# Cracking the Tinder Code: An Experience Sampling Approach to the Dynamics and Impact of Platform Governing Algorithms

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*This article conceptualizes algorithmically-governed platforms as the outcomes of a structuration process involving three types of actors: platform owners/developers, platform users, and machine learning algorithms. This threefold conceptualization informs media effects research, which still struggles to incorporate algorithmic influence. It invokes insights into algorithmic governance from platform studies and (critical) studies in the political economy of online platforms. This approach illuminates platforms' underlying technological and economic logics, which allows to construct hypotheses on how they appropriate algorithmic mechanisms, and how these mechanisms function. The present study tests the feasibility of experience sampling to test such hypotheses. The proposed methodology is applied to the case of mobile dating app Tinder.*

**Keywords:** Platform Studies, Audience Research, Experience Sampling, Algorithms, Tinder.

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## Introduction

Algorithms occupy a substantially wide array of spaces within social life, affecting a broad range of particularly individual choices (Willson, 2017). These mechanisms, when incorporated in online platforms, specifically aim at enhancing user experience by governing platform activity and content. After all, the key issue for commercial platforms is to design and build services that attract and retain a large and active user base to fuel further development and, foremost, bear economic value (Crain, 2016). Still, algorithms are practically invisible to users. Users are seldom informed on how their data are processed, nor are they able to opt out without abandoning these services altogether (Peacock, 2014). Due to algorithms' proprietary and opaque nature, users tend to remain oblivious to their precise mechanics and the impact they have in producing the outcomes of their online activities (Gillespie, 2014).

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Media researchers too are struggling with the lack of transparency caused by algorithms. The field is still searching for a firm conceptual and methodological grasp on how these mechanisms affect content exposure, and the consequences this exposure provokes. Media effects research generally conceptualizes effects as the outcomes of exposure (e.g., Bryant & Oliver, 2009). Conversely, within the selective exposure perspective, researchers argue that exposure could be an outcome of media users deliberately selecting content that matches their characteristics (i.e., selective exposure; Knobloch-Westerwick, 2015). A common strategy to surpass this schism is to simultaneously test both explanations within a single empirical study, for example through longitudinal panel studies (Slater, 2007). On algorithmically-governed platforms, the origin of exposure to content is more complicated than ever. Exposure is individualized, and it is largely unclear to users and researchers how it is produced. Algorithms confound user action in deciding what users get to see and do by actively processing user data. This limits the feasibility of models that only consider user action and "its" supposed effects. The influence of algorithms needs to be considered as well—which is currently not the case.

This article engages in this debate, both on a theoretical and methodological level. We discuss a conceptual model that treats algorithmic governance as a dynamic structuration process that involves three types of actors: platform owners/developers, platform users, and machine learning algorithms. We argue that all three actors possess agentic and structural characteristics that interact with one another in composing media exposure on online platforms. The structuration model serves to ultimately articulate media effects research with insights from (critical) political economy research ([C] PE) on online media (e.g., Fisher & Fuchs, 2015; Fuchs, 2014; Langley & Leyshon, 2017) and platform studies (e.g., Helmond, 2015; Plantin, Lagoze, Edwards, & Sandvig, 2016; van Dijck, 2013). Both perspectives combine a considerable amount of direct and indirect research on the contexts in which algorithms are produced, and the purposes they serve. (C)PE and platform studies aid in understanding the technological and economic logics of online platforms, which allows building hypotheses on how algorithms process user actions to tailor their exposure (i.e., what users get to see and do). In this article, we build specific hypotheses for the popular location-based mobile dating app Tinder. These hypotheses are tested through an experience sampling study that allows measuring and testing associations between user actions (input variables) and exposure (output variables).

## A tripartite structuration process

To understand how advanced online platforms are governed by algorithms, it is crucial to consider the involved actors and how they dynamically interact. These key actors—or agents—comprise platform owners, machine learning algorithms, and platform users. Each actor assumes agency in the structuration process of algorithmically-governed platforms. The actors continually produce the platform environment, whereas this environment at least in part shapes further action. The ontological fundaments of this line of reasoning are indebted to Giddens (1984) although we explicitly subscribe to a recent re-evaluation by Stones (2005) that allows for domain-specific applications. He proposes a cycle of structuration, which involves four intricately connected elements that recurrently influence each other: external and internal structures, active agency, and outcomes. In this article this conceptualization is unpacked and immediately applied to algorithmically-driven online platforms.

*External structures* refer to the wide contextual conditions in which action takes place. It involves the incessant interactions between social institutions that affect a myriad of socio-cultural practices (e.g., in science, politics, economics). Internal structures, on the contrary, strictly reside within the agents themselves. They reflect actors' durable dispositions and comprise the multitude of specific roles and positions actors take on in particular contexts, guided by their knowledge and prior experiences. Both forms of internal structures incite a degree of *active agency*, either based on subconscious routine, or explicitly reflexive in nature. Finally, the interplay between structures and active agency leads to *outcomes* that balance and shift between reproduction of structures or their elaboration and change (Stones, 2005).

Recently, this framework has been further elaborated to consider the relation between human and technological actors (Greenhalgh & Stones, 2010). This development is informed by Actor Network Theory (Latour, 1992), which explicitly attributes agentic properties to objects. Technologies are not merely the outcomes of human agency, they affect it as well. Technologies' structural properties have the ability to shape and constrain human action. In the context of algorithmically-driven online platforms, two categories of human actors are considered: platform owners and developers on the one hand, and platform users on the other. Both categories of human actors actively interface with algorithmic systems whose development is increasingly outsourced to machine learning algorithms.

More specifically, most *platform owners and developers* plan out a concept for a service and, as its earliest users, develop and refine its initial platform mechanics. In the first phase, the efforts are directed towards carefully constructing an attractive discourse that creates buzz, seeking out a growing user base (Gillespie, 2010). However, while progressing in the diffusion cycle, the quest for a viable business model prevails, especially when investors require a return. The commercial nature of most online platforms incites owners to invest in marketing communication, attracting and retaining a large and active user base (Kenney & Zysman, 2016). After all, a large set of users actively fuels further business development which translates into economic value. Revenue is generated either directly through paying users, or indirectly (e.g., advertising and data brokerage). This sequence of goals forms the internal-structural backdrop against which platform owners and developers exercise agency. This agency relates to a wide array of choices including the platform's interface design, its default settings, the protocols that govern it, what (meta)data are generated, and how these data are processed.

Algorithms, and *machine learning algorithms* in particular, inform or even (partly) account for these choices. Algorithms with independent learning capabilities are used to enhance a service by offering elaborate means for (real-time) (meta)data-analysis. These types of algorithms are used to continually enhance a platform's performance (Alpaydin, 2014). They are able to assist in selecting interface features, default settings, protocols, and (continually) tweaking platform algorithms. For instance, platform owners set out a desired outcome (e.g., increased and recurrent user activity or conversion to paid services) and define the available parameters for the learning algorithm to autonomously analyze patterns within (meta)data, seeking out the right recipe to maximize the outcomes and thus the platforms profitability. The process of machine learning is metaphorically equivalent to a farmer who sows crops, caters for the resources and conditions for them to grow, while eventually harvesting and selling the yield (Domingos, 2017). Accordingly, to feed these mechanisms, there is a need for an incessant stream of refined user data. In that sense, platform development is referred to as a virtuous circle of big data (Harrison, 2015): more data afford better services, and better services yield more data (and with it more income). Still, large platform developers' increasing reliance on machine learning implies that they could lose general oversight due to scale and complexity of the algorithms (Burrell, 2016). This means that absolute control over their technological structures is obscured: how they come into being, and how they further develop. Mackenzie (2013) suggests that the uptake of machine learning characterizes a shift from absolute control over data to the tendency to outsource control to data. Still, algorithms remain indebted to platform owners and developers as they set out the boundaries and the corporate strategy in which these technologies function.

*Platform users* exercise agency within the boundaries that a platform provides: they roam within a platform's architecture that is governed by protocols, default settings, and algorithms. These mechanisms aim to enhance users' experiences to entice them to stay active, and—when applicable—convert users into paying customers (Seufert, 2013). Still, users are not powerless in this relation, albeit to differing degrees, depending on their nature of using the platform (i.e., nature and intensiveness of use). First, as algorithms run on data, users are the key resource for them to learn and improve. Atypical user behavior, such as trying to play or trick algorithms, might provoke outcomes users specifically desire. For instance, by inconsistently liking objects on Facebook, users can try to confuse the algorithm in learning about consumer preference, which distorts individualized advertising (Bucher, 2017). Such behavior has the potential to disrupt technological structures implicitly, rather than sustaining them as they are. Moreover, some platforms explicitly allow user control and give feedback on a personalized information stream (e.g., by discarding/hiding specific content). Even more, beyond platform protocols, the widespread uptake of specific user practices can entice the development of new formal features (e.g., hashtags or retweets on Twitter).

Within the academic literature, the relationship between platforms owners and their algorithms is covered by (critical) studies into the political economy of online platforms and platform studies. The former is engaged with uncovering mechanisms of user commodification and digital labor (e.g., Fisher & Fuchs, 2015; Fuchs, 2014; Langley & Leyshon, 2017). Platform studies, on the other hand, widely focus on platform evolutions in technological interfaces, default settings, protocols, algorithms, and metadata, as well as the discourses that characterize these platforms (e.g., Gillespie, 2010; Helmond, 2015; Plantin et al., 2016; van Dijck, 2013). Most notably, van Dijck (2013) disassembles platforms as techno-cultural constructs and socio-economic structures. She considers platforms as technological infrastructures with specific rules and resources that, together with their users, produce social outcomes by drawing upon the contents the users provide. This process is rooted within an economic logic, in which ownership, governance, and business model development compose the context in which the aforementioned process takes place.

These perspectives provide the opportunity to take on the viewpoint of platform owners and developers, allowing to understand their internal structures and consequently their actions. This knowledge is especially valuable for media effects research, which traditionally focuses on users, but currently falls short in incorporating algorithmic governance into its conceptual and empirical models. Due to the influence of algorithms, exposure on algorithmically-governed platforms is highly individualized, hardly transparent and perhaps even involuntary. It is a function of user action, but not its direct result. This makes it hard to infer whether and to what extent exposure is molded by platform algorithms, thus obscuring the effects that follow from it. It is difficult to assess which factors provoke this, and how they can be resisted or turned around. Conceptually, we argue that media exposure on online platforms is an effect produced by both user action and algorithmic processing, which in turn likely provokes other effects (e.g., social and psychological consequences).What this algorithmic processing involves is largely unknown as platforms rarely inform the public. However, the technological and economic logics that pressure online platforms could help us to generate testable hypotheses on what algorithms possibly do.

## A glimpse into the black box

Systematic research on the dynamics of algorithmically-governed online platforms is challenging because of the proprietary, closed off nature of such environments. In order to protect privacy and safeguard their data assets, online platforms tend to seal off both raw and filtered data streams from direct harvesting through Application Programming Interface (API) calls (Lomborg & Bechmann, 2014). Even if such unrestricted platform data collection were possible, it still lacks valuable information as it is generally limited to behavioral data and hardly informs on the social and psychological effects that platform exposure brings about in its users. On the other hand, self-report data gathered through questionnaires that span a longer period of time are notoriously inaccurate because respondents are usually unable to properly recall high-frequent media behavior and the precise contents of exposure (de Vreese & Neijens, 2016).

We need a method that overcomes these problems in grasping user actions, exposure and effects on online platforms. Experience sampling method (ESM) is a feasible candidate to alleviate at least some of these methodological limitations. ESM is intended to repeatedly probe recurrent experiences as close as possible to when they actually occur (Hektner, Schmidt, & Csikszentmihalyi, 2007). A mobile device prompts a panel of participants to repeatedly fill out a compact questionnaire form on the most recent relevant experience. In this case, that would ideally be immediately after a platform is used. The ESM format allows for a limited set of questions on: (a) user activity on the platform, (b) what the platform delivered, (c) how users appraise the platform, and (d) what consequences it evokes. In this case, the ESM questionnaire form should involve the most important algorithmic input variables. It is equally important to capture the algorithmically-governed exposure (i.e., the output variables). This allows for general inferences concerning the underlying mechanism, despite the inability to directly examine this black box. These inferences are ideally based on conceptually sound hypotheses. This is where insights from platform studies and (critical) studies on the political economy of online media come into play (Figure 1, top half). It should be possible to construct informed assumptions on the mechanics of algorithms by considering the economic and technological logics that pressure platform owners and developers. That is where a proper grasp on platforms' technological architectures, data streams, governance politics, business models, public discourses and ownership structures are especially relevant.

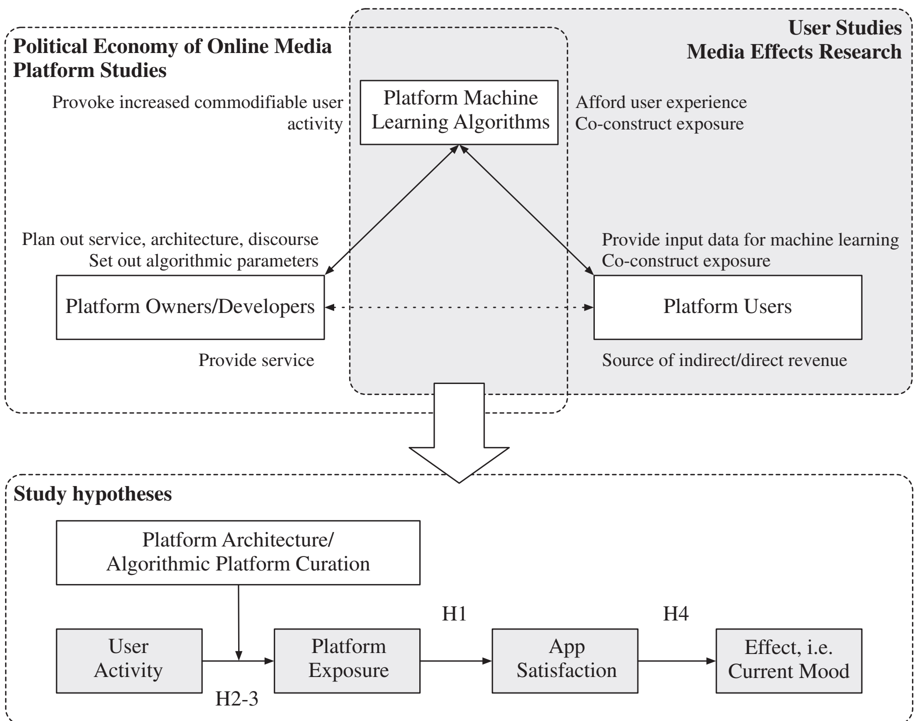


**Figure 1** Schematic overview of the conceptual model and study hypotheses.

Of course, such an approach does not directly reveal the mechanics of algorithmic filtering, nor is it capable of capturing all its finesses—especially when the platform's algorithms draw on a great many parameters. Still, this format could suffice in at least grasping its general dynamics. Moreover, in contrast to digital methods research, major advantages of this approach are the independence from platform APIs to collect data and the opportunity to move beyond behavioral data by delving into otherwise inaccessible social and psychological consequences through self-report measures. The issue of bias in self-report data persists, albeit to a lesser extent due to the reduced time interval between exposure and data collection (Hektner et al., 2007).

## Tinder's supposed mechanics

As a proof of concept, four hypotheses are developed for the case of Tinder (Figure 1, bottom half). We choose Tinder because the commercial platform is currently restricted to mobile devices, and because it draws upon a limited number of explicit input and output variables. Also, the mobile app invites considerable speculation on how it operates (Duguay, 2017).

Despite its efforts to construct a discourse of a fresh, bottom-up success story (Summers, 2014), Tinder was internally conceived within an incubator program, nested in InterActiveCorp (IAC, 2017). This large media company owns a broad repertoire of global online brands, such as Vimeo and HomeAdvisor. It includes the Match Group (IPO in 2015) that holds an impressive global portfolio of over 45 online dating platforms, based on various architectures and business models that target a wide range of consumer types (e.g., Match.com, OKCupid, Meetic). As a global brand, Tinder presents itself towards the supposedly unserved audience of emerging adults. It aims to be a playful means to instigate new contacts, directed to lower the practical and social barriers that characterize traditional dating platforms (MatchGroup, 2016). Since its inception, Tinder has been part of a well-thought through marketing strategy. Its uptake was promoted through local events, such as Tinder-themed parties (Bosker, 2013).

From the user's perspective, Tinder is a fairly simple app to use. This has been a key objective right from the beginning: to lower the barriers to form new online friendships and relationships. Users log on with their Facebook account, and quickly set up a profile that is predominantly made up by pictures. Moreover, they can indicate their sexual preferences, and determine the age range and the location radius in which they want to assess profiles. This assessment process is swift and playful: profiles are liked or disliked by intuitively swiping left or right (David & Cambre, 2016). The swiping process on Tinder remains anonymous until both users right swipe (like) each other, which means they match. Only after matching, are users allowed to initiate further contact through an instant messaging module. This implies that the design of Tinder is strongly focused on a dynamic of mutual attraction and consent (MacKee, 2016). Despite its simple appearance, there is more to Tinder than meets the eye. The platform draws upon algorithmic filtering, which curates whom gets to like whom, and when this happens. Although Tinder rarely communicates about its underlying algorithm, it does admit that each user has an individual attractiveness score, which is opaquely computed on the basis of popularity and user behavior indices (Kosoff, 2016).

Tinder originally started out as a service without a clear revenue stream, which is common if the objective is to gain critical user mass (Kenney & Zysman, 2016). Tinder's residing in a large, diversified media company relaxed the need to immediately generate revenue on its own, which allowed the postponement of the need for advertising or building paywalls (MatchGroup, 2016). However, Tinder has been experimenting with advertising, while gradually implementing paid services. Tinder is now a freemium app, offering basic functionality to non-paying users, while premium features are available through subscription (i.e., Tinder Plus) or micropayments (i.e., Tinder Boost). Tinder Plus is a monthly, bi-annual or annual subscription to a series of features, including unlimited likes, an increased number of Super Likes, the possibility to undo left swipes, flexible location settings and

Tinder Boost. Super Likes are a scarce resource that allow for indicating special interest in a profile. Tinder Boost is a pay feature that amplifies a profile's visibility for half an hour in the physical area where the user is currently located. The profile is put on top of others' stack of recommendations without indicating this to these other users. This feature is advertised as increasing the likelihood of getting matches (Tinder, 2016).

In essence, Tinder entices users by letting them swipe through interesting profiles. The key is to tease users by offering a wide range of fairly realistic opportunities. Based on Zhang (2016), we assume Tinder carefully doses matches, meaning that its governing algorithm monitors activity and intervenes in its outcomes to keep the user experience in check. Especially for the free service, the key is to keep users sufficiently satisfied so they do not abandon the service too quickly, but not too satisfied so they would be inclined to convert to paying services. This means that the algorithm needs to dynamically alternate between encouraging users and restricting them. Getting too few matches frustrate users, as well as getting too many. Even more, allowing an excessive number of matches would burn out a potentially lasting relationship with a user too quickly. Furthermore, Tinder's objective is not only to match, but also to incite conversations with matches that could perhaps even escalate to a physical encounter. It is however important to realize that, especially within the free service, restrictions are built in that try to push users to subscribe to paying services. A clear example of a limitation is the free users' protocological, yet supposedly algorithmically-governed restriction to only like a limited number of profiles in a particular time frame (O'Brien, 2015). To test whether these assumptions on Tinder's mechanics hold up, the following hypotheses are put forward:

*H1a:* Being able to: (a) swipe interesting profiles, (b) get matches, and (c) engage in conversations with matches is positively related to user satisfaction with the app.

*H1b:* Bumping into the restriction of free likes is negatively related to user satisfaction with the app.

Getting matches inevitably requires user action, while filtering mechanisms steer this process. Matches are the outcome of both actors' active agency. The algorithm determines who gets to see who and when (Zhang, 2016), while users can build all kinds of intuitive conceptions on how these mechanisms are best "played." This could be through experience, naïve impressions, or perhaps genuine insight in the logic that underlies the algorithm—there are ample blogs and online forums available on which users share tips and tricks. For example, one could speculate on the intuitive logic that casting a wide net is the most sensible recipe for more matches (i.e., a positive, linear association). The consequence of such an unrestricted linear mechanism is that users rapidly burn through their pool of potential of matches, which is problematic because matches are the platform's most valuable asset. To continually entice users, a controlled stream of matches would make more sense: the first likes quickly yield matches and invite continued activity, whereas at a certain point likes decline in success rate (i.e., a curvilinear association). The same logic makes sense for interesting profiles: these too are valuable assets that are best spread over time, rather than offered all at once. This leads to the following internally competing hypotheses:

*H2a:* Swiping and liking (i.e., swipe activity) is curvilinearly, rather than linearly, associated with the degree to which proposed profiles are interesting.

*H2b:* Swiping and liking (i.e., swipe activity) is curvilinearly, rather than linearly, associated with the number of matches users get during a session.

In a similar vein, user activity, or the lack thereof ought to be considered as a key factor in affecting the outcomes of the app. Retaining users is of the utmost importance to keep a service viable.

A user that remains inactive for a longer period could be considered as potentially on the verge of attrition. He or she needs extra incentives to remain motivated in using the app. Conversely, it makes sense to relatively discourage all too active users, as in the long run they are worth more anticipating the possibility of swiping interesting profiles and getting matches than when they effectively receive them. Again, the asset of high-quality profiles and matches needs to be handled carefully. This brings about a third set of hypotheses:

*H3a*: A longer interval in between app use is positively associated with the degree to which profiles are generally evaluated as interesting.

*H3b:* A longer interval in between app use is positively associated with the number of matches.

Thus far, we have mainly considered the app dynamics and how this translates into satisfaction with the app. The interplay of user behavior and the algorithmic curation explains the degree to which interesting profiles are shown and matches are made. This in turn explains how Tinder is appraised. Still, all of this sheds little light on the consequences of using the app. Prior research on online dating has indicated that within the shopping logic of online dating, a lack of quantity and quality in interaction is related to user distress (Heino, Ellison, & Gibbs, 2010; Zytko, Grandhi, & Jones, 2014). Those who receive little attention tend to feel ignored, whereas positive feedback boosts morale. Based on these insights, it is plausible that the degree of satisfaction with Tinder translates into situational positive or negative affect. Therefore, we propose a fourth and final hypothesis:

*H4:* Satisfaction with Tinder is positively related to current mood.

## Method

### Sampling and procedure

This study draws on a purposive sample of 88 Belgian Android Tinder users. The pool of participant consists of 42 females and 46 males, with an average age of 24.02 years ($SD = 3.02$). Most participants (93%) identified as straight, 1% as gay, and 5% as bisexual (1% chose not to disclose that information). Participants were recruited in the context of a research seminar, drawing upon: (a) student researchers' informal networks, while (b) also recruiting through a mailing list originating from the authors' prior studies on Tinder, and (c) inviting participants through promotional study accounts on the Tinder platform itself.

The participants were invited to first fill out an online intake questionnaire, inquiring sociodemographics and prior Tinder use and experiences. Next, they were requested to download the PACO app (www.pacoapp.com), an open source ESM app. Through this app, during six weeks in April and May 2017, requests were sent to participants to fill out a small form immediately after closing Tinder (a function only available in the Android version). To avoid sending excessive amounts of requests, which would induce unnecessary participant fatigue, a minimum time interval of 10 hours between consecutive requests was set. A total of 1,055 completed post-use forms were gathered (on average 12 forms per participant). Meanwhile, PACO exhaustively logged the participants' Tinder app activity, which led to gathering 16,820 individual log statements.

The data from the forms, intake survey and log data were merged into a single multilevel data set. In this data set, each row represents a post-use form (level one data). As each form is nested within a participant (level two), and is collected at a specific time, both *person* and *individual form chronology* identifiers were incorporated. Furthermore, per participant, the level two data from the intake survey were added. Finally, aggregated log data, reflecting the amount of Tinder activity between two forms were included as level one data.

## Measures

The intake survey consisted of several questions on prior Tinder use. The questions relevant to this study are the following: (a) the *month and year* the participants first subscribed to Tinder, which was recoded into months since their first Tinder experience ($M = 22.28$, $SD = 14.14$), (b) the rating of their own *perceived attractiveness*, in contrast to other people with the same age and gender as an albeit inflated proxy for attractiveness on a 9-point Likert scale, ranging from very unattractive to very attractive ($M = 5.49$, $SD = 1.63$), (c) a five-item measure of *satisfaction with life* (7-point scale, $\alpha = .81$, M = 3.55, SD = 1.61; Pavot, Diener, Colvin, & Sandvik, 1991), and (d) a one-item measure of *self-esteem* (7-point scale, M = 4.77, SD = 1.18; Robins, Hendin, & Trzesniewski, 2001).

The post-use forms sent after using Tinder focused on the participants' activities and experiences during *the most recent app session*. The measures relevant for this study are:

### *Swipe activity*

Swipe activity is a measure of the number of given likes, weighted by the amount of swiped profiles, i.e., the product of both variables ($M = 7.63$, $SD = 7.87$, $Mdn = 6$). The participants were first asked to approximate the *amount of profiles they swiped* during their most recent Tinder session. Because it is hard for participants to keep track of exactly how many profiles they swiped, categories were presented. The response categories, coded from 1–6, are none (0), very few (1–10), few (>10–25), somewhat (>25–50), many (>50–75), a great many (>75) ($M = 2.82$, $SD = 1.40$). Similarly, the *proportion of given likes* was documented through the following response categories, coded from 1–7: none (0), very few (up to 10% of the swiped profiles), few (up to 25% of the swiped profiles), somewhat (up to 50% of the swiped profiles), many (up to 75% of the swiped profiles), a great many (up to 90% of the swiped profiles), and (nearly) all swiped profiles ($M = 2.76$, $SD = 1.54$).

### *Number of matches*

In most cases, the number of matches are not as abundant as the number of swiped profiles and likes. Therefore, participants were asked to give a precise number ($M = .80$, $SD = 1.74$, $Mdn = 0$).

### *Interestingness of presented profiles*

The question how interesting, on average, the presented profiles were was followed by a 7-point Likert rating scale, ranging from (1) *very uninteresting* to (7) *very interesting* ($M = 3.06$, $SD = 1.27$).

### *Satisfaction with the app*

Weighing exhaustiveness of a measure with the participant burden of presenting multiple items, and relying on research on mobile quality of experience (e.g., Mateo Navarro, Martínez Pérez, & Sevilla Ruiz, 2014) we chose to measure this variable by a single 7-point Likert item ranging from (1) *not at all satisfied* to (7) *very satisfied* ($M = 3.65$, $SD = 1.02$).

### *Current mood*

For similar reasons, this variable was measured by a one-item 5-point faces scale, ranging from (1) *a sad smiley* to (5) *a happy smiley* ($M = 3.48$, $SD = .88$).

Furthermore, participants were asked whether they got a notification of temporarily exceeding their free number of likes (7% yes), and whether one or more of the following events applied to their most recent session: using Tinder Boost (.1%), using Tinder Plus (.1%), starting a conversation with a new match (7%), having a new match start a conversation (10%), continuing a conversation with a prior match (15%), having a prior match continue a conversation (23%).

The log files, gathered through the PACO app during the study, were first screened for indications of Tinder usage. From these data, a variable was computed that indicates the *number of hours it has been since Tinder was used* prior to the session that triggered the form request ($M = 36.21$, $SD = 63.77$, $Mdn = 16$).

## Results

The collected data had a multilevel structure: experience sampling forms and log data gathered over time from multiple participants, paired with cross-sectional measures from the intake survey. This requires that the proposed hypotheses were tested through multilevel growth models that account for the aspect of the chronology of participants filling in forms, as well as individual differences.

The first set of hypotheses proposed that user satisfaction with the app is positively explained by the ability to swipe interesting profiles, to get matches and engage in conversations with these matches (H1a). Furthermore, it was predicted that bumping into restrictions, such as running out of free likes negatively explains user satisfaction (H1b). To simultaneously test these hypotheses, a multilevel model was computed with satisfaction with the app as a dependent variable. The random part of the model allowed both participant intercepts and the nested individual chronology of the forms to vary freely. The fixed part of the model consisted of the variables of interest with regards to the hypotheses and additional control variables. These included the number of the study form, age, gender and months since participants' first experience with Tinder. Also, own perceived attractiveness was added as a proxy for genuine attractiveness, which we assume positively affects success on the app.

The summary of fixed effects in Table 1 shows that being able to browse interesting profiles and getting matches was generally positively related to satisfaction with Tinder. Moreover, starting conversations with new matches, as well as continuing a conversation was positively associated with this satisfaction. This means the expectations in H1a were supported by the data. H1b was also supported, as having run out of free likes was indeed negatively associated with satisfaction. An additional model, computing six cross-level interactions between the chronology of forms on the one hand, and matches, swiping interesting profiles, and the four conversation variables on the other hand did not yield significant effects. This implies that the found effects were stable at least for the duration of the study.

The second set of hypotheses predicted that swiping and liking activities are curvilinearly associated with profile interestingness (H2a) and the number of matches (H2b). The third set of hypotheses focused on the interval between app use, predicting that it is positively related with profile interestingness (H3a) and the number of matches (H3b). To test these hypotheses, two models were computed: one for interestingness and one for number of matches.

The profile interestingness model's random part included freely varying participants and nested individual form chronology. The fixed part was composed of the following control variables: chronology of forms, months since first having a Tinder account, gender, age, and self-perception of attractiveness. The hypotheses' variables were also included: swipe activity and its squared form, as well as the time between recent logins in hours. The results of the fixed part, shown on the left-hand side of Table 2 (column a), show that male participants were generally evaluated the offered profiles as more interesting. The results indicate that the association between swipe activity and profile interestingness was indeed a curvilinear one, in the shape of an inverted U-curve (H2a). The hour intervals however did not affect interestingness (H3a).

**Table 1** Estimates of Fixed Effects, Explaining *Satisfaction With Tinder*. An unstructured covariance structure was defined for the random part, computing the effects for participants and chronology of forms. The Residual variance amounts to ($Z = 18.63$) .03 (.02), $p = .000$. The random effects are UN (1,1) ($Z = 4.72$) .39 (.08), $p = .000$, UN(2,1) ($Z = 2.14$) .01 (.01), $p = .032$, UN(2,2) ($Z = 1.93$) .00 (.00), $p = .054$

| | Satisfaction with Tinder | | |
|---|---|---|---|
| | B | *SE* | *p* |
| Intercept | 1.943 | .698 | .005 |
| Chronology of individual forms | −.008 | .006 | .235 |
| Months since first Tinder experience | .003 | .006 | .608 |
| Gender (Male = 1) | −.112 | .167 | .501 |
| Age | .026 | .029 | .374 |
| Self-perception of attractiveness | .056 | .052 | .279 |
| Interestingness of proposed profiles | .268 | .023 | .000 |
| Number of matches | .036 | .015 | .018 |
| Starting new conversation with new match | .333 | .090 | .000 |
| New match starts conversation | .104 | .087 | .234 |
| Continuing conversation with prior match | .185 | .077 | .016 |
| Match continues prior conversation | −.002 | .069 | .974 |
| Ran out of free likes | −.234 | .093 | .012 |

Due to right skewness of the variable "number of matches," a negative binomial model was computed to cope with its particular distribution (Allison, 2012). Apart from that, the matches model shared the exact same definition as the prior profile interestingness model. The results, shown in the middle of 2 (column b), indicate that, on average, male participants and older participants gathered fewer matches. Interestingly, there was a negative effect of chronology of forms on the number of matches. This suggests that over time, the number of matches tends to decline. Furthermore, the model supports the hypothesis (H2b) of a curvilinear relationship between swipe activity and matches (i.e., an inverted U-curve). H3b was not supported, as we found no effect of hours between the two last logins.

Finally, the relationship between satisfaction with Tinder and current mood was tested (H4). This model's dependent variable was the participants' current mood. As in all prior models, this model's random part too included freely varying participant intercepts and nested individual form chronology. The fixed part was composed of seven control variables: chronology of forms, months since first having a Tinder account, gender, age, self-perception of attractiveness, satisfaction with life, and self-esteem. Satisfaction with life and self-esteem were considered as differential factors that were likely to structurally affect one's mood. Evidently, satisfaction with Tinder was also included as an independent variable.

The summary of the model's fixed part Table 2 (column c) yields two significant effects. First, it shows that a longer experience with Tinder was negatively associated with current mood, right after using Tinder. However, satisfaction with the app was positively associated with mood. This begs the question whether both variables (i.e., longer experience with Tinder and satisfaction with Tinder) possibly interact in explaining the target variable (i.e., mood). Therefore, a supplementary model was computed, also including an interaction term between time of experience with using Tinder and satisfaction with the app. This nullified the main effect by satisfaction, but not of having a longer

**Table 2** Estimates of Fixed Effects, Explaining: (a) Interestingness of Proposed Profiles, (b) Number of Matches, and (c) Current Mood. For all three models, an unstructured covariance structure was defined for the random part, computing the effects for participants and chronology of forms

| | (a) Interestingness of proposed profiles | | | (b) Number of matches | | | (c) Current Mood | | |
|---|---|---|---|---|---|---|---|---|---|
| | B | *SE* | *p* | B | *SE* | *p* | B | *SE* | *p* |
| Intercept | 1.716 | 1.053 | .104 | .869 | .937 | .360 | 2.440 | .538 | .000 |
| Chronology of individual forms | .002 | .009 | .849 | −.046 | .017 | .018 | −.005 | .005 | .254 |
| Months since first Tinder experience | −.003 | .008 | .681 | .001 | .007 | .911 | −.011 | .004 | .005 |
| Gender (male = 1) | .486 | .231 | .036 | −1.084 | .241 | .000 | .125 | .117 | .286 |
| Age | −.012 | .043 | .778 | −.154 | .036 | .000 | −.003 | .021 | .877 |
| Self-perception of attractiveness | .054 | .073 | .461 | .124 | .068 | .075 | .066 | .043 | .132 |
| Swipe activity | .181 | .015 | .000 | .207 | .036 | .000 | | | |
| Swipe activity$^2$ (squared) | −.003 | .000 | .000 | −.004 | .001 | .000 | | | |
| Hours between two last logins | .000 | .001 | .795 | .001 | .001 | .055 | | | |
| Satisfaction with the app | | | | | | | .243 | .025 | .000 |
| Satisfaction with life | | | | | | | .054 | .054 | .316 |
| Self-esteem | | | | | | | .011 | .049 | .817 |
| UN (1,1) | .72 | .18 | .000 | .54 | .25 | .031 | .19 | .04 | .000 |
| UN (2,1) | −.01 | .01 | .560 | −.02 | .02 | .382 | .00 | .00 | .804 |
| UN (2,2) | .00 | .00 | .131 | .00 | .00 | .123 | .00 | .00 | .000 |

experience using Tinder (B = −.05, SE = .01, $p$ = .000). The interaction term proved significant (B = .01, SE = .00, $p$ = .000). More experienced users that were satisfied with the app generally tended to report better moods right after using the app.

## Discussion and conclusion

This article presents a conceptual structuration model that considers algorithmic governance of online platforms as the dynamic interplay of three types of actors: platform owners and developers, machine learning algorithms and platform users. More specifically, platform owners design the architectures and construct the discourses tied to services (van Dijck, 2013). Within a technological and commercial logic, they set out the potential parameters and preferred targets for self-learning algorithms. These mechanisms work semi-autonomously in developing the recipe to push users into desired behavior (Alpaydin, 2014). Still, users are the key resource for this learning activity by providing the necessary data. This implies that users at least indirectly, and probably unknowingly, have a hand in how a platform operates and develops. Users have the ability to attempt to resist platform algorithms by trying to figure out the essence of their mechanics and act accordingly (Bucher, 2017).

We argued that in current models of media effects, the influence of algorithms is mainly ignored. This obscures how exposure comes about as an interaction between users and algorithms. Unfortunately, platforms rarely communicate on how their algorithms work, which complicates our understanding of how they affect exposure and users. To indirectly explain the interaction between algorithms and users, we argued in favor of adopting insights from the (C)PE of online media and platform studies. These perspectives have thoroughly analyzed the technical and economic backgrounds of numerous platforms. Still, they rarely involve larger scale quantitative research that assess algorithms' effects on users. As such, both perspectives are complementary and benefit from being jointed together. The unique combination allows to derive assumptions on how algorithms work, and allow to gather data to test hypotheses on associations between input, output, and effects measures. More specifically, we successfully appropriated experience sampling to measure user action (input), exposure (output), and effects immediately after a usage session. This offered a glimpse into the black box, without actually having to open it. It feeds back to media effects research by refining its conceptual model to fit algorithmically-governed platforms and by offering a method for empirical research. Moreover, evidence that follows from this approach provides (C)PE of online media and platform studies with statistical evidence that strengthens and/or nuances their assumptions on the user consequences.

This proof of concept focused on Tinder and the supposed general mechanics of its algorithm. It showed that swipe activity is curvilinearly, rather than linearly related to profile interestingness and the number of matches. Such findings suggest that, at least for non-paying users, more swipe activity does not necessarily relate to more outcomes (i.e., getting to see more attractive profiles or establish matches). These outcomes, that precede and enable further communication, are Tinder's key features that account for satisfaction with the app. It is reasonable to assume that Tinder deliberately limits these outcomes. It prohibits its major assets of attractive profiles and liked profiles to run out too soon. This could be considered as an element that frustrates users to convert them into paying customers. Tinder incorporates a mechanism that explicitly, and apparently successfully, dissatisfies users by restricting their number of free likes; a restriction that is taken away by simply buying a premium subscription.

However, the current data do not support usage frequency intervals as an important factor in showing interesting profiles and allowing matches. We assumed that this would point platforms to users that pose a potential threat for dropping out. Offering more matches could entice them to return, or become more active. However, we did find an effect of chronology of forms, which points to a similar logic, although based on the overall activity. The more Tinder is recurrently used, the lower the number of matches becomes. Still, we need to consider that this is only an indirect indicator in this study. We expected similar effects of interestingness of profiles, which could not be confirmed. A plausible explanation is that Tinder attempts to continually feed users anticipation of potentially getting attractive matches, regardless of activity frequency. Also, attractive profiles are a resource that are not as scarce as attractive profiles that warrant a match.

This study sheds preliminary light on possible effects that using the app provokes. The analyses show that the longer it has been since Tinder was first ever used, the more negative participants reported on their mood after using the app. However, this effect is less pronounced for participants who are more satisfied with the app. If we take into account that the key features explaining satisfaction (i.e., interesting profiles and matches), are affected by the interaction between users and the algorithm, it must be acknowledged that this interplay is likely responsible for the psychosocial consequences the platform provokes. This implies that research on online media effects that solely draws on either an exposure-effects or a selective exposure logic remains oblivious to the genuine complexity that underlies this exposure. Exposure to online platforms is a media effect in itself that provokes other effects. This study suggests that longitudinal efforts that closely focus on user activity and exposure as it occurs could help in overcoming this fundamental caveat.

This proof of concept of a structuration approach to research algorithmically-governed platforms not only fits Tinder, but virtually any platform. However, a significant challenge in generalizing its methodology is that platforms characterized by a wide array of input and output variables are probably too complex to capture in their entirety. It should be noted, however, that it is not our ambition to reverse engineer algorithms or capture their finest nuances, rather than uncovering and testing their general mechanisms. Still, this study is inevitably characterized by several limitations. Despite the considerable number of completed forms, it draws upon a relatively small sample of users. This only allows us to reliably test relatively simple statistical models. Due to required investment, it is difficult to engage a large number of participants. Also, the sample includes few paying users. It is unclear whether they are treated differently by the algorithm. However, the number of paying Tinder users was estimated at only 2% a year ago (McAlone, 2016). We also noticed that some participants struggled with setting up the ESM app, in spite of detailed user guides. Finally, we need to acknowledge that effects measures in this study are far from perfect. In order not to overburden participants, we chose for compact single-measure items incapable of capturing the phenomena's full complexity. For these reasons, we encourage further theoretical and methodological developments that render this logic applicable to more complex platforms with a wider range of less evidently identifiable input and output variables, and for a wider array of more refined media effects. The framework could also be applied in an experimental setting to test whether algorithmic awareness affects user agency and outcomes.

## References


Allison, P. D. (2012). *Logistic regression using SAS: Theory and application*. Cary, NC: SAS Institute.

Alpaydin, E. (2014). *Introduction to machine learning*. Cambridge, MA: MIT press.

Bosker, B. (2013). Here's one of the college kids helping tinder take over campuses. Available from http://www.huffingtonpost.com/2013/07/02/tinder-app-college-kids_n_3530585.html.

Bryant, J., & Oliver, M. B. (2009). *Media effects: Advances in theory and research*. New York: Routledge.

Bucher, T. (2017). The algorithmic imaginary: exploring the ordinary affects of Facebook algorithms. *Information, Communication & Society*, 20(1), 30–44.

Burrell, J. (2016). How the machine "thinks": Understanding opacity in machine learning algorithms. *Big Data & Society*, 3(1). doi:10.1177/2053951715622512

Crain, M. (2016). The limits of transparency: Data brokers and commodification. *New Media & Society*. doi:10.1177/1461444816657096

David, G., & Cambre, C. (2016). Screened intimacies: Tinder and the swipe logic. *Social Media + Society*, 2(2), 2056305116641976. doi:10.1177/2056305116641976

van Dijck, J. (2013). *The culture of connectivity: A critical history of social media*. Oxford, UK: Oxford University Press.

Domingos, P. (2017). *The master algorithm*. London: Penguin.

Duguay, S. (2017). Dressing up Tinderella: Interrogating authenticity claims on the mobile dating app Tinder. *Information, Communication & Society*, 20(3), 351–367. doi:10.1080/1369118X.2016.1168471

Fisher, E., & Fuchs, C. (2015). *Reconsidering value and labour in the digital age*. New York: Palgrave Macmillan.

Fuchs, C. (2014). *Digital labour and Karl Marx*. London, UK: Routledge.

Giddens, A. (1984). *The constitution of society: Outline of the theory of structuration*. Berkeley: University of California Press.

Gillespie, T. (2010). The politics of "platforms." *New Media & Society*, 12(3), 347–364. doi:10.1177/1461444809342738

Gillespie, T. (2014). The relevance of algorithms. In T. Gillespie, P. Boczkowski, & K. Foot (Eds.), *Media technologies* (pp. 167–194). Cambridge, MA: MIT Press.

Greenhalgh, T., & Stones, R. (2010). Theorising big IT programmes in healthcare: Strong structuration theory meets actor-network theory. *Social Science & Medicine*, 70(9), 1285–1294. doi:10.1016/j.socscimed.2009.12.034

Harrison, G. (2015). Google, Big Data, and Hadoop. *Next Generation Databases: NoSQL, NewSQL, and Big Data*. Berkeley, CA: Apress.
Heino, R. D., Ellison, N. B., & Gibbs, J. L. (2010). Relationshopping: Investigating the market metaphor in online dating. *Journal of Social and Personal Relationships*, 27(4), 427–447. doi:10.1177/0265407510361614
Hektner, J. M., Schmidt, J. A., & Csikszentmihalyi, M. (2007). *Experience sampling method: Measuring the quality of everyday life*. Thousand Oaks, CA: Sage.
Helmond, A. (2015). The platformization of the web: Making web data platform ready. *Social Media + Society*, 1(2), 2056305115603080. doi:10.1177/2056305115603080
IAC. (2017). About IAC. Available from http://iac.com/about/overview
Kenney, M., & Zysman, J. (2016). The rise of the platform economy. *Issues in Science and Technology*, 32(3), 61–69.
Knobloch-Westerwick, S. (2015). *Choice and preference in media use: Advances in selective exposure theory and research*. New York: Routledge.
Kosoff, M. (2016). You have a secret Tinder rating—but only the company can see what it is. Available from http://uk.businessinsider.com/secret-tinder-rating-system-called-elo-score-can-only-be-seen-by-company-2016-1?r=US&IR=T
Langley, P., & Leyshon, A. (2017). Platform capitalism: The intermediation and capitalisation of digital economic circulation. *Finance and Society*, 3(1), 11–31.
Latour, B. (1992). *Reassembling the social: An introduction to actor-network-theory*. Oxford: Oxford Univserity Press.
Lomborg, S., & Bechmann, A. (2014). Using APIs for data collection on social media. *The Information Society*, 30(4), 256–265. doi:10.1080/01972243.2014.915276
MacKee, F. (2016). Social media in gay London: Tinder as an alternative to hook-up apps. *Social Media + Society*, 2(3). doi:10.1177/2056305116662186
Mackenzie, A. (2013). Programming subjects in the regime of anticipation: Software studies and subjectivity. *Subjectivity*, 6(4), 391–405. doi:10.1057/sub.2013.12
MatchGroup. (2016). Business Overview. Retrieved from http://ir.mtch.com/phoenix.zhtml?c=254224&p=irol-irhome
Mateo Navarro, P. L., Martínez Pérez, G., & Sevilla Ruiz, D. (2014). A context-aware interaction model for the analysis of users' QoE in mobile environments. *International Journal of Human–Computer Interaction*, 30(12), 946–964. doi:10.1080/10447318.2014.925382
McAlone, N. (2016). More than 1 million people now pay for Tinder's premium tier. Available from http://uk.businessinsider.com/r-match-group-revenue-beats-as-tinder-attracts-more-paid-users-2016-5?r=US&IR=T
O'Brien, S. A. (2015). Tinder angers swipe-happy users. Available from http://money.cnn.com/2015/03/03/technology/tinder-plus/index.html
Pavot, W., Diener, E., Colvin, C. R., & Sandvik, E. (1991). Further validation of the Satisfaction With Life Scale: Evidence for the cross-method convergence of well-being measures. *Journal of Personality Assessment*, 57(1), 149–161. doi:10.1207/s15327752jpa5701_17
Peacock, S. E. (2014). How web tracking changes user agency in the age of Big Data: The used user. *Big Data & Society*, 1(2), 1–11. doi:10.1177/2053951714564228
Plantin, J.-C., Lagoze, C., Edwards, P. N., & Sandvig, C. (2016). Infrastructure studies meet platform studies in the age of Google and Facebook. *New Media & Society*. doi:10.1177/1461444816661553
Robins, R. W., Hendin, H. M., & Trzesniewski, K. H. (2001). Measuring global self-esteem: Construct validation of a single-item measure and the Rosenberg Self-Esteem Scale. *Personality and Social Psychology Bulletin*, 27(2), 151–161. doi:10.1177/0146167201272002

Seufert, E. B. (2013). *Freemium economics: Leveraging analytics and user segmentation to drive revenue*. Waltham, MA: Morgan Kaufmann.

Slater, M. D. (2007). Reinforcing spirals: The mutual influence of media selectivity and media effects and their impact on individual behavior and social identity. *Communication Theory*, 17(3), 281–303. doi:10.1111/j.1468-2885.2007.00296.x

Stones, R. (2005). *Structuration theory*. New York: Palgrave-McMillan.

Summers, N. (2014). As Tinder flirts with ads, is it worth millions—or billions? Available from https://www.bloomberg.com/news/articles/2014-01-03/as-tinder-flirts-with-ads-is-it-worth-millions-or-billions

Tinder. (2016). Skip the line with Tinder Boost. Retrieved from http://blog.gotinder.com/skip-the-line-with-tinder-boost/

de Vreese, C. H., & Neijens, P. (2016). Measuring media exposure in a changing communications environment. *Communication Methods and Measures*, 10(2–3), 69–80. doi:10.1080/19312458.2016.1150441

Willson, M. (2017). Algorithms (and the) everyday. *Information, Communication & Society*, 20(1), 137–150. doi:10.1080/1369118X.2016.1200645

Zhang, M. (2016). Building Tinder. Available from http://tech.gotinder.com/building-tinder/

Zytko, D., Grandhi, S. A., & Jones, Q. (2014). *Impression management struggles in online dating*. Paper presented at the Proceedings of the 18th International Conference on Supporting Group Work, Sanibel Island, FL.