Decoding Algorithms: Exploring End-users' Mental Models of the Inner Workings of Algorithmic News Recommenders

Marijn Martens[1,2], Ralf De Wolf[1,2], Bettina Berendt[3], Lieven De Marez[1,2]

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[1]*Dept. Communication sciences, Ghent University, Korte Meer 11, Ghent 9000, Belgium*

[2]*imec-mict-UGent, Miriam Makebaplein 1, Ghent 9000, Belgium*

[3] *DTAI, Dept. Computer Sciences, KU Leuven, Celestijnenlaan 200A, Heverlee 3001, Belgium*

Corresponding Author:

Marijn Martens, imec-mict-UGent, Miriam Makepablein 1, Ghent 9000, Belgium

Email: marijn.martens@ugent.bet

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Abstract

Algorithmic recommenders are omnipresent in our daily lives. While a multitude of studies focus on how people use algorithmic recommenders, far too little attention has been devoted to how they perceive and understand these complex systems. In this study we focus on Algorithmic News Recommenders (ANR). Drawing on 26 semi-structured interviews, we investigated how laypeople decode Google News and Facebook News. In our method we employ the scroll-back method, make use of visualizations and a double interview design. Our results differentiate between those with a high and low level of understanding. Those with a high level of understanding acknowledged the role of companies and developers in the workings of ANR. Others, who were less cognizant had a more instrumental view and mostly focused on the relation between their individual data disclosed and the ANR. More importantly, in both groups, their feelings (ranging from admiration to frustration) about and everyday interactions (both dominant and deviating) with ANR shape their general understanding. In the discussion we argue how it's necessary for future research endeavors and algorithmic literacy initiatives to be mindful of the interconnection between knowledge, feelings, and interactions to understand layman's perspectives.

Keywords: Algorithmic recommender systems, Algorithmic News Recommenders, Algorithms, In-depth interviews, Folk theories, Decoding

Introduction

Increasingly, algorithms play an important role in our everyday decision-making processes. Recommender systems can be considered as a specific type of algorithms that process data and tailor end-users' decision-making (e.g., provide information on what to read, who to befriend, who to rent to) (Newell & Marabelli, 2015). Driven by big data and other new technologies (e.g., deep learning), it is argued that these systems are becoming the power brokers in society (Diakopoulos, 2015). The range and power of such algorithms is only expected to intensify as implementations are widespread and grow in number and context (O'Neil, 2016).

When investigating algorithmic systems, social scientists have mainly focused on the inner workings of algorithms and their discriminatory consequences (Barocas & Selbst, 2016; boyd et al., 2014; Bozdag, 2013; Nissenbaum, 2001; Sandvig, 2016). Research in this area discusses, for example, how black people are perceived as gorillas by some image recognition software, how the criminal justice risk assessment algorithms are racially biased, or how job recruitment algorithms include gender bias (Barocas & Selbst, 2016).

Social networking sites (SNS), advertising companies, technology companies, publishing companies and news agencies are putting ever more effort into personalizing news, and hereby also employing Algorithmic News Recommenders (ANR) (Cools et al., 2021; Harambam et al., 2018; Joris et al., 2021; Thurman et al., 2018). ANR organize, select, and aggregate news to influence the decision-making of an end-user on what news to consume. They do so without a transparent explanation on the process. On the contrary, most technical details are hidden from the public and hereby actively but silently shape individuals' news exposures (Helberger, 2019).

ANR and algorithms in general are most often embedded in complex computational systems (Andersen, 2020). Recently, scholars have started devoting more attention to how end-users perceive and interpret algorithms (Bucher, 2017b; DeVito, 2017; Hargittai et al., 2020; Ytre-Arne & Moe, 2020) as "gaining a deeper understanding of user experiences is essential as datafication produces complex and potentially problematic outcomes in society" (Ytre-Arne & Moe, 2020, p. 2). Indeed, a fine-grained understanding of these algorithms can help individuals to critically analyze and evaluate them (Araujo et al., 2020). Moreover, such insights could enforce companies to better understand their users and create technologies that are in line with user's perceptions and expectations.

In this study we conducted in-depth interviews (n=26) with lay people on how they interpret and explain their Google News Feed and Facebook News Feed. Our theoretical framework is anchored in the much cited and promising work around the concept of folk theory (Gelman & Legare, 2011) repeatedly applied in the context of ANR (Eslami et al., 2016; Fletcher & Nielsen, 2018). To further understand why and how end-users build their knowledge models, we complement these folk theory with Hall's (1973) encoding-decoding model as adapted in the context of algorithms by Lomborg and Kapsch (2019). Combining folk theory with the encoding-decoding model enables us to go beyond an understanding of algorithms in terms of awareness and skills. We focus on their mental models and folk theories that are embedded in experiences and opinions. To gain further insights, we also look at the intersection of three structures of understanding, i.e. an individuals' knowledge, sentiment and interaction.

In what follows, we first discuss the conceptualization of algorithms and news(usage). Thereafter, we focus on folk theory and decoding algorithms to understand how people imagine and understand these systems. We then zoom in on the three structures of understanding when decoding algorithms, as proposed by Lomborg and Kapsch (2019). Specifically, we focus on how people 'know', 'interact', and 'feel' towards ANRs. After we discussed our double interview method and analysis, we delve into our empirical results to end with the implications for the field and recommendations for future research endeavors.

Theoretical Background

Conceptualization of algorithms and news

Algorithms can be seen as a combination of instructions or procedures to process input data into output data to complete a specific task (Gillespie, 2014; Seaver, 2013). Such a conceptualization, however, is unmindful to the further embeddedness of that algorithm in its' wider socio-economic and socio-technical context or assemblage (Seaver, 2017). Lee and colleagues (2019) define algorithms as 'folding data' to stress the interwoven relations within algorithmic systems. When investigating an algorithm, we should not only focus on the specific procedure, or the specific steps an algorithm takes, rather we should pay attention to the system in which the algorithm is embedded. In accordance with Seaver (2017) and Kitchin (2017), we do not treat algorithms as a purely technical or even a neutral set of rules, but as processes that embody human and corporate practices and choices.

News research traditionally focused on news as information that flow to and from news organization with journalists as gatekeepers. More recently, and especially in the context of a hybrid media environment, research examines audience perspectives, rather than focusing on how news is constituted by news services (Edgerly & Vraga, 2020). We argue that 'news' is shaped by technology, journalism practices, and end-users. The algorithmic logic embedded in SNS restricts end-users to distinguish between news content and other content (Boczkowski and colleagues, 2017). Journalists actively optimize their content for SNS, negotiating between what Peterson-Salahuddin and Diakopoulos (2020) call ‘newsworthiness’ and ‘interaction-worthiness’. This process of mutual shaping exists both in news consumption as in news production, further complicating the conceptualization of news (Cools et al., 2021; Jones & Jones, 2019). Indeed, what end-users perceive as news, let alone news personalization, is mostly unknown (Swart, 2021; Vraga et al., 2016).

As news increasingly exists on social network sites (SNS), scholars are paying more attention to news and news consumption on SNS, for example on how people consume incidental news on these platforms (Van Damme et al., 2020; Vergara et al., 2021) or which misconceptions exist on these platforms (Zarouali et al., 2021), hereby stretching the term news or news-ness and what it entails.

In this research, we follow the approach of Bengtsson and Johansson (2020) as they argued that “personalized news feeds on SNSs, based on a mixture of personal posts, shared content, photos, films, videos and adverts, are defined within the sites as ‘news’, making rigid distinction between ‘news media’ and ‘social media’ problematic” (p.2). We maintain our focal point on the digital lifeworld of the readers, and what they perceive as meaningful in that lifeworld, independent of the producer. Hence, we consider an individual’s Facebook News Feed or Google News Feed to contain elements of what people consider as news without further demarcating between news and non-news.

Google News and Facebook News differ from each other as Facebook News includes personal news and adverts, while Google News consists of more traditional hard and soft news. However, as we focus on what the end users perceive as news within ANR, we don't further differentiate between Google News or Facebook News as both ANR contain elements that individuals would define as news.

Folk Theories of Algorithmic Systems

The algorithmic systems producing ANRs could be considered as complex systems. From a design perspective, complex systems are mostly created in ways that users don't need a full understanding to be able to use them. Giddens (1990) labeled the latter as expert systems or "systems of technical accomplishment of professional expertise that organize large areas of material and social environments". However, lay people "tend to construct 'mental models' and theories about its functioning as a way of navigating and interacting with the world" (Bucher, 2017a, p. 40; Kempton, 1986). Such theories of the mind are called folk theories in the field of Human Computer Interaction (HCI) (Gelman & Legare, 2011).

Folk theories are used by users to make sense of experiences and explain algorithmic behaviors (Gelman & Legare, 2011). The concept is often used to explore and understand users' believes and experiences (for example DeVito et al., 2017; Eslami et al., 2016; Toff & Nielsen, 2018; Ytre-Arne & Moe, 2020). In line with Toff and Nielsen (2018), we argue that we, as scholars, need to understand how people perceive algorithmic systems to better grasp how they use these systems and how they evaluate them.

In the context of ANR, Eslami and colleagues (2016) found various folk theories about the automated curation on the Facebook News Feed. For example, their respondents argued how their new friends are being favored in the Facebook News Feed or how the format of a specific post (e.g., pictures, text, video) influences its reach. In their work it is noticeable how they tend to focus on the technical workings of an algorithm and exclude other elements, such as the companies (and their goals) involved (Seaver, 2017).

Ytre-Arne and Moe (2020) built further on this previous work and differentiated between folk theories on 'media experiences', 'user representation' and 'power structures'. These folk theories encapsulate more details of the algorithmic system than those proposed by Eslami and colleagues (2016). Ytre-Arne and Moe (2020) claim that their folk theories illustrate how people perceive the inner workings of algorithms. However, it remains difficult to understand why and how people formulate folk theories, as was also noted previously by Shin and Park (2019). Few scholars have investigated how people make sense of algorithms, taking into account their perceptions, feelings and actions, with the notable exception of Swart (2021).

An approach that includes how end-users understand algorithms (i.e., Folk theory) is laudable, however, it often neglects how their understanding develops and interconnects with their mental model. Folk theories put forward a holistic approach to understand how people imagine algorithmic systems and are mostly linked to a specific experience or belief, with some exceptions (i.e., Ytre-Arne & Moe, 2020). The latter approach, however, does not consider the experienced socio-technical assemblage of these algorithms (Seaver, 2017). An overarching understanding is thus missing.

In the following section we describe the work of Lomborg and Kapsch (2019) and their concept of 'decoding' to help us further understand the socio-technical assemblage of algorithms as imagined by users.

Decoding Algorithmic Systems

Lomborg and Kapsch (2019, p. 1) employed the concept of 'decoding' to "study the relationship that people experience with algorithms". Decoding algorithms (Lomborg and Kapsch, 2019) maintains a focus on the complete algorithmic assemblage and differentiates between how people understand, feel about, and interact with the algorithm to materialize their understanding.

Decoding as a concept originates from Hall's (1973) semiotic model in the context of broadcasting, as part of the process of encoding and decoding, with the latter being described as the act of giving meaning to a message. These processes are framed by so-called structures of understanding (Hall, 1973). Hence, when individuals make sense of these systems or when they form their folk theory, they base themselves on their knowledge model of the system, how they feel towards the system and how they interact with the system. Lomborg and Kapsch (2019), equally, differentiate between knowing the algorithm, feeling the algorithms, and interacting with the algorithm as three structures of understanding.

Knowing the Algorithm

A first structure of understanding is considered the cognitive knowledge people have of the algorithm (Lomborg & Kapsch, 2019). Being aware of algorithmic presence in everyday systems could be regarded as one of the most basic levels of this knowledge (Rader, 2014). Equally, Hargittai and Micheli (2019) treat algorithmic awareness as the first dimension of algorithmic skills. Powers (2017) found that students are often unaware of the algorithms that are used in services of Google News and Facebook News. Rader and Gray (2015), however, provide a more nuanced picture. Their respondents believed that Facebook or some kind of algorithm tweaked their News Feed. Sometimes, individuals even discuss the existence of algorithms, without necessarily calling it an algorithm (Gruber, 2021).

Understanding the algorithmic system could be considered the second level of algorithmic skills (Hargittai et al., 2020). This understanding is difficult to investigate as there is no ground truth in how these systems work or what is right or wrong. It is, therefore, argued to study the user's train of thoughts and how elaborate those are when explaining the inner workings of algorithms (Hargittai et al., 2020).

Echoing our conceptualization of algorithms (see above), Proferes (2017) and Van Dijck (2013) underline the importance of socio-economic and techno-cultural elements, including companies, people, and data, when investigating algorithmic systems. We should thus also investigate how people use these companies, people, and data in their understanding.

Rather than looking at algorithmic understanding or awareness, Lomborg and Kapsch (2019) focused on the origin of algorithmic knowledge. They differentiated between professional knowledge, experience-based knowledge, and third-party knowledge. While identifying the origin of someone's knowledge could help to better frame how someone constructs a particular understanding, it is less helpful to grasp what this understanding is.

Building further on the literature, we will focus on algorithmic knowledge as the cognitive understanding of algorithmic systems with algorithmic awareness being a prerequisite to form such understanding. We use the notion of knowledge models to focus on the different algorithmic elements (i.e., people, companies, and data) individuals use to explain their train of thought. This enables us to disentangle their cognitive knowledge from their sentiments and interactions, while also retaining the intricacy of the algorithmic system (Lee et al., 2019). Knowledge models thus focus on how people cognitively imagine the processes of these algorithmic systems, not whether these processes are right or wrong, in line with what Hargittai and colleagues (2020) defined as understanding algorithms.

While an algorithmic system is by no means defined only by the companies, people and data involved, these elements are undeniably part of the system. The knowledge models lay-people use to decode the algorithm is expected to influence how they feel and interact with these algorithms and is thus an indispensable part of peoples decoding of these algorithmic systems.

Feelings Towards the Algorithm

Another structure of understanding when decoding algorithms is embedded in how they feel about these algorithms (Bucher, 2017a; Lomborg & Kapsch, 2019). Bucher (2017a) found how certain journalists "developed a feeling for the algorithm" (p. 929) that influences how they interact with the algorithm. Moreover, this feeling differed between journalists, depending on how they imagined the algorithm to work. In other research, Devito et al. (2017) found how individuals expressed certain feelings towards algorithmic changes, ranging from positive (e.g., pleasure and excitement) to negative (e.g., frustration, sadness, or anger). Equally, Lomborg and Kapsch (2019) and Hargittai and colleagues (2020) discussed positive and negative sentiments towards algorithms, and how individuals evaluate the outcome of these systems. Lomborg and Kapsch (2019) found how positive evaluations aligned with a willingness to trade data for ads and more negative evaluations caused irritation.

Feelings are often anchored to specific situations and experiences. A positive sentiment is most often linked to an experienced convenience or effectiveness of the algorithm (e.g. selecting relevant content in an abundance of information), while negative sentiments are often linked to an imagined part of the algorithm, e.g. the imagined goal of the algorithm (Bucher, 2017a; Lomborg & Kapsch, 2019). Considering feelings besides cognitions could help to further understand how people understand these algorithms.

(Inter)actions With the Algorithm

To fully understand how people decode algorithms, Lomborg and Kapsch (2019) argued to also pay attention to people's interactions with algorithms. This can be seen as a final structure of understanding, besides knowledge and feelings. This idea, however, is not new. More than three decades ago, Norman (1998) highlighted the notions of affordances to be mindful to how an object, or technology, encourages specific actions over others. Equally, algorithmic systems push for a specific intended use (Shaw, 2017). Lomborg and Kapsch (2019) call these intended uses the 'dominant position' which reflects "respondents' embracing and praising of the smartness and convenience of algorithmic operations" (Lomborg & Kapsch, 2019, p. 11) often providing the system with more data in the process.

However, other non-intended uses also emerge in the decoding process (Shaw, 2017). These actions refer to a negotiation with the algorithmic system or an oppositional position towards the system (Lomborg & Kapsch, 2019). These non-intended uses cover rejecting the system or manipulating the system for example. Research by Henderickx and De Wolf (2019) investigated the phenomenon of 'instapods' where influencers try to manipulate the algorithm to show more of their content. Other examples include using VPN-services or other identity masking technology to trick the algorithm and feed it less data.

People adapt their behavior based on what their evaluation and sentiment towards the system is, and how they think the system functions. The decoding process thus includes the sentiment towards the algorithm, the knowledge model people use and their (inter)actions that align with or oppose to how the algorithm is meant to function (Lomborg & Kapsch, 2019).

Focus of Study

We put forward the following research question: what assumptions do end-users have about the inner workings of algorithmic news recommenders? In our empirical inquiry we conceptualize ANR as algorithms that make personalized recommendations based on (a combination of) different kinds of data. These data include, but are not limited to, the metadata of the news articles (=content-based filtering), information on what others liked (=collaborative filtering) and information of the users themselves (=knowledge-based filtering) (Helberger, 2019).

In our empirical study we investigate two specific ANR: Google News (that mainly uses collaborative filtering) and Facebook News (that uses a combination of knowledge based filtering and collaborative filtering) (Karimi et al., 2018). These two systems are readily available and accessible to everyone with a Google and Facebook account independent of a news-subscriptions to a local, national, or international news outlets. We investigate our respondent's decoding of the algorithmic systems following the conceptualization of Lomborg and Kapsch (2019) using their three structures of understanding. Namely, how they understand these ANR, how they feel towards these ANR, and how they (inter)act with these ANR.

Methodology

Procedure

To answer our research question, 26 semi-structured in-depth interviews were conducted. Respondents were recruited in real life in a public library as well as digitally using the social media of the faculty and the library (e.g., Twitter and Facebook).

As the presence of algorithms is often taken for granted and, it could be argued, remains an unquestioned and intrinsic feature of everyday life, we interviewed the respondents twice to facilitate a more in-depth interpretation and reflection. Each interview had an approximate duration of one hour. Before the second interview took place, the first interview was analyzed and used to further guide the second interview.

Just as Bengtsson and Johansson (2020) suggest, we didn't start our interview with a focus on News, rather we maintained a focus on two specific information flows in their digital lifeworld, namely Facebook News and Google News. The first interview allowed us to capture a first impression of how respondents imagine and understand the algorithmic system. We used the "scroll back method" as developed by Robards and Lincoln (2017) in which we asked the respondents to scroll through their Facebook News Feed and Google News Feed as a probe. During the interview, we aimed to understand how our respondents envisioned the inner workings of these two algorithmic systems and asked, among other questions; "How do you think your News Feed is produced?", "Do you think your News Feed would be different from the newsfeed of your friends?".

Afterwards, the respondents were asked to summarize their thoughts and visualize their 'knowledge models' using post-its available in three colors (see figure 1). These colors represent data (yellow), people (red), and organizations (blue), directing the respondent to focus on these structural elements. They are based on our conceptualization of an algorithmic system following Seaver (2017) and Kitchin (2017) suggestion to include the socio-economic and techno-cultural elements proposed by Profores (2017) and Van Dijck (2013). Each respondent visualized their own unique knowledge model using post-its. According to Mayr et al. (2016) a semi-structured visual representation facilitates the reflection on abstractions (here: participants' knowledge model). At the end of the first interview, we focused on the respondents' sentiment towards the system and its actors (e.g., "how trustworthy do you think these actors are?").

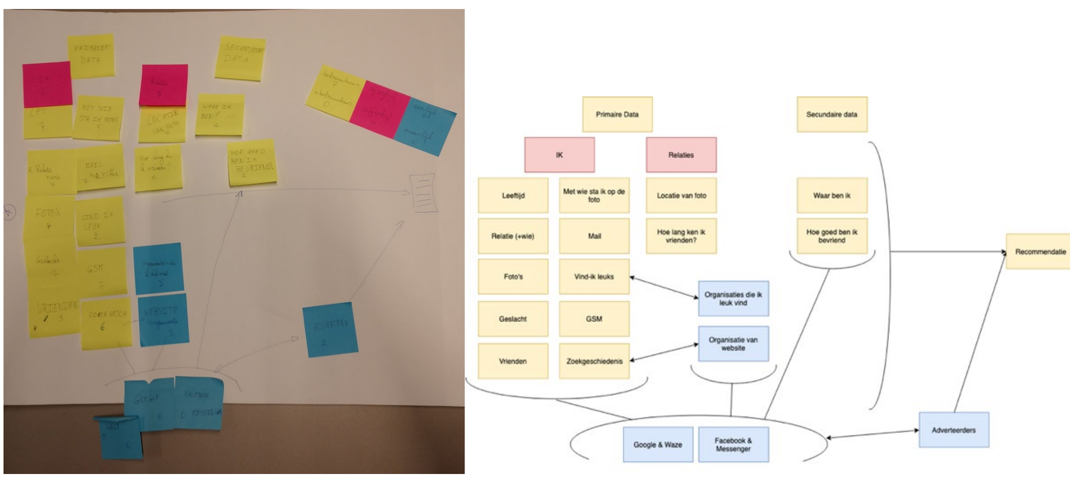

Figure 1 – On the left an example of a semi-structured visual representation of a knowledge model. On the right a translation of the example. The colors represent data (yellow), people (red), and organizations (blue) involved in the knowledge model.

The knowledge model from the 1st interview was digitized and used as input and starting point for the second interview. The second interview followed approximately one month after the first one and focused on a more in-depth reflection of their knowledge model. To start, a digitized version of the respondents' model from the first interview was presented to them. The respondents were asked to reflect on their own model (e.g., does it still make sense? Would you like to change something?). Afterwards, the respondent was probed to talk about how they would evaluate these systems (e.g., If you could change how these systems work, what would you change, and why? What do you (dis)like?...), the actions they undertake, and how that relates to their knowledge model.

At the end, the respondents were probed to contrast their own model with a model of the actual computational logic behind the system (see figure 2). This model was co-developed with the aid of computer scientist who develop decision support systems themselves with the goal to be an accurate, high-level model, but still comprehensible for lay-people. It was used to further elaborate on our respondents' model and to better grasp our respondents' understanding of the algorithmic system (Hall, 1973).

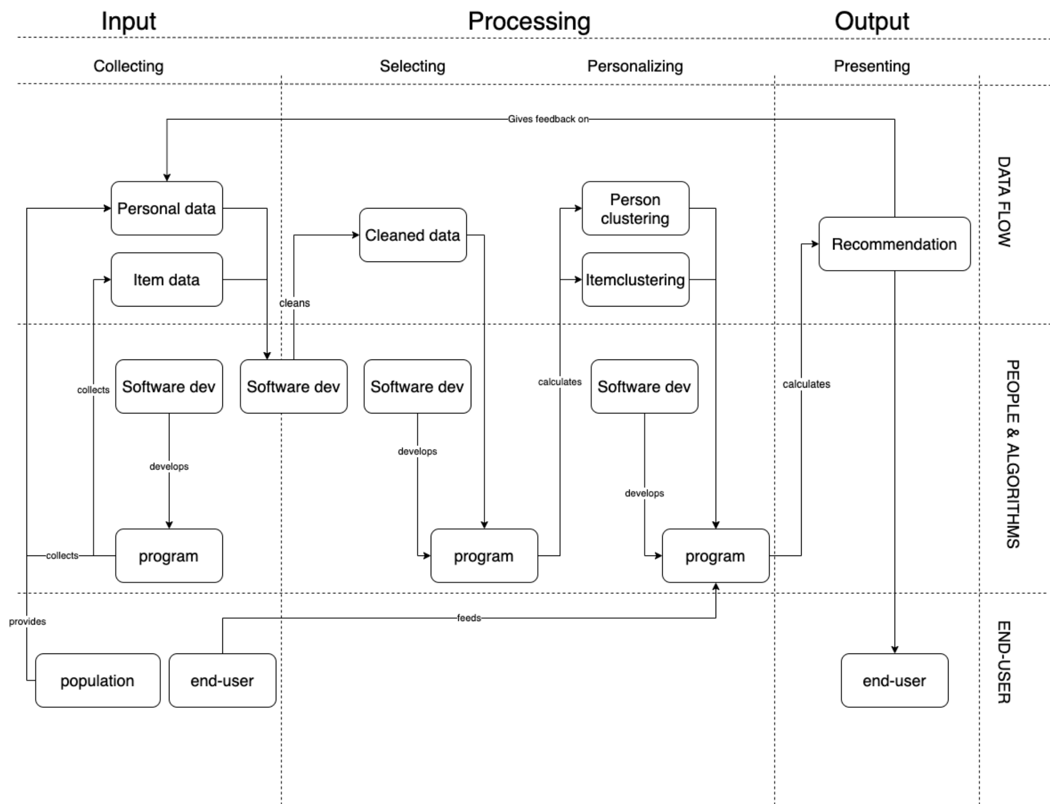

Figure 2 - the systems' computational logic of ANR

Participants

The respondents were recruited in [omitted for peer review]. 99% of the [omitted] population have access to internet and a computer and 98% use it at least weekly. With 79% monthly social media users, [omitted] is also a region with high social media usage ([omitted]). Generally, the [omitted] population has high levels of trust in traditional news agencies ([omitted]). Our respondents were recruited with a variation in terms of gender, digital and offline news usage in mind. We argue that especially a variation in digital and offline news usage is important to consider when investigating how people decode Algorithmic News Recommenders. Their experience, or lack thereof, could greatly impact how they decode these systems. These variables were measured using a drop-off questionnaire before the interview took place. For digital news usage we included questions on how often they use news websites, social media, and search engines (i.e. google) to read news. For offline news usage we included questions on how often people used the radio, paper newspapers, and television to consume news. All questions ranged from never (1) to multiple times a day (5). The values in table 1 are the means of all the questions of each category. Of the 13 respondents, 7 were female, 6 male, with a mean age of 38 (SD= 15,45). Our sample consists of a lot of respondents aged between 20-40 (9), most of our respondents are highly educated and work full time. The sample is not meant to be representative, rather it was our aim to allow variation in terms of news consumption and accommodate different viewpoints.

Respondent alias	Age	Gender	Digital News usage	Offline news usage	Maximal degree	Job
Maverick	28	Male	2.00	4.00	Bachelor	Full time
Johny	24	Male	2.00	1.50	Master	Full time
Syrah	22	Female	3.67	1.50	Secondary	Student
Pete	56	Male	3.67	2.75	Bachelor	Part time
Chrissy	57	Female	2.00	1.75	Master	Full time
Archi	34	Male	1.33	2.00	Master	Full time
Lewis	68	Male	1.67	2.00	Secondary	Retired
Annie	27	Female	1.67	4.25	Bachelor	Full time
Kate	29	Female	3.67	3.00	Bachelor	Full time
David	55	Male	4.00	3.75	Primary	Part time
Olivia	30	Female	3.67	3.50	Master	Not working
Tina	32	Female	5.00	4.75	Master	Full time
Cecille	27	Female	2.67	4.00	Master	Full time

Table 1 - Overview of respondents. The values on digital news usage (SNS, news websites, search engines) and offline news usage (radio, paper newspaper, television) are the means (ranging from never (1) to multiple times a day (5)) for each category.

Analysis

We conducted a thematic analysis based on the decoding framework adapted by Lomborg and Kapsch (2019). In the first interviews, we mainly focused on their knowledge models. To analyze these, we familiarized ourselves with the data and sought for the different elements respondents used to build up their knowledge model of ANR. We also made annotations where the respondents expressed feelings or interactions. Our respondents visualized their knowledge models at the end of the first interview, which was later digitized before the second interview (see above). This approach allowed us to develop an initial coding scheme with a focus on their knowledge model. After the second interview, our focus mainly went to thematically coding their (inter)actions and their feelings. Sometimes they reflected on the knowledge model they produced in the first interview during their second interview.

The first and second interview were executed in parallel as some respondents were interviewed for the first time, while on the same day we interviewed other respondents for a second time. This approach enabled us to modify the interview guideline of the first and second interview based on insights of the other respondents. For example, putting a more elaborated focus on how they see their own individual role in their knowledge model or how they evaluate the advertisers involved with Facebook News and Google News.

Results

When decoding the algorithm, we considered three structures of understanding. First, we investigated the knowledge models they used to structure their experiences and sentiments. Second, we discussed what sentiments they expressed when they discussed the algorithmic system. Third and finally, we investigated how they interacted with the system.

Knowing

When analyzing our respondents' knowledge models, we noticed that almost all their insights are based on experiences (cf., Experience based knowledge (Lomborg and Kapsch, 2019)). While each knowledge model is individually different and unique, to a certain extent, we found some clear differences in their levels of complexity. Our respondents did not think that their feed served similar information to their network nor argued how a summation of all news was displayed without anything or anyone intervening. They expressed a certain awareness of an algorithmic system or at least the personalized logic behind their News Feeds. Some respondents had a more extensive knowledge about the inner workings of ANR, while others where more superficial in their explanations. It was noticeable how both groups brought up the importance of 'data' and how it influenced their News Feed.

A first type of knowledge model makes a direct link between users' data and the content displayed on the News Feed. Cecille and Lewis argued, for example, that there is a direct link between what they and their peers do online and what they then see on their feed. All online interactions with these platforms, like searching something on Google or liking something on Facebook, are considered key actions that are responsible for the feed they get.

Interviewer: *"How do you think your News Feed is constructed?"*
Cecille: *"I think it has to do with what I do on Facebook. An article I like or interact with in my feed will definitely make [Facebook] show me more articles like that in my feed"*

This belief minimizes any tweaks made by the algorithmic system, effectively rendering the role of any other factor (i.e., the company or developers) obsolete. Consequently, in this knowledge model, the perceived quantity and accuracy of the data that is available to the algorithmic system is perceived as the most important element.

When discussing the role of human elements, such a direct link between the data and their feed made that some of our respondents had a mostly self-centered perspective. They emphasize the importance of their own behavior or that of their network. Indeed, they perceive themselves as the most important, and often only, human factor. When people tried to explain certain recommendations, they made a reference to their own behavior (i.e., searching for a specific subject online the day before). Interestingly, they also explained irrelevant recommendations by questioning their own behavior, rather than the accuracy of the system. For example, by talking about how their family could have used their devices and how this could lead to certain recommendations that are off topic.

A second type of knowledge model makes an indirect link between the output of the algorithmic system and the available data. Here our respondents argue how available data is used to build up a calculated profile with insights inferred from this data (i.e., inference of interest, political opinion). Someone's feed is then based on that calculated profile rather than on the raw data itself.

Interviewer: *"[...] what are the things that you think off that Facebook would use to decide what they show you?"*
Kate: *"Let's see, just the things that you like and do online. I guess they use that to make a personality profile with your interest and behavior or something like that."*
Interviewer: *"Okay."*
Kate: *"and maybe, yeah, what articles you open, then they know that I think that's interesting, and they'll change that in my profile"*

This belief gives extra levels of interpretation and extra degrees of freedom to the algorithmic system. As this knowledge model embeds interpretations, it includes (human) choices, and thus power. The respondents assigned most power to the developers who interpreted the data.

Maverick, for example, argued how the developers who decide what data is gathered and how it is employed to be more influential than those in charge of gathering as much data as possible.

Interviewer: *"you said earlier that not all developers have the same job, what do you mean by this?"*
Maverick: *"I mean, like if you look at the developers. I guess that some of them are just tasked with getting as much data as possible. I think these developers don't really matter; they just gather data. But then there are others who decide what data they will use and for what purpose. I think that they have the real power here. They decide what is relevant and what is not."*

In this second type of knowledge model, some respondents also questioned the comprehensiveness of their profiles. They described their digital information as 'monoliths of data' that are not nearly diverse enough to resemble the complex identity they embody rendering most of these calculated profiles useless. Maverick, for example, argued that the algorithmic system is unfamiliar to all his offline interactions and only has a narrow focus on online interactions.

When emphasizing the indirect relation between data and their feed, some respondents attributed an important role to companies. They argue that most often decisions in these systems are linked to a more economic rationale, (i.e., making revenue). Kate argued that what she sees on her feed is connected to how much money a news agency paid to be there. Tina, on the other hand, argued that the values and mission of the company behind the algorithmic system (i.e., Google or Meta) is equally relevant and influences what is shown in her feed.

When respondents were talking about the companies involved in ANR, it was notable how often they referred to Google & Meta. Other companies, like advertising companies or traditional news media were only mentioned as 'other types of users' of the systems designed by Google and Meta, downplaying the role and agency of these more traditional players.

Although our respondents claimed to be aware of the existence of the algorithmic system, they also voiced a certain level of uncertainty about their explanations. They expected reality to be much more complicated than what their own level of expertise could voice. This is true for both respondents expressing a detailed knowledge model and those expressing a less complex model.

***Cecille**: "I can imagine that I'm completely wrong in this idea. Like I could easily believe that what I'm saying is far from the truth.*
***Interviewer:** "You think you are wrong?"*
***Cecille:** "I'm just saying, it could be like this, but could very well be completely different."*

***Kate:"** I do think it will be much more complex than how I just explained it"*

Feeling

Our respondents voiced strong sentiments towards the algorithmic system, ranging from frustration through indifference and even admiration. Most of these feelings were linked to how effective the system was perceived, but also included elements of their knowledge model (see above).

First, the respondents who found the system performing effectively, voiced a feeling of admiration and were often surprised at what the system was able to derive from their data. Some felt that their feed was almost perfectly tailored to their interests. They base this sentiment on their feed, rather than their knowledge model. For some, like Annie, their astonishment is related to the unexpected types of data they think the algorithmic system used in constructing their feed. This exemplifies a knowledge model with a direct relation between the data and their feed.

***Interviewer:** "So if you look at your feed what is your first reaction?"*
***Annie**: "[when scrolling through her feed] Wow, this is funny, because yeah, I look at this soap daily. Err, and this, yeah this is also something I watch frequently. No way! That's the shop where I do my grocery shopping, like almost exclusively. Let's see what else is here. Vincent Van*

Gogh… Wow, this is crazy, I went to the cinema to watch a movie of Vincent Van Gogh.
Interviewer*: "That's crazy?"*
Annie: *"Yeah, those are four things that I've been doing, or I've been interested in the last week, that's really crazy!"*

For others, this feeling of admiration is linked to the possible inferences these algorithmic systems make rather than the sheer amount or diversity of the data they collect. This sentiment relates to a knowledge model with a more indirect relation between the data and their feed, as they believe that most valuable information (i.e., political preference) is inferred from their likes or behavior.

Besides admiration, there are those who show a more apathic feeling towards the algorithmic system. They are mostly indifferent to which content is displayed on their News Feed. Maverick, for example, only reads his News Feed when he tries to kill time. He doesn't really value the system.

Interviewer: *"If you look at your News Feed, what is your first reaction then?"*
Maverick*: "Most of the time the feed is not really interesting, lots of fait-divers, not really relevant to my interests."*

Some of these more apathic feeling people believe that their News Feed is constructed with only an economic goal in mind. They don't necessarily evaluate this as 'bad', however, they do evaluate the working of the algorithm with this perceived economic goal in mind. Hence, they look at Meta and Google as companies only trying to make money by selling their personal space as advertising space.

Pete: *"I don't think our News Feed is to distribute objective information. it's to feed us ads, while hiding some news in between."*

Third and last, there were also frustrations about an underperforming system. Specifically, they argued on how the different data types and the sheer amount of personal information they provided is inconsistent with what they received. Others were just frustrated that Facebook News or Google News don't really "get" them. On the same note, some respondents raise issues like feeling as if the system is narrowing their worldview by limiting the diversity of their information feed.

It should be noted that the respondents, especially those with a more elaborate knowledge model of the algorithmic system, also expressed frustrations because they disagree with its ideology, or the power concentration of the companies involved. Archi, for example, strongly disagrees with the commodification rationale behind the system, however, he does value the algorithmic system and the developers involved.

Interviewer*: "You discussed Google and Facebook [1]already in quite some length. Overall, how would you evaluate these companies?"*
Archi*: "they are gangsters, they are just trying to sell you stuff, they are not objective or honest at all"*
[…]
Archi*: "Removing my Facebook Account is a price I'm willing to pay because Mark Zuckerberg and his whole philosophy behind Facebook is just evil. I don't want anything to do with that."*

[Later during the interview, Archi shared his view on the accuracy of ANR]

Archi*: "Lets' see, yeah, those algorithms are trustworthy, I think the people that work at [Facebook & Google] are extremely intelligent. You always hear they have the best [personnel]. So, the people who make the algorithm, probably do a really good job. I think they know things about me that I or even my close relatives would not know. So yeah, I consider the algorithms to be trustworthy.*

[1] Meta, the company behind the social media platform Facebook was still called Facebook when the interviews took place.

(inter)Actions

In our conversation with the respondents, it became clear that there is a parallel between how people feel and how their actions materialize. When looking at how the respondents interacted with ANR we can differentiate between deviating and dominant actions.

Acting as expected by the system , or the "dominant action" as Lomborg and Kapsch (2019) called it, go hand in hand with perceiving the algorithm as something useful. Some respondents only used their News Feed to be up to date with the practices of their friends, to occasionally posts comments, or to like what they find interesting. Others, like David, also share news articles on their feed when they believe the content is important for their peers.

Another group of respondents deviates from this dominant inter-action, we call this deviating behavior. A first type of deviant behavior is productive deviant behavior, like trying to feed the system extra data to improve it. Annie, for example, purposefully performed a search query and looked up some friends and an artist she followed in the hope this would trigger the algorithm to show more relevant content.

Interviewer*: "You previously said that you don't always see what you want to see on your feed. Do you do something about that?"*
Annie*: "As a matter of fact I did, yesterday. There is a comedy couple I like, and I noticed that I hadn't received any updates from them in a while. So, I looked them up and watched some of their video's again to trigger the algorithm. I kind of missed them."*

Deleting information to improve the output of the algorithmic system, could also be considered as productive deviant behavior. Maverick, for example, "cleaned up" his outdated likes from his Facebook profile to improve the quality of his feed. He argued how these actions could have a positive impact on his "profile" and thus the relevance of his feed.

Maverick: *"I went through my "liked pages" the other day, I deleted almost half of them.*
Interviewer: *"Why did you do that?"*
Maverick: *"I think that they were relevant a long time ago. That doesn't mean that they are still relevant now. It doesn't fit my profile anymore. So, I removed them to improve my profile and my feed.*

When engaging in these productive deviant behaviors, the respondents treated the algorithm as a practical tool. Some wanted to be more cognizant on how their feed is constructed to know how they could interact with the algorithm and improve their experiences. The explanations they find, however, are often insufficient for respondents to effectively tweak their feed. They often end up puzzled by the fact that they keep on seeing the same irrelevant feed or dissatisfied with how superficial the information is they get. Indeed, productive deviant behavior does not necessarily improve someone's sentiment or understanding towards the algorithmic system, as our conversations with Johny illustrates.

Johny: *"Next to some posts in your feed there is the option to click "why do I see this", I don't know if this is still the case. Anyway, I used to click on those next to posts that I found irrelevant to try to understand why they would end up on my feed."*
Interviewer: *"Okay"*
Johny: *"but the explanation they give is incredibly superficial, like it is because you are a man or something. So that really doesn't help."*

Other respondents, reacted negatively towards the system, in line with the oppositional position conceptualized by Lomborg and Kapsch (2019). We call this other type of deviant behavior, contra-productive deviant behavior. Our respondents expressed contra-productive deviant behavior in varying levels of severity. Minimizing interactions with the algorithmic part of the platform, for example, is less severe than simply rejecting the platform or deleting your profile from the platform. Cecille, for example, ignored content that she thought was provided by an algorithm on her Facebook News Feed, while Archi stopped using Facebook altogether because he didn't agree with the philosophy of the platform. Interestingly, the motive behind a contra-productive deviating behavior is most often linked to how they perceive the goals of the complete system and companies behind them, rather than how effective the algorithmic system works. Archi explicitly expressed how good he thinks these systems work even though he deleted his account (see above).

In table 2, you'll find an overview of the different structures of understanding (i.e., knowledge models, sentiments and (inter)actions) discussed by the respondents. The different structures of understanding relate to one another in *how* and more importantly *why* they materialize. An indirect knowledge model facilitates more reasons for a specific sentiment towards the system and/or (inter)actions with the system to materialize than a direct knowledge model. However, for both knowledge models the same sentiments and (inter-)actions can occur.

Structures of understanding ANR		
Knowledge models	**Sentiment**	**(inter)actions**
Direct knowledge model Their feed is believed to be directly produced by the data they provide. For example, when they or their friend interact with a post, they expect their feed to show more information linked to that post.	Admiration They admire the system because of (1) how accurate it is, (2) how a variety of data they perceivably collect and (3) how good its inferences are	Positive Positive (inter)actions with the algorithmic system include (1) trying to get informed to better understand the algorithmic system, (2) feeding the system extra data or (3) controlling for misinformation that is no longer relevant.
Indirect knowledge model Their feed is believed to be produced by a calculated personal profile the company constructed based on their data, the data of others and company goals. Everything they and others do on the system enriches their profile.	Apathy They feel indifferent towards the algorithmic system. They don't value and necessarily agree with the perceived goals of the algorithmic system. However, they also perceive these systems as bad actors.	Negative Negative (inter)actions include minimizing interactions with the system and rejecting parts of the system, or the system as a whole.
	Frustration They feel frustrated because of an underperforming system, despite the amount of data they've shared. Or because they don't agree with the systems' goals.	

Table 2 - overview of the structures of understanding

Conclusion & Discussion

Many have previously argued that algorithms should be more transparent to enable people to understand and scrutinize them as they please (e.g., Pasquale, 2015; Wachter et al., 2017). Using the encoding-decoding model, we investigated how end-users understand and imagine the inner workings of ANR (Lomborg & Kapsch, 2019). We focused on three so-called "structures of understanding" to decode an ANR, consisting of knowledge models, feelings about the algorithmic system as well as interactions with these systems. We argue how these structures of understanding enable a more granular understanding of how people imagine ANR and the reasoning behind it.

Our respondents were aware of the presence of an algorithm in their News Feeds. We looked at the understanding, or knowledge, of our respondents as suggested by Hargittai and colleagues (2020) and the processes they use to structure their understanding, rather than employing a normative approach that treats their responses as right or wrong. Our respondents mainly differ from one another with concern to how they perceive the available data and how their data is tied to their newsfeed. The first type of knowledge models makes a *direct* connection between the data they and their peers produce and their feed. In this knowledge model, there are little to no degrees of freedom for the companies or developers involved. Yet, other knowledge models feature an *indirect* link incorporating extra levels of processing and other actors in the algorithmic system. While most often awareness and knowledge are seen as algorithmic skills, we investigated them to better understand how people imagine the workings of these algorithms to understand to what elements these individuals use to frame their sentiments and (inter)actions towards these systems.

When discussing respondents' feelings towards ANR, our research found how people express a feeling of admiration, apathy, or frustration towards the system. These feelings are not necessarily connected to their knowledge models. Both individuals with an elaborate or basic understanding of ANR cover the full range of sentiments. However, *why* our respondents felt how they did was often linked to the knowledge model they employed.

On the one hand, a direct relation between the data they produce and the feed they receive underlines the importance of data and data flows for them when trying to understand the algorithmic system, in line with the research by Seaver (2013). This understanding limits the reasoning behind their sentiments to these data flows. They focus on the quality, variation or amount of the available data and much less towards other actors in the system (i.e., developers, companies…).

On the other hand, a more indirect relation between the data and their feed opens up the reasoning behind their sentiment by also linking their sentiments to other actors of the algorithmic system, like the companies, people, or the economic logic involved. This allows for a more nuanced view where they weigh their different evaluations of the different actors against each other. This indirect knowledge model aligns with the understanding of algorithms as folding data (Lee et al., 2019) and the socio-technical construction of algorithms (Seaver, 2017). In these understandings, the system embedding the algorithms are found to be of paramount importance because of their influence on the output. Indeed, for them data is just one of the elements making up an algorithmic system, augmented with other socio-technical elements (i.e., socio-economic situation, companies, people).

Dominant, productive or contra-productive deviating (inter)actions of individuals are equally connected to the sentiment they have about the algorithmic system and its components – in line with previous research findings (Bucher, 2017a; Hamilton et al., 2014; Lomborg & Kapsch, 2019; Ytre-Arne & Moe, 2020). In a similar fashion to how their feelings are expressed, it was noticeable how their actions are shaped by the knowledge model they use to decode the algorithmic system. A more granular understanding of the algorithmic system goes hand in hand with various actions to tweak or reject the system. A less granular understanding, on the contrary, does not provide the same degrees of freedom.

It could be argued that individuals' actions are manifestations of their sentiments structured by their knowledge model. To better understand why individuals interact with an algorithmic system a specific way, an explicit insight in their knowledge models and sentiment is necessary.

This exemplifies the complexities embedded in these algorithmic systems and why it is important to enrich peoples' folk theories with how they decode, thus interact with, feel about, and understand them. In line with Swart (2021), our research shows that specific knowledge about algorithms doesn't necessarily mean that an individual can adequately interact with the algorithmic system. Indeed to better understand their algorithmic literacy, we need to know how their knowledge connects with their sentiment and (inter)actions.

In our research we did not treat algorithms as an abstract 'black box', but as a socio-technical construction that consists of data, people, and companies. Using these fine-grained elements to elaborate on how people imagine algorithmic systems enables an understanding of how people imagine these systems in much greater detail. Our research could thus be valuable to identify and inform individuals who are unaware of more complex elements of the algorithmic systems (i.e., those who do not see any human intervention, company involvement, etc.). Making them cognizant of specific elements and explaining them how these systems are not neutral but produced by people with specific goals in mind (i.e., Bucher, 2017b) could enable them to make a solid evaluation of algorithmic systems empowering them to effectively interact with these systems.

Limitations and Suggestions for Future Research

Because of the qualitative nature of the research, we cannot determine what elements play a bigger or smaller role in the construction of their decoding of ANR. Moreover, as structures of understanding are individually, culturally, and contextually bound, it is important to note that the study was conducted in a western, European country, with high media literacy and high internet adoption [omitted]. We included people with a variation in offline and online news consumption.

As many scholars have investigated *how* people (dis)trust algorithms (Hegner et al., 2019; Lee et al., 2019), we encourage future research endeavors to try to better understand *why* people (dis)trust a specific ANR. Future research could integrate their decoding and folk theories of these algorithmic systems in trust research because how people understand an algorithmic system could explain why they (dis)trust them. They could, for example, measure the weight of the different elements in their knowledge model in the construction of their (dis)trust towards the algorithmic system as a whole.

Moreover, we argue that the decoding approach, used in this research, could also be explored in other emerging algorithmic contexts, that are inherently different from journalism (e.g., medical decision support systems, education support systems). We believe that untangling how people interpret an algorithmic system using a decoding approach equally enables a detailed insight into their attitude (e.g., trust, privacy) towards systems in multiple contexts.

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Tables & Figures

Respondent alias	Age	Gender	Digital News usage	Offline news usage	Maximal degree	Job
Maverick	28	Male	2.00	4.00	Bachelor	Full time
Johny	24	Male	2.00	1.50	Master	Full time
Syrah	22	Female	3.67	1.50	Secondary	Student
Pete	56	Male	3.67	2.75	Bachelor	Part time
Chrissy	57	Female	2.00	1.75	Master	Full time
Archi	34	Male	1.33	2.00	Master	Full time
Lewis	68	Male	1.67	2.00	Secondary	Retired
Annie	27	Female	1.67	4.25	Bachelor	Full time
Kate	29	Female	3.67	3.00	Bachelor	Full time
David	55	Male	4.00	3.75	Primary	Part time
Olivia	30	Female	3.67	3.50	Master	Not working
Tina	32	Female	5.00	4.75	Master	Full time
Cecille	27	Female	2.67	4.00	Master	Full time

Table 1 - Overview of respondents. The values on digital news usage (SNS, news websites, search engines) and offline news usage (radio, paper newspaper, television) are the means (ranging from never (1) to multiple times a day (5)) for each category.

Structures of understanding ANR		
Knowledge models	**Sentiment**	**(inter)actions**
Direct knowledge model Their feed is believed to be directly produced by the data they provide. For example, when they or their friend interact with a post, they expect their feed to show more information linked to that post.	Admiration They admire the system because of (1) how accurate it is, (2) how a variety of data they perceivably collect and (3) how good its inferences are	Dominant Dominant (inter)actions with the algorithmic system include (1) trying to get informed to better understand the algorithmic system, using the system as intended or (3) controlling for misinformation that is no longer relevant.
Indirect knowledge model Their feed is believed to be produced by a calculated personal profile the company constructed based on their data, the data of others and company goals. Everything they and others do on the system enriches their profile.	Apathy They feel indifferent towards the algorithmic system. They don't value and necessarily agree with the perceived goals of the algorithmic system. However, they also perceive these systems as bad actors.	Deviating contra-productive Negative (inter)actions include minimizing interactions with the system and rejecting parts of the system, or the system as a whole.
	Frustration They feel frustrated because of an underperforming system, despite the amount of data they've shared. Or because they don't agree with the systems' goals.	Deviating productive Positive deviating behavior imply behavior that has the goal to improve the algorithmic system, like feeding the system more data, or deleting irrelevant information.

Table 2 - Overview of the structures of understanding of ANR

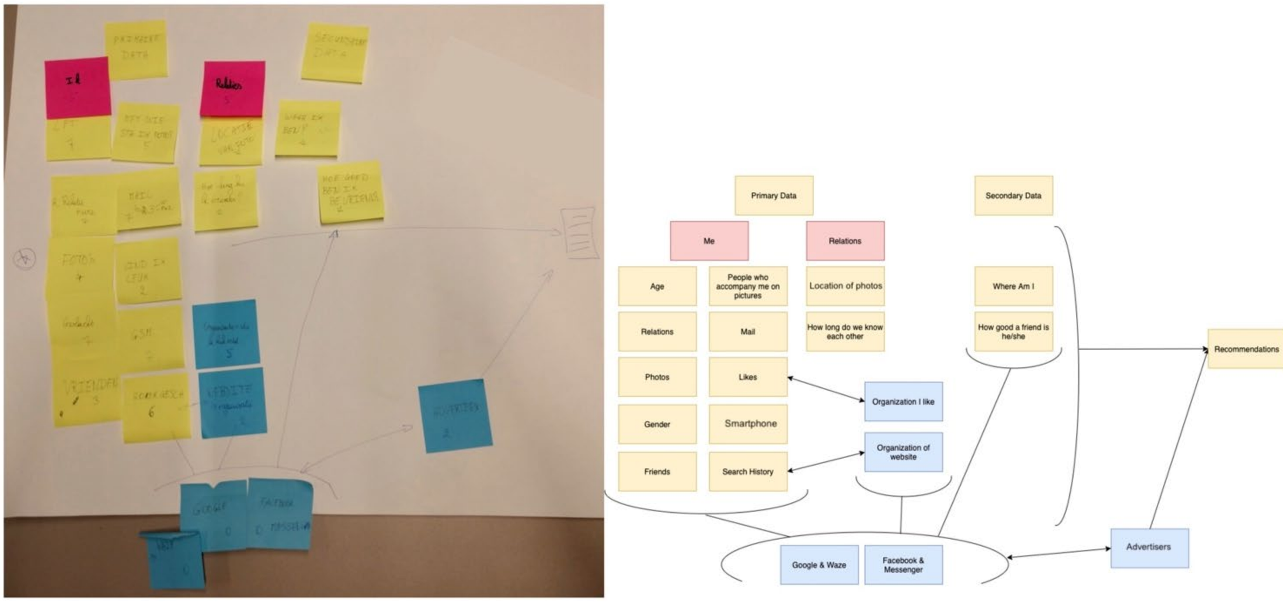

Figure 1 - On the left an example of a semi-structured visual representation of a knowledge model. On the right a translation of the example. The colors represent data (yellow), people (red), and organizations (blue) involved in the knowledge model

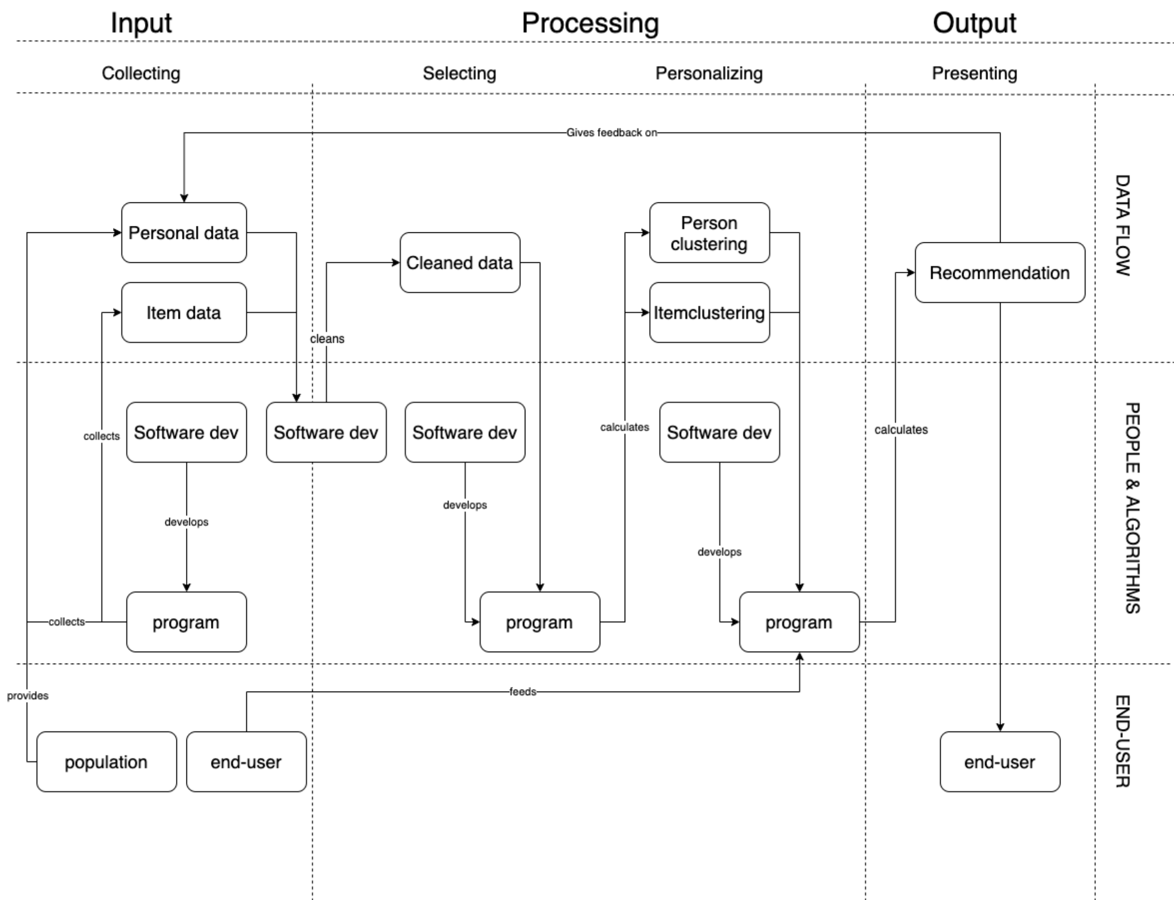

Figure 2 - The systems' computational logic of ANR