subject matter of articles the user may have authored", but no indication was found to identify how these topics are selected by the system. This vagueness is also reflected in the classification of information. Several attributes present in the data set could be classified as "Information pertaining to the user's work" or "Personal data", but the company did not make clear how this information was being used.
- **Content in the platform**: Content posted by the user within the platform fits this category. The HTML files contain "Messages" (three attributes, including the full content of the messages left on ResearchGate) and "Questions" (no attributes were mapped here because the first author did not publish any question within the platform at that time, hence the file came empty).

- **Scores / stats**: This refers to many aggregated metrics keeping track of the achievements of the user that are considered milestones. Examples include reads (the so-called success stories represent the number of reads the publications have across time), number of citations, likes on the user's publications and research projects (the button Recommend in the interface is equivalent to the Like button on other social media, and it is counted as a like in the HTML files). They also list the most relevant publications considering the h-index[17] on ResearchGate. The files "H-Index", "RG Score", "Account Stats", "Success stories" and "Top Publications by H-Index" total 18 attributes.

The HTML file "RG score" contains the composition of this metric (percentage distribution that comes from publications, questions, answers, and followers). For example, 99.48% of the first author's RG Score comes from publications, while 0.52% comes from followers. If the first author had posted or answered any question, this would also be part of the equation, but it was not the case. The platform dedicates a page to explain how the RG Score is built, but it does not show if and how it may influence the ranking of researchers recommended to the user (under the label "Who to follow").

As for the tailored advertising content (this content appears in the interface as "sponsored content"), ResearchGate listed the following information categories used: "personal data provided by the user; personal data collected by the platform; and personal data inferred by the platform based on the use of the Service and the Internet". Some of this information is provided by the users themselves, some is collected by the platform, and some is inferred by the platform using a combination of data already in their possession. In the typology of privacy lawyer Simone van der Hof (van der Hof, 2017), those categories of data would fit as follows: personal data

17 The h-index is a bibliometric index given by the number of articles that have a number of citations equal to or greater than the number itself. If the researcher published 15 articles that obtained 15 or more citations each, then their h = 15. It was created in 2005 to assess the relevance of researchers, but rapidly spread across other entities and today it is applicable to researchers, institutions and journals.

provided by the user is equivalent to data given; personal data collected by the platform is equivalent to data traces; and data inferred by the platform based on the use of the Service and the Internet is equivalent to inferred data. The three categories informed by the company are broad enough to include any kind of personal data used in the platform without necessarily specifying where the data come from and how the data are used in the advertisement. This classification is vague because it does not inform which data are considered personal by the platform.

The company also presented inconsistent information when answering the question on the logic involved in recommendations. ResearchGate denies automated decision-making: “We do not engage in automated individual decision-making, including profiling, as proscribed in GDPR Article 22.” However, when asked about personal data usage, the company claims that: “For the personal data where we provide a description of the data categories we cannot provide a copy of the data because the data is in an aggregated format.” The aggregated format can normally be seen as profiling (General Data Protection Regulation (GDPR), 2016; van der Hof, 2017).

Hence, apparently, there is confusion about the meaning of profiling. In Art. 13(2)f and 14(1)f, the GDPR requires a platform to provide information regarding the existence of “solely automated decision-making”, including profiling. The law also requires that where such systems are deployed, meaningful information is given about the logic involved, as well as the significance and envisaged consequences of such processing for the individual. ResearchGate did not provide the explanation asked about the logic of the recommender system because of commercial secrecy. When explicitly requested to explain the logic behind the recommender system, the company responded with the following: “*This request goes beyond your right to access deriving from Art. 15 GDPR, and an explanation of the set-up and specific functioning of our system would involve providing you with information we regard as business secrets*.”

Summarising the results of the company inquiry (step ii), ResearchGate provided a long document explaining the recommendations together with a data set containing what the company claims to be all the data they have about the first author. However, this was received by the researchers at the third contact attempt, after an extensive request on behalf of the researchers with several specific and law-based questions. In the company's first answer (sent by the support team from Berlin), they provided two lines of explanation and a link to the cookies policy. We believe that the standard answer does not offer a complete overview about what is used to recommend content and how this process happens. At that moment, the company said they use data provided by the user to offer better personalised service and briefly referred to metadata (names of published articles and user's past interaction with the site) obtained partly by cookies, which are only two of the many attributes mapped in our research. Their final answer, sent by the privacy team with no location given, was obtained six weeks after the first request. In the final answer, more information was provided, but the data set was still incomplete. For example, ResearchGate sent us PDF files with the publications authored and uploaded by the first author on the platform. However, the terms used to index the content of the publications were not revealed. It was not clear if this answer came from the data processor (Lotame) because there was no indication of location. From the absence of a nominal signature, we interpret that further contact on behalf of the user is not encouraged.

Even after receiving a document that is supposed to explain the logic of the recommendations, the information we received was vague and sometimes inconsistent. Regarding examples of the vagueness, there is a lack of accuracy in describing what is considered personal data (used to recommend regular and sponsored content); there is no information about how the inferences are made in the keywords used in recommendations; and there is no information regarding how much of the RG Score contributes to the ranking of researcher's recommendations, even though this is an important metric created to measure the reputation of researchers, as ResearchGate states on the interface. As for inconsistency, two occurrences were reported: first, the discrepancy between stating they only keep the number of pages visited when they actually keep detailed data about the user's behaviour on the platform. And second, affirming that they do not use automated decisions while admitting to profiling users with a data processor.

2.4 Discussion

Analysing the artefact and communicative practices of ResearchGate against the body of literature on interests of ASM users, we observe that most of what users seek is mediated by algorithms, even though this is not always clearly communicated to the user. For example, Jeng et al. (Jeng et al., 2017) pointed out that ASM platforms can facilitate scholarly information exchange, which in ResearchGate is possible through the section “Questions”. Because Question is one of the entities shaped by recommender algorithms on this platform, the information-seeking that starts in this particular section receives algorithmic mediation. It is clear to the users that the information available in the “Questions” section receives automated curation, however it is unclear how much inference is happening behind the scenes. Moreover, the statement on the interface that the platform employs the users’ skills and expertise to show relevant questions and that the users can edit their skills and expertise at any time can misinform the user. From these sentences, users can be misled to think that they are in total control of the mediation, when in our study we found that nearly 67% of the keywords in the user profile were inferred and act behind the interface, not being available to manual edition by the user.

Previous studies identified practices of the ASM users regarding contents usually available in these platforms. Our analysis can add to this knowledge showing the algorithmically mediated entities related to these specific contents. According to Nández and Borrego (Nández & Borrego, 2013), researchers use ASM to follow and get in touch with other scholars. That involves the entity Researcher, which is used to recommend content and is also recommended in the platform. Users also disseminate their research results (Nández & Borrego, 2013) via self-archiving (uploading one’s own publications), motivated by accessibility (Lee et al., 2019). The entities Researcher, Research Projects and Publications are directly involved in these actions. The recommendations used in Job positions are clearly based in collaborative filtering: “Other researchers apply for”. However, differently from the other entities, the information provided here is generic, not disclosing which researchers applied for that specific vacancy, or how many. This might be a strategy from the platform to boost employment without jeopardising privacy and inner competition in academia. The competitive aspect of job seeking changes the configuration of the information provided, possibly to avoid jeopardising the negotiation between the Institution offering the position and the Researcher. This informs about how social arrangements, practices and artefact are mutually shaped (Lievrouw, 2014), as a specific feature in the artefact reflects a social conduct and a certain "way of doing" that is professionally accepted by the academic community. By recommending a Job position this way, the platform protects the relations between the nodes of the network (imagine two colleagues knowingly running for the same vacancy) and the institution that offers the job (by not showing how many researchers have applied, the platform does not denounce how disputed that job vacancy - really - is).

2.4.1 Algorithmic selection and prioritisation of information

The company stated in their email that they use the recommendation engine to present content that they think might be relevant and interesting to the user. Analysing this, we see the platform selection (van Dijck et al., 2018) in practice. While the users are browsing, they are both actively providing data (on their profile or login history) and receiving recommendations that are based on these preferences. The users may provide information about their topics of interest (data given), publications (data given and data traces in case the metadata about the publications are collected by the platform in other databases) and what they like to see (by simply navigating and staying longer on a certain page these data are collected through the login history). However, it is the algorithm that decides how this information will be selected, processed and weighted, which ultimately defines what other content will be shown and in which order (prioritisation) (Bozdag, 2013; van Dijck et al., 2018). In the context of recommendations in ASM, this means that although users have agency on the content that is published and consumed (e.g., uploading papers or inserting the institution name where the researcher works), how this content is used in the algorithm, namely, which attributes will be matched and which ones are more relevant in the ranking of recommendations, is a decision coming from the platform (automated decision-making). The mutual shaping characteristic between the artefact and the practices (Lievrouw, 2014) is expressed in the way that users can freely engage with whatever content they want, while the platform nudges them to connect with certain items and forums through personalised recommendations (e.g., "you might like this" or "we think you can answer this question"). The user can decide what to click on, however, through automated filtering, the universe of choice is narrowed by the recommender algorithm. By promoting recommendations from the users' most active connections and downgrading the actions of the less active ones, algorithmic mediation has two instances of control. On the one hand, the system determines incoming information, because not every content available will be seen by the researcher. On the other hand, platforms also control "the outgoing information and who the user can reach" (Bozdag, 2013, p. 211), because other users will not visualise all the content shared by the researcher.

2.4.2 Commodification of scientific knowledge in ASM

ASM are designed in a way that the platform can benefit (economically and strategically) from the researchers' practices. For example, ResearchGate values the interactions within the platform, which is concretely expressed by the RG Score, that quantifies all these interactions. The interactions quantified in the RG Score (uploading full text publications, engaging in Q&A forums, and acquiring followers) are also beneficial to the platform: questions engage users, uploading full publications feeds into the database of the company with machine readable scientific content (that otherwise is protected by paywalls) and followers increase the trust in the digital environment. Probably not coincidentally, the RG Score is one of the few elements shown in the short profile of the researcher. The platform also nudges researchers to invite their coauthors to become users as a way to "help their publication gain visibility" (sentence used in emails sent by the platform).

ResearchGate rewards the researcher that makes the upload of full text pub- lications in two ways: adding up the users' RG Score and recommending new publications from "relevant" authors (that are inferred based on the list of references of the publications). By encouraging this practice (sharing the researchers' own work), the platform can then offer the publication free of charge to other users, which might increase the adherence of new users. This can be identified as the mechanism of commodification that "involves platforms transforming online and offline objects, activities, emotions, and ideas into tradable commodities" (van Dijck et al., 2018, p. 37).

Users receive reading recommendations based on a match between their own interests (keywords, readings) and the previous publications they wrote themselves. At the same time, they can also recommend content produced by others and, therefore, influence the way that publications are ranked in the platform (including for themselves). This recommendation is made through the button "Recommend", which is part of the design of the container for several types of content on the interface of ResearchGate, and it can be seen in previous figures (Figure 2.1 and Figure 2.2). In a typical case of collaborative filtering, when user A recommends a certain content item, this item will appear to other users (users B, C, D) endorsed by user A. Prior research has shown that the collaborative filtering technique in recommender systems is inherently driven by social influence, as the "follow by example" pattern is automated by the algorithm (Jameson et al., 2014; Ramos et al., 2020). This may explain why ASM platforms facilitate trust among users, as they consider the site to be an extension of their professional activities, therefore perceiving other members as trustworthy (Koranteng & Wiafe, 2019). Hence, when a researcher connected to the user endorses a certain content, that content becomes more appealing and more likely to attract the user's attention and trust, which might be a strategy from the platform to increase their interest and to get users to trust more in the recommended content.

2.4.3 Algorithmic user profiling

The three categories of personal data used in the digital environment are data given, data traces and inferred data (van der Hof, 2017). Regarding the types of data used in recommendations, ResearchGate mentions the use of personal data specifically when referring to tailored advertisement (sponsored content), as shown in step ii (company inquiry). However, data from all of these categories, particularly inferred data, are used for a number of different recommendations (not only sponsored content), connecting users and content on ResearchGate. For example, our research results have shown that only 33% of the keywords in the user's profile (in the HTML files) were stated by the author in the field named skills and expertise. The company did not say how these inferences are made and what is the exact information used to generate them.

Nevertheless, the results in step i (interface analysis) show that the entity Question is associated with keywords that are not listed in the user's profile or in their list of skills and expertise. Additionally, it is difficult to state which data are considered "personal" by ResearchGate because this was not detailed in the document. ResearchGate also did not specify which categories of information are shared with Lotame (data processor). Presenting customised content recommendations can be considered automated decision-making, where recommendations depend on a profile that has been built out of the characteristics or interests of the user. Therefore, it would be desirable for the company to clearly explain to its users the process of automated profiling, either by design of the interface or upon request. The right to a meaningful explanation is ensured to the users by GDPR (General Data Protection Regulation (GDPR), 2016), and it is crucial to help them understand the mechanisms underpinning their interactions within the platform (Millecamp et al., 2019).

2.4.4 ResearchGate's communication strategy

Van Dijck and Poell (van Dijck & Poell, 2013) have stated that the technological mechanisms in social media are often invisible. We were able to endorse this statement in our data collection, with the delayed, vague and sometimes inconsistent answers to the company inquiry (step ii). This also goes towards Millecamp's claim: "the rationale for providing individual recommendations remains unexplained to users" (Millecamp et al., 2019, p. 397). Unfortunately, most people only have a vague idea of how recommender algorithms work, because these systems are often presented as a "black box" (Bozdag, 2013), which was also the result we got from company inquiry, when the company argued that the information asked regards business secrets.

The vagueness and inconsistency can have two motivations. On the one hand, it can be because of the recency of GDPR requirements and the lack of experience in providing detailed and meaningful explanations about the algorithmic mediation to users. On the other hand, it may be a conscious effort to keep the algorithmic logic safe from competitors (commercial secrecy). Nevertheless, transparency through design (Monteiro-Krebs et al., 2019) is a must regarding recommendations in ASM. Providing tardy, unclear and discrepant explanations jeopardise the algorithmic transparency of ResearchGate and do not contribute to the user's understanding of the recommendation mechanisms.

2.5 Conclusion

In this chapter, we conducted a socio-technical analysis of the recommendations on ResearchGate in light of the mediation framework (Lievrouw, 2014). Using the walkthrough method (Light et al., 2018) in two steps (interface analysis and company inquiry) we delved into what the platform communicates regarding the use of recommender algorithms via design or upon request. We identified the main entities involved in a recommendation: Researcher, Institution, Publication, Research project, Job and Question. Considering ASM are one type of social media, we analysed how artefact and arrangements mutually shape each other. We also verified how the mechanisms of platform selection, commodification and profiling (van Dijck et al., 2018) apply to the platform. We conclude that recommender algorithms mediate most of the content in the platform and that the mutual shaping characteristic of social media logic is also reflected in this particular ASM. Even though the company denies automated decision-making, our results point towards profiling (prediction based on inferred data). By reflecting on ResearchGate's communication strategies via visible interface elements and upon request, we suggest that the company implements tools to make sure the users are informed in a clear, agile and meaningful way about the algorithmic mediation.

chapter 3

TRESPASSING THE GATES OF RESEARCH: identifying algorithmic mechanisms that can cause distortions and biases in academic social media[18]

We need ethics of technology so technology leads us to the places we want to end up - not some other random place that we couldn't think about. There is a phrase from Churchill which says that 'We shape buildings and afterwards buildings shape us' and whoever is familiar with the Panopticon, for example, has a good sense of what he meant. This is true also for technology. We design technology and then technology design us, or shape us back. Artificial Intelligence, all the suggestions, all the ways in which it profiles the reality around us. Ethics is there to make sure that ***we*** *design technology in such a way that, when technology is shaping us, it shapes us in the best possible form or place that we might think of.*

Mariarosaria Taddeo, Interview (2020, pt. 14'06", emphasis from the author)

18 This chapter was published as a journal paper: Monteiro-Krebs, L., Zaman, B., Caregnato, S.E., Geerts, D., Grassi-Filho, V. and Htun, N.-N. (2021), "Trespassing the gates of research: identifying algorithmic mechanisms that can cause distortions and biases in academic social media", Online Information Review (OIR), Vol. ahead-of-print No. ahead-of-print. https://doi.org/10.1108/OIR-01-2021-0042.

3.1 Introduction

Many scholars have written about potential risks that social media logic and automated filters can bring (Barassi, 2017; van Dijck, 2013; van Dijck & Poell, 2013). For example, Bozdag outlines the multiple possible biases that can result from algorithmic filtering (Bozdag, 2013). The author details how information filtering in online web services are influenced by the audience, advertisers, ranking system, user's interpersonal networks, location, personalisation system, human operator, information selection and prioritisation, source selection, user interaction history and user preferences. Regarding the ethics of recommender systems, Milano, Taddeo and Floridi highlight six areas of concern based on literature review (Milano et al., 2019). The authors propose a taxonomy comprising the different kinds of ethical impacts of algorithmic recommendations: Biassed recommendations, Unfair recommendations and Encroachment on individual autonomy and identity are areas that present immediate harm, according to the authors; whereas Opacity, Questionable content, Privacy and Social manipulability and Polarisation are areas that offer exposure to risk (Milano et al., 2019, p. 15).

Regarding exposure to content, it has been argued that the internet in general and social media in particular increase the number of viewpoints, perspectives, ideas and opinions available, leading to a very diverse pool of information. However, critics claim that algorithms used by search engines, social media platforms and other large online intermediaries actually decrease information diversity (Bozdag, 2013; Pariser, 2011). A limited access to plural and diverse points of view in the network is a concern that Pariser addresses with the concept of filter-bubble (Pariser, 2011).

Empirical studies show that recommender systems influence people's decisions. Zhu, Huberman and Luon proved that people significantly sway their own opinions when confronted with other people's opinions through recommendation (Zhu, Huberman, and Luon 2011). Schwind and Buder provide some evidence that confirmation bias is reduced when recommendations are consistent with the preference of the participant, regardless of the mindset (collaborative or competitive). While confirmation bias is reduced in both mindsets through preference-consistent recommendations, evaluation bias is reduced only under a cooperative mindset (Schwind and Buder 2012). Therefore, the design of the system might - intentionally or not - act against or reinforce certain behaviours, by showing to the user content that has the highest degrees of similarity with previous content. Current research on ASM platforms do not yet fully grasp the complexity involved in the influence of platforms in users' decision-making, despite the existence of some previous studies.

ASM platforms are sociocultural artefacts embedded in a mutually shaping relationship with research practices and economic, political and social arrangements. Given the great popularity of social media in scientific environments, and the extensive use of recommender systems in ASM, it is quite intriguing how these questions have been addressed in previous research on algorithms in social media in general, but almost nothing has been published about the way algorithms might shape scholarly communication.

In this chapter, we contribute to the debate focusing specifically on the role of recommender algorithms in scholarly communication. Especifically, by taking ResearchGate as a case study, we focused on the following research question: ***How may algorithmic mediation, through recommender systems in ASM platforms, uphold biases in scholarly communication?*** The inquiry is further led by follow-up questions, including: What are the main entities involved in ResearchGate recommendations? How does the design of recommendations in these specific ASM platforms enforce potential biases?

3.2 Research design[19]

To address our research questions, we used a three-steps approach of the walkthrough method (Light et al., 2018) including a patent analysis, an interface analysis and an inspection of the web page code. With this method, we could inspect the artefact while also expanding the analysis to arrangements (Light et al., 2018). The patent analysis (phase 1) explored the engineers' explanation of how the system works, via a document normally read by professionals and engineers. The interface analysis (phase 2) helped to identify the recommendation elements that are visible to the users. The code inspection (phase 3) focused on the attributes working behind the interface - that is, what the company normally would not communicate to the average user.

3.2.1 Phase 1: Patent analysis

In phase 1, we analysed ResearchGate's patent entitled "Online publication system and method" (Madisch et al., 2018). This patent, which comprises 38 pages, is described by the United States Patent Office. It was registered by the three cofounders of ResearchGate (Dr. Ijad Madisch, Dr. Sören Hofmayer, and computer scientist Horst Fickenscher), as well as 6 other authors, all of whom have current or past affiliation with Ijad Madisch's lab. The Current Assignee of the patent is ResearchGate GmbH, from which it can be inferred that the patent explains the ResearchGate system. In the patent, the engineers explain the architecture of ResearchGate and provide examples of how the recommendation works. The latter was the focus of this analysis.

19 The platform analysis was performed once, however the results are divided in two analytical focuses that are described in chapter 2 and 3 respectively: each chapter looks at different sets of data to answer different sub-questions. Since both studies were previously published independently, there is some overlap between them, i.e. the identification of the entities involved in the recommendations, which is one of the outcomes of the interface analysis, used in both studies.

3.2.2 Phase 2: Interface analysis

The interface analysis was performed on ResearchGate with the first author's login using *Google Chrome Version 75.0.3770.100 (Official Build; 64-bit)* as a web browser. The data collection occurred in August 2019, and the analytical procedure consisted of three steps. First, we identified all communicative interface elements (content labels) that are somehow linked to recommendations. More particularly, we looked for *visual evidence of a recommendation* in the interface that identified content labelled as a suggestion or recommendation (e.g., when the word "suggested" or a button called "recommend" was shown). Through this search, we detected five content labels (header of a container) that we found were potentially showing recommended content. The labels were as follows: "Suggested for you", "Who to follow", "Jobs you may be interested in", "Suggested projects" and "Questions we think you can answer". These content labels were located in the interface above certain types of content. Every time we found one of those labels, we clicked on the label's link, to see whether it was leading to a new page. If the communicative element led to an independent page with further information and the attributes found there were also connected to other entities, we inferred that the element was an entity.

The second step of the interface analysis consisted of inspecting each entity in depth and its corresponding (visible) attributes. For example, the entity *Researcher* has an independent page and is detailed by several attributes, such as name, RG Score, degree and current affiliation. We did this until the saturation point was reached (when no new entity was found, only repeated ones). This process resulted in the mapping of six main entities involved in recommendations on ResearchGate: *Researcher, Institution, Publication, Research Project, Job* and *Questions*. Screenshots and the description of the entities can be found in the results section.

Thirdly, we researched the terms and conditions of ResearchGate (ResearchGate, 2020) to find information about content moderation and examined the definition of the RG Score, one of the most relevant metrics in the platform. This metric appears next to each researcher's name on the interface and it is important for recommendations since it establishes "researchers' reputation" within the platform. The findings from this step substantiate the discussions revolving around content moderation and researchers' reputation.

3.2.3 Phase 3: Code inspection

For phase 3, we used the "Developer Tools" in the browser to check if and when the application was "calling" a recommender engine. We used Google Chrome Version 75.0.3770.100 (Official Build; 64-bit) on macOS Mojave 10.14.6 to sign in to ResearchGate, using the first author's login. The data collection occurred in September 2020. After reaching the initial page of the platform, we clicked on the three dots in the upper right corner of the browser and selected More Tools > Developer Tools. The Network tab showed all the traffic occurring while the page was rendering, meaning all HTTP requests and HTTP responses that were exchanged between the server (platform) and client (user's browser) during the interaction. Thus, the commands and files (such as URLs, CSS and scripts) exchanged in real-time could be viewed and read. With the Network tab open, we refreshed the page (using F5), and performed the following three inspections: inspection (i) focused on the information arising from the data processor used by ResearchGate that described the navigating user; inspection (ii) examined the request for recommendations on "Who to follow"; and inspection (iii) searched the server (using a search string) and examined the response that recommended other publications to read (label "Similar Research"). All inspections searched for potential attributes in the code (i.e., the metadata used to describe the entities). The next paragraphs detail each inspection.

Code inspection (i): A company called Lotame is the data processor used by ResearchGate[20]; therefore, we searched for the string "Lotame" in the code of the page, and found the ID of the first author used by Lotame, a five-digits number. Then, using the find function (Ctrl+f), we searched for this code among the answers to the request "Who to follow", which appeared in the Network tab. The code appeared in three scripts (*cc.js, commom.a56cf6.js, manager.js*) and one URL. We examined these files seeking for attributes that were potentially used to recommend (such as topics of interest and keywords). We found a URL that delivered the Lotame ID (five digits) and several attributes (demographic, geographic and of interest) in the script *manager.js*.

20 This information is presented in the Privacy Policy (https://www.researchgate.net/ privacy-policy) of ResearchGate.

Code inspection (ii): Using the find function (Ctrl+f) we searched for the expression "recommend* OR suggest*" (which recovers all files containing variations of the radicals in the search expression: "recommendation", "recommendations", "recommender", "recommended", "suggestion", "suggestions", "suggested" and "suggest"). The result showed a recommendation service, denoted by the URL https://www.researchgate.net/recommendations.FollowSuggestionsPromo.html?context=homeFeedRightColumn. This recommendation service returned a JSON file containing recommendations of "Who to follow". The attributes found are described in the results section.

Code inspection (iii): To understand the recommendations of the publications (publications, projects, etc.), we searched for a random term ("soybean"), and after receiving a response from the server, we randomly picked a link to click on (it was the third link on the list. This link redirected to this website: https://www.researchgate.net/publication/334848488_Soybean_Biorefinery_Economic_Evaluation. Then, we pressed F12 to activate the Developer Tools from the browser (Google Chrome), and observed all the traffic needed to request not only the main page but also its recommendations. Analysis of the main page HTML source revealed the following declaration in the tag <head> : <scriptcharset="utf-8"src="https://c5.rgstatic.net/javascript/bundles/ResearchDetailRelatedSimilarResearch.58d29f.js"></script>. The results section presents the meaning of this command.

Together, these three elements of analysis provided the material necessary for mapping the entities and attributes and their interconnectedness in this particular platform.

3.3 Results

This section presents the results of the three phases of the walkthrough method: patent analysis, interface analysis and code inspection.

3.3.1 Patent analysis

Figure 3.1 shows part of the system's architecture as depicted in the patent document. The system "100" provides the search functionality, combining the system "130" (search engine) with the system "132" (recommendation engine). The recommendation engine is explained on item [0012] of the patent (Madisch et al., 2018, p. 5).

The patent analysis revealed the use of the recommendation engine for two purposes: to recommend content to a user directly and to find experts among users to evaluate content. Regarding the first purpose, to automatically provide a list of potential publications of interest based on a user's profile, the engine uses several parameters, which included: (i) a list of the user's research interests, (ii) a list of the user's own publications and (iii) prior search and browsing history within the platform.

In the patent (Madisch et al., 2018, p. 5), the engineers state that recommended publications are ranked according to the following criteria:

- Relevancy to the user's request (in case of active searching),
- Matching publication and user's general interests,
- Recency of the publication,
- Feedback received by the publication,
- Reputation of the publication's authors and
- Number of citations the publication received.

As mentioned above, the second purpose of the recommender system is garnering recommendation from an expert. In a recommendation-based system, the content that is automatically ranked must be relevant and consistent to the recipients. Besides the quantitative metrics (e.g., number of views or downloads), the evaluation of such content can be done qualitatively by experts in the field. In the patent, the engineers describe how the system infers who is a suitable user to provide a review or feedback for content.

Experts are identified "using machine-implemented recommendation logic, based at least in part on a comparison of contents of the selected publication portion with the contents of documents (publications, reviews, etc.) published by the various candidate experts" (Madisch et al., 2018, p. 5). Hence, the users' own publications and reviews or other feed-

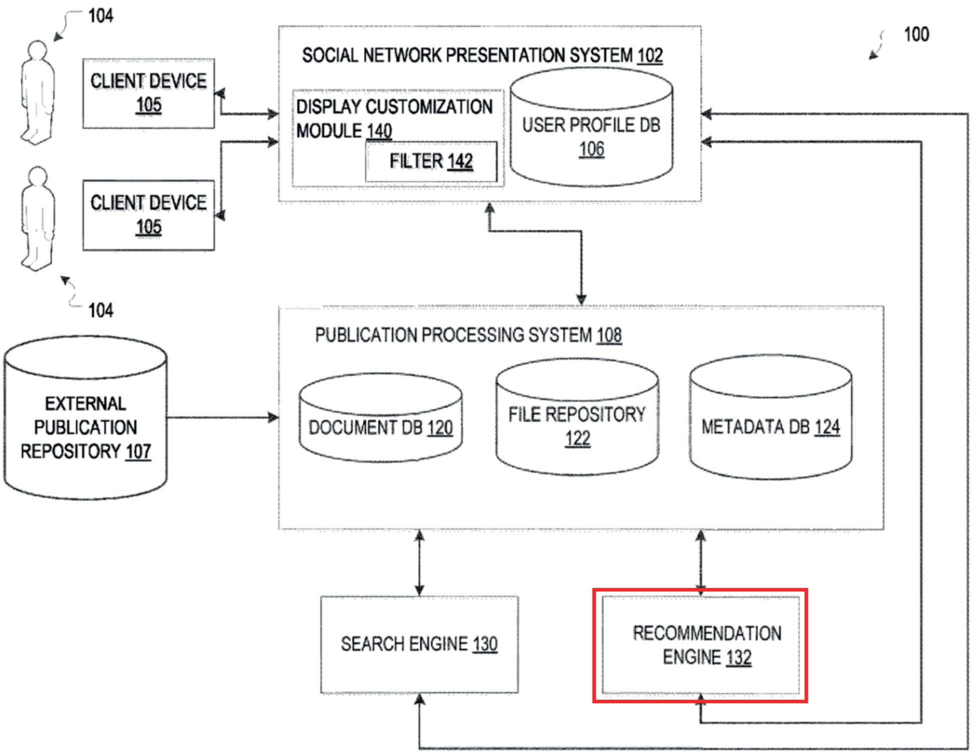


Figure 3.1 – Patent (Madisch et al., 2018)

back they have provided previously are compared with the content on which feedback is requested. The experts' research areas, general reputation and other criteria are also examined. However, the patent does not specify these other criteria.

3.3.2 Interface analysis

We identified six entities in ResearchGate that are closely tied to recommendations: Researcher, Publication, Research project, Job, Question and Institution. These entities represent almost all the content in the platform, since the vast majority of profiles, documents and job offers provided in ResearchGate fit under these overarching categories of information.

- **Researcher**: The recommendations under the label "Who to follow" show other researchers' profiles to follow, such as authors cited in previous publications, co-authors, colleagues and researchers with similar interests. On the recommended researcher's page, a short description emphasises the researcher's RG score, the institution to which the researcher is affiliated and the relationship between the user and the recommended researcher (such as "you have the same skill" or even "you co-authored a publication"), followed by a link to show the item in question (the shared skill or publication) as "proof" of relevance of that recommendation.
- **Publication**: The labels "Suggested for you" and "Similar research" on the home page present publications from authors connected to the user. The publications are of different types, such as articles, book chapters, preprints and data sets. User and publication metadata are used to recommend the user's research interests, previous publications by the user and prior searches and browsing history within the platform. The recommended publications are then organised (ranked) in the feed according to several parameters, including the publication's relevance to the user's search, the suitability of the match between the recommended publication and user's interests in general, the recency of the publication, the feedback the publication received from other researchers, the reputation of the authors of the recommended publication and the number of citations the publication received.
- **Research project**: The label "Suggested projects" considers the user's connections to recommend research projects. The relationship between the user and the researchers engaged in that project plays an important role in this recommendation, either by showing which user connections follow that project or by ordering project participants in a way that shows users' connections first.
- **Job**: Career opportunities are offered under the labels "Jobs you may be interested in", "Researchers also applied for", "Discover more" and "View more". The recommendations are based on the user's academic degree, as well as the user's career level, (inferred) career stage and location. The attributes "Disciplines" and

"Skills and expertise" of the entity Researcher also are relevant for job recommendation; "Disciplines" can be matched with "Areas of research" in the job offer, and a link on the interface to improve job suggestions leads to the "Skills and expertise" registered on the user's profile. Thus, when the user edits the list of skills and expertise, it is implied that those edits will be reflected in the job suggestions. For the label "Researchers also applied for", the co-occurrence of application to that position among users is key. However, unlike what happens with the other entities, the platform does not disclose the name of the researchers that are also interested in that job position.

- **Question**: "Questions we think you can answer" are based on the user's skills and expertise, while questions shown on the home page (feed) are those made or answered by the user's connections (other researchers on the platform that the user follows). Skills and expertise, together with other keywords that are collected and inferred by the platform, are used to recommend relevant questions to the user (see Figure 3.2).
- **Institution**: The institution is an entity that has a specific page on ResearchGate where several types of information are provided. The institution can be a university, faculty, research institute or company. The page presents an overview with many statistics about the institution, its contribution to the scientific community (through publications) and its affiliated members and their stats and job positions. Even though the institution does not have a specific label that indicates a clear recommendation on the home page (feed), this entity has a vital role in the recommendation of other entities. For example, having an institution in common in the user profile is also a motive to recommend other researchers to follow, and research projects from colleagues in the same institution are often recommended on the home page (feed). Likewise, for recommended jobs, the institution is one of the few pieces of information that appears with great prominence in the vacancy summary on the home page. The name of the institution, its location and logo are three of the four pieces of information about the position that appears on the home page, along with the title of the vacancy.

3.3.3 Code inspection

The code inspection is divided into three protocols (i, ii and iii). The **code inspection (i)** examined the description of the navigating user, which is recovered by the script "manager.js". We found 15 attributes that describe the entity Researcher, creating a profile that is used by Lotame to recommend content. To preserve sensitive data of the authors, we replaced the data in the response from the server with a description and examples. The 15 attributes belong to three categories: 11 of the attributes are *demographic*, one is *geographic* and three attributes are related to *interest data*, which are used to index content of interest to the user.

The *demographic* attributes are listed below:

- *loggedIn*: a binary attribute to inform if the user is logged in.
- *ProfileInstitution*: the name of the university.
- *ProfilePosition*: the position of the user, which can be, for example, professor, PostDoc or PhD student.
- *ProfileCareerLevel*: the career level of the user, for example, "PostDoc".
- *ProfileCareerStage*: the career stage of the user, for example "early-career".
- *Degree*: the user education level, for example, "Doctor of Philosophy".
- *IsBusinessAccount*: a binary attribute to inform whether the account is commercial.
- *IsLabPI*: a binary attribute to inform whether the user is the principal investigator for a grant project.
- *IsCLS:* a binary attribute that refers to "clinical laboratory science".
- *Gender*: the user's gender.
- *ProfileInstType:* the profile type of the user, for example "academic".

The attributes used to index content *(interest data)* are divided into three subsets, as follows:

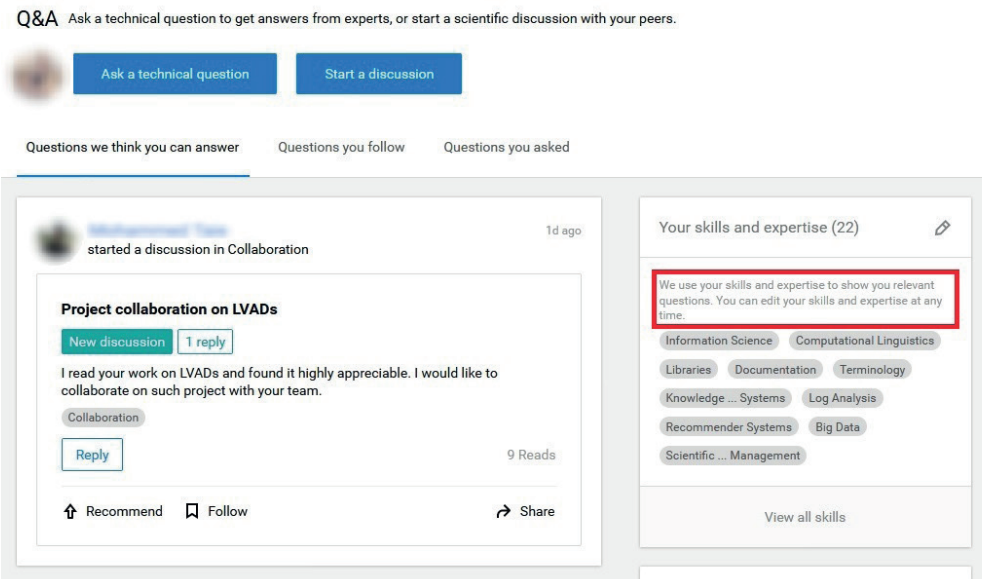


Figure 3.2 – Suggested questions

- *Profile1stLvlScience:* the values of this attribute describe the user's main area(s) of interest, at the *first level*, such as "Computer Sciences" and "Linguistics". These areas are informed by the user in the field "Disciplines" on the ResearchGate interface, and the user can add up to three disciplines.
- *Profile2ndLvlScience:* the user can add up to three sub-disciplines for each discipline in the field "Disciplines" on the interface, and these subdisciplines are the values for this attribute. They correspond to the *second level* such as "Artificial Intelligence" and "Cognitive Linguistics" (Artificial Intelligence is a branch of Computer Sciences and Cognitive linguistics is a branch of Linguistics).
- *ProfileInsPresets:* 42 keywords corresponding to research areas (RA) were found in the script. The profile of the first author had 33 general RA (e.g. "RA-General Information Science") and 9 specific RA (e.g. "RA-Internet of Things"). The keywords were not equivalent to any field completed by the

user; thus, the values of this field were attributed automatically (i.e., by inference) based on the user's behaviour. In this same field, 7 other parameters were found that could not be identified (e.g. "CU-GB-5509 first test preset"); these likely correspond to commands.

Only one geographic attribute was found, as follows:

- *Country*: the country in which the user is located.

These attributes describe the users at the profile level, the main fields of knowledge in which they are interested, where they are based and so on. The keywords corresponding to the user's research areas of interest *(ProfileInsPresets)* correspond to inferences made by the data processor (Lotame).

The **code inspection (ii)** regarded the recommendation service that is called while the web browser is rendering out the main page. The recommendation service returns a JSON file containing recommendations of "Who to follow". One of the returned fields, called *sourceRaw*, indicates how the recommendation engine suggests other researchers with which to connect. For each recommended researcher, who is recommended for unique reasons, six distinct attributes appear on the field sourceRaw. These attributes refer not to inherent properties of entities (like the researcher's gender, for example), but rather the relationship or interactions between entities, as follows:

- *departmentColleague:* the user and recommended researcher work in the same department.
- *coauthor:* the user and recommended researcher have a publication in common (i.e. they co-authored a publication).
- *institution:* the user works in the same institution as the recommended researcher.
- *publicationReading:* the user reads a publication from the recommended researcher.
- *citedByMe:* the user cited a publication from the recommended researcher.
- *profileVisiting:* the user visited the profile of the recommended researcher.

The relationship between researchers was inferred based on other entities (e.g., the co-occurrence of Institution between Researchers [colleague], or co-occurrence of Publication between Researchers [co-author, both authoring the same paper]). On the interface label, some of these relationships were not explicit. For example, while "Co-author" was expressed on the interface with the same label (Co-author), recommended profiles that the user visited before were labelled as "Extended network" on the interface. In other words, for recommendations based on navigation, which is the case for when the user visited another researcher's profile, the label was quite vague. This vague label seems to be the platform's attempt to make the collection of browsing history feeding that particular recommendation less explicit.

In the case shown in Figure 3.3, the recommendation was primarily based on the entity *Institution*, where the user works and, more specifically, one of the entity's attributes, the university department. The recommended researcher was one of the user's colleagues.

In the case of people working in the same university but who are from other fields or departments, topics of interest, represented by keywords, play an important role in creating recommendations. In recommendations of researchers from the same university with topics of interest in common, the code presents the institution and the list of keywords that the user and the recommended researcher share[21]. On the interface, the label "You have the same skills" is shown, and the user can click to see the keywords that show the shared skills.

Researchers that share "Similar interests" with the user but are not colleagues are also recommended, although in the web page code, these interests are not identified. Differently from the recommendations presented in the previous paragraph, the field source shows "topics" for similar interest, and the value found is "true", not a list of topics as was expected. As demonstrated in the previous paragraph, the keywords are explicit both in the code and in the interface; here, the topics are not. Thus, the match based on similar interests follows a hidden criterion. The exact

21 The list of keywords shared by user and recommended researcher appears in the field *sourceInfo > data > keyword* of the code.

attributes used in ranking is also secret, as the ordering of the page contents follows a list ranked by the server. Therefore, the information provided in the patent was used to make conclusions about the ranking.

With the inspection (ii) we decoded some of the factors used by the algorithm to make recommendations of other researchers. Keywords and the relationship between the user and recommended researcher were some of these factors. We found that the entities *Institution* and *Publication* (more specifically, the citations) are mobilised to recommend Researchers, along with information about the users' profile, such as "Skills and expertise" and browsing history. We identified six attributes describing the interaction between entities.

The **code inspection (iii)** on the main page HTML source found the following declaration in the < head > tag: <scriptcharset="utf-8"src="https://c5.rgstatic.net/javascript/bundles/ResearchDetailRelatedSimilarResearch.58d29f.js"></script>. In HTML such a command is responsible for loading a script, written in JavaScript (JS), during the page rendering. When analysing this script, we found calls to server functions requesting recommendations. Such JS functions make Asynchronous JavaScript and XML (AJAX) calls to a central server requesting recommendation links that are related to the publication being shown. Using the Network tab from Developer Tools, the following call was found: https://www.researchgate.net/research.tabContent.ResearchDetailRelatedSimilarResearch.html?id=PB3A33484848, where ID is ResearchGate's internal code for the actual Publication.

In addition to the ID of the publication, cookies are sent together in the request. Based on their names, the cookies seem to represent the identification of the logged-in user, and they are probably used as filters. Therefore, the above-mentioned request for recommendations used a combination of a query parameter called "ID" (the unique code of the publication) and cookies (representing the logged user) as the main inputs to show publications similar to the one that the user was visualising. Such a request has the semantics of "give me some N articles that are related to paper with id = X", and the response for this request can be seen in the *Response* tab of the *Network* tab in JSON format. Analysis of the response found that all the links were shown in the section "Similar research", denoting that every time a publication web page is rendered in the browser, ResearchGate offers a tailored set of content similar to that publication.

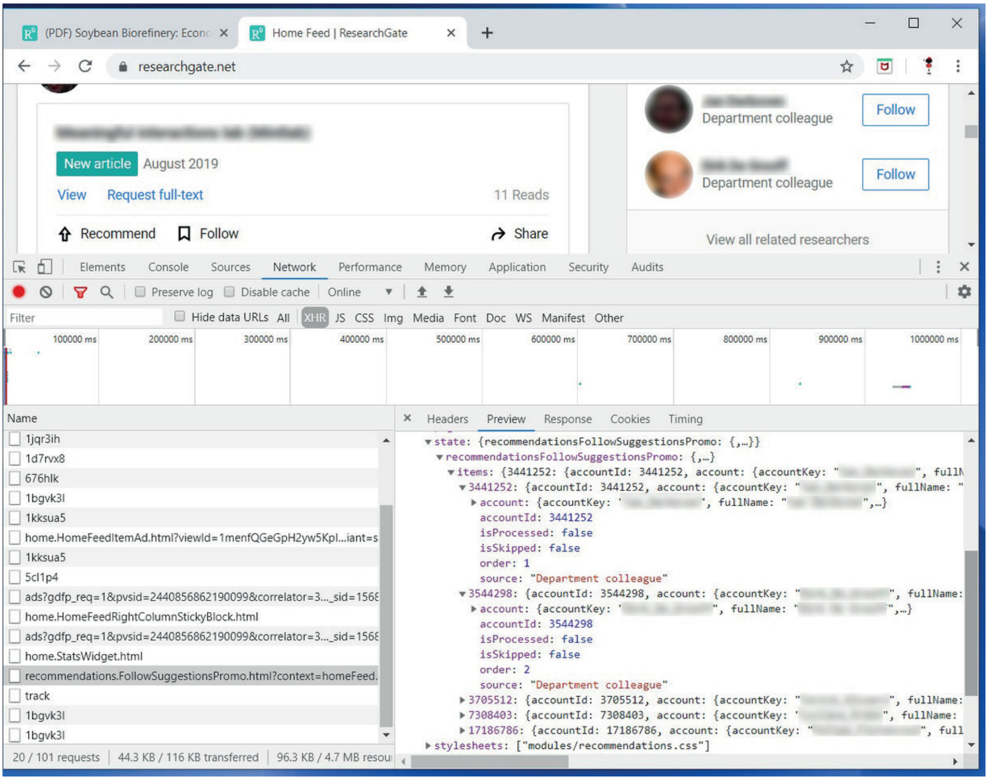


Figure 3.3 – Code inspection

Phase 3 showed that cookies and the publication's ID is used as a query parameter and combined with cookies (representing the logged user) to serve as input for the recommender engine. The cookies contain personal data, including identification and behavioural data (more specifically, browsing history of the user). Resuming the three code inspections, the starting point to recommend is identifying the researcher who is browsing (the platform is only accessible through user/password identification), as was shown in code inspection (i). We demonstrated the recommendations for other researchers to follow (code inspection ii) and other publications to read, denoted by the label "Similar research" (code inspection iii). In these three code inspections, we identified 21 attributes that are tied to profiling and recommendation.

3.4 Discussion

In this section we discuss some of the findings in light of the literature. These findings include the platform selection, the content prioritisation, the Matthew effect, the influence of the audience, datafication and profiling.

3.4.1 Platform selection and the homogeneity bias

Examining the two purposes of the recommender engine in the patent (phase 1), it is possible to see the mutual shaping characteristic of the platform selection. Regarding the first purpose of the recommender engine (to recommend content directly), users provide data and receive recommendations based on their preferences. The algorithm deploys automated decision-making to define the content that will be shown to the user. Even though the user can decide on what to click, automated filtering narrows the universe of choice of content. This is consistent with previous studies that showed that social media tend to exhibit more homogeneity bias when compared to search engines (Nikolov et al., 2019). Homogeneity bias is "the selective exposure of content from a narrow set of information sources" (Nikolov et al., 2019, p. 219).

In the second purpose (to find expert candidates to endorse content to other users), the recommender algorithm also reinforces the platform selection and therefore, the mutual shaping characteristic is also clear. Users receive reading recommendations based on a match between their interests (keywords, readings) and previous publications they wrote. The users can also be picked by the platform to help assess content produced by others and, therefore, influence the way that publications are ranked in the platform (including for themselves). These two purposes express how artefacts and practices (Lievrouw, 2014) are mutually shaping (van Dijck et al., 2018). The selection of what is shown goes beyond the content within the platform, as not everything is available online (Bozdag, 2013, p. 215), and revolves around arrangements that go beyond the digital environment. For example, the metric for reputation on ResearchGate (RG Score) considers factors that are possible to track within the platform but disregards many other types of academic recognition. RG Score relies on publication count, questions, answers and followers (inner content of the platform), while ignoring prizes, honourable mentions, distinguished scholarships, peer review activities, board positions, and many other prestigious academic positions (information that is not registered inside ResearchGate). Since the later type of information is often unstructured or nonuniform, it is harder for the crawler to find and index. Furthermore, even among what is online and structured, technical challenges prevent content from being indexed, such as paywall protection or the lack of interoperability patterns. This can affect even the more objective metrics (like citations). Therefore, a clear bias exists in the so-called academic reputation that the RG Score claims to measure. Previous empirical research on RG Score (Orduña-Malea et al., 2016) shows that the score is an appalling indicator of scientific performance for two main reasons: (i) it does not measure academic prestige but only the degree of participation in the platform, so its purpose is misaligned with what the platform officially communicates; and (ii) the platform's lack of transparency regarding the factors that compose the index and the volatility in the algorithm makes the indicator irreplicable and unreliable (Orduña-Malea et al., 2016, p. 310).

3.4.2 Prioritising and discrimination

The order of the content is relevant in an information overload scenario. Users will not read all the platform's content, so results that appear first and/or in privileged places on the interface have a greater chance of receiving user attention (Goldhaber, 1997). Thus, the ranking system is a valuable asset in any platform, and the design of this algorithm is typically well protected by commercial secrecy. However, the three phases of the analysis provided indications of how the platform favours some content over others in the feed and within the information containers.

To rank publications in the feed, one of the factors cited in the patent (phase 1) is relevance. The interface analysis (phase 2) showed that, when someone in the user's network is part of a project, that researcher appears first in the list of collaborators of that particular project, regardless of his or her role in it (the list appears to follow an order of relevance to the user, not the general order of importance in the project). This is classified as the use of an interpersonal network to filter information (Bozdag, 2013). In the code inspection (phase 3), many attributes related to the user were depicted (i.e., the profiling factors), although the exact attributes used to order content in the feed were not found. However, this does not mean that no rule for prioritising content exists; rather, it shows that technological mechanisms in social media platforms are often invisible (van Dijck and Poell, 2013). Diakopoulos (Diakopoulos, 2016) claims that algorithms must be held accountable for prioritising the content on platforms, which is the function of ranking systems. According to the author, by bringing attention to certain things at the expense of others, prioritization is, by definition, discrimination (Diakopoulos, 2016, p. 57).

3.4.3 Inferred reputation and the Matthew effect

According to the data set obtained in phase 2 (interface analysis), the short profile of "Who to follow" recommendations shows the RG Score of researchers. Previous studies (Orduña-Malea et al., 2016) have concluded that the indicator RG Score does not measure the prestige of the researchers but rather their level of participation in the platform. However, this does not prevent the platform from claiming that RG Score is a reputation metric or from using it to filter information. In fact, the platform states in the interface that the RG Score is used to measure the scientific reputation of the researchers.

Meanwhile, the patent analysis (phase 1) showed that the "Reputation of the authors" is one of the factors that impact on recommendations, both for the ranking of publications and identifying candidate experts (the latest based on their research areas, general reputation and "other criteria"). As these other criteria are not specified in the patent, what else is considered and what is its weight are unclear. Assuming that research areas and general reputation are the main aspects (since they are worthy of mention in the patent by the engineers), it is arguable that, through the experts inference process, authors with a higher reputation in the platform gain more attention on the feed. They are moved closer to the top of the recommendations list, which can lead to even more reads and citations and, hence, higher reputation.

This phenomenon characterises what Merton called the *Matthew effect of accumulated advantage* in science (Merton, 1968). The effect is found when the credit for joint work is given to the best-known investigator in a field regardless of their contribution in the research project, and the investigator thereby becomes even better-known, triggering an autocatalytic process (Merton, 1988, p. 88). Considering the factors disclosed in the patent by the company, the platform is likely to trigger a Matthew effect, corroborating previous research (Polonioli, 2020). It might be the case, though, that the company tries to increase serendipity and diversity when making recommendations. Unfortunately, any mention of serendipity or other form to try to counter the exponential growth of reputation could not be found in the patent. At the same time, the Matthew effect can not be exclusively credited to recommender systems, since it is already known in the academic environment for almost sixty years (De Solla Price, 1963; Merton, 1968). However, current research practices depend heavily on ASM platforms, and this combined with the lack of algorithmic transparency make the employment of automated recommendations particularly hazardous and worthy of attention.

3.4.4 The issue of the audience

Interactions with a publication, such as likes, shares and downloads, are indicated by the patent (phase 1) as important for the algorithm to make recommendations. These factors fit the issue of audience (Bozdag, 2013), in which the feedback provided by other users determines the content relevance. In prior studies on social media platforms, the audience feedback was tied to the popularity bias, which is defined as the tendency to expose users to content from popular sources (Nikolov et al., 2019, p. 219). The number of profiles in the user's network affects how many reactions the new content will have, but not only quantitatively. On the interface, ResearchGate states that their algorithm considers how peers receive the user's contributions and who these peers are. This means two things, one of which is related to the user's interpersonal network (Bozdag, 2013) and the other to the overall reputation of the researcher who interacts with the content.

First, the results of the code inspection (ii) showed that the professional network in which the users are embedded offline (colleagues, co-authors) is mobilised to encourage the users to amplify their online network. This is aligned with van Dijck and Poell's statement on how platforms influence human interaction, "while the worlds of online and offline are increasingly interpenetrating" (van Dijck and Poell, 2013, p. 4). Collaborative filtering in recommender systems is inherently driven by social influence, whereas the "follow by example" pattern is automated by the algorithm (Jameson et al., 2014; Ramos et al., 2020). In the context of ASM, if a known researcher endorses certain content, that content becomes more appealing and more likely to attract the user's reliability. Therefore, as demonstrated in the patent analysis, showing recommendations of certain content by connected researchers might be a strategy from the platform to increase the user's interest and get users to trust the recommended content.

Second, on the page that explains the RG Score, the company says that "the higher the RG Scores of those who interact with your research, the more your own score will increase" (ResearchGate, 2020). Therefore, the more recognized the researchers who interact with the user's publications are, the higher the user's score will become. However, this again reveals the issue of skewed prioritisation, in which researchers receive an already limited universe of options to interact with based on their reputation, connections, popularity, publications, etc., that therefore *taints* the recommendations. If the researcher decides to endorse that content, it will, from that moment on, appear to others as "a recommendation from someone". However, as the users cannot recommend content that they do not see, this decision is actually biassed by previous algorithmic decisions that narrowed the options by selecting and prioritising the set of available content.

The finding that recommended content is based on the reputation of the authors and number of citations of the publication opens a discussion on how an algorithm makes automated decisions regarding relevance. In a datafied environment, the concept of relevance might easily be relegated into what is more likely to be clicked, which would then lead to more quantifiable interactions, which are desirable for the company. However, this logic does not consider the possible biases in the automated filtering. It ignores, for example, how diverse or inclusive the recommended publication is. Automatic full text scrapping could be used to find different points of view, variable tones and styles, instead of a perfect match. Several techniques introduce serendipity in recommendations, which is considered a best practice in the design of recommender systems (Reviglio, 2019).

3.4.5 Datafication and the myth of neutrality

Networked platforms have the ability "to render into data many aspects of the world that have never been quantified before: not just demographic or profiling data volunteered by customers or solicited from them in (online) surveys but behavioural meta-data automatically derived from smartphones such as time stamps and GPS-inferred locations" (van Dijck et al., 2018, p. 33). The quantification of demographic data was also identified in this study (phase 2); six entities and 21 attributes are used in ResearchGate to recommendations. Metadata about the researcher (demographic, geographic and interest inference), publications and research projects serve to create a profile that is enriched at every interaction with the content in the platform - every read, like, download and share counts. The amount and richness of data gathering that occurs in ASM can be characterised as the phenomenon of datafication, a term coined by Mayer-Schönberger and Cukier (Mayer-Schönberger and Cukier, 2013). To them, "to datafy a phenomenon is to put it in a quantified format so it can be tabulated and analysed" (Mayer-Schönberger and Cukier, 2013, p. 78). The danger in datafication lies in the claim that "data are 'raw' resources merely being 'channeled' through online veins" (van Dijck et al., 2018, p. 34). The neutrality implicit in this assertion, in which data are collected only to *monitor* user's interactions, is a misleading belief. In fact, platforms convey a human factor in two ways. One is in the design of the system, wherein designers choose certain attributes and not others to feature in the algorithm. The second is in the content moderation, wherein humans decide, based on the platform's terms of use, which content should and should not be banned. As stated in the terms and conditions of ResearchGate, the company curates the content:

> We reserve the right to delete, modify, demote, or reformat any materials, content, or information submitted by you when, in our sole discretion, we deem it to be necessary or appropriate, including if we determine that the content may expose us to harm, potential legal liability, or is in breach of these Terms (ResearchGate, 2020).

However, ResearchGate does not indicate the criteria used to decide what is harmful content, content that exposes the company to potential legal liability or even content that violates the company's terms of use. According to Bozdag, omitting these criteria is common among other platforms (e.g Facebook and Twitter) (Bozdag, 2013, p. 217), which allows for subjective judgements from the designers and moderators.

3.4.6 Profiling and the expected use

Some of the information used in recommendations is provided by the users themselves *(data given)*, some is collected by the platform *(data traces)*, and some is inferred by the platform *(inferred data)* using a combination of data already in the platform's possession (van der Hof, 2017). Combined, these data allow for clustering user profiles in a way that helps the system recommend relevant content to users. Although profiling is an essential feature of recommender systems, it has also been reported as a source of misconceptions and inaccuracy (Bozdag, 2013; Milano et al., 2019; Pariser, 2011; Polonioli, 2020) as big part of the data is based on inferences. Therefore, transparency on how the inferences are made is essential to establish fairness and avoid biases. For example, the findings of the code inspections showed that gender is a demographic attribute used for profiling, but why ResearchGate considers gender relevant in a professional/scientific network is unclear.

In this study, we found that inferred data are used for a number of different recommendations, bridging data gaps between users and content. As reported in the code inspection (i), all the keywords found to describe the researcher's areas of interest were inferences based on the behaviour of the user. These keywords refer to topics that provide recommendations of other papers to read, job positions to apply for and researchers with the same interests to follow. Additionally, the interface analysis (phase 2) revealed that the *Questions* are associated with keywords that are not always listed in the user's profile, nor in their list of skills and expertise. In the code inspection (phase 3), the analysis revealed that recommendations regarding job positions are based on a combination of data given by the user (i.e., skills and expertise) and attributes based on inferences. The current position of the user (expressed in the attribute *ProfilePosition*) is informed by the user. However, the attribute *ProfileCareerLevel*, which suggests the next career level to pursue, is not informed by the user. The system infers this without input from the user and then only suggests positions that match this attribute. For instance, for users who are at the PhD level, the system recommends only PostDoc positions. Since the users never select this explicitly, they are not able to choose what is meaningful to pursue (which can be a PostDoc position, but can also be something else for that particular person in that moment in time). Instead, the profile is already established, and there is no option to change it, as it is based on inferred data that is hidden, not visible on the interface. Likewise, the attribute *ProfileCareerStage* is an inference based probably on the date the degree was obtained. These examples show how customised content recommendations are, in fact, all instances of automated decision-making, in which recommendations depend on a profile that has been built from the characteristics or inferred interests of the user. For the sake of transparency, the company should clearly explain the process of automated profiling, either by design or upon request.

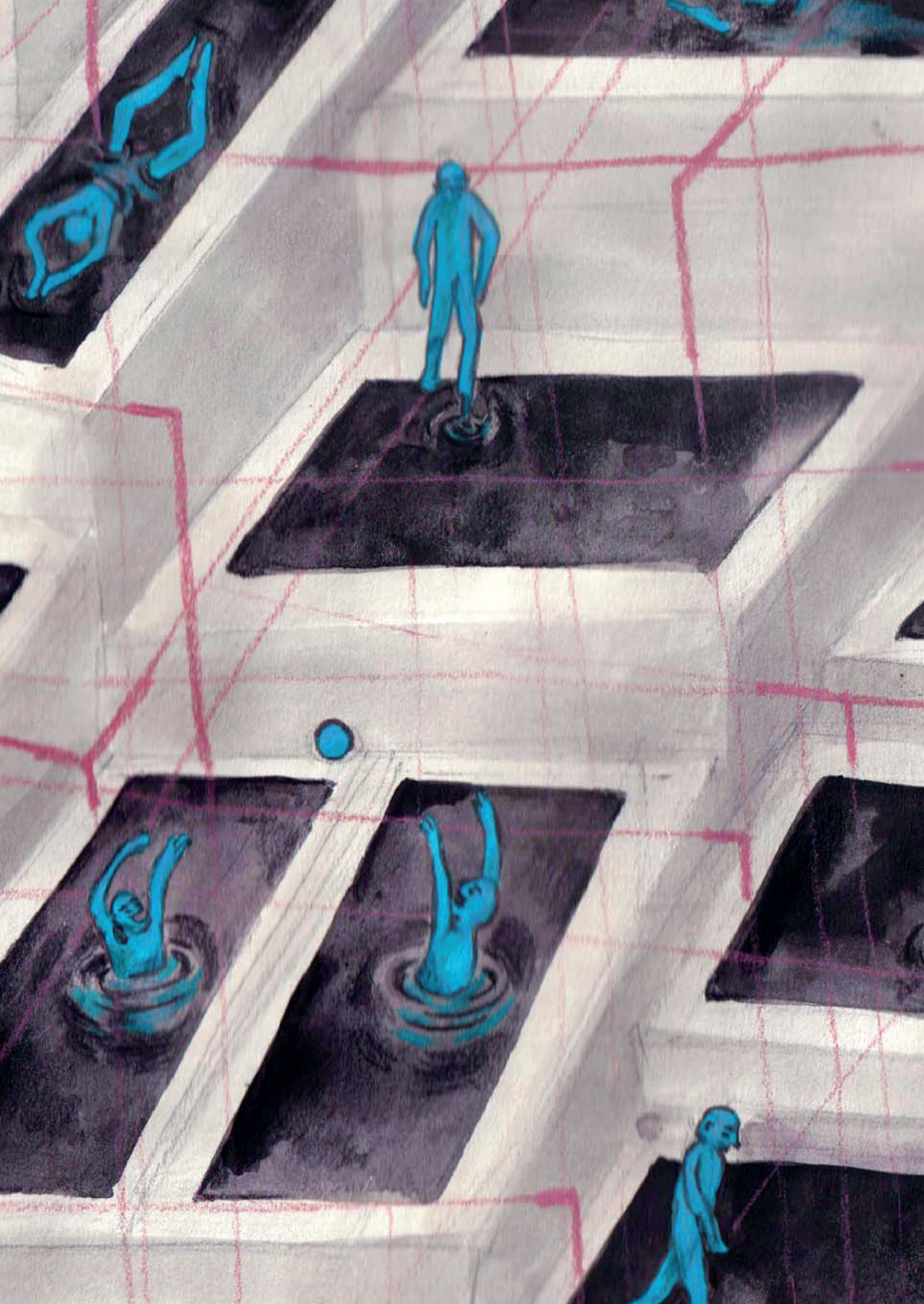
3.5 Conclusion

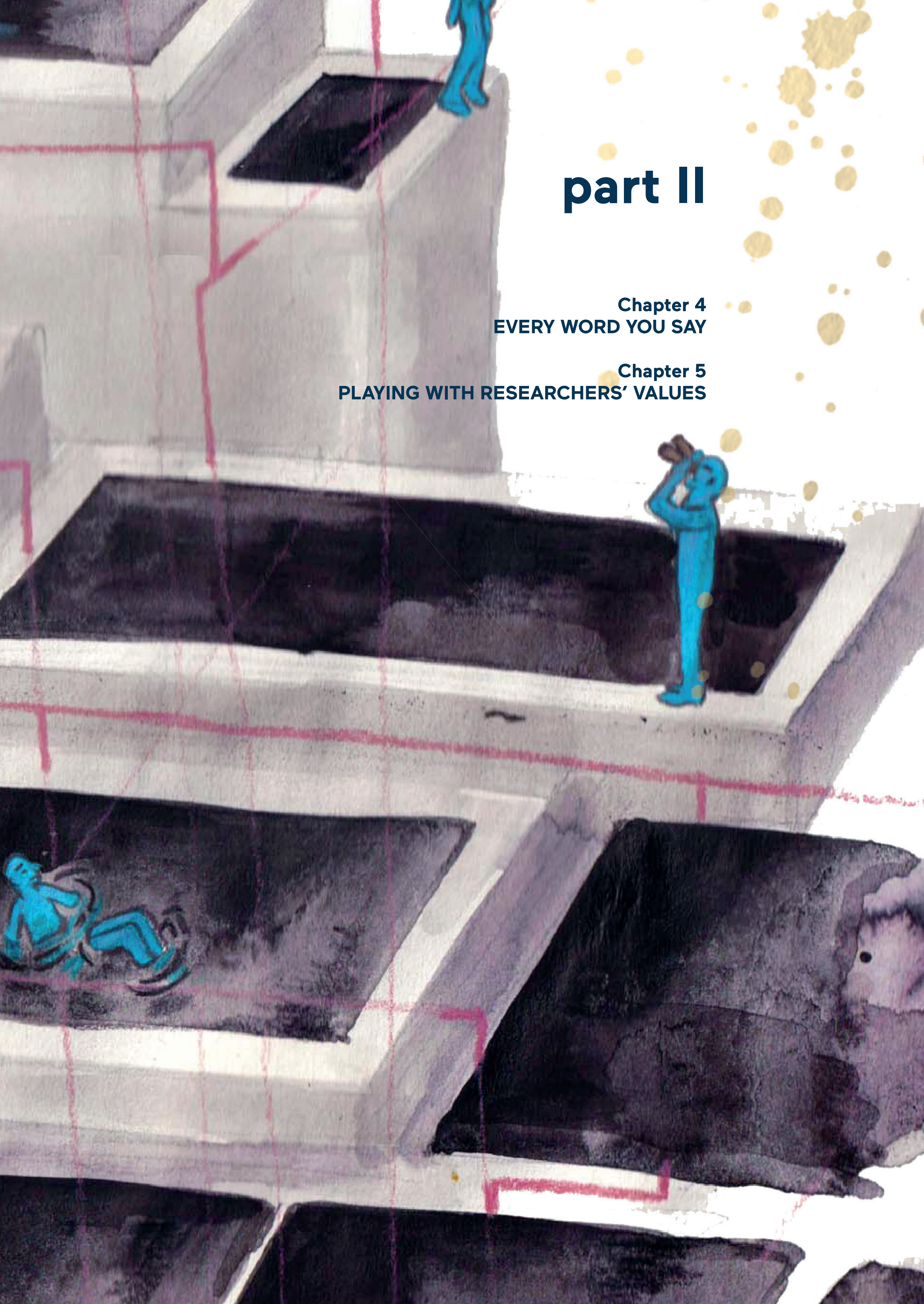
This study presented a socio-technical analysis of recommendations in the platform ResearchGate using the walkthrough method. Its goal was to analyse how algorithmic mediation through recommender systems in ResearchGate may uphold biases in scholarly communication. We collected data by focusing on evidence of recommendation and information from different sources, including the public interface and also information that the company does not disclose in an accessible form to the average user, namely web page code and patent content. Works on the topic of Explainable AI (XAI) might offer solutions for the platforms to make the algorithmic mediation less complicated to the users and implement algorithmic transparency by *design*. Additionally, companies should also fully comply with the GDPR legal framework, promptly providing the complete information requested by the user in an intelligible and accessible language.

The main entities involved in recommendations were identified; these included *Researcher, Publication, Research project, Job, Question* and *Institution*. We also identified 21 attributes used by the platform to recommend content. Reflecting on these entities and attributes, we discussed potential biases that derive from recommendation systems or are boosted by them, including biases linked to platform selection, prioritisation, the influence of the audience, datafication and profiling. A potential Matthew effect was identified in the logic of the platform when choosing an expert, as the platform relies heavily on the reputation of the researchers as one of the factors of recommendations. Furthermore, we discussed the need to foster serendipity and algorithmic transparency *by design*.

The data collection confirmed that the algorithmic mediation is opaque both on the interface and behind it (web page code). Code inspection (phase 3) showed that recommendations based on browsing history remain implicit to the user (see the example of "extended network"). Creating implicit labels for recommendations based on historical behaviour might be a platform strategy to make users less aware of the fact that the navigation is registered in detail and used to feed recommendations. By suppressing this information, the platform ensures that the users are not immediately triggered by the label regarding their potential privacy concerns. The analysis was inconclusive regarding the factors used by the platform to recommend researchers with "similar interests". Therefore, the findings are in line with those of previous researchers, who have argued that recommender systems are likely to serve as a "black box" for the users and therefore need explanations (Millecamp et al., 2019).

Considering that the platform can influence users' interaction with the system by suggesting, for instance, what to read, who to connect with, where to work or which solution to purchase, it is just fair that users understand that they are guided through their decision-making by the design, especially considering that the company profits from the research practices and arrangements.





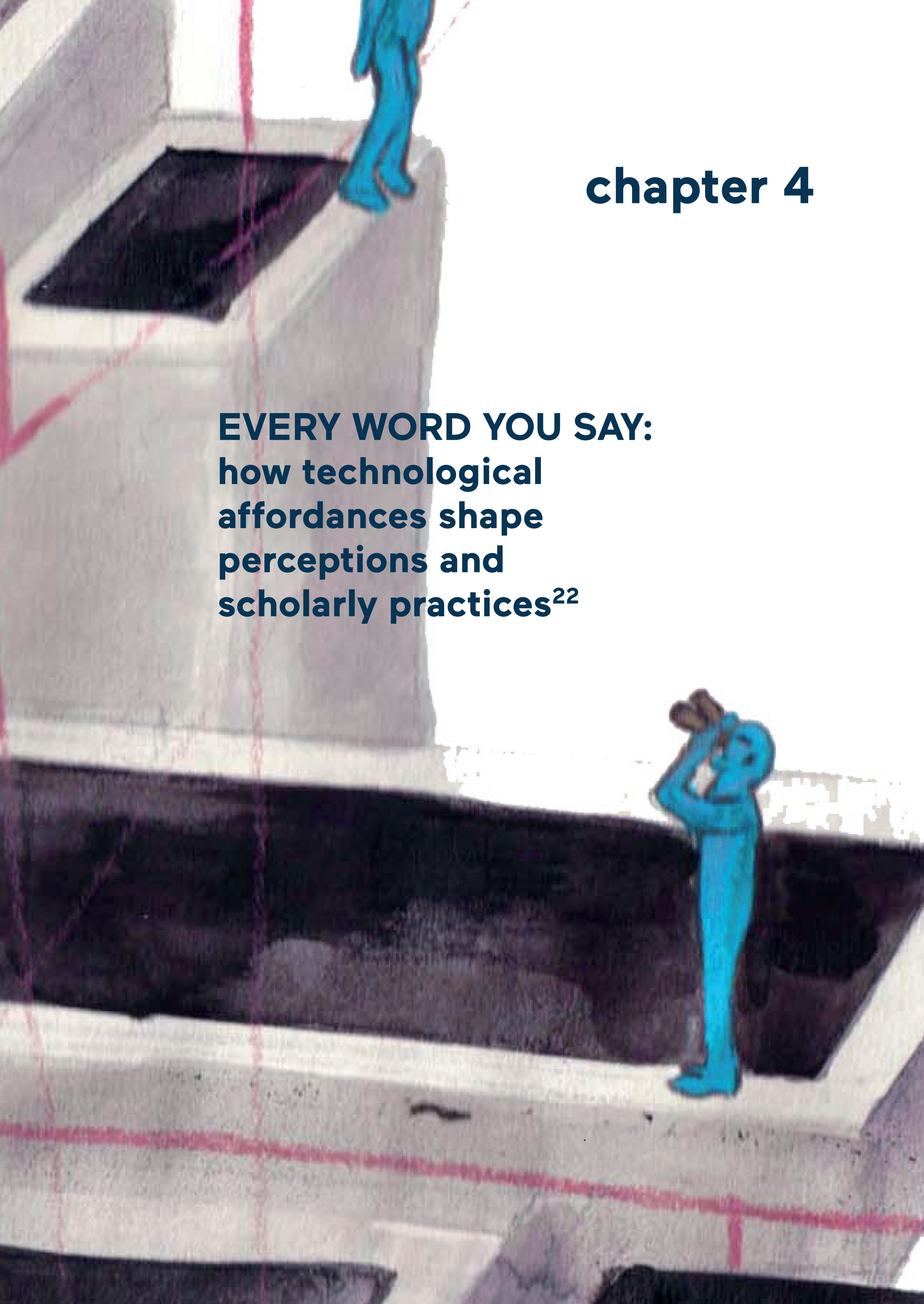
part II

Chapter 4
EVERY WORD YOU SAY

Chapter 5
PLAYING WITH RESEARCHERS' VALUES

chapter 4

EVERY WORD YOU SAY: how technological affordances shape perceptions and scholarly practices[22]



The desire to be taken seriously is precisely what compels people to follow the tried and true paths of knowledge production around which I would like to map a few detours.

Jack Halberstam, The Queer Art of Failure (2011)

22 This chapter has been accepted for publication at the Special Issue "AI for People" of the journal AI & SOCIETY (ISSN: 1435-5655). At the time of submission of this thesis, it was under final revision.

4.1 Introduction

ASM platforms combine the functions of a scientific repository with social media features such as personal profiles, followers and comments on content. They store scientific content, from publications to data sets and metadata from research projects, selectively distributing this content using personalised feeds and recommendations. The mediation across the platform goes from the feed to suggestions to weekly digest emails. As shown in the previous chapters, to deliver personalised information to scholars, ASM platforms employ several mechanisms, such as profiling, information selection and datafication. Datafication is "the ability of the platforms to quantify, i.e. 'render into data', aspects of the world that have never been quantified before" (Mayer-Schönberger & Cukier, 2013). By collecting behavioural metadata automatically derived from smartphones and browsers, datafied environments detach themselves from other types of systems, which use only demographic or profiling data given by users (van Dijck et al., 2018).

In previous chapters, we analysed mediation processes (Lievrouw, 2014) both at the level of the artefact and the social and economic arrangements in which ASM platforms operate. In this chapter, we complement the analysis of the mediation processes in ASM from the perspective of the end users. We argue that ASM platforms have an impact on the way scholars communicate and perceive each other, which can have both positive and negative consequences. We therefore uphold the need for accountability and algorithmic transparency.

The characteristics of data-driven systems are not neutral and are likely to shape their uses and effects. Studying a particular app, Jacobsen found that by generating narratives about individuals, algorithms are exercising social power (Jacobsen, 2020). By ordering, weaving together and presenting data, people's experiences and temporalities, algorithms present coherent and frictionless narratives about individuals, in a process Jacobsen calls "algorithmic emplotment" (Jacobsen, 2020, p. 13).

Yet the artefact features do not yield predetermined effects as they are also shaped by the users' motivations (Williams, 2003), meaning making processes and their everyday practices. Indeed, rather than being passive receivers or consumers of content mediated through ASM, people are also actively engaged and critical about what they see and interact with (Lievrouw, 2014). For instance, the perceived visibility that these platforms afford shape people's motivations to self-archive in ASM (Lee et al., 2019). Visibility is the capacity to find a piece of information and "the relative ease with which it can be located" (Evans et al., 2017, p. 42).

With the notion of affordances, we aim to account for this interaction between the ASM artefact's features and users' agency. Therefore, we consider affordances not as predetermined characteristics of the system, but as possibilities for action, acknowledging that these "affordances emerge in the mutuality between those using technologies, the material features of those technologies, and the situated nature of use" (Evans et al., 2017, p. 36). Complementing the majority of research that has focused on a one-sided analysis of the platform features, we adhere to a relational view on affordances. In this chapter, we aim to answer the following research question: ***How the technological affordances shape perceptions and scholarly practices?***

4.2 Method

As we wanted to gather in-depth knowledge of our participants' perceptions and experiences, we combined semi-structured in-depth interviews with the show and tell technique. Prior to the study, ethical clearance had been obtained from the institutional review boards: in Belgium by SMEC[23] and in Brazil by the Brazilian Ethics Committee[24].

23 Dossier number G-2019 09 1745.

24 CAAE number: 38406720.2.0000.5347

4.2.1 Participants

Participants were researchers who had prior experience with ASM. They were recruited through posts on social media (see Appendix 1. Call on social media) and via email to Graduate programs. We used our personal accounts on Facebook, Twitter and LinkedIn to share the recruitment form (see Appendix 2. Recruitment form), both in our profiles as well as in groups aimed for recruitment calls (such as ExperimentKUL in Belgium). A total of eleven participants (n=11) with diverse profiles were selected. For an overview of their characteristics, please see Table 4.1.

4.2.2 Procedure

Interviews occurred in April, 2020 (Europe/US) and February, 2021 (Brazil). Participants used their own computers to get as close as possible to their natural behaviour. Prior to the video-conference meeting (using Skype), participants received an Informed Consent via email that they signed in advance (see Appendix 3. Informed consent).

By interviewing participants we aimed to “dig deeper and search for critical comments” (Lazar et al., 2010, p. 179). We followed a script (see Appendix 5. Interview protocol) with 15 open questions to encourage reflection and consideration about the users’ meaning making processes, which includes (but is not limited to) their perceptions about possible impact of the algorithmic mediation in the participants’ practices.

To complement the self-reported data and to access the researchers’ practices, participants were invited to show and explain their use of the platform (a.k.a. Think Aloud protocol (Genise, 2002)). No tasks were given to the participants so they could freely navigate in the interface how they usually do. The meetings, including interview and show and tell, lasted 50-75 minutes.

4.2.3 Data analysis

The online data gathering process was recorded in audio and video (using OBS Studio), then transcribed and pseudonymized. We analysed the data using thematic analysis, recognizing its recursive nature, and “moving

ID	Gender	Years of Experience	Degree (complete)	Field	Position	Country	Freq. of ASM use
B	F	1-3	Master	Social Sciences	PhD Student	Belgium	Daily
C	F	13+	PhD	Engineering	Professor	US	Weekly
D	F	4-6	PhD	Engineering	Postdoc Researcher	Belgium	Weekly
E	F	4-6	Master	Humanities	Industry Researcher	The Netherlands	Weekly
F	F	1-3	Master	Social Sciences	PhD Student	The Netherlands	Weekly
G	F	1-3	Master	Humanities	PhD Student	Belgium	Daily
H	M	4-6	Master	Medicine	PhD Student	RS/Brazil	Daily
I	M	10-12	PhD	Social Sciences	Professor	AL/Brazil	Daily
J	F	4-6	PhD	Social Sciences	Industry Researcher	RS/Brazil	Monthly
K	F	1-3	Master	Social Sciences	PhD Student	RS/Brazil	Monthly
L	M	13+	PhD	Engineering	Professor	PB/Brazil	Weekly

Table 4.1 – Participants

back and forward between the entire data set" as needed throughout the phases (Braun & Clarke, 2006, p. 86). At the beginning of the transcription process, we got familiarised with the data and created initial open codes inductively, with two approaches. On the one hand, we identified what the participant was showing (e.g., "ask for publications to authors", "use ASM as a searching tool"). On the other hand, we created codes to represent how participants expressed their motivations and beliefs, disclosing why certain practices were meaningful or not (e.g., “it’s time consuming”, “system sends inputs based on user behaviour”). We associated the codes with specific expressions from the participants, using the software NVivo.

In further analysis phases, we organised the codes in convergent themes (i.e., “recommender system helps to find new ideas” and “recommendations are pleasant surprises” were gathered under the umbrella theme “expands exposure to content”). This was an iterative process in which the authors reviewed the themes, solving thematic issues, such as themes that were not the main goal of the study. For instance, some participants verbalised their ideas on how the system could work, which would be interesting for a design study meant to improve the platform, but this was not the case for our study. The themes resulting from this phase were discussed in a peer debriefing process, as quality criteria to validate the findings (Saldaña, 2013). The authors presented the preliminary findings in the form of main themes to two researchers from outside the pool of participants. These researchers had a background in Human-Computer Interaction: researcher one has a PhD and is Latin-American; researcher two has a Master Degree and is European. The authors presented the nodes to the researchers, who commented on them. This dynamic made the authors think about the results more thoroughly and reflect on the findings in more depth. This eventually challenged some of the preliminary themes and ultimately led to the decision to sharpen the relationships between themes. For example, the first visual representation of the results looked like a cycle where bigger nodes (more prominent themes in the interviews) were all connected with arrows. After the reflective exercise initiated in the peer debriefing, it was decided to remove the arrows because, even though for some participants the nodes were connected as if one could lead to the other, for other participants these nodes were completely separated. A few themes were also found to be convergent with broader themes which were already represented in the schema, such as “academic etiquette” and “serendipity”. “Academic etiquette” was integrated into the theme “to see and to be seen” - this theme denotes how researchers observe their peers through the platform to learn about their way of interacting with it. “Serendipity” was merged with the theme “Algorithmic impact on exposure to content”. The final set of themes from the interview results can be found in Figure 4.1.

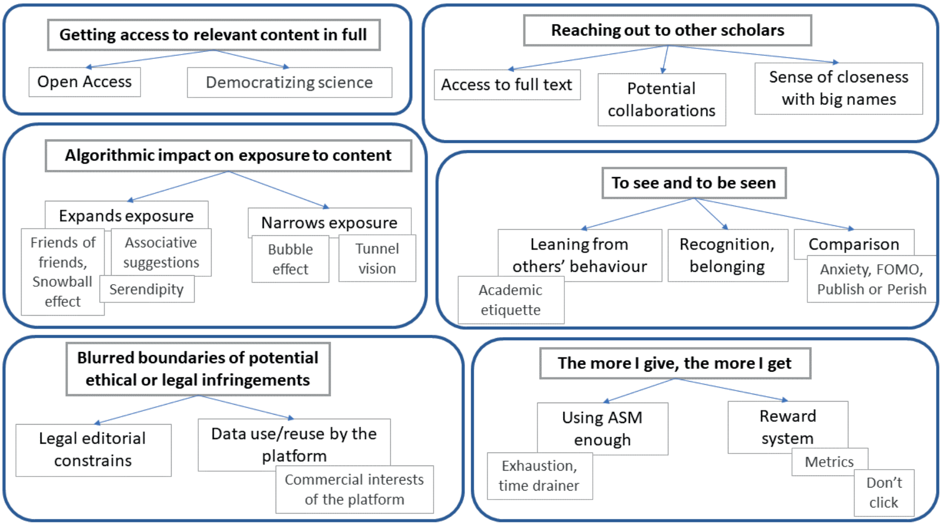


Figure 4.1 – Participant's perceptions on ASM affordances

4.3 Results

The data analysis phase resulted in six main themes that represent participant's perceptions on ASM affordances. The themes are "Getting access to relevant content", "Reaching out to other scholars", "Algorithmic impact on exposure to content", "To see and to be seen", "Blurred boundaries of potential ethical or legal infringements", and "The more I give, the more I get". See Figure 4.1 for the visualisation of the main themes.

4.3.1 Getting access to relevant content in full

The possibility to find the full text of publications, not only their metadata, is an important motivation for using ASM. They appreciate having access to content that would otherwise be behind paywalls and some attribute that to the "increasing focus on open access". For example, Participant E said: *"What*

I really like about Academia[.edu] is that, especially with the increased focus on open access, a lot of scholars are using the platforms to share their works, which usually would be behind a paywall".

Getting access to relevant content in full can be achieved by simply browsing in the feed, using the search tool and/or triggered by personalised emails with recommendations. The ASM platforms offer easy, quick and free access to scientific full-texts, and participants often compare them with institutional scientific repositories and online catalogues in the academic library.

4.3.2 Algorithmic impact on exposure to content

Recommendations are perceived as vectors that can expand or narrow the exposure to potential interesting content. These recommendations can be found behind labels such as "Related papers" in Academia.edu and "Related research" in ResearchGate. Participants had divergent opinions on this feature, but they all seemed to agree that algorithmic recommendations have some impact on what is presented to them.

Some participants focused on the **expansion** of exposure to interesting content. For example, Participant G said that the list of co-authors (recommended researchers via authorship) is interesting: *"For instance, over here, you also see the co-authors, then I think 'is this an interesting article? Do I already follow this person or not?' Because when they publish something on our topic that is closely related, I can broaden my scope with new people in this network"*. Other participants appreciated to see that recommendations are "more associative". *"And I love to use slightly wider fields than when you're just very specifically looking for any one particular paper"* (Participant E).

Contrarily, some participants believed that platforms are narrowing their exposure and that there is less serendipity in the content that is recommended to them: *"It also makes sure that you stay inside your bubble"* (Participant B). Participants were worried that they don't really get exposed to other researchers or other perspectives, because the recommendations are based on previous things that are on their profile. They mentioned

'tunnel vision' and **'being stuck in a bubble'**. *"There is obviously the concern that algorithms do promote a certain tunnel vision, both politically, socially and just interpersonally, it's still an external party that curates what you see"* (Participant E). In a similar sentiment, another participant stated:

> If you just look at the recommendations they send you, you can be stuck in a bubble, just see some kind of papers and don't see how the field is really publishing. This is not great, because you have these portals shaping how researchers see their field. And it will be a limited view of the field. (Participant H)

Some participants have shown concern about those **who are not in the platform** and the potential biassed view on the field this can cause when using ASM. For example, Participant G mentioned *"an extensive bias of certain people being subscribed and other people won't be"*. Similarly, Participant H shared this impression, saying that in multidisciplinary fields or topics, when the ASM platforms have more users from a specific background sharing their work, this will influence what other users see, which, in his opinion, can shape the field itself.

To counter the alleged exposure to limited content, some participants use a combination of platforms. For example, Participant B thinks ResearchGate recommendations are limited in comparison to Twitter:

> On ResearchGate I see only things from people that I'm actually following, while on Twitter, it's more also things from people that are followed by those I follow. That's how you more easily come to interesting content. Outside your own bubble, outside to people you're already following. By retweeting, Twitter enhances the exposure to content. (Participant B)

4.3.3 Blurred boundaries of potential ethical or legal infringements

The findings further pointed to the blurred boundaries between legal and illegal practices, and ethical and unethical behaviour in terms of concerns regarding both the platform's and users' practices within ASM platforms.

Regarding the platforms' practices, several participants uttered concerns about **the way platforms deal with people's data** and openly questioned how ethically platforms operate in this regard. Participant E said:

> Increasingly, over the years, I've become more skeptical about how certain platforms are run, especially in terms of production of your information and the way your information is used, if you are consenting to it being reused. I feel this obligation to really weigh to what extent platforms operate ethically, the way that they actually use your information, and also the way the algorithms work. (Participant E)

In this context, several participants also had their doubts about the intention of the platform owners. More specifically, they mentioned the monetizing system and potential biases that can emerge from the **commercial interests** of the platform owners. For example, Participant E said: *"All the information that you do feed into these platforms and in their algorithms, are not just obviously monetized, but also used for other purposes. And I do find that quite problematic"*. She didn't elaborate on what those purposes would be. Participant H, on the other hand, explained his concern with recommendations potentially designed to meet commercial interests and the lack of transparency on behalf of the platforms about it:

> When I mark a bell to receive results of my search on PubMed, I know what will come. Because I know how it was selected. But in Mendeley I don't know, ResearchGate either. This is a problem. I don't even know who the owner of ResearchGate is. Because if you own a social platform and you own journals, you can recommend your own journals on these platforms. And you shape the Impact Factor. (Participant H)

Regarding the user's practices, participants were preoccupied with **how they should behave** within ASM. The main concern seems to be the fear of trespassing ethical and legal rules. An example is the practice of authors sharing papers with other users through the platform. Even with specific features in the platform that allow this action, some participants were worried about legal constraints for editorial ownership.

> They also can ask you for a PDF if they don't have access. But that's something I don't really do. Because I don't always know if it's allowed or not, in terms of the regulations, depending on the journal. (Participant D)

Some participants were mindful about obeying the rules despite what the features in the platform afford them to do. Participant C said *"it is hard to know if I am doing the right thing in putting the papers up there"*. The first impressions of ASM platforms were that they are *"kind of scammy"* (Participant C) or looked like *"clickbait"* (Participant F). And it was uncertain whether other parts, such as the journal editors, would agree to sharing the papers in their profile. *"Sometimes I feel like, 'Am I allowed to put the papers up?' I'm like, do they care? I don't know"* (Participant C).

4.3.4 Reaching out to other scholars

When full texts are not available, some participants also appreciate being able to contact the authors to ask for the content in whatever format, that can be the published full text or a non-edited preprint. Contact between users is offered by several features, such as following or being followed by other profiles, sending messages and interacting with content shared by other researchers (by liking or recommending it). Reaching out to request full-texts was one of the most mentioned functions by participants. Participant L said *"Is very effective. [...] Recently I talked to a professor in South Africa, and he sent me his article. It was very, very important for our work"*.

Beyond being an added value to the findability of publications, the possibility of reaching out to other users is also valued because it gives the opportunity of connection between scholars. This seems to boost a **sense of higher proximity** between researchers, especially big names in the field.

> I feel social media made other scholars more accessible. For example, I follow these [...] really important professors and big names within the field. And I find it now very easy to just respond to something or comment on a project that they're doing, or maybe sometimes even send them a message for a paper, which I would never

> do in real life. If you think about [the time] before social media, it was much harder, I feel, to reach certain people like that. (Participant B)

Some participants reported **collaborations** that were initiated in ASM. They think some features are particularly relevant in such approaches, such as "send a message". Participant I reported that his last two collaborative work papers started from ResearchGate. *"A researcher approached [me] and sent me a message there, told me she was working in the same kind of research that I was in that period, and invited me to join her in her research. And we worked together and published together and it was fantastic"* (Participant I). For him, if they weren't both ASM users, this collaboration wouldn't have happened. *"Because she saw my research there, then asked me there, and invited me there"* (Participant I).

The possibility to contact researchers was valued for various reasons, from asking for full text publications to following influential scholars. In the participant's perception, collaborative work among researchers is also potentialized through ASM.

4.3.5 To see and to be seen

In ASM there's information available about the researchers themselves. For the participants, to be seen and followed is one of the main assets of ASM. This sense of recognition is especially important for certain profiles, like young researchers. Participant I said *"In our career it is so difficult to be seen, depending on your field and your country. And if you are an early career researcher, you have more difficulty to be seen and recognized"*. He thinks that ASM platforms have a special role in boosting his academic visibility: *"Because you're there. You put your research, your results, your output, and anyone can see and download it and ask for the paper"* (Participant I).

The visibility afforded by ASM has two perspectives. One refers to researchers letting their work be seen by others. The second perspective refers to the researchers themselves seeing their peers' work through the platform. In fact, for something to be visible, someone must see it. Participants found this observer perspective very interesting too. To see users' connections in the form of co-authors, who they follow and who follows them, seemed particularly relevant for the participants in terms of their academic **network expansion**.

> Through ResearchGate, I saw that some of my friends were related to other ones that I've not heard from before. And now I started building my own network by getting these suggestions. Like, Hey, you know this one or you know that one. (Participant G)

Algorithmic recommendations can also be presented behind labels such as "Who to Follow" on ResearchGate. Once following other researchers, these might influence other users by example. Participants claimed to have a better sense of the field by seeing how these relevant others interact with each other and act upon established practices. For instance, participants would follow the example of peers by observing their online behaviour. Apparently being active in ASM allows them to learn what are considered good practices in the field.

> I like the things I see on ResearchGate are from huge names, in all research fields, then you definitely take the things that they are doing in your own work, about the methodology, the way they reproduce findings, the way they make themselves visible on these platforms. (Participant G)

When researchers share their own achievements, it could be considered a performative act. However, **traces of online behaviour**, less intended to be visible, are left behind too, such as which publications a user liked or saved. These traces can be - and often are - actively interpreted by other researchers. Many participants said they observed their peers' interactions. Participant J stated that *"you can see what people are researching about [by] looking at it"*. Participant C said that her initial behaviour in ASM was posting the publications in the "private option" and if people asked her, she would send them the full text. But after seeing senior colleagues, highly respected in the community, acting differently, she began to rethink her posture:

> People that I really admire, very senior within our field, were just, like, 'Here's all the papers. Public'. Then I think 'maybe I should be doing that... I'm being naive here'. I should just put the papers out there, because the point is to get them read and cited. And I am kind of going by their way of interacting with it. They give it legitimacy. (Participant C)

Observing other researchers' practices can be inspiring, but can also bring **anxiety**. Participant B declared that when a colleague starts following a certain topic, she feels the urge to start following it as well. She believes it occurs because of the **Fear of Missing Out (FOMO)**. Seeing someone else's work getting attention usually appeared associated with the idea that the researcher is not doing enough, as was expressed by five participants (Participants B, C, E, F and J), including both more junior and senior scholars.

> To be completely honest, sometimes it makes me feel a bit anxious, because I see fellow PhD candidates uploading a lot of papers, and then I'm sitting here like, okay, I'm very impressed. I'm also very happy for them. But I have not published anything yet. So, it also gives me pressure sometimes. On the other hand, it also gives me this feeling of admiration, I want to be like that. It sets a bar. (Participant F)

The **comparison** between researchers seems inevitable, whether it is for inspiration and incentive to produce more or for feeling diminished. Participant E says *"seeing what your peers, your seniors, or even your juniors are up to in such a platform can foster both stress as well as competition. It is a constant reminder of what other people are doing, how productive they are"*. The comparison is not only about productivity, i.e. the number of publications, but also in terms of career path and achievements, i.e. who's got tenure or moved institutions. Also here, participants seemed to have a twofold trigger, both positive and negative. *"I notice a certain frustration in myself when I see people I did my Masters with having careers that are developing vastly quicker than mine. It does add a certain feeling of competition and striving for improvement"* (Participant E).

Such exposure puts pressure on the user to be productive and proactive in sharing within ASM, thus exhibiting **participatory behaviour**. Even if the user does not want or does not have the time to be so active on ASM, they still feel obliged to share content and engage with what is already there. Participant C says *"It's exhausting trying to keep up with these things. I could spend all my time trying to promote my work. Or I could do my work and hire someone to promote it"*. She points towards the pressure to promote one's own work in academia. *"There is that sense in academia that you are supposed to be out there, trying to get this international recognition"* (Participant C). And to some of the participants, adopting participatory behaviour feels like a burden.

> Social networks demand that you access it from time to time. Sometimes I forget to do it, and there's a lot of things happening. And you feel the responsibility of knowing what is happening, or what people are asking you, your notifications. Also, as a social network, you feel like "I have to interact, I have to answer it". I **have** to do this kind of stuff that people that don't like these social things a lot avoid doing. (Participant J)

4.3.6 The more I give, the more I get

Each interaction within ASM, from posting questions to acquiring followers, is traced and becomes a metric that is used for ranking and recommendations. Participants were aware of the implicit trade-off between the fact that they feed the system with data and that the system, in turn, sends them adapted content.

> I realised, from Mendeley and ResearchGate, they send you emails with interesting papers. They see a little bit of your profile, depending on what you fill in. And then they give some recommendations for you. The world of the papers is so big. And now and then you see new things popping up. And I really like it because they [are] searching for me. I don't like to start it all the time. (Participant D)

Participants see recommendations as a service, a helper that is "**searching for them**" and saving time so they don't need to start the search all over again. They also believe that the algorithmic mediation **depends partly on their own effort**. The participants feel that they can "teach" the system what is relevant for them by sharing data and using the platform extensively. The quality of what is recommended is, therefore, a shared responsibility among the platform and the user. Hence, according to the participants' perceptions, when the recommendations do not work properly or as expected, it is also partly the user's fault.

> If I would now start to follow more researchers in advertising, I would probably also get better recommendations based on that. But I don't use ResearchGate actively enough, I think. So the platform is probably a bit delayed, because the information I put in there is also delayed. I think it's something that depends on me as well. (Participant B)

Some participants showed great appreciation for receiving reports about how other users interact with what they post. The metrics available on ASM (e.g., "Stats" in ResearchGate, "Analytics" in Academia.edu) allow users to see who is visiting their profile, how many reads or citations their publications received, etc.. Participants explained that learning about their audience gives a **sense of reward**. For example, Participant I compared ASM with institutional repositories. He thinks the latter are boring because they are designed for the university, and not for the researchers themselves, since repositories do not provide notifications about the impact of the researcher's work (who is reading, how many downloads, etc.).

A participant shared a strategy to make sure **the reward granted by ASM metrics** is not given away recklessly. This researcher showed knowledge about how the metrics are created and how valued they are in a datafied environment.

> Sometimes when I read the title or the abstract, I'm not sure if it is good [material]. And I don't want to 'give a read' for this person. So I pick up the DOI to go to the base of the journal. Because we are living in a metrics time. You cannot give metrics all the time to everyone. (Participant I)

The language used by Participant I resembles either the financial environment, as if reads and likes were tradable goods or some sort of currency; or a game, in which "giving a read" is a move that benefits the opponent player. The 'work around' Participant I illustrated is a practice that actually circumvents the predefined built-in features in the system. Picking up the DOI number and refraining from reading the paper inside the platform can manipulate the number of views, which are used to build other metrics in the system, such as the RG Score on ResearchGate. In a way, the user is ensuring their peers don't get higher scores than him, even if the material will be read anyway - outside the platform, where the "read" will not be counted.

4.4 Discussion

This paper revolved around the question how users make sense of ASM platforms and how the technological affordances shape user perceptions and scholarly practices. In this section, we address this question by discussing issues of datafication and visibility/findability. We will argue that algorithms in ASM not only "construct and tell narratives about us" (Jacobsen, 2020, p. 1), but also shape people's encounters with others, rendering an algorithmically constructed image of the other that is participatory and productive.

4.4.1 Datafication and the participatory user

In our study, we found that participants valued having a platform searching for relevant content for them. Participants believe that, to receive appropriate recommendations, they should provide enough data to the system. The implicit message is: the more one invests in sharing, navigating and building a knowledge base within the platform, the better the personalisation will become. While acknowledging they need to engage in participatory behaviour, some participants shared their worries about potential misuse of their personal data by the platform. For the platforms, encouraging users to interact within the platform as much as possible and keeping track of these interactions is important so the user's online behaviour can be measured to enhance profiling.

How algorithmic mediation can reflect the interests of the service's sponsors appeared to be quite unsettling to some of the participants. The main concerns revolved around how much the recommendations are influenced by commercial interests. To offer the service for free to the users, platforms must support the interactions of dozens of millions of users every day, both with each other and with millions of documents, which requires a considerably expensive infrastructure. Some ASM platforms are owned by publishers and others rely on sponsored content from advertisers to support their business model. For advertisers, it is profitable to sponsor recommended content to users because, due to profiling, this content is statistically more likely to be relevant to the user: "using the built up user profile in online services, advertising networks can closely match advertising to potential customers" (Bozdag, 2013, p. 220). If the *'platform apparatus'* is responsible for defining "how connections are taking shape" (van Dijck & Poell, 2013, p. 8), depicting precisely how ethically the companies will be in designing recommendations can be quite difficult.

In a datafied environment, **participatory behaviour** is mandatory because the platform itself survives at the expense of content provided by the users (van Dijck et al., 2018). ASM platforms usually nudge researchers to keep their profile updated, upload their publications, interact with other researchers and invite potential new users to join the platform. Through messages such as "Your coauthor can help your publication to gain more visibility", ResearchGate wants to encourage current users to personally invite their colleagues to the platform, which increases the platforms' user numbers. This way the platform capitalises at the expense of existing relationships between researchers. Some participants find these constant "pokes" exhaustive and others simply do not appreciate the "social" aspect of it.

Due to datafication, users' interactions are notified across the network asynchronously. For example, when a user shares something, or when they follow someone, the users in their network (followers) receive notifications. But even when the users are offline and someone else interacts with their content, their network gets notifications about citations and recommendations received. Hence, the persistent recording and notifications of users' activities generates an **amplified impression of online presence**.

Data is also needed to build metrics in ASM. Some participants were not only aware that their own online behaviour was being registered, but they were also eager to learn about their audience's preferences through these tracking mechanisms. These participants showed appreciation for the analytic reports provided by the platform, referring to them as "rewards".

However, if users focus too much on the metrics, they might forget that there are many interactions that are not being recorded in the platforms. ASM platforms usually count reads, downloads and shares, actions considered part of the so called "active" use. This follows a logic that overlooks people from the scientific community **who are not in the platform**, "passive" users or even those who chose, intentionally and thoughtfully, to not click on content they spent time viewing (Ellison et al., 2020). In our study a participant reported he deliberately does not click on a publication even when interested in reading it, to avoid "giving a read" to the authors, something he considers a reward.

This practice shows a creative use that was not intended by design. It also shows how relevant it is to investigate algorithmic mediation in a comprehensive way (including the artefact, people's practices and social arrangements), since certain practices extend beyond what is considered default by design.

Datafied environments tend to reduce human behaviour to metrics formulated by the counting of interactions within the platform, and then using these metrics to select and rank content to users. It is important to stress that only a small portion of human behaviour can be objectively quantified.

4.4.2 Visibility/findability and the productive user

In our study we found that participants perceive ASM as tools that assist in various research practices. ASM users both consume and produce content through the algorithmic mediation of platforms. Thus, visibility can be discussed from two perspectives: of the reader and of the writer.

From the reader's perspective, the platforms offer publications in a personalised feed, tailored according to the user's preferences and past behaviour when they are in search of literature. When the researcher needs the full text of scientific papers, ASM platforms serve as a scientific repository. In the discussion about algorithmic impact on exposure to content, participants mentioned the agency of the platform. The platform makes decisions on behalf of the users in features such as “Related papers” on ResearchGate or “Related” on Academia.edu. These features list algorithmically chosen publications that the platform itself infer are relevant for readers. By doing so, the platform leaves out many other papers. The users can choose whether or not to read that content, but the universe of choice was already outlined by the algorithm.

While some participants see potential expansion on the exposure to content through ASM, others see more constraints in algorithmic mediation. Recommender algorithms are, by definition, filtering systems, that select and prioritise content, pointing towards certain documents (and not others) using predefined parameters, history, relevance inference, etc. (van Dijck et al., 2018). This means that while ASM platforms expand access to content via aggregated disposal of publications from different sources, a specific and individually tailored parcel of that universe is shown to each user in their feed, via algorithmic mediation. Therefore, the perceived amplification of the exposure to content, as well as the perceived tunnel vision are both true, reinforcing that affordances do not determine the outcome, but depend greatly on how users make sense of the technological features (Evans et al., 2017). Empirical research shows that “recommender systems expose users to a slightly narrowing set of items over time” (Nguyen et al., 2014, p. 677), even though the users that effectively consume the recommended items “experience lessened narrowing effects and rate items more positively”. In other words, while users are being exposed to fewer items, the convenience of seeing content that is mostly aligned to their preferences makes them less aware of the narrowing effect. This might be an attention point, as it attempts against individual **users’ autonomy and agency** (Koene et al., 2015; Milano et al., 2019). Many authors discussed how recommender systems can create biases in the distribution of content in social media (Bozdag, 2013; Nikolov et al., 2019; Pariser, 2011; Tufekci, 2019). **Serendipity** and **explainability** are some of the potential solutions to counter these biases.

Regarding the perspective of the writer, our study results show that the visibility afforded in ASM has its advantages and pitfalls for users. On the one hand, it can provide the sense of being seen and **recognized in the field**. Participants valued the visibility they can have in ASM, aligned with previous research (Lee et al., 2019). On the other hand, some participants were in doubt whether they would **commit legal infringements** by sharing freely a paper that is behind a paywall. Interested in gaining visibility, but uncertain about the legal and ethical norms, participants usually **watch their peers** to learn the best practices.

Observing their peers' profiles and interaction triggers a constant **comparison** that can both inspire and frustrate participants. In the user's feed, there is always new content, by someone that uploaded something or was cited, which gives the impression that colleagues and peers are highly productive and successful. While some participants use this information as a fuel to become more productive themselves, others feel anxious, stressed and experience FOMO, especially for daily users, because it is a constant reminder of how much the others are producing.

Those who suffer from the latter feelings might benefit from knowing that algorithmic mediated environments are likely to contribute to a popularity bias (Bozdag, 2013). In these platforms, the feed mainly shows publications that are already the point of attention of someone else, as the feed ranking is heavily based on algorithmic measures of relevance, such as popularity and similarity. For example, it is common to see a recommendation on the feed saying "Someone cited this publication". Once this information is ranked in the feed, users are more likely to interact with the content that was already liked by another user, making it even more appealing to the next user who sees it.

When focusing only on the merits of visibility, we disregard what is invisible in ASM. Platforms aggregate researchers from many countries, fields, seniority levels, etc. in the same environment, which might spark a sense of closeness and equality. However, the context in which these researchers work might differ greatly, influencing their productivity. For instance, many graduate students in developing countries have side jobs, devoting less time to scientific production than those with full funding, because they need to provide for their families. Moreover, people change topics, suffer from mental health issues, lose their relatives, and have children. Inequality in these contextual elements certainly affect the academic career. The problem with a comparative approach is that, although researchers are all on the same platform, using the same features and receiving the same "milestones" and scores, people are hardly comparable, let alone in a fair way. Thus what users see is shaped by specific factors chosen by the platform designers to form that perception. And these choices leave out many aspects of researcher's lives that are intertwined with their scientific outcomes but surpass meritocracy. In other words, how the algorithmic recommendation is built shapes how someone's work is seen, which might not represent people in their integrity.

The faith in recognition and rewards through social media is not a coincidence, it is designed. ASM designers cleverly use our biological reward system to make us feel connected to other people (Lembke, 2021). Believing in 'building your own reputation' by relying on social media metrics is a dangerous path, which requires attention for its drawback. If the logic is that all the likes, the high RG Score (which, according to ResearchGate "measures the researchers' reputation") and shares are something researchers earned, and therefore, deserve; then, when they do not receive likes and public recognition, or do not increase their "reputation metric", this is also something they deserve. Because they "are not doing enough" to get that reward, which implies that they are "at the bottom" because this is the place they deserve to be.

> The problem is, if you really believe in a society where those who merit to get to the top, get to the top, you'll also, by implication, and in a far more nasty way, believe in a society where those who deserve to get to the bottom, also get to the bottom and stay there. In other words, your position in life comes to seem not accidental, but merited and deserved. And that makes failure seem much more crushing (Botton, 2009, pt. 5'56").

This idea disregards several social, economic and political arrangements that interfere directly in academic performance. It is not only illegitimate, but also reductive, and excludent.

4.5 Conclusion

The use of ASM is increasingly intertwined with research practices and perceptions, mediating access to academic content, connections, and career opportunities. Our study aimed to understand how ASM affordances shape users' perceptions and scholarly practices.

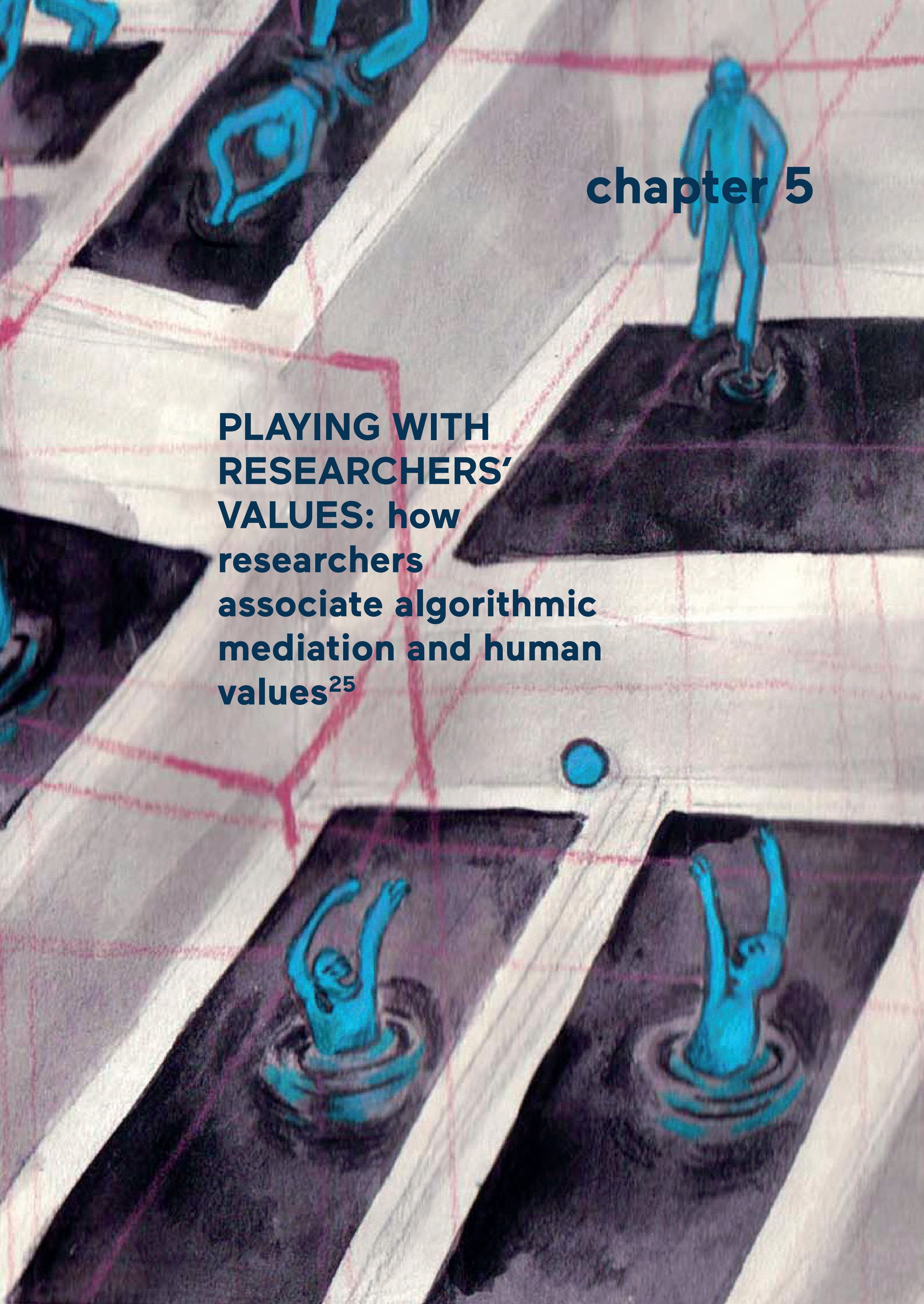
Datafied environments tend to foster participatory behaviour that can be exhausting for users. More algorithmic transparency can be beneficial to ensure recommendations attend the best interests of all parties involved. Datafication also gives the impression that the information displayed represents the objective truth. We should account for the many things that are not being calculated, such as people who are not on the platform or those who are, but knowing the 'rules', also game the system.

Addressing visibility/findability, we discussed the participants' twofold perception of algorithmic influence in expanding or narrowing down one's exposure to content, the fear of legal infringements and the comparison among peers that can promote anxiety and FOMO. We also discussed what is not visible, such as contextual inequalities.

We conclude that datafication and visibility algorithmically construct an image of the relevant other that is both participatory and productive. To acknowledge that the image of the other is algorithmically mediated could help to study and design platforms that portrait success from a more nuanced, gentle and kinder perspective.

chapter 5

PLAYING WITH RESEARCHERS' VALUES: how researchers associate algorithmic mediation and human values[25]



In science it is much complex if you consider 'discovering a truth' to be your goal. It is much easier if your objective is to 'finish the PhD'. Even more easy if your objective is to 'finish the paper' at hand or 'do today's lab work' by simply following the prescribed rules. To be able to follow the prescribed rules, one needs to distill methods that more or less guarantee verisimilitude in one's work. That is why there is so much buzz in science to refine and define its practices. Specialization in science can certainly be seen as a response to complexity. It helps compartmentalize information in a certain context. This compartmentalization can be compared with a game's magic circle. It defines the arena by marking its boundaries. It also helps define the goal. Scientists are then reduced to following the sub-goals (pursuing academic capital) under the illusion of it being the real goal. In other words, the gamification of science helps reduce stress and confusion, increases the desirability and the value of the work being done, gives clarity to the steps involved and motivates scientists to persevere. But it would be a mistake to understand this gamification to be an intentional process. In the spirit of Wittgenstein, the game of science emerges out of the practice of science, since you have to play it before you call it a game.

Baijayanta Roy, "In What Sense is Science – a Game" ([20--?], p. 25)

25 This chapter has been submitted to publication and at the time of this thesis submission it was under peer review.

5.1 Introduction

Throughout the previous chapters we investigated an ASM platform as an artefact (chapters 2 and 3) and the researchers' perceptions about algorithmic mediation (chapter 4). We wrote about the role of the platforms in recommending content to researchers and, how the platform communicates about recommender systems with its users, the different biases algorithmic mediation can reinforce and how technological affordances can shape people's perceptions and scholarly practices. In this chapter we look into how these practices happen in interactive academic situations.

Scholarly communication is fundamental for the exercise of science, since earlier scientific developments form the base on which contemporary researchers rely to create their own building blocks, which will, in turn, be used as a ladder to the advancement of knowledge by researchers to come. Sharing research results, in the form of publications, is so important that it has become a form of evaluation of academic performance, used in relation to individual researchers, research institutes, academic departments, universities, fields of knowledge and even countries. In the realm of the Open Science paradigm, sharing not only the results but also raw research data gained immense relevance for methodological transparency and as a form of justifying funding.

In the Harbingers research project, David Nicholas and his team found that early-career researchers hold great appreciation for the sharing culture. However, "they are concerned about sharing unpublished papers, interim results, data, and ideas because of competition and the possibility of people stealing information/ideas and making them their own" (Nicholas et al., 2020, p. 6). Due to the inherent competitiveness in the academic environment, it is understandable that researchers think carefully before making their assets public and accessible before the research is published. It seems that the ambition for credit, recognition, status and financial support leads to specific communicative strategies that are often shaped by the ways scientific capital is measured.

In digital environments, scholarly communication happens through multimodal systems involving different stakeholders, institutions, technologies and tasks. Researchers, who "write publications and act as reviewers" (Björk, 2007, p. 6), can also be readers or editors in other moments of the process. Not only different stakeholders take part on the scholarly communication processes (such as publishers, scientists, readers), but researchers themselves wear different hats during their careers on a wide range of activities that go way beyond research and publications, from teaching students to the application of scientific knowledge in practice (Björk, 2007, p. 43).

These dynamic scientific practices are surrounded and shaped by academic arrangements, such as incentives for research projects in collaboration, the competition for funding, the increased awareness of the Open Science paradigm and affordances of ASM platforms. Previous research has shown that the motivations for using ASM are various, among which contacting other researchers, disseminating research output and following other researchers' activities (Nández & Borrego, 2013).

Academic literature still needs to consider how people make sense of algorithmic recommendations in ASM platforms. In our research, we are interested in what are the human values that drive the communicative practices through ASM and how these are related to the specific recommendation features in the platform. Especifically, in this chapter our inquiry is led by the following research questions: ***How do researchers relate human values to algorithmic recommendation features in ASM platforms? How are collaboration and competitiveness reflected in people's choices in ASM platforms when performing different academic roles?***

Methodologically, we opted for using a creative method from Participatory Design in HCI to build a tailor-made serious game meant for research purposes. The design of the game envisioned providing us data to answer our research questions. By implementing game design elements in our research protocol, we also aimed to create a pleasant experience for the participants and ensure that all participants can have their say (Slegers et al., 2015).

We relied on the Serious Game Design Assessment Framework (SGDA) (Mitgutsch & Alvarado, 2012) to design the AMASS[26] research game. The SGDA framework creates a principled approach towards the design of a research game, considering its conceptual design, its elements, and how these elements are interwoven with the game's purpose. We designed a research game that emulates some recurrent situations in scholarly communication, where researchers interact with each other and are faced with challenges they need to overcome using ASM. The dynamic of the game mirrors an academic conference. The participants need to choose cards that represent their strategy to accomplish the given tasks and also present aloud their decisions. The data collected for analysis consists of both the card choices and the oral presentations. The building process of this game is explained in the next subsections. By presenting detailed explanations about the design decisions, we aim to comply with methodological transparency encouraging replication research as an Open Science practice. We believe this can be a valuable contribution to research on the topic of algorithmic mediation in ASM, in addition to the analysis of the results.

The data obtained from the game sessions were analysed separately for each research question. In this chapter, after fleshing out the game design, we first present how we analysed the data to answer the first research question, followed by the results of this analysis (section 5.4 Human values and recommendation strategies). Then, we present how we analysed the data to answer the second research question and the results of this analysis (section 5.5 Approaches and tasks). The discussion of the results (section 5.6 Discussion) and the conclusion closes the chapter (section 5.7 Conclusion).

26 AMASS research game is named after the research project Algorithmic Mediation in Academic Social Systems. To learn more about the project please visit: https://soc.kuleuven.be/mintlab/blog/project/amass/.

5.2 Research instrument: designing the AMASS research game using the SGDA Framework

The AMASS research game is the result of an iterative design process that took months of planning, development, prototyping and playtesting. While crafting its elements, we performed five physical pilots and one online pilot with Human-Computer Interaction designers, who provided feedback on the game elements and dynamics. The game's constituent components specified by the SGDA framework are: *Purpose*; *Mechanics*; *Content & information*; *Fiction and Narrative*; *Aesthetics & Graphics*; and *Framing*. The next subsections show how we created the game.

To facilitate the understanding of the following subsections, we briefly describe the game: players are given academic tasks and have to use cards to choose how they would solve them. From their cards, each player chooses an approach, one or two recommendation strategies and one or two values that motivate their decisions. The approach can be "collaborative", "competitive" or "ambivalent". Then, they each present their board to the other players, after which each player votes for the best presentation (players cannot vote for themselves and votes are secret). After four rounds, the player with the most votes wins the game. The recommendation strategy(ies) are chosen from a cards set based on the platform analysis (chapters 2 and 3) and a scholarly communication model (Björk, 2007). And the motivation cards represent human values, chosen from a cards set based on (Schwartz, 2010). The participants justify their choices aloud, seeking to earn "citations" (votes) from the other players and providing argumentation for their own votes.

5.2.1 Purpose

The purpose of a serious game is always twofold, as it encompasses both the aim of the players within the game, as well as the goal of the game designer (Mitgutsch & Alvarado, 2012), which in the case of a research game is the intended research goal.

The research goal of the AMASS research game is collecting data on how people relate human values to algorithmic recommendations and how collaboration and competitiveness are reflected in people's choices in ASM when performing different academic tasks.

The aim of the players during the experience is to present a plan of action to accomplish academic tasks related to scholarly communication in order to collect as many citations as possible. They do so by planning their actions through an ASM platform, and they need to choose a suitable approach, recommendation strategies and plausible motivations.

5.2.2 Mechanics

The game mechanics define what are the possibilities for players within the game, which are expressed by the rules. Besides the pivotal in-game aim of the players, the SGDA Framework also highlights the importance of "the operation of the reward system, the main playful obstacles/challenges, and the difficulty balancing and the win condition" (Mitgutsch & Alvarado, 2012, p. 124). The aim of players in the AMASS research game is to present their plan of action and collect as many citations as they can. The game is played in four rounds. Each round starts with players being challenged by a card (task card) to solve a certain academic situation. All players need to solve the same task, but are free to choose the strategy and motivations that they like. The task cards are read by the moderator. Players receive an individual board (see Figure 5.1) and cards they will choose from to build and defend a strategy to solve the task. Participants must choose an approach; a recommendation strategy and a motivation placing the chosen cards on their board (for more on the cards, see 5.2.3 Content & Information). The approach, which should be collaborative, competitive or ambivalent, was added in the presentation because we are interested in knowing whether participants see some activities as competitive, collaborative, or ambivalent, and why. We intentionally did not explain to the participants what we meant with these terms, and left it up to their interpretation.

In turns, the players are given the chance to present aloud their plan of action with the chosen approach and strategies, substantiating their choices with the motivation cards. They also need to explain why they believe the chosen approach is collaborative, competitive or ambivalent. After all the presentations, the players vote secretly for which strategy they think is the best to solve the task of the round. The players can not vote for themselves and must justify their votes. The voting process is made in a written private message to the moderator, who counts the votes. At the end of the round, each player receives a citation (represented by the book miniatures, see Figure 5.9) for each vote they had received. The game ends once all rounds (all four task cards) have been played. The participant who collects the largest number of citations at the end of the game wins the game.

5.2.3 Content & Information

This component of the game refers to "information, facts and data visible to the player" (Mitgutsch & Alvarado, 2012, p. 124). In order to provide information and awareness about recommender algorithms to participants, we designed cards whose content was inspired by previous studies. Information was provided in three forms: spoken, visual and written, as explained in the following paragraphs. The set-up of the physical game can be seen in Figure 5.2.

First, for the **spoken** content, the rules of the game were explained by the moderator before the activity began. These rules are detailed in the subsection 5.2.2 Mechanics.

Second, the content provided via **visual** elements gives structure to the phases of the game, as each one is used in different moments, organising the interactions among the participants. The game has three major visual elements. The *presentation* is an individual board on which the users can place their cards to assist the moment they defend their idea. The points are counted through *citations*, represented by book miniatures

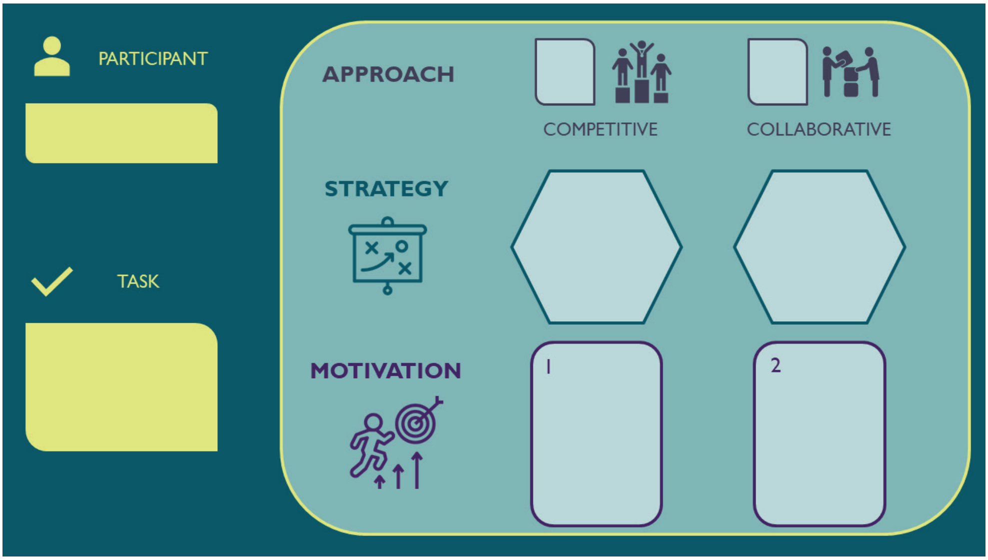


Figure 5.1 – Player's individual board (plan of action)

Figure 5.2 – Set-up of the physical game

placed on the participant's individual bookshelf. The *cards* are the most descriptive elements of the game, and their content is explained in the next paragraphs.

Third, **written** content is provided through the cards of the game that are divided in three sets: the **task cards**, the **recommendation strategy cards** and the **motivation cards**. Each set was built based on previous research, as follows:

- *Task cards*: Each task card contains different activities related to scholarly communication (such as "write a paper" and "select a journal to publish your work") and the role to be played by the researcher in performing these tasks (see Figure 5.3). For the content of these cards, we drew inspiration from the scientific practices described in the *"Model of Scientific Communication of a Global Distributed Information System"* (Björk, 2007). Because our research refers to algorithmic mediation in the digital environment we only selected tasks from this model that could be performed through academic social networking sites. The model provides a clear overview of how the actions that a researcher performs within the scientific process of conducting research are affected by contextual factors. These contextual factors can include previous or future research actions or the role that the researcher fulfils during different parts of the process (Björk, 2007, p. 6). To allow the participant to picture themselves in the situation of performing the task provided on the task cards, information about these contextual factors such as the role of the researcher when performing the task (see Figure 5.3, role), or the place of the task in the research process (see Figure 5.3, description) is provided on the task cards. Lastly, each task card contains a number, which, during analysis, allows the researcher to identify which task was being discussed by the participants. In total we designed four task cards[27] (see Figure 5.4). Ultimately, each task corresponds to

27 According to game pilots, more than four tasks would make the activity too tiring for the participants.

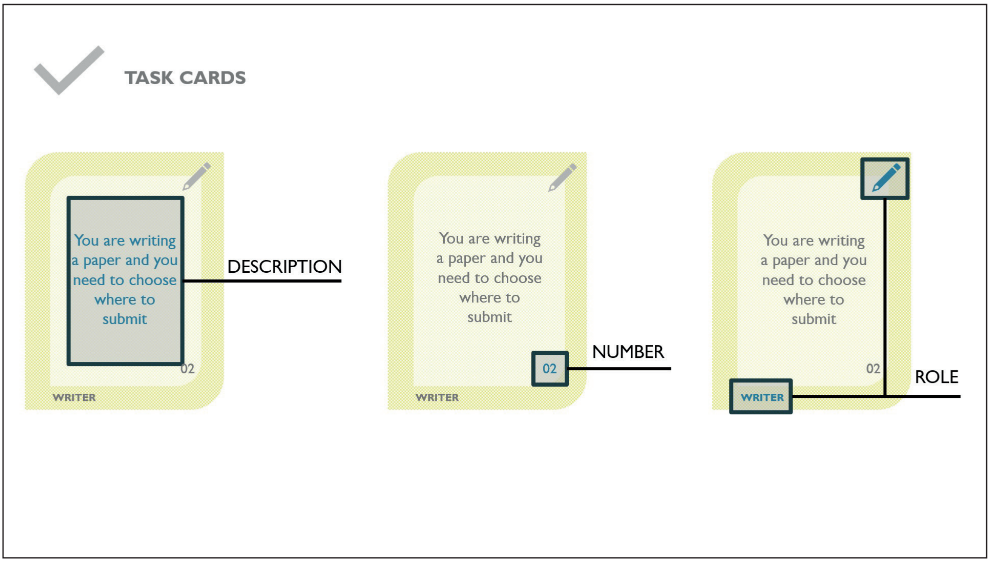


Figure 5.3 – Task cards explained

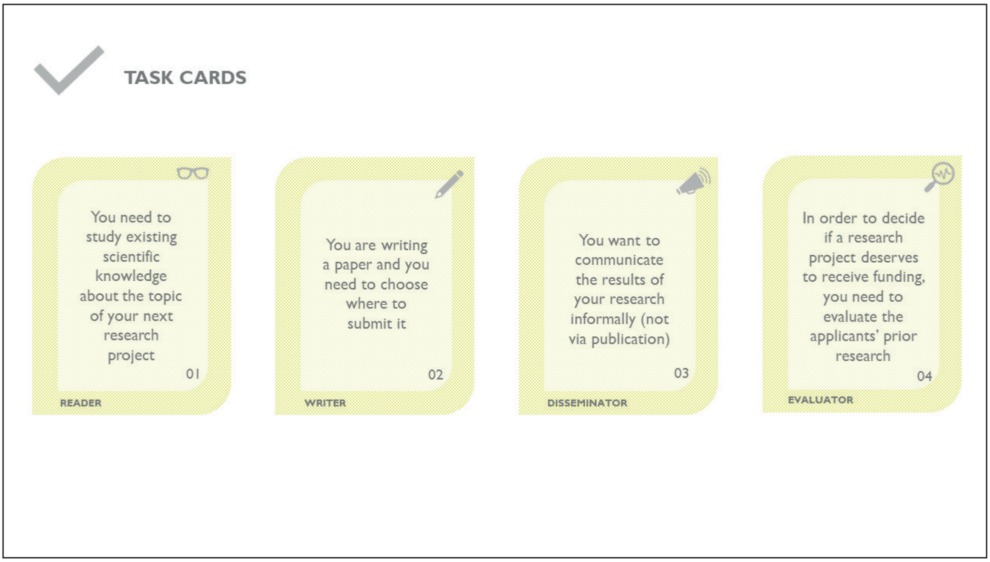


Figure 5.4 – Full set of Task cards

one role, task 1 being related to the "reader", task 2 referring to the "writer", task 3 referring to the "disseminator" and task 4 referring to the "evaluator".

- *Strategy cards:* the strategy cards (see Figure 5.5) refer to the recommendation processes used in many ASM (see Table 5.1) and serve to assist the participant in accomplishing the task presented on the task card. The entities used in the strategy cards were identified in previous studies, more specifically the platform analysis (Chapter 2 and 3). For example, the card "Matching authors" reflects content-based filtering involving the entities Researcher and Publication, whilst the card "Researchers I work with" reflects collaborative filtering and the entities Researcher and Institution. The entities from the platform analysis used to inspire these cards are highlighted in the figure (see Figure 5.5) with a rectangle.

Table 5.1 shows the strategy cards description and the entity, attribute, data type and technique used in each different recommendation strategy.

Figure 5.6 presents the full set of the strategy cards.

- *Motivation cards:* In order to understand which values our participants associate with algorithmic recommendations, we designed a total of 10 motivation cards, each motivation containing a human value and its respective definition (see Figure 5.8).We relied on the operationalization and categorization of values as identified by Schwartz (2010) because it is a thoroughly theoretically and empirically validated categorization that has been tested in 20 countries with great cultural variety. According to the author, values are "the vocabulary used to express the goals in social interaction" (Schwartz, 2010, p. 223). Theorists from both psychology and sociology "view values as the criteria people use to select and justify actions and to evaluate people (including the self) and events" (Schwartz, 1992, p. 1). Therefore, values motivate people's behaviour and are situated, meaning they acquire relative importance according to each specific situation. The definitions were provided to ensure that all participants would interpret the values in the same way (see Figure 5.7). Participants were asked to choose among the cards and place them according to a hierarchical order in each round. To see the full set of cards, see Figure 5.8.

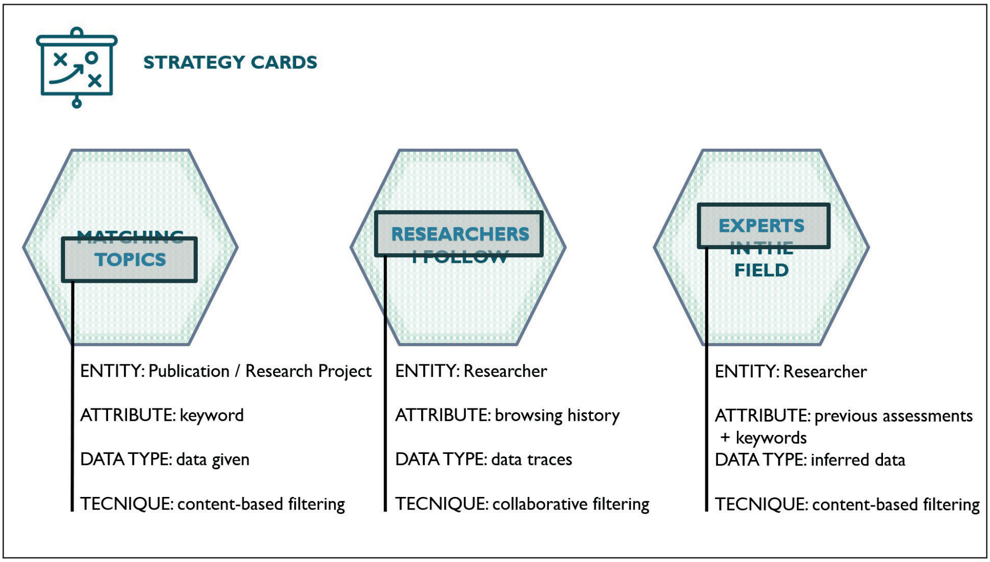


Figure 5.5 – Strategy cards explained

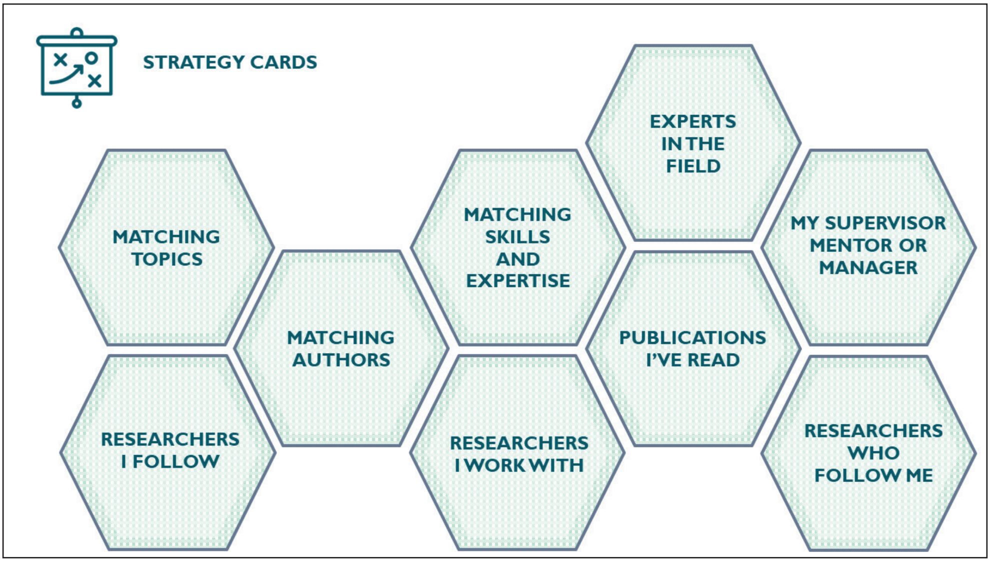


Figure 5.6 – Full set of strategy cards

Card description	Entity	Attribute	Data type	Technique
Matching topics	Publication / Research project	keywords	data given	content-based filtering
Researchers I follow	Researcher	browsing history	data traces	collaborative filtering
Matching authors	Researcher + Publication	name /author	data given	content-based filtering
Matching skills and expertise	Researcher	keywords	given data + inferred data	content-based filtering
Researchers I work with	Researcher + Institution	name	data given	content-based filtering
Experts in the field	Researcher	previous assessments + keywords	inferred data	content-based filtering
Publications I've read	Publication / Research Project	browsing history	data traces	content-based filtering
My supervisor mentor or manager	Researcher + Institution	name	data given	collaborative filtering
Researchers that follow me	Researcher	browsing history	data traces	collaborative filtering

Table 5.1 – Strategy cards and the elements used to create them

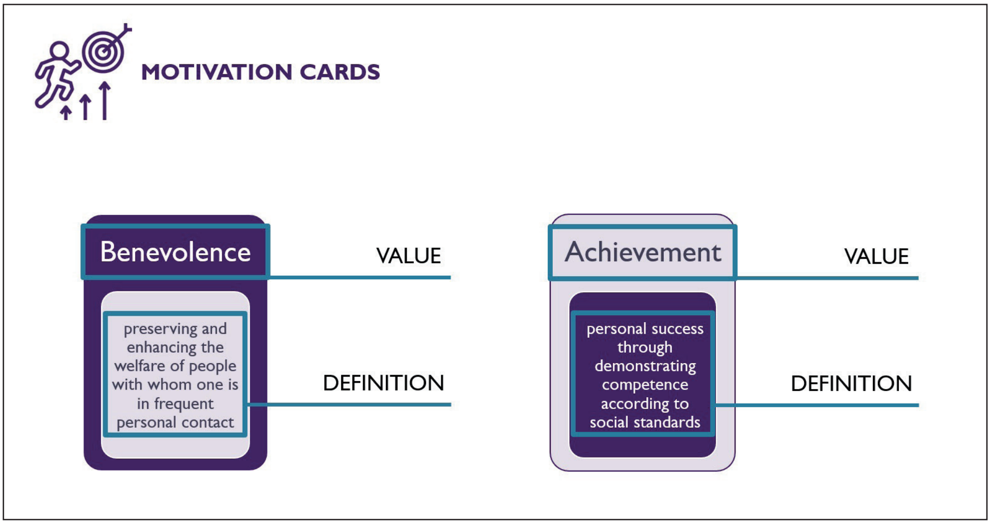


Figure 5.7 – Motivation cards explained

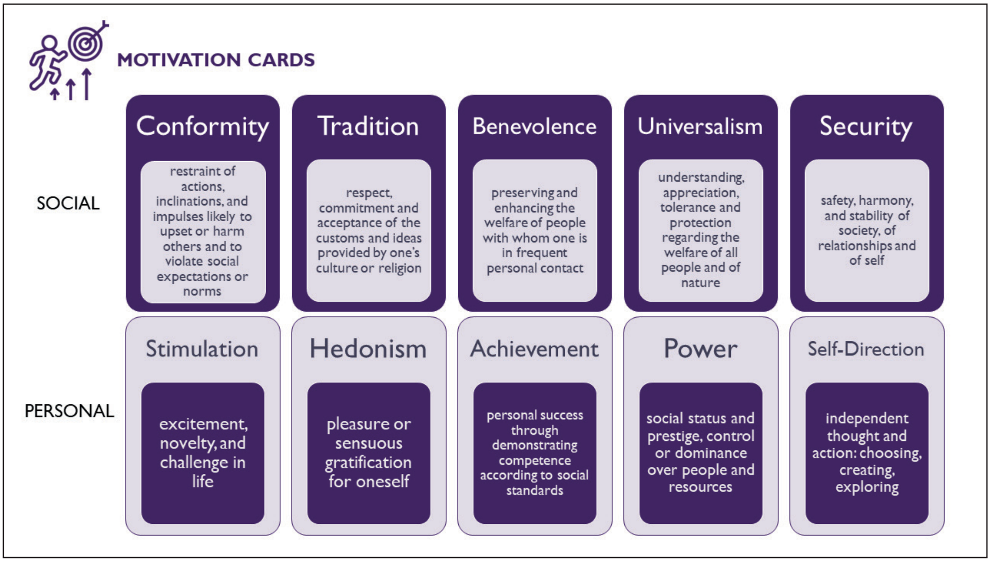


Figure 5.8 – Full set of motivation cards

5.2.4 Fiction & Narrative

The fictional context of a game refers to the "setting, narrative, story, scenario, characters, back story, problem, and so on for the game play" (Charsky, 2010, p. 192). In the AMASS research game, participants are researchers who impersonate different roles performed by researchers in real life (whether by writing and disseminating one's own publications, or reading and evaluating others' work). Players are challenged (task cards), come up with viable solutions (strategy cards) motivated by human values (motivation cards) and get rewarded (citations) by convincing their peers of the value of their ideas.

This dynamic was designed to resemble some real life academic interactions. The role on the task cards represent the different "hats" researchers need to wear during their academic path, and are to be considered by the participants while solving the tasks. Some of these roles are more common in "senior positions", such as assessing and choosing a research project to grant funding; whereas other roles are less linked to a specific position and are inherent to the researcher's daily activities, such as writing the results of a research project. All of these positions are inspired by Björk's Model, as explained in section 5.2.3 Content & Information (Björk, 2007).

Participants present their strategy to solve the task (strategy cards) and the motivation behind their choices (motivation cards). This presentation emulates scientific conferences, where researchers exhibit their ideas to solve research problems. Normally in these venues there is an opportunity for interactions, providing and receiving feedback to/from peers, and this moment is represented in the game by the voting phase, during which participants cast a vote for the best solution to the task, and explain why they believe that solution is the best.

Having achievements acknowledged by peers characterises the *scientific communities* (Kuhn, 1970) and also the *invisible colleges*, the "informal collectives of closely interacting scientists" (De Solla Price, 1963). Recognizing the quality and merit of researchers' work is commonly done through citations, which are considered a form of scientific reward (Merton, 1973). In the AMASS research game we replicate the scientific reward system by giving each participant a bookshelf, to which the player can add

Figure 5.9 – Bookshelf and reward books (citations)

Figure 5.10 – Colour palette 164925. Source: Color hunt

citations in the form of miniaturised physical books each time someone votes for their plan of action (see Figure 5.9). Citations are also widely used as “indicators of scientific activity” (Vanz & Caregnato, 2003, p. 248). They constitute the calculus in university rankings, journal quality assessments and researchers' reputation, including in ASM.

5.2.5 Aesthetics & Graphics

All the elements of the SGDA framework (the content, the fiction, the target group, the setting and the mechanics) are framed by formal aspects reflected in the aesthetic of the game (Mitgutsch & Alvarado, 2012). In our research game, we followed an elegant colour palette carefully put together by Color Hunt[28] (see Figure 5.10). Using cold tones (purple, blue-green, grey) and matte shades (not bright or somewhat juvenile shades), we aimed to reflect professionalism to be in line with the target group (framing) and the fact that the game resembles daily research practices (fiction and narrative).

Whilst keeping the “serious” colour palette, we appealed to playfulness with cute little books representing the citations. We hoped that this way, these reward elements could bring the experience to a joyful and mild place and alleviate the potentially stressful decision-making embedded in the game dynamics. The books and bookshelves are handmade using recycled material, which is less austere and dry than a score board.

5.2.6 Framing

In the SGDA Framework, framing includes the “target group, their play literacy and the broader topic of the game” (Mitgutsch & Alvarado, 2012, p. 126). The target group of the AMASS research game consists of researchers who are also ASM users. It is expected from these players to have

28 http://www.colorhunt.co

basic knowledge on how ASM platforms work (at the user level) and also to have experience with research practices. This prior knowledge is necessary to make sense of the task and strategy cards, which also connects with the play literacy. The literacy of the participants was considered in the recruitment for the study: through a form filled out by the participants, we chose those who had at least a completed Master's degree and were a user of at least one of the following ASM platforms: Academia.edu, ResearchGate or Mendeley.

The interactions within the game are designed to be relatively simple and familiar to researchers, as the play literacy needed to master the game is very basic compared to most casual games, such as board games. To keep participants engaged throughout the game, we established short time windows: each participant had 3 minutes to formulate their strategies, 2 minutes to express their solution aloud, 30 seconds to vote and 1 minute to justify their votes in writing. This dynamic was designed so they could exercise different cognitive activities: participants are challenged to creatively come up with a strategy (*solve*), to show a convincing narrative on how the strategy is aligned with human values and what is the best way to solve the task (*present*), to pay attention to the other participants' presentations and choose the best one (*vote*), and to highlight the strengths of their peers' solution (*justify*).

5.3 Procedure

Following the protocol approved by SMEC[29] and Brazilian Ethics Committee[30] participants were recruited through social media (Facebook, Twitter and LinkedIn). Four workshops were held in total, two in Belgium and two in Brazil, with three to four participants per workshop. The work-

29 Dossier number G-2019 09 1745.

30 CAAE number: 38406720.2.0000.5347

shops occurred online, using a video-conference software (Skype) and a whiteboard platform (Miro). The sessions were recorded in audio and video (OBS Studio). Following the games' balanced dynamic, it was possible to have around 3 hours of data collection with three to five participants per workshop, without tiring the participants too much.

The Informed Consent was sent in advance to the selected participants, who were given ample time to read and sign the document before the start of the activity (see Appendix 3. Informed consent). Before the meeting, the participants also received a video with instructions on how to access and use the game environment. The platform Miro[31] was used to accommodate the individual boards. In Miro, the participants were given access to the game elements (board, cards and rules) at least two days before the activity. To play the game the participants were using their own computers. The workshop consisted of two play sessions, with a short break in-between the sessions after about 45 minutes of gameplay. Once the second session had finished, the researcher thanked the participants for their time and debriefed them. After the data collection, we analysed the data in two different processes, one for each research question. We present these procedures separately and followed by its corresponding results in sections 5.4 and 5.5.

5.3.1 Participants

The participants were chosen using purposeful sampling. We did not aim for representativeness nor a balanced sample, even though the participants are varied in terms of background, years of experience, agen and nationalities (see Table 5.2).The players (n=13) were gathered in groups of three or four participants by their disciplines (two groups of social sciences and humanities, and two groups of engineering, exact and medical sciences). However, we did not analyse the data from these sessions separately: this division occurred solely to facilitate the communication among the players.

31 https://miro.com/

ID	Gender	Y.O. Experience	Field	Position	Age	Country	ASM used
SABE_P1	F	4-6	Social Sciences	PostDoc Researcher	18-30	Australia	ResearchGate, Mendeley
SABE_P2	M	4-6	Social Sciences	PostDoc Researcher	31-40	The Netherlands	Academia.edu, ResearchGate
SABE_P3	F	1-3	Social Sciences	PhD Student	18-30	Belgium	ResearchGate, Mendeley
SABE_P4	Non-binary	1-3	Social Sciences	PhD Student	18-30	Italy	Academia.edu, ResearchGate, Mendeley and other social media for academic purposes
SBBE_P1	F	7-9	Natural Sciences	PostDoc Researcher	31-40	Spain	ResearchGate, Mendeley
SBBE_P2	M	1-3	Engineering	PhD Student	18-30	Spain	Other social media for academic purposes
SBBE_P3	M	1-3	Engineering	PhD Student	18-30	Spain	Other social media for academic purposes
SABR_P1	F	4-6	Humanities	PostDoc Researcher	31-40	Brazil	Academia.edu, ResearchGate
SABR_P2	F	4-6	Social Sciences	PhD Student	31-40	Brazil	Academia.edu, ResearchGate and other social media for academic purposes
SABR_P3	M	4-6	Humanities	PhD Student	31-40	Brazil	Academia.edu, ResearchGate, Mendeley and other social media for academic purposes
SBBR_P1	F	4-6	Natural Sciences	PostDoc Researcher	31-40	Brazil	Academia.edu, ResearchGate, Mendeley
SBBR_P2	F	1-3	Medicine	PhD Student	41-50	Brazil	ResearchGate
SBBR_P3	M	4-6	Natural Sciences	PhD Student	18-30	Brazil	ResearchGate, Mendeley

Table 5.2 – Participants

5.4 Human values and recommendation strategies

To answer the research question "***How do researchers relate human values to algorithmic recommendation features in ASM platforms?***", we aggregated the associations all participants made between the strategy cards (algorithmic recommendations) and the motivation cards (human values). This analysis considers all participants from all sessions.

5.4.1 Data analysis on human values and recommendation strategies

We followed two main proceedings for this data analysis. First, we organised the quantitative data. We started by anonymizing and transcribing all participants' data (using MS Excel) including socio-demographic data (position, age, gender, etc.), social media data (which ASM platforms the participants use) and the game data (card choices made by the participants during the game sessions). The output of this step was tables with quantified associations between different sets of cards. For example, we quantified the amount of times someone chose a particular combination of cards, such as the strategy card "matching authors" and the motivation card "power". With the associations between **recommendation strategies** and **human values** mapped, we drew a data visualisation (Figure 5.11) in the form of a network using Miro[32]. In the visualisation, the line suggests the strength of the association: the more people chose that particular association between two cards, the thicker the line connecting the cards.

We opted for quantifying the cards choices as the first step due to the large number of possible combinations of cards. As Figure 5.11 shows, all cards were chosen by the participants during the workshops. Since there

32 http://miro.com/

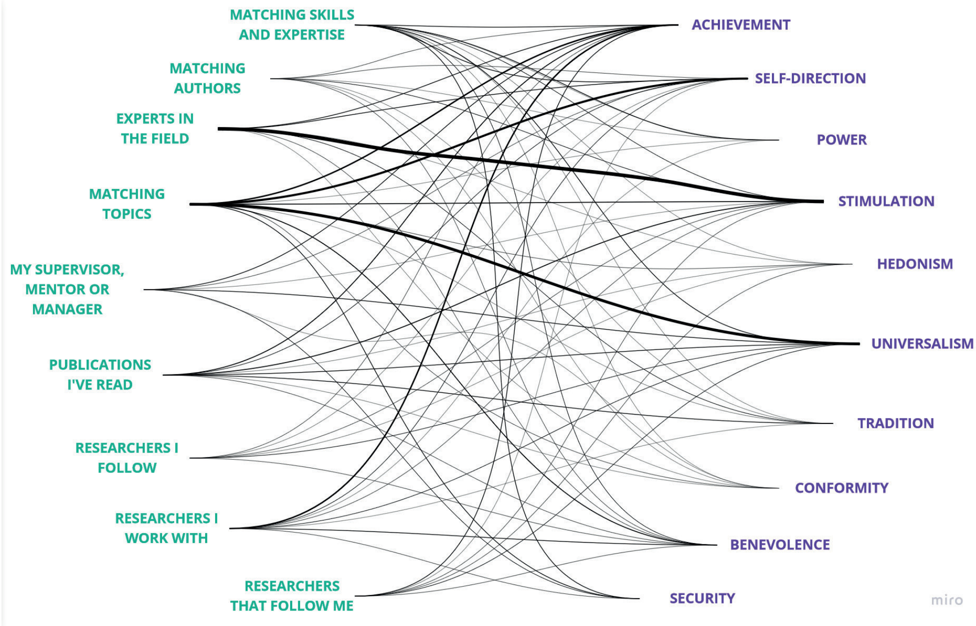


Figure 5.11 – Human values X Recommendation Strategies

are 10 cards of human values, and 9 cards of recommendation strategies, describing all the potential associations would represent the qualitative analysis of people's justification for 90 associations, which would not be possible due to time constraints. Also, because all card combinations were possible, describing all of them would mean to explain more our decisions as designers of the cards then representing what the participants actually chose. Our decisions as game designers were already fleshed out in subsection 5.2.3, whereas the most frequent card associations made by the participants' are more relevant to our research question. Therefore, we continued with a subsequent, qualitative data analysis with the three most frequent associations made by the participants.

Second, we performed a thematic analysis (Braun & Clarke, 2006) with the qualitative data from the game. We began by separating the transcriptions of the participants' presentations per session, participant and per round of the game, i.e. we had the excerpt of what participant X said during their presentation of task Y on session Z. Then, we created metadata to label these excerpts (in NVivo) with the card combinations the excerpts were referring to. This description allowed us to query the dataset in order to gather all the excerpts that referred to a certain combination of cards. Using the example given in step one, we could gather all the excerpts where participants explained why they chose the cards "matching authors" and "power". We then focused on the three strongest associations to gain a deeper understanding of participants' motivations for choosing these combinations. Regarding the combinations between **human values** and **recommendation strategies**, the three strongest combinations are: "experts in the field" and "stimulation" (n=9); "matching topics" and "universalism" (n=8); and "matching topics" and "self-direction" (n=7). We examined the corresponding sets of excerpts which contained one of these three combinations. After reading the excerpts, we created inductive open codes representing the participants' reasons for choosing the card combinations, such as "challenge the status quo" and "keywords help scan literature". We then went back and forward through the sets of excerpts to find patterns among the participants' reasonings. We concluded the thematic analysis by organising the codes around meaningful themes, such as "fair and egalitarian science" and "desire to overcome the experts".

5.4.2 Findings on human values and recommendation strategies

The results of the data analysis encompasses three associations ("stimulation" and "experts in the field"; "universalism" and "matching topics"; and "self-direction" and "matching topics") and five reasons why people make these associations (respect and admiration for the experts; desire to become better than the experts; creating positive impact in society; fair/egalitarian academic environment; and independent thought).

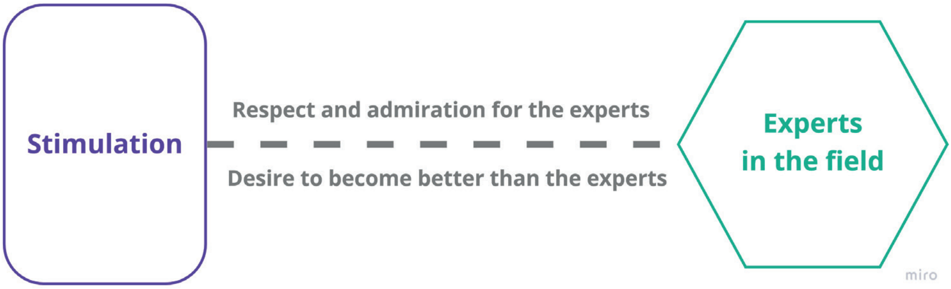


Figure 5.12 – Stimulation and Experts in the field

5.4.2.1 Stimulation with Experts in the field

Our findings showed that participants find it exciting to be able to count on experts in the field for two main reasons. The first one is the respect and admiration they nurture for these experts, meaning that they find it fruitful to look up the main references to either learn from them or to be looked at by them. Participant SBBE_P3 said *"I think many times you want to reach experts in the field or maybe not in the whole field, but at least in the particular topic you are looking at in your papers. You really want to reach these people that are looking into similar things and that you kind of admire in a sense, you know? The motivation behind trying this strategy is stimulation"*. Still in the sense of admiration, Participant SBBR-P1 claimed *"If you don't have the matching skills and the expertise, I think you should mirror yourself to the experts in the field. So you can get those expertise that you don't have or you want to improve"*.

The second motive shows a desire to become better than the experts, not mirroring them, but rather distinguishing themselves from those perceived as authorities in the field. Participant SABR_P2 said: *"Usually, I have a little more of a competitive look at the experts in the field. So I look at the experts and see what they're doing, how they're doing. And then I start to look at what they are not doing"*. Participants feel stimulated by the challenge of working with something new and finding problems to work on what other researchers did not solve yet. Figure 5.12 represents the association between stimulation and experts in the field.

Figure 5.13 – Universalism and Matching topics

5.4.2.2 Universalism with Matching topics

Participants expressed two main reasons for choosing the association between "universalism" and "matching topics". One reason was to achieve a <u>positive impact in the real world</u> through research. Participants that referred to the "greater good" science can bring to society wanted to make sure the topics they were addressing would serve the broader public. Participant SABE_P3 mentioned the importance of thinking about the audience when sharing one's research results via ASM: *"Where do I want this research to end up? Who are the people that I want reading this research? How can I best help?"*. The participants further explained that it is important to be able to connect, through the relevant research topic, with groups from outside academia (society in general). Some participants mentioned the Open Science paradigm as a way to achieve this connection and participant SBBE_P1 referred to the taxpayers as those to whom researchers should ultimately report to.

A second reason for associating "universalism" with "matching topics" was the need for a <u>fair or egalitarian science</u>. Some participants said to pay special attention to less privileged groups, such as minorities, and to prefer research practices that include these marginalised groups within academia. For instance, Participant SABE_P2 referred to the need *"to seek out who is not being cited, who's being marginalised in the literature."* This participant further said to deliberately consider who to collaborate with in an attempt to *"kind of magnify beyond these usually small circles of people*

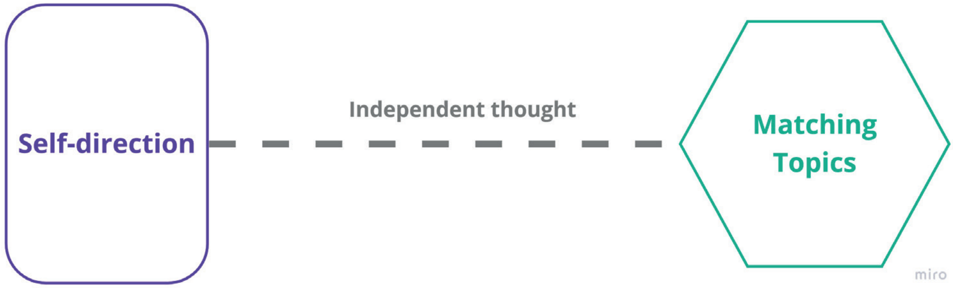


Figure 5.14 – Self-direction and Matching topics

that have been doing the same research on that same topic for the past 20 years probably." It seems that these participants use ASM platforms also to look for literature that is less known and to find authorship blind spots. Thus, researchers motivated by "universalism" prefer recommendations based on "matching topics" in ASM in the hope to positively impact both academia and civil society. Figure 5.13 represents the association between universalism and matching topics.

5.4.2.3 Self-direction with Matching topics

Participants who chose "self-direction" and "matching topics" value independent thought, whether for exploring literature in the beginning of a research project, or to disseminate one's work, or even for deciding where funding should go to. According to Participant SBBE_P1, *"You want to make your decision in an independent way. You want to make sure that what you decide is based on freedom, and that you are not pressured and you just want to choose the best candidate for that money to go to"*. In their presentations, participants showed appreciation for autonomy. For them, matching topics is an organised and somewhat objective way to perform the tasks without interference. Participant SBBE_P1 said: *"When I'm drafting a new project or a new research, my motivation is self-direction, definitely, because literature review is something that should be done in a very organised way. And just by yourself"*. Figure 5.14 represents the association between self-direction and matching topics.

5.5 Approaches and tasks

When participants presented their plans to action, they often justified choosing an approach based on the type of task rather than the recommendation strategies or the human values that motivated their choices. To answer the research question "***How are collaboration and competitiveness reflected in people's choices in ASM platforms when performing different academic roles?"***, we looked at the possible approaches (collaborative, competitive or ambivalent) and observed in which tasks (1, 2, 3 or 4) these approaches appeared more often.

5.5.1 Data analysis on approaches and tasks: building the archetypal profiles

The collaborative approach was the most popular approach among all the tasks, which could overshadow the other alternatives. Therefore, we decided to examine in detail the specific subsets of participants' plans to action according to the approach and task. Looking more closely at the subsets of plans to action, it is possible to explore some relevant but less popular preferences, such as the competitive and the ambivalent approaches.

We also observed that some approaches were more common in certain tasks, as shown in the matrix of the tasks and approaches chosen by the participants below (Table 5.3). Participants who chose the collaborative approach mainly did so in tasks 1 (reader) and 3 (disseminator). Participants chose the competitive approach most frequently in task 2 (writer). For the ambivalent approach, the higher number appears in task 4 (evaluator).

We also were able to visualise how the choice of approach impacts the rest of that participant's choices, such as the values and recommendation strategies. As a result of this analysis we describe archetypal profiles for each task, which were defined by applying the following protocol.

	Collaborative	Ambivalent	Competitive
Task 1 - Reader	11	1	1
Task 2 - Writer	6	3	4
Task 3 - Disseminator	10	2	1
Task 4 - Evaluator	6	5	2

Table 5.3 – Number of plans to action per task and approach

First, we filtered the participants' plans to action according to the approach and task choices (using a spreadsheet in MS Excel). This filtering resulted in four subsets of plans to action (task 1 - collaborative; task 2 - competitive; task 3 - collaborative and task 4 - ambivalent). Each subset was formed by all the plans to action that corresponded to the approach and task choices mentioned above, e.g. plans to action where participants chose collaborative approach for task 1, plans to action where participants chose competitive approach for task 2, etc.. In the spreadsheet, each plan to action contained the participant's socio-demographic information and the cards the participant chose for that task.

Second, we counted the participants' choices in the plans to action subsets and registered the most frequent choices in terms of the cards (i.e. recommendation strategies and values).

Third, we analysed the participant's socio-demographic characteristics (such as position and years of experience) in relation to the approach they chose in order to decide which characteristics should go to the final archetypal profiles. In this case, we isolated the plans to action by salient characteristics forming groups (PhD students *versus* PostDoc researchers; People from Engineering and Medical Sciences *versus* Social Sciences and Humanities, etc.). Because some groups were slightly smaller than the others in the sample, using the simple majority could bias the results, so we compared the percentage of a particular characteristic within each group with the percentage in total (including all participants). If the percentage of the group was at least 10% higher than the percentage in total, we considered the characteristic as relevant for the archetypal profile (see Table 5.4).

Variable	Subgroup	Plans to action	Collaborative		Competitive		Ambivalent	
General	All players	52	33	63%	8	15%	11	21%
Domain/Field	Engineering and Medical Sciences	24	14	58%	6	**25%**	4	17%
	Social Sciences and Humanities	28	19	68%	2	7%	7	25%
Position	PostDoc Researcher	20	11	55%	5	**25%**	4	20%
	PhD Student	32	22	69%	3	9%	7	22%
Experience	1-3 y.o. experience	20	15	**75%**	2	10%	3	15%
	4-6 y.o. experience	28	16	57%	4	14%	8	**29%**
	7-9 y.o. experience	4	2	50%	2	50%	0	0%

Table 5.4 – Characteristics by approach (collaborative, competitive, ambivalent)

This analysis showed that some characteristics are notably different depending on the choice of approach, which was useful to know which characteristics were relevant to integrate the archetypal profile. The domain / field of expertise is quite remarkable in this sense. Researchers from Engineering and Medical Sciences chose the competitive approach 3,5 times more than researchers from Social Sciences and Humanities. Similarly, the position seems to have a big impact in the approach choice. PostDoc researchers choose the competitive approach 25% of the moves, which represents almost 3 times more than the PhD students (9%). Gender and continent did not show significant differences in relation to the total of all players.

Considering all tasks, the collaborative approach is the most frequent, followed by the ambivalent approach. The competitive approach is the least chosen approach. However, when splitting the plans to action by profile characteristics, we see archetypal characteristics of people who choose the different approaches. We can see that people who choose the collaborative approach are, archetypically, from Social Sciences and Hu-

Task-Role	Approach	Recommendation strategies	Human Values	Characteristics
1. Reader	Collaborative (n=11)	- Matching topics - Experts in the field	- Stimulation - Self-direction	PhD student on Social Sciences and Humanities, 1-3 years of experience, User of general social media and ResearchGate
2. Writer	Competitive (n=4)	- Matching topics - My supervisor mentor or manager	- Achievement - Stimulation	PostDoc researcher on Engineering or Natural Sciences, 4-6 years of experience, User of Other ASM (such as Twitter)
3. Disseminator	Collaborative (n=10)	- Researchers who follow me - Matching topics	- Achievement - Universalism	PhD student, 4-6 years of experience, User of general social media and ASM (ResearchGate and Mendeley)
4. Evaluator	Ambivalent (n=5)	- Matching skills and expertise - Publications I've read	- Stimulation - Benevolence	PostDoc researcher on Social Sciences and Humanities, 4-6 years of experience, User of general social media and ASM (Academia. edu, ResearchGate and Mendeley)

Table 5.5 – Archetypal profiles by task and approach

manities, PhD Students, with 1-3 years of experience. The competitive approach is chosen prototypically by researchers from Engineering and Medical Sciences, in a PostDoc position, with 7-9 years of experience. The ambivalent profile usually is situated within the domains of Social Sciences or Humanities, and is a "final-stage" PhD student with 4-6 years of experience.

These discoveries were particularly relevant in building the profiles whenever a tie occurred (same number of people with different characteristics). In those cases, we used one of the previously verified relevant characteristics as a tiebreaker. For example, in the case of people who chose a collaborative approach for task 1, there was a tie in the experience time characteristic, as there were the same number of people with 1-3 years of experience and people with 4-6 years of experience. Since we know position is a relevant variable, we selected the PhD students, and the time of experience from this subgroup (task 1, collaborative approach, PhD student) was used in the ultimate profile: 1-3 years of experience.

The analysis of all the profiling characteristics with the cards choices resulted in four archetypal profiles, representing which choices people would make depending on the task and the preferred approach (see Table 5.5 in section 5.5.2 Findings on approaches and tasks). The archetypal profiles are called: the collaborative reader, the competitive writer, the collaborative disseminator and the ambivalent evaluator.

5.5.2 Findings on approaches and tasks

We examined the ways researchers approach different academic tasks through ASM. We found that, even though the collaborative approach was preferred in the majority of the plans of action, the participants engaged more frequently with the competitive and the ambivalent approaches in certain specific tasks. Participants tend to be more competitive when looking for journals and venues to publish their papers, whilst the ambivalent approach (both competitive and collaborative) appears more often when the participants are evaluating other researchers' work. We also produced four archetypal profiles with the choices and characteristics more frequent in each task: the collaborative reader, the competitive writer, the collaborative disseminator and the ambivalent evaluator. Each archetypal profile has a different set of choices and characteristics, which are a result from filtering the participant's choices per approach and task, as explained in the previous section. Table 5.5 shows the four profiles and their corresponding characteristics. In the following paragraphs we detail each profile illustrating these choices with quotes from the participants.

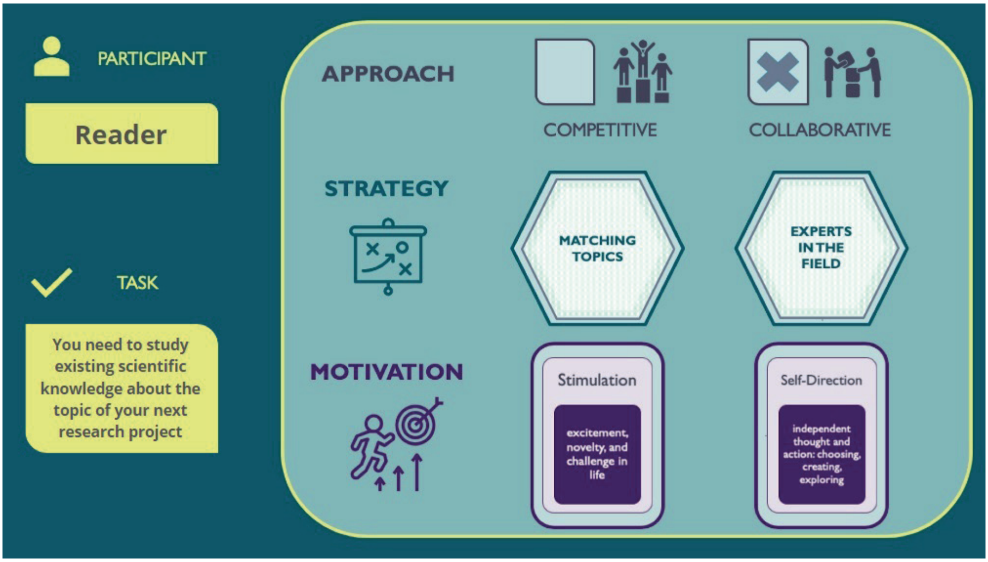


Figure 5.15 – Profile "collaborative reader"

5.5.2.1 The collaborative reader

The profile **Collaborative reader** (see Figure 5.15) is based on the first task presented to participants: "You need to study existing scientific knowledge about the topic of your next research project". The collaborative approach was the archetypal choice for this task. Participant SABE_P4 explained that in their career stage (initial phase of a PhD) receiving help from others is crucial: *"I decided on a collaborative approach in the process of reading and tried to think how to find new ways to move forward in a certain field. This approach would be better than a competitive one. And it's kind of the situation in which I'm in now, in the in the initial phase of my PhD, where I don't have enough expertise, enough skills, to say that I'm better than other people, or I can move forward the field by myself, I have to collaborate necessarily with others, and still learn a lot from from other people."* Participant SBBE_P3 referred to collaboration in a more abstract sense, not a direct collaboration with people around him, but a more broad and universal knowledge building: *"I selected a collaborative approach because I think the most important thing in reading is to build up on other people's work and learn from them"*.

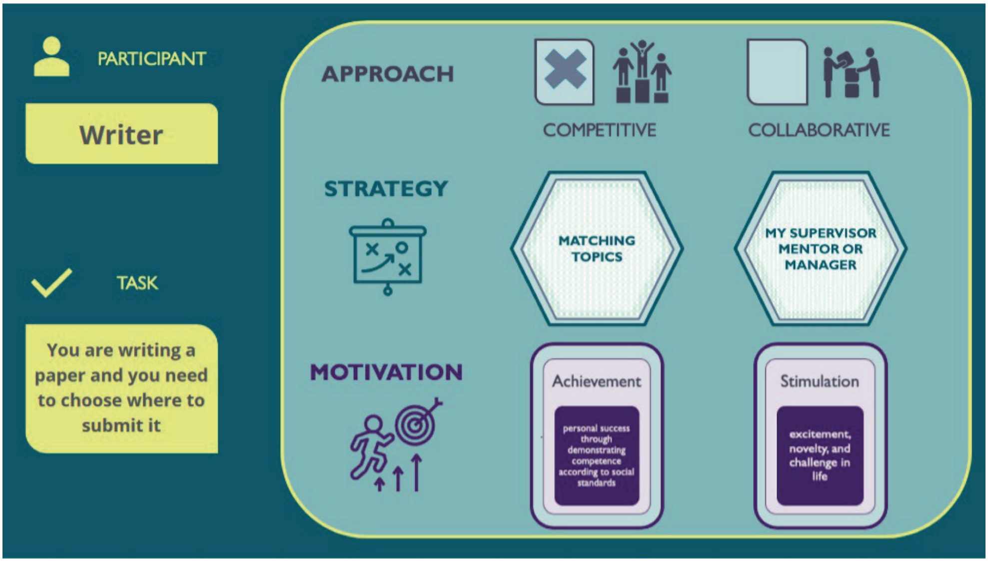


Figure 5.16 – Profile "competitive writer"

The Reader normally chooses "matching topics" and "experts in the field" as recommendation strategies. These recommendation strategies belong to different types of recommendation, the first one content-based filtering and the second one collaborative filtering. The choices regarding recommendation features in this profile reflect the topic exploration through keywords search in ASM while, at the same time, following the lead of the experts to find relevant scientific content in the field.

As for the human values, participants chose "stimulation" and "self-direction". These values, according to Schwartz's model of human values, have a personal focus, which is aligned with the nature of the task (looking for literature for one's own future research project). Participants with this profile refer to the excitement and novelty in this phase of the research while also appreciating some level of freedom to explore new topics. The choices of the Reader profile coincide with two of the main associations made in the first analysis, namely "experts in the field" with "stimulation" and "matching topics" with "self-direction" (see 5.4.2 Findings on human values and recommendation strategies).

5.5.2.2 The competitive writer

The profile **Competitive writer** (see Figure 5.16) refers to task number 2, which was described as follows in the game's card: "You are writing a paper and you need to choose where to submit it". This task received the highest number of competitive approaches during the game. To justify the choice for a competitive approach in this task, SBBR_P1 said: *"For this task I took the competitive approach, because I'm looking for somewhere to publish my material, my findings. So I need to be competitive because we are in academia. So we all know that we need to be competitive, at least in my field. So you have to publish. And you have to publish in good papers, in good magazines and in good places. So I want to be very competitive"*. Participant SBBE_P3 refers to a competition that is not necessarily against others but against oneself to "survive" in academia: *"I selected a competitive approach, although I would like something more like survivorship or something like that, because I think publication is the worst kind of competition. Not because you compete against others, but you many times compete for yourself and your existence in academia"*.

Participants who chose the competitive approach for task 2 prototypically chose the following recommendation strategies: "my supervisor, mentor or manager" and "matching topics". These strategies belong to different types of recommendation, similar to the recommendation strategies on the Reader profile: "my supervisor, mentor or manager" is considered as collaborative filtering and "matching topics" as content-based filtering. Although the strategy types are the same as the ones adopted by the Reader profile, this time the participants seem to look for more personalised guidance. Not from the experts in the field but from researchers that know them personally (supervisor, mentor or manager) and are familiar with their research topic. This makes sense for recommending the right venues or journals, since there has to be a good match to succeed in publishing. Participant SABE_P1 said: "*In terms of strategy for choosing a place to publish, I would first turn to my supervisor, mentor or manager, whoever we want to talk about. Because I think that often more experienced academics just know the field better, know which journals are options, what they publish, and what would be a good match for a particular paper"*.

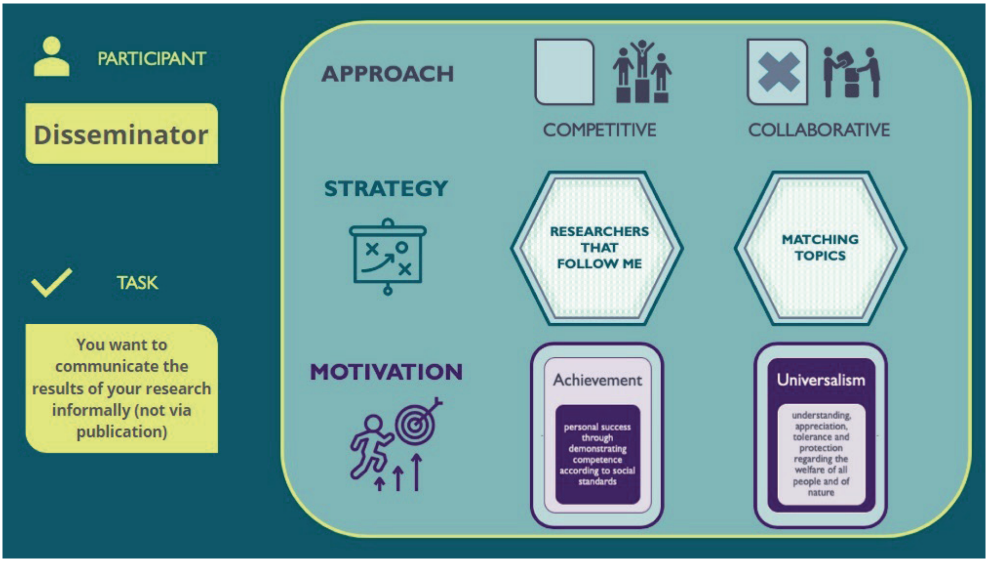


Figure 5.17 – Profile "collaborative disseminator"

Regarding the human values in Writer profile, "achievement" and "stimulation" are prominent, both with personal focus. Participants mentioned these values because of the potential benefits to one's career and the satisfaction that one can get from publishing: "*My motivation is personal achievement, because I want to get published, to get people to cite my work, people to see my work. And I also want this to be a stimulus not only for me, but also for everyone in the field*" (SBBR_P1).

5.5.2.3 The collaborative disseminator

The profile **Collaborative disseminator** profile (see Figure 5.17) refers to task 3 of the game: "You want to communicate the results of your research informally (not via publication)". The majority of participants chose the collaborative approach for this task. When impersonating the disseminator (task 3), Participant SBBR_P3 expressed a bidirectional collaborative motivation: on the one hand, the feeling of joy when sharing the research output with an audience and, on the other hand, the expectation to receive feedback from the audience regarding the results. He declared: *"I choose the collaborative approach to spread the news about my results. Because I believe that when you're trying to report your results in an informal way, you don't need to justify that your work is the best in the world. You just need the people to know your work. [...] And I will do that to rejoice from the work that I've done, for people to know that I spent a lot of time doing that research and that I'm happy with the results. And even if I'm not that happy, maybe people can give me some new insights. And not just to myself, not just to show that I am the one doing that, that I'm the one that achieved that goal, but to show to people that this kind of question was solved, that this kind of question already has an answer"* (SBBR_P3).

The most frequent recommendation strategies in the Disseminator profile are "researchers who follow me" (content-based filtering), and "matching topics" (collaborative filtering). The first strategy shows awareness about how social media distributes content to followers and the second strategy focuses on the search precision through keywords. Both are exemplified in the explanation from Participant SABR_P2: *"When I'm disseminating my work and not in a paper, I'm usually trying to engage people or researchers that follow me in this kind of social network. And I also take care to put the right tags and things like that, and a good title too, to make it easy to match topics with my paper"*.

The values on this profile are "achievement" and "universalism". Participants explained that one can only disseminate the work that is already finished (at least partially, like finishing a paper or reaching some conclusion from the research data). Therefore, having something to share means they already achieved something and can be somehow proud of their own work. Also important is to whom the dissemination is directed to, and in this case, it is society. SBBE_P1 chose these two values and explained his choice as follows: *"Regarding motivation, something I consider quite important while disseminating is the social aspect of what we are doing. And at the end, what you want is to share what you've done for the society and also make people understand or the taxpayers know where their money is going. So in that sense, I selected universalism. On the other hand, of course, we are always proud of what we did, and we always want to share our achievements and what we have done so I think it's always a double motivation, like, the personal and the social one"*. Other participants, when using the "universalism" card for this task, also referred to the importance of bridging the gap between science and society, usually through the Open Science paradigm. *"Usually my motivation to put this kind of work as an open share for everybody is a kind of universalism. I do believe that all knowledge should be free, and should be open to anyone. And I don't need any kind of payment for that... like, I need a payment to do my research, but not to make my publication and my final considerations and all the things open"* (SABR_P2).

5.5.2.4 The ambivalent evaluator

The last profile is the **Ambivalent evaluator** (see Figure 5.18) and refers to the fourth task in the game, described as follows: "In order to decide if a research project deserves to receive funding, you need to evaluate prior research of applicants". The ambivalent approach had its frequency peak in this task. The participants who chose the ambivalent approach frequently justify it by a twofold reasoning: on the one hand, the inherent competitiveness fostered by the limited amount of money to be distributed; and on the other hand, a collaborative approach in the sense of providing feedback in an encouraging and positive way. Participant SABE_P1 said: *"I put a competitive approach because I think you always have to have a critical view when you're evaluating any project, which is kind of inherently competitive. Even if it's not putting yourself against those applicants, or putting applicants directly against each other, but like, putting them against certain standards in the field, for that funding application. But I kept collaborative because I would never want to cut someone down with criticism or feedback, but rather have a more positive feedback approach"*.

The most common recommendation strategies on this profile are "matching skills and expertise", which is content-based filtering, and "publications I've read", which is collaborative filtering. Participants would use both of them to see if the applicants have what it takes to accomplish the projects' ambitions. SABE_P1 said: *"When looking at their previous publications, I guess I would look at the publications and the projects in the sense that I would match other skills and expertise that they demonstrate in those publications demonstrated in the funding application, or in the project application. Is the topic the same? Do they know what they're talking about? Did they have a history of being able to do this sort of research? And is that evident in the project's application as well?"*.

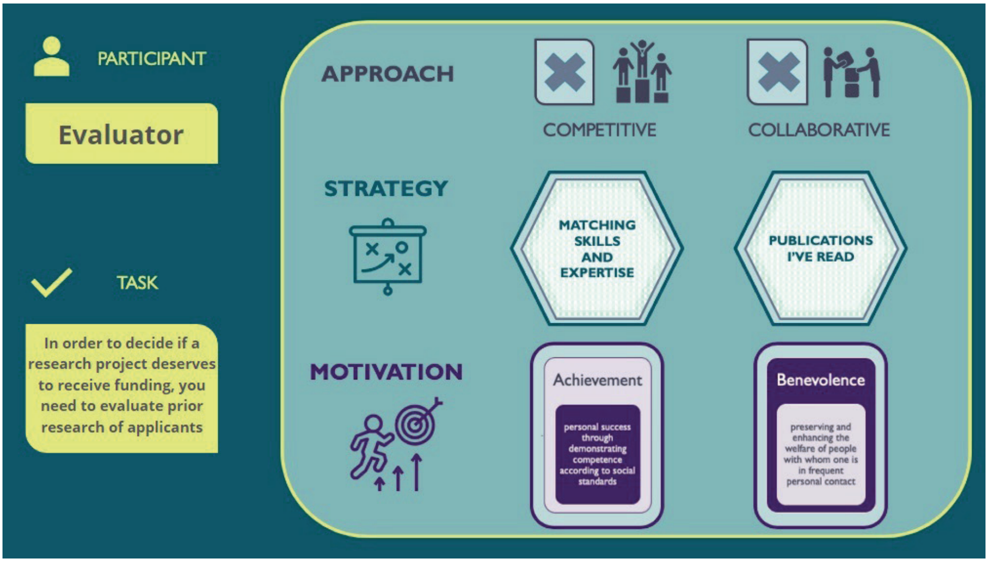


Figure 5.18 – Profile "ambivalent evaluator"

Researchers would use their own experience and knowledge on the field to assess the project's and team's merits, often associating this strategy with the value "achievement". For example, SABE_P4 said: *"I also went for an 'only publications' strategy, trying not to be influenced, let's say, by others' comments or ideas about this person. And I think it's also linked with the fact that I go with 'less is more'... so try to see the quality of what is being published, rather than the quantity of how much this person has published. And for this reason, I also pick achievement as a motivation. To highlight, let's say, this focus on the quality"*.

As for the value "benevolence", several participants mentioned a fair distribution of the money considering the size of the lab and potential to grow in detriment of experienced and already successful research groups. Participant SBBR_P3 seems to look for fairness in his decision: *"My motivation to choose one project over another is to choose which of the applicants will receive the best incentive, if this is an already senior laboratory, which has already received much more money and a lot of prestige, or if it is a new laboratory with new researchers. And in the latter case, I have to be benevolent by giving maybe money to those that have not yet received this chance"*.

5.6 Discussion

In this study we investigated how people make sense of algorithmic mediation via a qualitative research game study. More particularly, to answer the research question "***How do researchers relate human values to algorithmic recommendation features in ASM platforms?***", we employed an analysis that included all plans to action from all players.

In the first analysis we fleshed out the three strongest associations between recommendation strategies and human values within the game. In these three associations we see both content-based filtering (matching topics) and collaborative filtering (experts in the field) as recommendation strategies. There does not seem to be a preference for one type of recommendation strategy, which means the participants can change the recommendation feature depending on the goal they aim to achieve. Participants also seemed to have a certain mastery of and familiarity with recommendation features in ASM.

We also see, in the three strongest connections, human values from both main categories proposed by Schwartz (1992), namely values with a personal focus (stimulation and self-direction) and values with a social focus (universalism). In the first analysis (including all plans to action), no preference by one specific type of recommendation or one focus regarding the values appeared. We can conclude that there is a spectrum of motivations going from personal gain to complete altruistic attitudes. This finding is aligned with the "disinterestedness" institutional imperative proposed by Merton (Merton, 1973). According to this imperative, "every researcher pursues the primary goal of the advancement of knowledge, indirectly gaining personal recognition" (Bucchi, 2015, p. 235). However, Merton emphasised that the imperative "should be considered valid from the institutional point of view, not from that of the scientist's individual motivations" (Bucchi, 2015, p. 235). Indeed, in our game, the participants did not always choose the "social" value first. In fact, many times the value card with personal focus would appear first and the social card would appear in second position on the board (or not at all). In the next paragraphs we discuss each of the strongest associations found in this analysis.

5.6.1 Algorithmic mediation and who gets to be the digital influencers in ASM platforms

Our participants found it stimulating to receive recommendations from experts in the field who do similar research as they do. Two main reasons were brought by participants for this connection between “experts in the field” and “stimulation”: on the one hand, the respect and admiration for the domain authorities and, on the other hand, the aspiration to overcome the experts. It seems like the maxim written by Isaac Newton in a 1675 letter still holds true: “If I have seen further it is by standing on the shoulders of Giants”.

As reported in previous studies of this research project (see chapter 4), ASM platforms allow researchers to reach out to other scholars, which can bring the sense of closeness with big names in the field. This contact happens through functions like “follow” on several platforms such as ResearchGate, Academia.edu, Google Scholar, LinkedIn and Academic Twitter. Once the connection is made, algorithmic mediated content is in charge of feeding the researcher with updated activities of the experts, bringing excitement and novelty to the followers. Some participants also reported the challenge of trying to outdo the specialist as a stimulus. This competitive instance was brought to attention by Pierre Bourdieu (Bourdieu et al., 2004), to whom the legitimacy of methods and theories in any field is in constant dispute.

The findings suggest that, in ASM, the experts resemble the digital influencers in regular social media (such as Facebook, Instagram, TikTok, etc.). Their activities are closely watched by followers who are either using the experts’ inputs as inspiration to build their own knowledge or using them as beacons from which to deviate in their research projects - in attempts to surpass them. Either way, the experts are truly important actors to define what is relevant to be studied and what is not (topics); which are the appropriate means to do so and which aren’t (methods); and who gets the credit for new discoveries (through their citations). Therefore, it is not surprising that ASM platforms pay special attention to experts, giving them rewards (such as the RG Score in ResearchGate) and even defining who they are within the platform. In fact, in previous chapters (platform analysis), we found that ResearchGate infers who are the experts in a certain topic through a recommender system using automatic scraping of full text publications and metrics such as the "researcher's reputation".

RG Score, a metric created by ResearchGate to represent the "researcher's reputation", is partly based on the users' ability to figure out which online behaviours the ASM value and play accordingly, as the users literally get points the more they interact within the platform. Such composition of the metric has its benefits, such as helping early-career researchers, with less publications and citations than senior researchers, to break the silos of traditional reputation metrics (e.g. h-index) and get some visibility. However, the logic of tying the researchers' reputation with their digital literacy can be problematic. One of its consequences is that it becomes easier to artificially increase one's own RG Score by overusing the platform - which cannot be considered academic reputation. By doing so, platforms might be employing unfair assessment to researchers less skilled in digital technologies.

5.6.2 Algorithmic mediation and the (relative) free will in choosing topics of research

Our study shows that our participants aim for "universalism" in their research practices, for two main reasons: they want to make a positive impact in the world through their research and also to create fair and egalitarian academic environments, while connecting with less privileged groups in academia. Schwartz's definition of universalism as a human value ("understanding, appreciation, tolerance and protection regarding the welfare of all people and of nature" (Schwartz, 2010, p. 224)) is closely related to the "universalism" foreseen by Robert Merton as one of the 'institutional imperatives' of science (Merton, 1973). Universalism in this context means that "Scientific claims and results are to be judged regardless of the characteristics, such as class, race or religion, of their proponents.

Scientists are to be rewarded solely on the basis of their results" (Bucchi, 2015, p. 235). The reference to minorities by the participants shows that they understand the importance of shedding light (though citations, for example) on those who often receive less prestige for reasons that surpass their own competence. The conscious effort to valorise groups historically less privileged in academia in detriment to the experts was surprising. As we saw in a previous study (Chapter 4), one of the main reasons why users sign in to ASM is to get "closer" to the experts in the field, which was also confirmed by the results of the first analysis of this study, in the first strongest association ("experts in the field" and "matching topics"). This shows a certain balance in the participant's preference between following the traditional leaders, which still seems to be the majority of cases, and encouraging low-profile researchers through citation. This practice is aligned with insights from Mason and colleagues (Mason et al., 2021), to whom "citation is an area in which researchers can exercise agency and an opportunity to reflect our own sometimes constrained practice" (Mason & Merga, 2021, p. online document).

The recommendation feature "matching topics" at a first glance can give the impression that it is a neutral feature, free from power dynamics and academic provenance. However, topic-driven recommendations can also suffer influence from platform providers, ultimately conveying a certain vision of what is valuable and worthy of users' attention. Of course this influence is subtle and often hidden from the user, but should not be underestimated. One weighty factor refers to language. The most popular ASM platforms (ResearchGate and Academia.edu) follow the "English is the universal language of science" dogma. Which means that publications written in any other idiom, whatever is the quality of the journal where they were published, will receive poorer indexation and, consequently, score badly in recommendation rankings.

Another weighty factor refers to provenance. Some ASM platforms consider how important someone is in their field[33] to recommend and rank their content to other users. This means that even in topic-driven recommendations, depending on one's reputation, they will appear higher or lower in other people's feeds. What the algorithms do is literally placing publications from important people first, following the attention economy (Goldhaber, 1997). Therefore, despite a clear intention on behalf of the user to reach equity, the algorithmic mediation in ASM acts in a silent and subtle way to ensure attention to those who already have high prestige and recognition within the field. The idea that searching for matching topics or accepting the topic-driven recommendations will eliminate power dynamics and external interference in the search can be naive. Unless clear and effective affirmative measures to counter inequalities are taken by the platforms, they will continue to (unintentionally) reinforce the traditional asymmetries. Even when factors such as socio-cultural background, race, gender, expertise and other characteristics that historically justify biases in academic recognition are not explicitly included in the algorithm, the way the system works (focusing on English, expertise, etc.) might have the unwanted effect of reproducing unfair practices.

5.6.3 Algorithmic mediation and the users' interests

The third strong association and last node of the first analysis shows that the participants value self-direction. Participants further explained their aspiration for independent thought and freedom in making decisions, which is exercised through "matching topics" in ASM. However, the autonomy aimed by people can be threatened by recommender

33 According to the evidence presented in Chapter 3 (platforms analysis), ResearchGate infers who are the experts in a certain topic "using machine-implemented recommendation logic" (Madisch et al. 2018, 4). They do that by comparing different candidate experts using excerpts of these users publications and other (non disclosed) criteria.

systems not only due to the already discussed algorithmic influence on topic-driven recommendations, but also due to the high level of inference of the users' profile. Our platform analysis study (Chapter 2) showed that 67% of the tags used for profiling were not informed by the user, but algorithmically inferred, probably based on data traces of the user's online behaviour. These tags are not only hidden from the user, but impossible to change (because they work by filtering content in the backend, therefore not accessible or editable by the user).

Other authors already signalised the need to study algorithmic recommendations to understand in which ways the users' autonomy and agency can be ensured or threatened by the platforms (Koene et al., 2015; Milano et al., 2019). Indeed, researchers' agency in ASM is constrained by many factors defined by the platform. Some of them include the way the documents are indexed, the use (or not) of terminological variants in search results, the ranking system and the order of presentation of the content on the feed, and most importantly, the keywords algorithmically attributed to the users' profile, which allegedly represent their interests.

5.6.4 Different approaches for each academic task: reflections on collaboration and competition

To answer the research question "***How are collaboration and competitiveness reflected in people's choices in ASM platforms when performing different academic roles?***" distilled four archetypal profiles, one for each specific task that was presented in the game. These profiles can be taken into account for design purposes in ASM, because they bring specific features that researchers use to achieve certain goals and the motivations behind these choices.

Our study has shown some interesting findings about collaboration and competition in academia. The collaborative approach was chosen in the majority of the plans to action, and was especially prominent in tasks related to literature exploring and output dissemination (tasks 1 and 3). We can relate the collaborative approach in these activities to one of

Robert Merton's institutional imperatives of science: Communism. Following the Communism imperative, "results and discoveries are not the property of the individual researcher. Rather, they belong to the scientific community and society as a whole. This imperative is grounded on the assumption that knowledge is the product of a collective and cumulative effort by the scientific community" (Bucchi, 2015, p. 235). Participants showed preference for collaboration in activities where the goal was either learning from others or sharing one's research results (sometimes using their peers' network to do so). Collaboration is afforded by ASM platforms, as these digital technologies allow users to connect with other researchers facilitating collaborations at a distance.

Our study has also shown some interesting findings about competition in academia. The competitive approach appeared more prominently on plans to action related to writing and submitting a publication. This was not surprising, since the publications and citations are the main metric used to measure productivity, impact, and ultimately weigh one's merits whether or not to receive job opportunities, funding, prizes and all sorts of academic recognition. During the game, some participants referred to the inherent competition in academia to justify their plans to action with either a competitive or an ambivalent approach. Contrarily, collaboration and impact (the latter fundamentally tied to citations) were the two activities that grew the most in the interest of early-career researchers during a longitudinal study (Nicholas et al., 2020), and not competitiveness as our participants expressed. Collaborative approach finds support in arrangements such as policy incentives for interdisciplinary collaborations and funding schemes that encourage national or international collaborations. The longitudinal study showed that scholars between 20- and 40-years old value working in collaboration but are still keen to reach a stable position, therefore the importance of the impact. "For ECRs, every scholarly activity has a goal, which is to increase their competitive edge in order to obtain that prized secure position" (Nicholas et al., 2020, p. 7). The rationale behind this can be the need to collaborate in order to better compete, since studies show that collaboration increases citations (Bornmann, 2017; Shen et al., 2021).

5.7 Conclusion

In this chapter we investigated how people relate human values to algorithmic recommendation features in ASM and how collaboration and competitiveness are reflected in people's choices in ASM when performing different academic roles. We designed a research game, using it as a method to engage participants in sharing their reasoning about recommendations in ASM. The results show that participants feel stimulated by the possibility to keep in touch with the experts in the field for two reasons. First, because of the respect and admiration they nurture for these experts. In this sense, the ASM platforms allow them to feel close to people they admire. Second, because of the desire to become better than the experts, filling scientific gaps. This is afforded by ASM platforms by allowing the participants to see what experienced researchers are doing, and, by consequence, what they are also missing in terms of potential scientific developments.

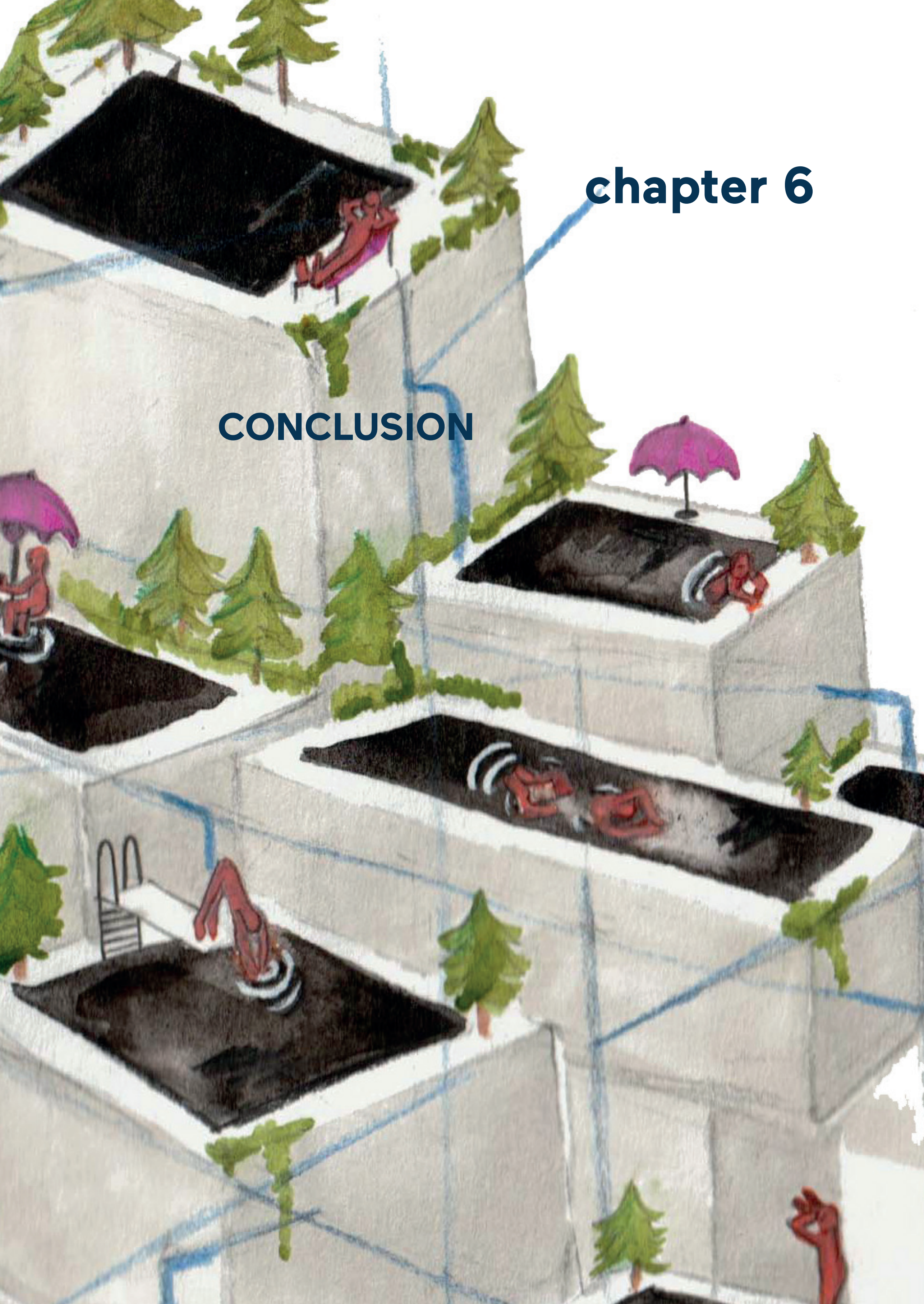
Participants believe that using social media can help them in making a positive impact in the real world, as well as contributing to a more fair and egalitarian science. They argue that the feature matching topics is connected to the human value universalism in two ways: on the one hand, because social media helps researchers to achieve broader audiences in society including groups from outside academia (aligned with the Open Science paradigm); and on the other hand, because these platforms allow them to find and actively valorise groups that are historically less privileged within academia (women, black people, etc.). We argue that traditional asymmetries can be reinforced by algorithmic recommendations, by privileging publications in English, for example. We suggest that clear measures to counter inequities should be considered by the platforms. In the meantime, the role of the ASM user in actively choosing to look for and valorise the work of fellow colleagues who are in less privileged positions is fundamentally important.

Self-direction appeared as an important value for the participants, also connected with the feature matching topics. The participants believe that this feature affords independent thought and freedom of action, since the choice for topics can be done without interference.

We reflect on the approaches people chose for academic tasks. Our results show that for certain tasks, the competitive approach and ambivalent approach appear more prominently, even though people choose the collaborative approach frequently. The competitive approach gained more relevance when the task was to write and publish publications, whereas the collaborative approach was most relevant in tasks related to literature exploring and output dissemination. The ambivalent approach was most prominent in the scenario in which scholars need to evaluate someone else's work. The four evidence-based archetypal profiles that were defined in this study, represent people's choices in the game. Friedman and colleagues (Friedman, 1997) affirm that systems designers necessarily convey social and moral values in their work. The archetypal profiles offer support for future research and for value-sensitive platform design (Friedman, 1997), as they show the values and recommendation strategies people mobilise when executing specific tasks.

chapter 6

CONCLUSION



The fourth lesson has to do with the much-touted issue of filter bubbles or echo chambers — the claim that online, we encounter only views similar to our own. This isn't completely true. While algorithms will often feed people some of what they already want to hear, research shows that we probably encounter a wider variety of opinions online than we do offline, or than we did before the advent of digital tools.

Rather, the problem is that when we encounter opposing views in the age and context of social media, it's not like reading them in a newspaper while sitting alone. It's like hearing them from the opposing team while sitting with our fellow fans in a football stadium. Online, we're connected with our communities, and we seek approval from our like-minded peers. We bond with our team by yelling at the fans of the other one. In sociology terms, we strengthen our feeling of "in-group" belonging by increasing our distance from and tension with the "out-group"—us versus them. Our cognitive universe isn't an echo chamber, but our social one is. This is why the various projects for fact-checking claims in the news, while valuable, don't convince people. Belonging is stronger than facts.

Zeynep Tufekci, How social media took us from Tahrir Square to Donald Trump (2018)

In the last decades, scholarly communication has been drastically transformed by technological platforms that mediate knowledge sharing, relationships among researchers and scientific practices and opportunities, from cross-continental collaboration to job seeking. ASM platforms play a huge role in this shift to a more ubiquitous and personalised way of communication in the academic environment. Through algorithmic mediation, these platforms are increasingly intertwined with research practices and knowledge development in the academic environment.

Despite its importance, algorithmic mediation of scientific information remains underinvestigated. So far, existing studies have covered bibliometric indicators such as the RG Score on ResearchGate (Delgado-López-Cózar & Orduña-Malea, 2019; Orduña-Malea et al., 2016); the added value perceived by researchers in using ASM platforms (Elsayed, 2016; Lee et al., 2019; Nández & Borrego, 2013); online knowledge sharing practices (Jeng et al., 2017; Koranteng & Wiafe, 2019), and the impact of ASM for academic publishers (Laakso et al., 2017). Studies on ASM platforms usually disregard the recommendation algorithms.

This thesis sheds light on the ways in which ASM platforms may shape scholarly communication. Building on the mediation framework (Lievrouw, 2014; Lievrouw & Livingstone, 2006), our investigation considered the mutually shaping relations between the ASM artefacts, the practices and the social arrangements linked to scholarly communication. Each part of the thesis focused on at least two of these factors. More particularly, in Part I we dealt with the artefact and the arrangements. In Part II, we focused on the human practices and discussed the results in light of the arrangements.

6.1 RQ1. How do recommender systems of academic social media shape what users can see and how users interact with the platform? (Part I)

Part I of this manuscript addressed **RQ1** by means of a socio-technical analysis of ResearchGate conducted in light of the mediation framework (Lievrouw, 2014). This analysis was presented in chapters 2 and 3.

What are the main entities involved in the recommendations on ASM platforms?

In Chapter 2, we analysed the data from two steps of the walkthrough method (Light et al., 2018), namely the analysis of the interface and a company inquiry. We delved into the mechanisms of mediation and the communication arrangements employed by the platform. Considering ASM platforms are one type of social media, we analysed how artefact and arrangements mutually shape each other. Analysing one of the most popular ASM platforms, ResearchGate, we identified that almost all of the content shared in the platform is algorithmically mediated. Information related to the entities **Researchers**, **Publications**, **Research Projects**, **Questions**, **Institutions** and **Jobs** are recommended to users through the webpage, app and e-mails. We also fleshed out hundreds of attributes used by the system to build the recommendations.

Which mechanisms can be identified in the ASM platforms?

The question on what mechanisms can be identified in the platform was also answered in chapter 2. In our research we found that the algorithmic mediation in ASM platforms happens through several mechanisms that shape the ways in which information is gathered, processed and presented to the researchers. We verified how the mechanisms of **profiling,**

selection, prioritisation, commodification and **datafication** apply to ASM. In the next paragraphs, we will explain these mechanisms and their consequences in more detail.

Profiling is often completed by algorithms. With profiling, data from the platform users is processed by the system, sometimes even combined with other data sources, to find patterns and correlations (van der Hof, 2017) that eventually allow to aggregate users by their characteristics and past behaviour. These aggregated user groups are labelled with a specific cluster tag for which the algorithm makes tailored recommendations. This process thus shapes how the researcher is classified by the platform and determines which content this researcher gets to see in the ASM feed. For example, job opportunities for PostDoc positions are likely to be shown to PhD students, not Master students. This differs from non-algorithmic mediated systems, where users see all job opportunities and decide by themselves what is relevant or not.

Profiling presents some pitfalls. First, because the system collects the user's past behaviour, the inferences might not reflect their current interests. Second, the tags used to classify the user are neither completely visible nor accessible for the user to change. Indeed, automated decision-making limits the user's agency in deciding how the content will be curated. This study has shown that the ResearchGate platform offers to researchers the option to add and edit some of their preferences, but these cover only a small part (33% to be more precise) of all the attributes used for profiling, considering only the keywords. The platform also uses personal data (105 attributes), information pertaining to the user's work (29 attributes), historical data (18 attributes), followers and follows (6 attributes), the subjects of the researcher's own publications (without disclosing how they index this material), messages exchanged between the researcher and their connections and questions posted by the researcher. The majority of this information is not accessible nor editable by the user, unless upon explicit request using the rights ensured by GDPR (General Data Protection Regulation (GDPR), 2016).

Next, through **selection** and **prioritisation** of information, ASM platforms algorithmically choose publications, research projects, researchers and other types of content to display to the user in their feed. The system infers which content will be considered relevant by the user, when this content will be shown and the particular order that the content will appear in in the user's feed. In systems that do not employ these mechanisms, all users see the same items in the same order regardless of who the user is (e.g. following a chronological order). This prioritization takes into account what the platform considers the user will find relevant. However, relevance is a subjective concept that depends on many factors. For example, how the user makes sense of the content, which are the individual motivations for using the platform, how much time the user has to find the information needed, which other sources the user consulted previously, what is the language the user prefers to read, among many other factors. When algorithmically deciding what the user gets to see and what will be seen first, the platform is virtually projecting the user's subjectivity, shaping the user's attention.

Furthermore, the process of **commodification** consists in "platforms transforming online and offline objects, activities, emotions, and ideas into tradable commodities" (van Dijck et al., 2018, p. 37). ASM platforms use this mechanism to strategically and economically benefit from the researchers' practices, by nudging the users to upload their publications and to invite their coauthors to join the platform. Through rewards such as milestones (number of reads or downloads of the researcher's papers) and the RG Score, the platform encourages the user to populate the platform with content (publications) which attracts other users. These platforms also capitalise on the researcher's networking, since the pattern "follow by example" is automated by the algorithm, making collaborative filtering inherently driven by social influence (Jameson et al., 2014; Ramos et al., 2020). Previous research has shown that users consider ASM platforms to be an extension of their (offline) professional activities, and therefore perceive other platform users as trustworthy (Koranteng & Wiafe, 2019). This means that an endorsement of a piece of content shared by a researcher on a certain user's network makes that content more appealing and more likely to attract that user's attention and trust. By liking, rating and recommending items on the platform, the user is adding value to this content that, in turn, is used by ASM as a commodity to convince other users to join the platform. According to van Dijck and colleagues, "the massive amount of user data collected and processed by online platforms provide insight into users' interests, preferences, and needs at particular moments in time" (van Dijck et al., 2018, p. 37). Hence, the commodification process is strengthened by another mechanism identified below, the datafication.

Finally, platforms have the ability "to render into data many aspects of the world that have never been quantified before" (van Dijck et al., 2018, p. 33), a mechanism called **datafication** (Mayer-Schönberger & Cukier, 2013). In our research we noticed the importance of this mechanism, as the platforms use not only demographic or profiling data provided spontaneously by the researchers, but also behavioural data collected from users' navigation and interactions within the platform. This data provides extremely detailed information about the user, such as the pages visited, the place from where the platform was accessed, how much time the user spends on a page, and every reaction to the content. The interactions have a special importance because they are amplified by the platform and used to recommend content to other users (recommendations such as "Your connection [name] liked this content"). In combination with datafication and platform selection, ASM platforms "trigger and filter user activity through interfaces and algorithms" (van Dijck et al., 2018, p. 40). At the same time, users "influence the online visibility and availability of particular content, services, and people" (van Dijck et al., 2018, p. 40) through their interaction with these items. This reinforces the mutual shaping nature of the platform environment and human practices.

How do ASM platforms communicate with its users about the recommender algorithms used in the platform?

The question on how ResearchGate communicates with its users about the platform's recommender algorithms was answered in chapter 2. By exercising the right to an explanation as specified in the GDPR (General Data Protection Regulation (GDPR), 2016), we found that the algorithmic mediation of ResearchGate is not clearly explained to users, neither by design nor upon request, as the company's communication strategy was to shy away from providing details on automated profiling. Their reply to our company inquiry was sent after a relatively long period (six weeks), and three formal requests. The reply was vague and at times inconsistent with the data we received or collected during the interface analysis. Even though the company denied doing automated decision-making, our results did nonetheless point towards profiling (i.e., predictions based on inferred data). We found that some visual cues on the interface could even misinform users. For instance, one of the messages shown on the platform in the Questions section) suggests that the keywords in the researcher's profile are used by the algorithm to recommend questions and that the user can change these keywords at any time. Yet by looking behind the scenes and inspecting the data set with the profiling data provided by the company, we found that the majority (67%) of the keywords that determine the user profile in the backend are inferred by the system and are neither visible to the user nor changeable.

How may algorithmic mediation, through recommender systems in ASM platforms, uphold biases in scholarly communication?

In chapter 3, we showed that algorithmic mediation can uphold biases in scholarly communication. We collected information that the company does not disclose in an accessible form to the average user, namely web page code and patent content. Adding this information with empirical data from the public interface, we generated new insights. The findings of chapter 3 revealed how mechanisms of selection, prioritisation, profiling and datafication influence processes of algorithmic recommendations within the platform. We also fleshed out the Matthew effect of accumulated advantage and the issue of the audience.

The mechanism of selection narrows the universe of choice of the user by filtering the items to be shown in the feed, which leads to the **homogeneity bias** (Nikolov et al., 2019). Homogeneity bias is defined by Nikolov and colleagues as "the selective exposure of content from a narrow set of information sources" (Nikolov et al., 2019, p. 219). Such bias can lead to a scenario of superspecialization (Torres, 2004, p. 85), where the researcher will always receive content similar to what has already been shown, in terms of topics, format, domain and/or authors. Since people have a limited amount of time to consume information (Goldhaber, 1997), content that appears on the feed is more likely to receive the researcher's attention than content that does not appear on the feed. Even unintentionally, recommender systems might reinforce stereotypes. For example, due to the current gender gap in some fields (Makarova et al., 2019), by simply tracking the next most likely item to be clicked on, the system might recommend books from the Humanities for women and from STEM for men. By doing so, Tufekci says a feedback cycle is created: "If you keep being shown coding books, you're probably more likely to eventually check one out" (Tufekci, 2019, p. online document). The platform's metrics also possess a selective character, as some attributes are chosen, at the expense of others, to constitute the metrics within the platform. For example, the RG Score is based on quantitative indicators that include publications, questions, answers and followers (inner content of the platform). However, other attributes in the researcher's career, that could potentially be considered for "reputation" measure, are left out. Some examples include prizes, honourable mentions, distinguished scholarships, and board positions.

The platform also prioritises content in the user's feed. By reordering the content in the feed, the platform brings attention to certain items over others, which is, by definition, **discrimination** (Diakopoulos, 2016, p. 57). Even if a researcher strictly uses the search bar to look for a particular topic within the platform, the search results are often presented in a customised list that prioritises some documents over others. Our research showed that algorithmic recommendations in ResearchGate are more anchored in information created by the platform (inferred) than in data given by users themselves, which was demonstrated by the high level of inference on the user's profile. In the process of selection of the items for the feed, the system matches the content available in the platform with alleged interests of the user. It might be said that the platform controls not only how the match is made (how each descriptor is weighted), but also the profiling descriptors themselves, by the high level of inference on the user profile.

Algorithmic mediation also has the potential to trigger the **"Matthew effect of accumulated advantage"** in science (Merton, 1968), since the reputation of the researchers is used for recommendations. The Matthew effect of accumulated advantage consists in crediting only the best-known researcher for joint work, triggering an autocatalytic process where the researcher becomes even better-known (Merton, 1988, p. 88). Our findings showed that both the ranking of recommended publications and the identification of candidate experts are influenced by the researcher's reputation. This finding corroborates previous research on recommendation algorithms in ASM (Polonioli, 2020). The process of repeatedly giving more prominence to already-recognized researchers while removing those with little or no reputation from the spotlight "will lead to the rich getting forever richer while the poor become poorer" (Merton, 1988, p. 610). Through this logic, we argue that the algorithm reinforces the reputation of eminent researchers, since authors with a higher reputation in the platform get more attention in the feed. These authors are shown first in the recommendations list, which can lead to more reads and citations and consequently higher reputation. Yet the Matthew effect cannot be exclusively credited to recommender systems in social media, since it is already known in the academic environment for almost sixty years (De Solla Price, 1963; Merton, 1968). However, the ubiquity of ASM platforms in scientific practices combined with the lack of transparency tends to raise the already growing inequality of scientific capital.

The **influence of the audience** in digital platforms is pointed out by Bozdag as an issue that can also cause bias (Bozdag, 2013). Our analysis showed that the feedback from a user's connections also affects the recommendations, where not only the quantity of reactions matters (source of the popularity bias (Nikolov et al., 2019, p. 219)), but also from whom these reactions are. This means that a publication that was "liked" by expert researchers is shown to more users than a publication with the same number of reactions from an audience formed by people with lower reputation. Again, it is important to stress that the researchers' reputation on ResearchGate is inferred algorithmically and expressed by the RG Score. Thus, the platform's inference of who the experts are can bias the content distribution, as the content liked or shared by these "experts" gain more visibility in the feed.

Datafication means quantifying a phenomenon "so it can be tabulated and analysed" (Mayer-Schönberger and Cukier, 2013, p. 78). In a datafied environment, recommendations are based on quantified interactions (e.g. number of reads, likes, downloads, etc.) and also in the quantification of less objective concepts, such as a researchers' reputation and the relevance of certain content to the user. Delegating subjective decisions (such as deciding how relevant a piece of content is) to automated systems might incur biases for two reasons. First, by recommending what is more likely to be clicked, the system **ignores other important aspects in knowledge production**, such as how diverse or inclusive a publication is. In the attempt to find the perfect match between content and user, the system misses the opportunity to offer publications with different points of view and tones, which underpin democratic societies, and to recommend based on public and human values. José van Dijck highlights the need of digital platforms to go beyond more consumer-oriented values, such as security, transparency, accuracy and privacy; and aim for values concerning society as a whole, such as fairness, inclusiveness, autonomy, accountability and democratic control (Van Dijck, 2021). Floridi and colleagues, in the aim of establishing the basis for a so-called "Good AI Society" pinpoint its five ethical principles, namely beneficence, non-maleficence, autonomy, justice and explicability[34] (Floridi et al., 2021). These AI ethics principles, which we argue are not easy to quantify, were developed to guide the design, assessment and policy making of digital platforms addressing their core opportunities and risks. Second, automated filtering can be biassed by the company's vision on what is worthy of attention. We found that ResearchGate, in their Terms and Conditions, claim the right to remove and modify any content or information submitted by the user "when, in our sole discretion, we deem it to be necessary or appropriate, including if we determine that the content may expose us to harm, potential legal liability, or is in breach of these Terms" (ResearchGate, 2020). This is problematic because ResearchGate not only focuses on what can **cause *them* harm** (not worrying on what could harm their users nor societal principles) but also because the company **omits the criteria** used to make these decisions, not explaining what they understand as harmful content for example. This omission was also observed in other platforms such as Twitter and Facebook (Bozdag, 2013, p. 217) and it allows for subjective judgements from the designers and moderators.

Finally, profiling has also been reported as a source of misconceptions and inaccuracy (Bozdag, 2013; Milano et al., 2019; Pariser, 2011; Polonioli, 2020) because a large part of the data is based on inferences. Our analysis showed a lack of transparency on behalf of the platform on how the inferences are made and why certain data are collected. For example, gender is a demographic attribute used for profiling in ResearchGate, but why the company considers gender relevant in a professional/scientific network is unclear. Also, information about the career level of the researcher (expressed in the attribute ProfileCareerLevel) is established via inference. This profiling data is used to indicate the next career level for the researcher to pursue and reflects the job positions to be recommended. However, the career level is not accessible for the user to visualise or to change it, which

34 According to the authors, Beneficence refers to "promoting well-being, preserving dignity, and sustaining the planet"; Non-maleficence refers to "privacy, security and 'capability caution'; Autonomy refers to "the power to decide (whether to decide)"; Justice refers to "promoting prosperity and preserving solidarity" and Explicability refers to "enabling the other principles through intelligibility and accountability" (Floridi et al., 2021, p. 19)

compromises the autonomy of the user in looking for vacancies that do not reflect what the platform thinks is the “obvious next step”. For example, for a PhD researcher, only PostDoc positions are recommended. However, if the researcher would like to “go back” to start a Master’s degree in another field, there is no possibility for the user to change this attribute in the profile, because it is hidden behind the interface. Therefore, profiling can bias the content distribution depending on **which characteristics the ASM platform considers relevant** (such as gender) or on **what the platform portrays as the user’s future aspirations** (which can or cannot hold true).

In the analysed documents, we did not find any mention of serendipity or other strategies to counter the mentioned biases. However, it does not mean that the company ignores the issue. It might be the case that ResearchGate tries to increase serendipity and diversity in their recommendations, but we just could not find evidence of these practices - not even through our in-depth four-steps socio-technical analysis.

6.1.1 Summarising Part I

With the walkthrough method, we could inspect the artefact while also expanding the analysis to arrangements, hereby providing “a frame from which to identify embedded cultural values” (Light et al., 2018, p. 888). In sum, chapters 2 and 3 addressed **RQ1 (*How do recommender systems of academic social media shape what users can see and interact with within the platform?*)** and showed that recommender systems shape the content and the interactions of researchers within ASM platforms through different strategies, including profiling, selection, prioritisation, commodification, and datafication. These mechanisms can trigger distortions and biases in scholarly communication, such as the homogeneity bias, discrimination, the Matthew effect of accumulated advantage, the popularity bias, and the influence of the audience. We also highlight that datafication tends to oversimplify subjective decisions and overlook broader societal values (that extrapolates the relationship between user and platforms). By predicting the future aspirations of users, profiling can entrench people to specific predetermined paths, which might jeopardise people’s autonomy.

Our findings show that ResearchGate refrains from clearly explaining how they implement algorithmic mediation, even though they provided some information upon request. Their explanation was, however, delayed, vague and at times even conflicting with the remaining empirical data we gathered through the patent analysis, web code analysis and interface analysis. We believe algorithmic transparency (Diakopoulos, 2016) is important for recommendations in ASM. However, transparency solely can subject users to get lost in information overload, when the information provided is too technical, too extensive or provided in inaccessible formats. We therefore encourage transparency through design in the form of clear and meaningful explanations (EUROPEAN COMMISSION, 2016) both in the platform and upon request, that should be provided in a user-friendly and ethically responsible manner. It is also the platforms' responsibility to care for potential harm to their users and for societal values that can be jeopardized through their activities.

6.2 RQ2. How do researchers make sense of their interactions online within academic social media? (Part II)

Part II of this manuscript addressed **RQ2** via interviews and a research game to better understand the participants' reasoning about recommender algorithms, as elaborated in chapters 4 and 5.

How do technological affordances shape perceptions and scholarly practices?

In chapter 4, we described the results of a qualitative study based on online in-depth interviews (n=11) with ASM users in Belgium, Brazil, The Netherlands and The United States of America. Our findings show that algorithmic mediation not only constructs a narration of the self, as Jacobsen

(Jacobsen, 2020) fleshed out, but also a narration of the relevant other in ASM platforms. Datafication and visibility/findability algorithmically construct an image of the relevant other that is both participatory and productive. In the next paragraphs, we will discuss these two aspects in more detail against the existing body of literature.

Datafied environments tend to foster **participatory behaviour**. Following the datafication logic, ASM platforms incite the users to exchange their data for full access to publications and personalised recommendations. In a sort of interaction game, researchers get rewards (such as an increment on their RG Score) for their participatory behaviour. In a datafied environment, participatory behaviour is mandatory because the platform itself survives at the expense of content provided by the users (van Dijck et al., 2018). Participants showed to be aware that the more they use the system, the more the system will be able to infer what they are looking for and provide better suggestions. Some ASM users suspect that the platforms might not always deal with their data in the most ethical way, following advertisers' interests rather than the users' interests. Other participants shared their concerns regarding what the platform nudges them to do (e.g. share their publications) whereas there might be legal constraints involving other stakeholders, such as publishers. However, by observing peers and more experienced researchers, participants learn from their practices: the respected researchers in the field seem to give legitimacy to the online practices.

Algorithmic mediation also shapes the ASM user's perception regarding their peers' **productivity**. Participants understand that ASM platforms can help them to get a "sense of the field" through visibility/findability, meaning that they can learn what are the current topics being investigated, which are the most used methods and who are the most relevant researchers to follow by observing the feed. Observing other researchers was also pointed out by the participants as a source of insecurity, bringing anxiety and Fear of Missing Out (FOMO). Comparison and competitiveness have always been part of the academic environment, however ASM platforms put researchers in an online arena that extrapolates what they are used to in the physical world. "Social media promotes comparison, which is normal in every-day situations, but can be overwhelming when we are comparing ourselves to thousands of people we do not know online" (Lembke & Harris, 2021). In "real life", this experience could be similar to an international conference, for example, where researchers have the opportunity to get to meet researchers from around the world and to know their work. But the contact happens in a certain period of time, and it is limited by physical constraints, as it is only possible to be in one room at a time. Anxiety and FOMO occur also among general social media users, as reported by previous research (Rosen et al., 2013). The implicit demand for posting more, interacting more and to be continuously focused on what is happening on the platform is fostered by reputation metrics (such as RG Score), push notifications on the smartphone, emails that incite the user to login and recommendations on the feed. Participants find these "pokes" annoying and exhausting, because they are constant reminders that the users' colleagues, peers and academic references are publishing, being cited and acquiring more followers, i.e. growing their scientific capital. The discomfort with the automated messages sent by ASM platforms was also reported in previous research (Van Noorden, 2014). The algorithmic impact on exposure to content has a twofold perspective. On the one hand, some participants believe that the algorithms expand the access to content they would not have access to otherwise (due to paywall constraints, for example). On the other hand, other participants find that the algorithms narrow down the content displayed to them in their personal feed, referring to phenomena already reported in literature as the "filter-bubble" (Pariser, 2011). Previous empirical research shows that "recommender systems expose users to a slightly narrowing set of items over time" (Nguyen et al., 2014, p. 677), even though the users that consume the recommended items "experience lessened narrowing effects and rate items more positively". Therefore, while users are being exposed to fewer items, the convenience of seeing personalised content makes them less aware of the narrowing effect. This could threaten individual users' autonomy and agency (Koene et al., 2015; Milano et al., 2019). The visibility that users' publications can reach through ASM platforms is much valued, a finding that corroborates previous research (Lee et al., 2019).

We argue that there are distortions in data-oriented digital environments because many things are not being calculated in such platforms. For example, contextual inequalities, people who are not on the platform or people who game the system by non-clicking (Ellison et al., 2020), to prevent other researchers from increasing the number of "reads" in their profile.

ASM users believe that digital platforms impact their scholarly practices in six ways: (1) providing access to relevant publications in full, (2) exposing them to content algorithmically selected, (3) tensioning some ethical and legal frontiers, (4) allowing scholars to reach out to one another, (5) offering a space to researchers to see and to be seen by their peers, and (6) data exchange between user and platform.

How do researchers relate human values to algorithmic recommendation features in ASM platforms?

Chapter 5, built on an empirical study by means of four sessions in which participants (n=13) played a research game that was deliberately created to collect data to address our research questions. Among the human values proposed by Schwartz (1992), our data shows that researchers associate algorithmic recommendations with values from both main categories (personal focus and social focus). In general, there was no preference for one specific type of recommendation or one focus regarding the values. This indicates a spectrum of motivations going from personal gain to completely altruistic attitudes. This finding is aligned with the “disinterestedness” institutional imperative proposed by Merton (Merton, 1973), according to whom “every researcher pursues the primary goal of the advancement of knowledge, indirectly gaining personal recognition” (Bucchi, 2015, p. 235). Merton stressed, however, that the imperative “should be considered valid from the institutional point of view, not from that of the scientist’s individual motivations” (Bucchi, 2015, p. 235). That is precisely what we observed in our game: many times the participants first chose the value card with personal focus to only afterwards choose the value card with a social focus. Among the values selected by the participants within the game, the most frequently associated with algorithmic recommendations were stimulation, universalism and self-direction.

The findings suggest that, in ASM, experts resemble the so-called “digital influencers” in general social media (e.g. Facebook, Instagram, TikTok). Researchers find the contact with experts in the field through ASM platforms an exciting activity. Through the association of the human value “stimulation” with the recommendation feature “experts in the field”, our participants expressed two main interests: feeling close to people they admire and/or becoming better than the experts in their field. In previous chapters of this thesis, we found that ResearchGate infers who are the experts in a certain topic through automatic scraping of users’ publications and metrics such as the “researcher’s reputation”. Therefore, who gets to be the “digital influencers” in the ASM platform is also algorithmically mediated. In this sense, we argue that linking researcher’s reputation (expressed by RG Score in the case of ResearchGate) with their digital literacy can be problematic because, by doing so, the platforms might downgrade the importance of researchers who are relevant for the field but are not skilled in digital technologies.

The study also showed that participants aim for “universalism” in their research practices, for two main reasons: to make a positive societal impact and to create fair and egalitarian academic environments. Valorizing less privileged groups and minorities in academia is a way to counter inequalities. While the majority of participants still prefers to follow the traditional leaders, some participants like to actively empower historically underprivileged researchers through citation, which is coherent with Mason and Merga: “citation is an area in which researchers can exercise agency and an opportunity to reflect our own sometimes constrained practice” (Mason & Merga, 2021, online document). We believe that such actions, although commendable, are still insufficient to counter systemic inequalities. Since algorithmic recommendations can reinforce traditional asymmetries, by favouring publications in English, for example, we suggest the adoption of clear measures on behalf of the platforms to counter inequities.

ASM users also value “self-direction”, for they appreciate independent thought and freedom of action. Our participants associate this human value with the recommendation feature “matching topics”, since they think the choice for topics can be done without interference. Our study suggested that there are nonetheless many constraints in the user’s agency within the platform, due its system design. For example, the user profile is used to recommend content that allegedly meets the users’ interests, but the keywords which define the profile consist of a high percentage (67%) of algorithmic inferences. Other examples include the way that documents are indexed in the platform (usually in English) and the ranking system in the feed (which places publications in a certain order, algorithmically inferring relevance for the user). The second analysis in this chapter refers to the following question:

How are collaboration and competitiveness reflected in people’s choices in ASM platforms when performing different academic roles?

ASM users have different approaches depending on the role they are taking up at that moment. People adopt a collaborative approach for most of their activities. Whether to look for literature for a new research project, or to disseminate their work through ASM platforms, collaboration is preferred. We can relate the choice for collaboration in these activities to one of the institutional imperatives of science coined by Robert Merton. According to the Communism imperative, "results and discoveries are not the property of the individual researcher. Rather, they belong to the scientific community and society as a whole. This imperative is grounded on the assumption that knowledge is the product of a collective and cumulative effort by the scientific community" (Bucchi, 2015, p. 235). By allowing connections among researchers, ASM platforms facilitate collaboration, also at a distance.

However, it caught our attention that, for some specific tasks, participants prefer a competitive approach or an ambivalent approach (both competitive and collaborative). In our analysis we found that for activities related to paper writing and publication, people tend to become more competitive, whereas for activities related to the assessment of other people's work, the ambivalent approach is preferred.

The competitiveness found was not surprising, since publications and citations are frequently used to assess a researcher's productivity, impact, access to job opportunities, funding, prizes and all sorts of academic recognition. The inherent academic competitiveness was mentioned by some participants to motivate their approach choices. In contrast, a longitudinal study showed that early-career scholars or ECRs (20-40 y.o.) enjoy working collaboratively even though they are also keen to reach a stable position, for which impact (fundamentally tied to citations) is important. "For ECRs, every scholarly activity has a goal, which is to increase their competitive edge in order to obtain that prized secure position" (Nicholas et al., 2020, p. 7). We assume that this might be an attempt to collaborate in order to better compete, because studies show that collaboration increases citations (Bornmann, 2017; Shen et al., 2021).

Our findings resulted in four archetypal profiles, representing people's choices for each different activity. These profiles are aimed to inspire value-sensitive design or to serve as a source for new research. They summarise the approach, recommendation strategies and values chosen more frequently by participants, and also present the archetypal socio-demographic characteristics of the researchers.

The first archetypal profile is called "the collaborative reader". Archetypically, this profile is from a PhD student on Social Sciences and Humanities, with 1-3 years of experience, and is a user of general social media and ResearchGate. Motivated by the human values of stimulation and self-direction, the collaborative reader uses recommender features to find topics in common with the experts in the field. The main activity of the collaborative reader is finding relevant literature for new research projects.

The second archetypal profile, called "the competitive writer", is a PostDoc researcher on Engineering or Natural Sciences, with 4-6 years of experience, who is a Twitter user. The competitive writer seeks the human values achievement and stimulation, and relies greatly on the research topics recommended by their supervisor, mentor or manager. Writing and publishing papers is the main activity of the competitive writer.

The third archetypal profile is "the collaborative disseminator". Focused on informally communicating the results of research projects (not via publications), this is the profile of a PhD student, with 4-6 years of experience, who uses general social media and ASM (ResearchGate and Mendeley). The collaborative disseminator knows that good keywords in their posts can help to spread research results to their followers. Achievement and universalism are the human values that drive the collaborative disseminator.

The last archetypal profile is called "the ambivalent evaluator". The archetypal characteristics of this profile are: PostDoc researcher in the Social Sciences and Humanities, with 4-6 years of experience, user of general social media and ASM (Academia.edu, ResearchGate and Mendeley). The ambivalent evaluator usually matches skills and expertise of the researchers being assessed with knowledge previously acquired through publications they have read. This profile values stimulation and benevolence and the main activity is to assess other people's work in order to choose who would receive funding.

6.2.1 Summarising Part II

In sum, chapters 4 and 5 addressed **RQ2 (*How do researchers make sense of their interactions online with academic social media?*)** by fleshing out the researchers' perceptions on algorithmic mediation and how they relate recommendation features with human values.

In chapter 4, we showed that the participants perceive ASM platforms as spaces to amplify visibility/findability, i.e. “to see and to be seen”, something that can trigger comparisons and boost anxiety. They also believe to have agency over the content recommended to them, following the logic “the more I give, the more I get”, which makes them partially responsible for the quality of the algorithmic mediation. The participants also reported on the effects of “algorithmic mediation in exposure to content” via ASM. whereas some believe the algorithms create a tunnel vision, others argue that the platforms expand the content they can access, that otherwise would be protected by pay walls. The participants also showed concerns about potential ethical and legal infringements that both them and the platforms could be incurring. In the discussion we showed that, through datafication and visibility, ASM platforms algorithmically construct an image of the other that is both participatory and productive. These findings build upon the research of Jacobsen who proposes that “people’s lives are rendered sequential, ordered, and ultimately meaningful and actionable by algorithmic processes” (Jacobsen, 2020, p. 1).

Chapter 5 brought the perspective from human values and how they relate to recommendations in ASM. The values stimulation, universalism and self-direction were the most frequent values in our data. According to Schwartz’s model (Schwartz, 1992), stimulation and self-direction are both values with a personal focus, while universalism has a social focus. The results show a spectrum of motivations going from personal gain to complete altruistic attitudes, however participants often chose values with a personal focus first, and only then chose the value with the social focus. These results can be compared with the institutional imperative proposed by Merton called “disinterestedness” (Merton 1973), according to which researchers mainly pursue the development of science, receiving personal recognition as an indirect consequence. We found that, indeed, our participants have shown altruistic motivations. However, first, they ensure their actions meet their personal interests.

We also found that people employ different approaches depending on the situation, and even though most of the time people prefer the collaborative approach, for specific tasks the competitive approach or the ambivalent approach also were chosen.

6.3 Reflections on the findings

Although the recommendation culture predates the advent of social media, deep personalisation and networked customization (supported by content-based filtering and collaborative filtering) are new elements in the context of scholarly communication. What is made accessible to researchers in the platform, including the frequency and where on the feed the content is placed, is decided algorithmically. In this thesis we have shown that the criteria used by the platforms to make such predictions is not always clear, neither by design nor upon request. Knowing what kinds of content (entities) are recommended, which mechanisms are involved in these recommendations and how this is communicated to the user is important because, departing from these findings, we could unfold the potential distortions and biases that ASM platforms can uphold. The ways in which users make sense of algorithmic mediation is also relevant because it will eventually shape the practices of these researchers. What motivates the researchers to engage in ASM platforms as well as the users' concerns determines not only **if** scholarly practices take place within the platforms but also **how** the interactions occur. Ultimately, we prefer systems that meet the users' needs and aspirations, and that are ethically anchored and oriented to the role science plays in society, rather than satisfying purely commercial interests. However, deciding on what is good and important for the researcher is not a simple task. Neither is it to decide on what is the best for the social group that this researcher is part of, or how, in the long term, algorithmic mediation will impact society.

6.3.1 Automated decision-making in science

On the one hand, algorithms do not work properly. They are likely to make wrong inferences, recommend things that are not exactly a match for what one would want to see. When that happens, people get disappointed and, sometimes, blame themselves. However, there are different reasons for poor recommendations that cannot land on the user's shoulders, as they are essentially design issues. For instance, algorithmic systems are based on the user's past behaviour, and eventually are "too late" in meeting the user's current interests. Also, our studies show that nearly 70% of the keywords that define the ResearchGate user profile are inferences, which has been reported in literature as a source of misconceptions and inaccuracy (Bozdag, 2013; Milano et al., 2019; Pariser, 2011; Polonioli, 2020).

On the other hand, algorithms are also likely to work perfectly, maybe frighteningly well as a surveillance panopticon. To recommend exactly what one was thinking, they are, for sure, using a huge amount of data, cookies, information from other websites, collecting and correlating a scary amount of data about this user. However, such a curatorship that is so flawlessly delivering what is expected, needed and likeable, is probably depriving us of accessing the other side of this selection process, i.e. every content that might not be so convenient but that is also part of our reality.

There is one concern that, as a researcher, I believe is dangerously escaping from our focus in the realm of recommender systems in ASM, and it revolves around finding what contradicts our beliefs and research findings. Of course this is not an exclusive issue of recommender systems. The psychological tendency to seek or interpret information in ways that are partial or biassed to existing beliefs, or a hypothesis in mind is already known as confirmation bias (Nelson & McKenzie, 2009; Nickerson, 1998; Roy, 2017). However, recommender systems are prone to increase the feedback cycle, as pointed out by Zeynep Tufecki: "If you keep being shown coding books, you're probably more likely to eventually check one out" (Tufekci 2019, online document).

If the systems that retrieve information and recommend content to assist the users are capturing what Clapp and Murra called the "units of thought" (Clapp & Murra, 1955), it is extremely important to know precisely through which lenses such "thoughts" are being captured, represented and redistributed across the network. Moreover, we should also learn which "thoughts" are being left behind. Because as we have shown throughout this thesis, not only the human practices, but the broader social, political and economic arrangements are equally affected by the workings of the artefact.

6.3.2 Competitiveness and collaboration in science mediated by ASM

Throughout time, different authors have presented distinct motivations to the activities that researchers perform. Particularly, I would like to call the reader's attention to two main ideas used to describe scholarly communication: collaboration and competition. Thomas Kuhn studied the structure of scientific revolutions and described science as a convention. For Kuhn, science is not the practice of the truth, but what an established group of scientists understand and share as the best way of solving and clarifying investigation topics (Hochman, 1994, p. 202). Therefore, the scientific community is fundamental and it is through collaboration that these problems are solved. The theories are built under the umbrella of a paradigm that Kuhn defines as "[...] universally recognized scientific achievements that for a time provide model problems and solutions to a community of practitioners" (Kuhn, 1970, p. x). For Kuhn, the scientific revolutions are needed because they are vital to the development and progress of science. The actors involved in this process are individual scientists, but a revolution is only legitimate when a sufficient number of researchers agree with the new ideas. The scientific community is the only entity who can legitimise scientific knowledge, and it is defined by those who share the paradigm (Kuhn, 1970, p. 176). There are various examples of the collaborative aspect of scientific practices. Researchers often work in teams; bibliometric studies show that in scientific production, collaboration is increasing over time in most different fields (Bornmann, 2017; Shen et al., 2021); and the Open Access movement is gaining more and more strength.

Another angle to observe the research practices is through the lenses of competitiveness. Pierre Bourdieu (Bourdieu, 1975) emphasises the role of power in the studies of science and portrays a much more "motivated" practice of science in comparison to the one presented by Kuhn. He refutes the term "scientific community" and argues that researchers actually allocate themselves in the Scientific Field, which is a ground of constant dispute, competing for symbolic profit and prestige. By doing so, Bourdieu puts scientific practices in a broader context, with no differentiation from regular social dynamics from outside academia. This scientific field is "the universe in which the agents and institutions that produce, reproduce or disseminate [...] science are inserted. This universe is a social world like the others, but which obeys more or less specific social laws" (Bourdieu et al., 2004, p. 20). We can also list examples of competitiveness in science. On the individual level, researchers often compete for grants, academic positions, recognition in the form of prizes and other status symbols; on the institutional level, the scientific production (commonly measured by the number of publications) and impact (commonly measured by the number of citations) is heavily used in universitary rankings. These rankings have an impact on the decisions of potential students and employees, influencing the level of quality of the students and employees the institution attracts and hereby, in turn, again impacting the productivity of research.

In our studies, participant's excitement about being able to follow experts in the field reflects two motivations, on the one hand admiration and on the other hand the challenge to be better than the specialists. This constant observation between users sets the bar for what is considered legit (for example, whether or not to share preprints or published papers that are behind paywalls) and successful. While some researchers observe experts in order to surpass them, in a competitive attitude, others prefer to follow the experts' lead, which makes experts a kind of "influencers" within the academic world. It could also be argued that the latter motivation (admiration, respect, and following in the specialists' footsteps) is also a form of competitiveness. As discussed in citation studies, aligning the research with the strongholds of the field is also a form of persuading the reader in order to guarantee scientific capital (Bornmann & Daniel, 2008; Gilbert, 1977). Thus, it could be understood as competitiveness through collaboration. From this perspective, it seems like "big names" are assuming the role of "digital influencers", as people look up at what the experts are doing regularly, sometimes even on a daily basis, as inspiration for new research.

People cope with academic challenges in various ways. We also demonstrated that, depending on the situation, researchers will act collaboratively, competitively or in between these two extremes, with an ambivalent approach. The researchers' approach usually reflects their motivations (anchored in human values) and it has an impact on their choices of which features to use.

6.3.3 User's needs and the agency of the platform

Predictions about individual users' needs are orchestrated by the interests of the platform owners and advertisers forming the basis for online content calibration (van Dijck and Poell 2013). Using data from several sources, algorithmic meditation creates an individual tailor-made digital environment that shapes the browsing experience. Through different mechanisms (such as information selection and prioritisation), platforms construct a narration of the self (Jacobsen, 2020) and of the relevant other in ASM, which triggers certain behaviours, such as increasing posting and interactive practices in the platforms. The mechanisms reflect a vision of how the platform is "expected to be used" (what a user can or cannot do in the online environment), but also what is expected from the user him or herself. ASM platforms reward, via internal metrics, the most active users, the most digitally skilled, and those who create the most engaging content. By doing so, these platforms are nudging users to be productive and participative, i.e. to share as much content as they can, to interact with their audience, and to produce content as commodities that will attract more users to the platform. Such behaviour does not always benefit the user, and can bring anxiety and FOMO to researchers. Additionally, the fact that both experts and non-experts share the same digital space and are susceptible to the same metrics, gives the (misleading) impression that they are, in fact, comparable. However, typically the experts in the field are people with decades of experience in their career and, naturally, could not be compared to an early-career researcher.

The implication of the comparison could be an increase in competition fuelled by these emotions of anxiety and FOMO, which is likely to compromise the mental health of researchers and decrease the quality of scientific developments (see for instance predatory journals and flaws in the peer review dynamic (Smith, 2021a, 2021b)). However, adapting the platform's design seems to be insufficient to deal with the underlying problem to be faced, since the design of ASM platforms also resembles the way science is valued and measured. For example, ResearchGate uses researchers' publications as one of the values to build its main indicator, the RG Score. Current ASM platforms are datafied environments that build a narrative of the winner where publications, interactions and people's achievements are commodified (e.g. the "seals of achievement" whenever a publication is read a certain amount of times on ResearchGate). It is important to stress that the successful profile one sees online is mediated by the platform that explores human vulnerabilities to increase the engagement for profit. This is also an example of how the artefact and social arrangements are mutually shaping.

In this sense, not only platform designers but also university policy-makers could pursue alternative scenarios where competitiveness is not chased at all costs. For example, demystifying failure (instead of encouraging the canonical idea of success), promoting knowledge sharing regardless of quantitative metrics, and valorising interdisciplinary serendipity. These changes in academic culture, combined with the redesign of the artefacts, could help researchers to reframe the academic experience as a whole, escaping from the platform's nudging strategies that lead to unhealthy competition. Halberstam's invitation to see "the perspective of the loser in a world that is interested only in winners" (Halberstam, 2011, p. 3) is refreshing, because it shows how failure is also part of the growing process. The quantification of achievements, supported by datafication, can be a shallow and simplified representation of the actual scientific process, which includes risk-taking, failure and learning. Halberstam says: "The desire to be taken seriously is precisely what compels people to follow the tried and true paths of knowledge production around which I would like to map a few detours" (Halberstam, 2011, p. 6). Therefore, embracing the uncertainties of scientific labour is beneficial not only for the researcher's mental health, but also for learning processes and scientific innovation. The spaces scholars occupy (including the digital ones) could be safe spaces within academia to fail, honouring "endurance, struggle, and contradiction" (Devendorf et al., 2020, p. 26) which are inherent to everyone's career anyway. Maybe a certain level of algorithmic literacy is needed to help users to better cope with what they are exposed to, while the academic culture is in transition.

6.3.4 The human agency in ASM platforms

Any technology is subject to human agency: not only to the designers' aspirations during development phases, but also to the users' motivations during their use of technology, which can lead to uses that are unexpected by the designers and that are even sometimes subversive. The reasons why people do what they do build on their perceptions about the platform's functions and their conceptual model of how they think it works. For example, users may refrain themselves from "liking" certain content they don't want to be publicly associated with, if they think that the platform will show the "like" it to other users. There are many motivations for people not to engage actively with ASM. The existence of a certain button or search bar on the interface does not imply that people will necessarily interact with it (Ellison et al., 2020). This is why it is crucial to investigate people's perceptions regarding the technological tools that are intertwined with their daily practices. Agency is constantly negotiated between users and the platforms. While users are posting and reading, the platform is tracing and iteratively recommending content.

In this thesis we also highlighted the importance of the user interactions in ASM, as part of the mutual shaping nature of such platforms. While the platform nudges the researchers to connect with certain publications and people through personalised recommendations (e.g., "you might like this" or "who to follow"), the users have freedom to interact or not with the content, for instance by choosing when to login, what to read and what to click on. However, our findings also emphasised how, through several mechanisms of automated filtering, the user's universe of choice is narrowed by the recommender algorithm.

Participants believe ASM platforms could help them to exercise universalism, via, for example, finding less privileged groups in academia. I believe the valorisation of specific groups depends more on the conscious effort of the user in choosing to read and cite these groups than on the system, as the pure algorithmic selection tends to act in a silent and subtle way to privilege in ranking those who already have a high reputation, as demonstrated in this thesis corroborating the Matthew effect of accumulated advantage in science (Merton, 1988). The same seems to apply to the researcher's self-direction in recommendations of topics to follow. In our study, participants see matching topics as an affordance for independent thought and freedom of action, without interference of the platform. However, the high amount of keywords that define the users' profile and also biases in indexation processes puts in question the level of autonomy that the researchers actually have in such platforms.

6.3.5 The challenge to reconcile individual aspirations (user's needs) with the broader scientific goals

Even when researchers are individually gaining more than losing in the use of ASM platforms, it is not a given that the broader scientific community is also thriving. When relying on AI applications for driving directions, for example, we relegate to the systems relatively easy decisions to make. However, even those easy decisions are made in a way that represents a certain vision of the world. What is the best path from point A to B? It depends if the driver prefers the quickest or the wooded path, the usual or the recently renewed (and safer) path. Assuming there is a car crash on the road and an ambulance must arrive as soon as possible to the place of the accident. Shouldn't the system recommend alternative paths to the other drivers to clear the way for the ambulance? This would possibly delay the journey to some of the drivers. How can the system then reconcile the individual needs with what is the best from a broader perspective? How can the system decide what is the right thing to do for the sake of the injured person but also for the other individuals? To the best of my knowledge, this is still an open question in the Ethics of AI.

What would this mean, then, for research? The content in ASM platforms is mediated through mechanisms of profiling, selection, prioritisation, commodification, datafication, among others. Algorithms therefore shape the categories in which the researcher "fits in" (profiling), what the researcher will read (selection), what the researcher will see first (prioritisation), which content is more likely to foster interactions (datafication) and what the researcher can bring to the platform (commodification), such as content and people. Additionally, they shape how researchers see themselves and the relevant other. All these decisions are partially based on data given and data traces, but mostly inferred by the system. This configuration puts automated decision-making in the position to influence several subjective choices made by users of ASM platforms. For example, what is a good topic to investigate? Which are the most relevant theories in a domain? What is the best method to employ in a certain research project? Which variables are relevant and which are not? Which researcher is the best in this field? On whose opinion should one trust? Which communicative practices will allow the most fruitful results for one's career? Where should one submit their paper? Where should one apply for a position? In our research we analysed artefact, practices and arrangements and concluded that algorithmic mediation in ASM traverses all these entities, from documents to researchers and job positions. ASM platforms such as ResearchGate also infer who are the experts in a certain topic "using machine-implemented recommendation logic" (Madisch et al., 2018, p. 4). In this sense, algorithmic mediation influences who people might consider as influencers. The recommender algorithms could be defining who researchers consider the experts of a certain topic, depending on how much they rely on recommendations.

More than projecting the future of researchers, the algorithmic inferences can be also shaping the future of science as a whole. With the current opacity of ASM platforms, it becomes increasingly difficult to grasp to what extent these platforms could interfere in the flow of scientific information across universities, disciplines or even countries. Scientific endeavours have a tradition to care for the greater good, to achieve collective development and welfare. However it is uncertain how the platforms could reflect not only individual aspirations, but also the Universalism, Communism, Disinterest and Organized Skepticism that constitute the *ethos* of science (Merton, 2013).

6.4 Limitations and future work

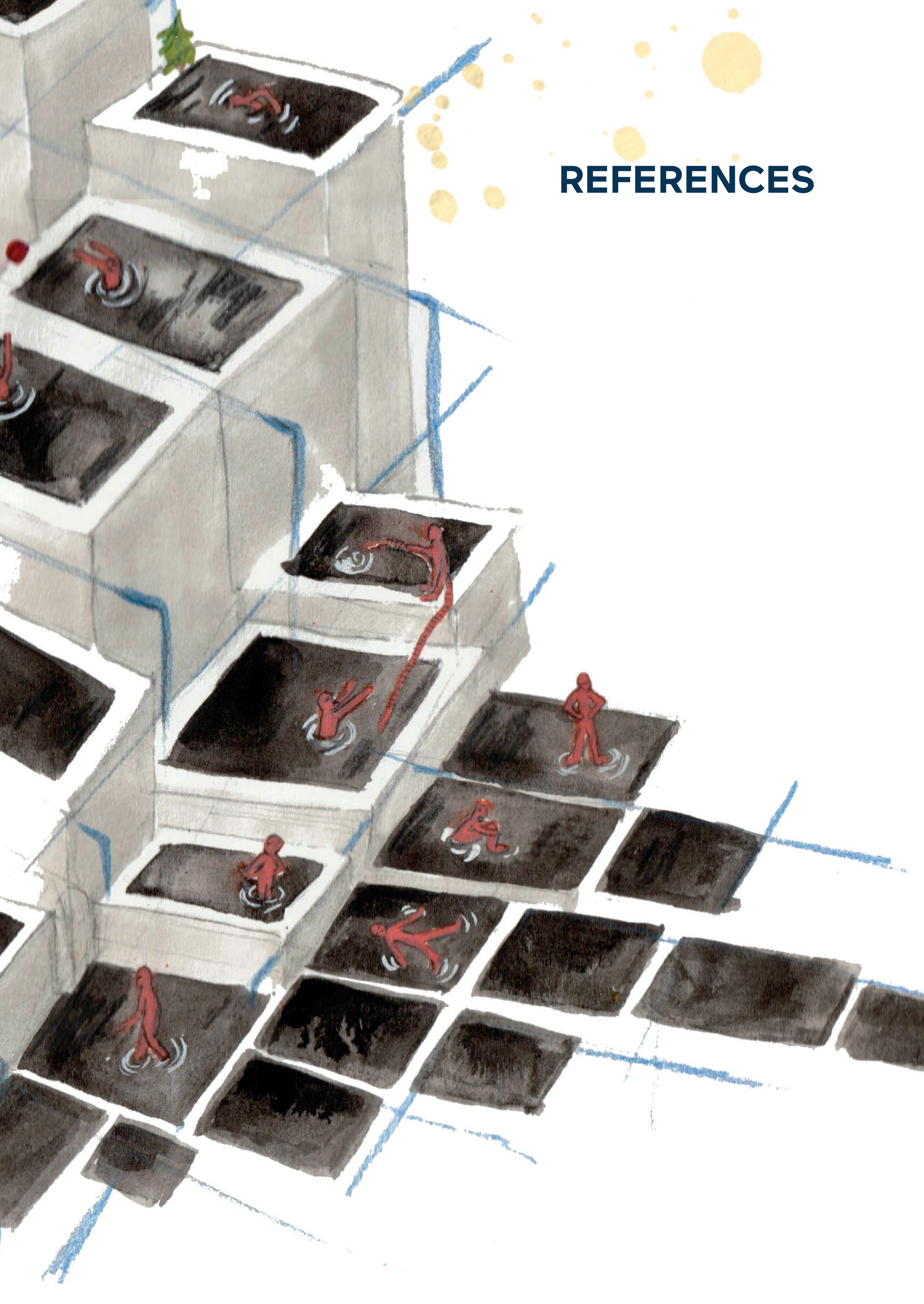
Part I and Part II of the thesis draw on a different paradigmatic perspective. Although our pragmatic approach in which an interpretative lens (cf. Part I) is combined with a post-humanistic view might be unconventional, we believe it has the added value of yielding a comprehensive analysis on the mutual shaping of people's interactions with and by ASM platforms. In our choice of our methods, we feel supported by previous literature that has argued that the way platforms guide users via their design and communication strategies can be investigated via a thorough inspection of the artefact, just like we did in Part I of this thesis. Recent literature in Human-Computer Interaction (HCI) (Light et al., 2018; Barassi, 2017; van Dijck, 2013; van Dijck & Poell, 2013) has shown how researchers can investigate the way platforms guide users through activities via their design and communication strategies. Some examples are information infrastructure studies (Bowker et al., 2010), digital ethnography (Pink et al., 2016) and the walkthrough method (Light et al., 2018). In the intersection between science and technology studies (STS) and cultural studies, these approaches allow for "[...] identifying the technological mechanisms that shape - and are shaped by - the app's cultural, social, political and economic context" (Light et al., 2018, p.886). In order to understand how people make sense of the interactions with and through ASM platforms, a perspective we adhered to in Part II, a more human-centric method was deemed more relevant, in line with exemplary studies using interviews (Turfekci, 2013; Genise, 2002; Saldaña, 2013) and research games (Mitgutsch & Alvarado, 2012; Slegers et al., 2015).

As for the analysis performed in Part I, we acknowledge that the artefact-centred perspective could never be complete, as the details of the working of ASM platforms are protected by commercial secrecy. We only could perform indirect observations of what was decided by design. Moreover, we also haven't collected data that would reveal the underlying designers' intentions. It is hard to investigate the exact impact of algorithmic mediation and its potential to entrench biases, because there is no single shared webpage that can be scrutinised. Each and every user has their private feed, that is refreshed every other minute, and to which no other researcher has access to. Additionally, data about social media use also rapidly becomes obsolete, as the programming codes are constantly being rewritten. Hence, the present study is limited to the information we had access to in a particular period, including the data provided by the companies, what we identified following visual clues on the interface, and documents such as the patent and web code. At the time of publication and reading this manuscript, the platform, its logic and its effects in the platform might have changed. An in-depth scrutiny is further hampered when companies provide little or no meaningful information about the algorithmic process, which was the case for our company inquiry.

The platform analysis focused on one particular ASM (ResearchGate), leaving other ASM out of this analysis. Although no systematic analysis was performed on Academia.edu or the social media features in Mendeley, it is still very plausible that these other ASM employ similar features as they are at the heart of what characterises them as social media. Examples of these social media features include the personal profile that people can build and manage, the connections made by following and being followed by others, the "portfolio-like" features revolving around sharing content, and the interactions that the platform allows in terms of liking, commenting, sharing, etc. These interactions turn into metrics that inform the users and their connections in their "online performance" in order to recommend content algorithmically. Even though the results cannot be generalised, we deem the transferability of our main findings nonetheless very plausible. Future studies might investigate other ASM using the same approach to verify this.

As for the studies described in Part II, i.e., the interviews and a research game), our results are limited to the profile of the participants. Since part of my joint PhD was done in Porto Alegre (Brazil) and the other part in Leuven (Belgium), many of the participants of the empirical studies concentrated in those regions, which, by consequence, exclude every other part of the world. The purpose of this thesis is not to offer definitive answers nor generalizable results. By the nature of the methods chosen for Part II, if a different set of participants were selected to the studies, it is plausible to believe that the results could be distinct. However, I went in-depth with the chosen set of participants and to reach a better understanding of their sense-making and practices. The resulting themes were discussed with supervisors in an iterative process and a peer debriefing process was performed. New inquiries could involve more participants or draw comparisons between different demographic groups.

Overall, we purposely deviated from the typical known paths. This thesis is unique in combining the artefact-centred data analysis with a human-centric one while also reflecting on it in the mutual shaping with broader arrangements. To the best of our knowledge, this is the first academic work to research the role of algorithmic recommendations in academic social media platforms. I believe that studies on ASM would benefit greatly from more comprehensive analysis like the one presented in this research. Both in the multi-angled perspective as well as in the methods chosen, we did not choose for the most evident or easiest options. The end result is that the PhD thesis can serve as food for thought for future research in many ways. It presents an innovative multi-method research protocol to study ASM in particular and recommendation systems in general. It shows how researchers can use their civic and legal rights to obtain data about themselves as users, data that also has strong intrinsic academic value for further analysis. The protocol also has didactical value, in that the methodological details allow for replication research and may inspire students and scholars to conduct similar research. For instance, people can use the letters of the company inquiry as a template to make similar data requests in the future. Future scholars can also be inspired to triangulate artefact-based interface data by also incorporating data from a web page code inspection and a patent analysis. Another example is the description of the research game creation process, which also allows and hopefully encourages future researchers to undertake a similar endeavour in the future. From a societal perspective, we initiated the debate on how public values (instead of purely economic and commercial values) may steer future discussions on how to shape a positive digital society based on values such as justice, autonomy, explicability, fairness, and democratic control.



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APPENDIX

Appendix 1. Call on social media

[English]

Você é um pesquisador...
...e utiliza redes sociais acadêmicas?
Participe da pesquisa e nos ajude a melhorar as tecnologias de personalização na ciência
O que precisamos:
• Pesquisador(a) 18 anos ou mais (todas as áreas do conhecimento)
• Usuário(a) de redes sociais acadêmicas (perfil ativo no ResearchGate or Academia.edu)
• Inglês fluente
Benefícios da pesquisa:
• Conhecimento sobre o funcionamento de recomendações nas redes sociais acadêmicas
Para se inscrever, acesse o link na descrição ou comentários da imagem!
KU LEUVEN
mintlab
meaningful interactions lab
GRUPO DE PESQUISA COMUNICAÇÃO CIENTÍFICA
PPGCOM – FABICO – UFRGS
UFRGS
PPGCOM
CAPES
Este estudo foi aprovado pelo comitê de ética da UFRGS, CAAE nº. 38406720.2.0000.5347

[Portuguese]

Appendix 2. Recruitment form

Thank you for your interest in contributing to our research. Please fill in the form below.
Based on this information we will make contact with you (max. one week) in case your profile is eligible for this study.

Name: ______________________________
Gender: ( ) F ( ) M ( ) Other
Mother tongue: _____________________
Profession/Title: _____________________
Field/Domain: ______________________
When did you start your PhD (year)? ____
Age: ______ E-mail address: _________________

The research will have two phases, and participants can choose which phase they want to join. All the activities will take place at the university [insert the address of KU Leuven or UFRGS depending on the country]. Please select the preferred activity:
( ) Interview/Observation (duration 1 hour max.) individual activity – we will contact you to schedule the best suitable date and hour.
( ) Research Game (duration 2 hours max.) collective activity – the activity will happen in [date / hour].

Thank you for your availability.
Feel free to contact us if you have any doubts.

Luciana Monteiro Krebs
PhD researcher
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Mintlab, KU Leuven. Parkstraat 45 bus 3605
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Appendix 3. Informed consent

[English]

Participation in research "Recommendations in Academic Social Media"

Contact Information

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1. Goal and course of this part of the research

This part of the research consists of a research game and semi-structured interviews combined with observation. You've been selected to join only one of these activities. These research techniques aim to investigate how the researchers of different domains make sense of recommendations on academic social media. The selection criterion for the participants is to be an active user of the academic social network ResearchGate. No preparation is needed.

2. Rights of the participant

Participants to this research receive the following guarantees and rights from the organising researchers:

- All collected data is handled confidently and anonymously. As this is a PhD research, only the PhD student and their supervisors (Dr. Bieke Zaman and Dr. David Geerts – KU Leuven; Dr. Sônia Elisa Caregnato – UFRGS) will have access to the collected data, and this only for the duration of the research. The data will be used for no other goal than for analysis in the context of this research project.
- When results of this research project are shared (for example in publications or presentations), no data will be shared that would identify participants.

- Participation is voluntary, which means that at any moment participants can decide to cease participation without providing any account for their decision. The expected duration of the research game is 2 hours. The expected duration of the interview is 40 min. (which may vary according to the dynamic of the dialog).
- During or any time after the research game / interview, the participant may ask for further information about the research. To do so, access the contact information at the header of this informed consent.

3. Consent
By signing this document, the participant gives consent to the KU Leuven and UFRGS to use, for this research project the collected data, audio and video recordings. The participant grants permission to use this material in future scientific publications. The data will always be treated as confidential and personal information will never be made public.

4. Agreement
I, undersigned, ... declare to have read the information below and accept participation in this research in the context of the project "Recommender Algorithms in Academic Social Networks".
I have received a copy of this signed and dated form. I have received information on the character, goal, duration and objectives of the project and the research trajectory. I have had the opportunity to ask questions about the project and its trajectory; on all questions a satisfactory answer was provided. I understand what is expected of me and what my rights are as a participant.
I know that the data collected and analysed here, will be used for research.
I agree with participation. By doing so, I grant permission to use the data collected from pictures, audio and video recordings during the research game / interview. The results will be published without mentioning my personal details. I thus grant permission to summarise the results anonymously in scientific publications. After I login in the platform via computer, the login data will be immediately erased from that computer and the cookies will be cleaned.
At each moment, it is possible to withdraw my agreement, without having to account for my decision.

Date (DD/MM/YYYY):
Name and signatures
Of the participant: Of the researcher:

[Portuguese][35]

Termo de Consentimento Livre e Esclarecido (TCLE) para participação na pesquisa "Recomendações em Redes Sociais Acadêmicas"

Convidamos a participar da pesquisa Algoritmos de Recomendação em Redes Sociais Acadêmicas, coordenado pela pesquisadora Luciana Monteiro Krebs (Doutoranda do PPGCOM-UFRGS e K.U. Leuven) sob a orientação das doutoras Sônia Elisa Caregnato (UFRGS) e Bieke Zaman (K.U. Leuven) e do doutor David Geerts (K.U. Leuven).
Nesse TCLE você vai encontrar as informações necessárias para consentir ou não com sua participação na pesquisa. Em caso de dúvida com relação ao protocolo de realização dessa pesquisa, sinta-se à vontade para contatar os pesquisadores ou ainda o Comitê de Ética da UFRGS (CEP UFRGS), cujas informações de contato encontram-se a seguir.

Informações de contato
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Comitê de Ética da UFRGS
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1. Objetivos desta parte da pesquisa
Esta parte da pesquisa consiste em um jogo de pesquisa e entrevistas semi estruturadas combinadas com observação. Você foi selecionado para participar de apenas uma dessas atividades. Essas técnicas de pesquisa visam investigar como os pesquisadores de diferentes domínios interpretam as recomendações nas mídias sociais acadêmicas. O critério de seleção dos participantes é ser usuário ativo da rede social acadêmica. Nenhuma preparação é necessária.

2. Direitos do participante
Os participantes desta pesquisa recebem as seguintes garantias dos pesquisadores organizadores:

35 The document is in Portuguese as it was presented to the participants.

- Todos os dados coletados são tratados com segurança e anonimamente. Por se tratar de uma pesquisa de doutorado, apenas a aluna de doutorado e suas orientadoras e co-orientador terão acesso aos dados coletados, e isso apenas durante o período da pesquisa. Os dados serão usados para nenhum outro objetivo que não seja para análise no contexto deste projeto de pesquisa.
- Quando os resultados deste projeto de pesquisa forem compartilhados (por exemplo, em publicações ou apresentações), nenhum dado pessoal (que identifique os participantes) será compartilhado.
- A participação é voluntária, o que significa que a qualquer momento os participantes podem decidir cessar a participação sem prestar contas pela sua decisão. A duração prevista do jogo de pesquisa é de 3 horas. A duração prevista da entrevista é de 40 minutos (que pode variar de acordo com a dinâmica do diálogo).
- Durante ou a qualquer momento após o jogo de pesquisa ou entrevista, o participante pode pedir mais informações sobre a pesquisa. Para isso, acesse as informações de contato no cabeçalho deste consentimento informado.

3. Riscos e benefícios

Os riscos dessa pesquisa são baixos e se limitam a potencial cansaço dos participantes em participar da entrevista e do jogo de pesquisa. Como a atividade será realizada online, através do computador pessoal do(a) participante, onde normalmente realiza suas tarefas diárias, e que a fará sentado, não há previsão de desconforto físico. Em relação à privacidade, reforçamos que as gravações são necessárias apenas para compreender o contexto em que as falas são feitas e, portanto, serão anonimizadas para a análise dos dados. Para mitigar o fator cansaço, destacamos que o participante pode, a qualquer momento, fazer uma pausa. Lembramos também, em relação ao desempenho no jogo de pesquisa, que o objetivo do estudo é entender como os participantes interpretam as recomendações algorítmicas. Portanto, não há "maneira correta" de usar as recomendações ou a resposta desejada.

Além das vantagens de abordar as preocupações da sociedade nos principais objetivos da pesquisa, nossas escolhas metodológicas também visam benefícios para os participantes. A maioria das pessoas tem uma vaga ideia de como funcionam os algoritmos de recomendação, porque esses sistemas são frequentemente apresentados a eles como uma "caixa preta". Nas entrevistas, as perguntas abertas estimularão a reflexão e consideração sobre o impacto dos algoritmos de recomendação em suas práticas. Ao fazer isso, esperamos ajudar os participantes a compreender seu próprio comportamento na rede social acadêmica da qual são usuários. As principais vantagens de um jogo de pesquisa utilizado como método são: (a) os participantes se sentem à vontade; (b) a dinâmica do jogo estrutura as conversas dos participantes; (c) o jogo garante que todos os participantes possam ter espaço para se manifestarem. Neste estudo em particular, os participantes usarão um conjunto de cartões com base em uma análise de plataforma (análise de interface, inspeção de script, inquérito da empresa e análise de patente) de um estudo anterior. Isso lhes dará uma ideia melhor de quais elementos são usados nas recomendações do ResearchGate. Portanto, os participantes ficarão mais cientes dos recursos de recomendação e de suas funções. Acreditamos que isso possa empoderar o participante no sentido de que, ao melhorar seu entendimento sobre como determinados conteúdos estão sendo distribuídos, eles possam enquadrar melhor seu trabalho e tentar tirar proveito da tecnologia disponível.

4. Consentimento
Ao assinar este documento, o participante dá consentimento ao KU Leuven e à UFRGS para utilizar, para este projeto de pesquisa, os dados coletados, gravações de áudio e vídeo. O participante concede permissão para publicações científicas deste material. Os dados serão sempre tratados como confidenciais e as informações pessoais nunca serão tornadas públicas.

5. Declaração
Eu abaixo-assinado, ..., declaro ter lido as informações abaixo e aceito participar desta pesquisa no âmbito do projeto "Recomendações em Redes Sociais Acadêmicas" (Recommender in Academic Social Media).
Recebi uma cópia deste formulário assinado e datado. Tenho recebido informações sobre o caráter, meta, duração e objetivos do projeto e da trajetória de pesquisa. Tive a oportunidade de fazer perguntas sobre o projeto e sua trajetória; em todas as questões foi fornecida uma resposta satisfatória. Eu entendo o que é esperado de mim e quais são meus direitos como participante.
Eu sei que os dados coletados e analisados aqui serão usados para pesquisas.
Concordo em participar da pesquisa. Ao fazê-lo, concedo permissão para os pesquisadores usarem os dados coletados em fotos, gravações de áudio e vídeo durante o jogo de pesquisa / entrevista. Os resultados serão publicados sem mencionar meus dados pessoais. Portanto, concedo permissão para resumir os resultados anonimamente em publicações científicas.
Estou ciente de que a qualquer momento posso me retirar do estudo, sem necessidade de justificar minha decisão.

Data (dia/mês/ano):
Nome e assinatura do(a) participante:
Nome e assinatura da pesquisadora:

Appendix 4. Comprehensive company inquiry

This is the email sent to ResearchGate after their first answer.

Dear Kyle,

First of all, I would like to thank you for your reply.

Unfortunately, your reply does not include all the information I requested. As there seems to be some uncertainty as to the scope of my request, I have tried to specify as clearly as possible all of the information I would like you to give me. It would be particularly helpful for both of us if you could align the structure of your response to the list below.

Based on Article 15 GDPR (read together with Article 12 and 22), I would like to obtain:

1. A copy of all my personal data held and/or undergoing processing, in a commonly used electronic form (Article 15(3)). Please note that this might also include any audiovisual material (e.g. voice-recordings or pictures) and is not necessarily limited to the information contained in your customer database and/or the information you make available through the 'manage my profile' functionality.
2. Confirmation as to whether or not you are processing any special categories of personal data, also called 'sensitive data' about me (cf. Article 9) and if so a detailed list of that data.
3. If any data was not collected, observed or inferred from me directly, precise information about the source of that data, including the name and contact email of the data controller(s) in question ("from which source the personal data originate", Article 14(2)(f)/15(1)(g)).
4. If these data have been or will be disclosed to any third parties, please name these third parties along with contact details in accordance with Article 15(1)(c). Please note that the European data protection regulators have stated that by default, controllers should name precise recipients and not "catego-

ries" of recipients. If you do choose to only name categories, you must justify why this is fair, and be specific, i.e. naming "the type of recipient (i.e. by reference to the activities it carries out), the industry, sector and sub-sector and the location of the recipients". (Article 29 Working Party Guidelines on Transparency WP260 rev.01, p37).

5. All purposes of the processing for which each category of personal data collected are intended, as well as the lawful ground (cf Art.6(1)) for each specific purpose. For all uses of "legitimate interests", please explain what those interests are (Article 14(2)(b)) and how you consider your interests to override mine.
6. Confirmation as to whether or not you consider yourself making automated decisions (within the meaning of Article 22, GDPR). If the answer is yes, please provide meaningful information about the logic involved, as well as the significance and the envisaged consequences of such processing for me in particular. (Article 15(1)(h))
7. Confirmation on how long each category of personal data is stored, or the criteria used to make this decision, in accordance with the storage limitation principle and Article 15(1)(d).
8. Confirmation on where my personal data is physically stored (including backups) and at the very least whether it has exited the EU at any stage (if so, please also detail the legal grounds and safeguards for such data transfers). If you make use of cloud-services, please provide me with detailed information about where their servers are located and the details about your data processing arrangement with these providers.
9. Details on the security measures you undertook to safeguard my personal data (including, for example, encryption, access restrictions, data minimisation strategies, storage methods, etc.).
10. Confirmation as to what data subject rights you consider I have vis-á-vis you and how you would accommodate them
11. Confirmation on whether or not at any stage, you have recommended content to me on the basis of my personal data.
12. Explain the logic behind your news-/content-recommendation system as applied to me in particular. For example:

- What part of the content I consumed was personalised or recommended on the basis of my profile?

- A comprehensive list of concrete (categories of) personal data involved in the recommender system (as applied to me specifically(merely giving examples of data that are being used to that end is not sufficient)
- Why the respective (categories of) personal data were considered relevant for the recommender system
- The weight of the different categories of personal data feeding the recommender system;
- Details on how your recommender system was designed, without having to give trade secrets or IP protected information (i.e. background of people involved, is it an ongoing process, etc)
- What priorities have guided the design of the recommender system?

Thank you very much.

Best wishes,

Luciana

Appendix 5. Interview protocol

Metadata of the interview
- Place and date of the interview
- Number of the participant
- Gender

Opening
- Researcher KU Leuven and UFRGS (card)
- Topic: Academic Social Networks
- Interview and “walk through” / “thinking aloud” – showing some practices (camera)
- ~30min
- Informed consent

Profile
- Field / Domain / Background
- Affiliation
- Nationality
- What type of researcher are you? PhD, postdoc, professor, research manager, other?
- How long have you been a researcher?
- Which general social media do you use and how often do you use them?

Questions
1. Do you see pros and cons in the use of these platforms? Can you give me examples?
2. In your opinion how do these platforms shape scholarly communication?
3. Do you use academic social media? Which one(s) do you use?
4. How often do you use academic social media?
5. Do you remember when you started to use them?
6. Why do you use academic social media?
7. Can you show and explain to me a little bit of what you normally do when using academic social media?
8. What do you look for in academic social media? What are the advantages of using ASM?
9. Which activities suit these platforms better and which should be done in other channels?

10. What do you think about the content of the platform? How does it meet your needs and expectations?
11. When receiving recommendations of other researchers' accomplishments, what do you normally do? Can you show me?
12. How does it feel to receive these recommendations? Can you give an example?
13. Do you think the platforms encourage some sort of collaboration? In what ways?
14. Do you think the platforms encourage some sort of competitiveness? Why do you think that?
15. Overall, how do the recommendations shape your activities on the platform or your research in general??

Closing protocol:

- Answer any questions from the participant
- Say thanks
- If the participant is interested in a follow up of the research, ask for their card (or contact info) to send the results (although it might take one year to do so)

Appendix 6. Artistic composition of the thesis

This thesis was enriched visually by the competent work of Chloé Dierckx and Anelise De Carli. I wanted to illustrate the thesis with meaningful drawings/paintings which could help the reader to interpret the content of the academic work while at the same time spark other feelings in the readers' mind, which is a very prominent characteristic of visual effects. Instead of creating "data visualisations" from the research, I wanted to explore these other possibilities, playing a bit with symbols and images that could go beyond aesthetics and really build up more meaning and knowledge creation. These two amazing artists and researchers did an amazing job about which I would like to share a little more.

I invited Chloé to join me giving her one only reference as briefing: "many images in one". The idea was to picture somehow the complexity and multiple dynamics interwoven the online platforms, which somehow form a coherent whole.

Cholé is a brilliant artist and researcher, "on a mission to blend art, philosophy and social science", as she says herself, who I had the pleasure to have as a colleague and friend at the Meaningful Interactions Lab (Mintlab) at KU Leuven (Belgium). She created the images for the cover from scratch for the thesis. Departing from very short summaries of the thesis that I provided, and the final results of each chapter, she captured the essence of the theoretical framework and translated it into the beautiful and meaningful images you see across the manuscript. This is her vision for the drawings:

> I always imagine online platforms as parallel worlds you can dive into. What you see on the screen of your device is only the surface of a complex system enabling countless possibilities. Water is also something dynamic, something that changes shape when you dive into it, something that flows, just like data flows through a recommendation system. That is probably why I immediately visualized 'the artefact' as a pool. In her summary of her research, Luciana mentioned there is often a lack of transparency in recommendation systems (2nd chapter), which is why I chose to make the water

> of the pools black and untransparent. To represent the Matthew effect (3rd chapter), some pools are very deep, while others are only a thin layer of water. The pools are connected with a watering system, which represents the social arrangements. This system decides how the water flows. The users of the platform are represented as swimmers, some are diving, others just dipping their toes. Since the 4th chapter of Luciana's thesis is on the psychological effects of using the platforms and how observing other users might lead to anxiety, one swimmer is looking at the others with binoculars and others are almost drowning. The 5th chapter emphasizes the game-like qualities of academic social media platforms, which is why some swimmers are playing together. (Chloé Dierckx)

After receiving the drawings from Chloé, I talked to Anelise, who is also a brilliant researcher in Communication, Imaginary, Philosophy of Image and Visual Culture, whom I also had the pleasure to have as a colleague at the Graduate Program of Communication and Information Science (Federal University of Rio Grande do Sul, Brazil). She designed the layout of the cover of the book and worked at the typesetting of its internal parts and chapters. Aligned with the idea Chloé presented in her drawings, Anelise and I discussed "covers" for each part of the thesis. Namely Part I, Part II and Conclusion (chapter 6). In Part I we focused on the surface of the pools/screens and on the watering system. This decision reflects the fact that chapters 2 and 3 both comprise a platform analysis. These studies include the analysis of the interface of the system and the discussion of biases reinforced by the algorithms. In Part II we focused on people interacting with the system and among each other, as this part presents the sensemaking of human values. Finally, for the conclusion, Anelise gave the idea to present the alternative version of the drawing made by Chloé, a version that is more colourful. She said: "after reading the thesis, the reader hopefully has a "new look" at the phenomenon, and therefore the colours become more vivid".

> For me, it is very important to find a way to combine scientific inventions with the way that this knowledge is shared. I was aware of the rigor of this research and its methodological creativity, as I have followed Luciana's dedicated work over the years. Therefore I proposed a graphic design project that would account for all the thoroughness here – which deserved to be presented as a reference book – and also for the authorial creation – exploring visual elements aligned with the author's aesthetic preferences. Luciana is a researcher and also an artist (a supergifted vocalist) and I wanted to show

> it in some way. My goal was that we could look at this finished book and think: this thesis belongs to Luciana and no one else. (Anelise De Carli)

I became friends with both Chloé and Anelise way before this thesis emerged. But this piece of work, interwoven by our six hands (and the hands of so many others who contributed for it to happen) is the materialisation of the gestures of kindness, sorority, and competence, for which I'm forever grateful.

Chloé Dierckx is a PhD researcher at the University of Leuven, Faculty of Social Sciences and member of the Research group Social, Methodological and Theoretical Innovation/Kreative (SoMeThin'K) and the meaningful Interactions Laboratory (MintLab) at KU Leuven. She has a background in Visual Arts and Anthropology and Cultural Politics. Her research is concerned with how techniques from art and design can be used to disseminate social scientific research. Her main focus is on implementing these techniques within an academic context, both in education and research, by overcoming the art-science divide. You can see some of her artistic projects in daniodean.org/works and in instagram.com/chloe.dierckx.

Anelise De Carli is a visual artist and researcher in Image Philosophy and Visual Culture. She is a professor at the School of Fine Arts at the Federal University of Rio de Janeiro (UFRJ) and at the Association for Research and Practice in the Humanities (APPH). She has a PhD degree in Communication at the Federal University of Rio Grande do Sul (UFRGS), with a internship as a guest researcher at the international research group "Vivre par(mi) les écrans", at the Institut de Recherches Philosophiques de Lyon (Université Jean Moulin Lyon III). She coordinates the Image Thinking Research Group (GPPimg) and co-organizes the Age of the Earth Network.

Appendix 6. List of all PhD in Social Sciences/PhD in Social and Cultural Anthropology

Doctoraten in de Sociale Wetenschappen en in de Sociale en Culturele Antropologie: soc.kuleuven.be/fsw/doctoralprogramme/ourdoctors