Folk Theories and User Strategies on Dating Apps

How Users Understand and Manage Their Experience with Algorithmic Matchmaking

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Abstract. The goal of this paper is to understand the experience of users with algorithmic filtering on dating apps by identifying folk theories and strategies that users employ to maximize their success. The research on dating apps so far has narrowly focused on what we call algorithmic pairing–an explicit pairing of two users together through a displayed compatibility score. However, algorithms behind more recent dating apps work in the background and it is not clear to the user if and how algorithmic filtering is mediating their interaction with other users. This study identifies user goals and behaviors specific to dating apps that use algorithmic filtering: while some users employ various strategies to boost their "attractiveness score" to match with as many people as possible, others attempt to teach the algorithm about their unique preferences if they believe that the filtering is not working in their favor. Our research adds to the growing literature on folk theory formation by introducing dating apps as a novel context for research. Since folk theories are developed with specific goals in mind, they reveal user concerns around algorithmic filtering. Our hope is that this paper starts a conversation on the practical and ethical question of algorithmic intervention on sexual and romantic preferences and behavior.

Keywords: Algorithmic filtering · Dating apps · Human-AI interaction · Folk theories · User experience

1 Introduction

With the success of recommender systems on platforms for online shopping and streaming services, dating apps are using similar methods to filter and recommend users to one another. As most new couples in the United States meet online [1, 2], algorithmic filtering is shaping romantic and sexual relationships by influencing the profiles a dating app user can see and match with. This paper explores how users respond to the invisible algorithm that is affecting their dating life.

M. Smits (Ed.): iConference 2022, LNCS 13192, pp. 445–458, 2022.
https://doi.org/10.1007/978-3-030-96957-8_37

The promise of algorithmic matchmaking rests on the assumption that romantic and sexual preferences can be predicted. Some dating apps give users explicit compatibility scores. For example, eHarmony uses its 32 Dimensions of Compatibility to match users together. They claim that they use scientific research to determine dating behavior [3]. OkCupid uses a Match % to help user identify potential partners [4]. Other dating apps keep their algorithm in the background and give the user no indication of their compatibility with others. Apps like Tinder and Bumble pre-selects the profiles that a user can browse through by filtering them based on compatibility [5]. However, the user is not told that the profiles that they see are selected by an algorithm.

Outside of dating apps, recommender systems have been extremely effective in affecting user behavior and preferences [6]. "At Netflix, 2/3 of the movies watched are recommended; at Google, news recommendations improved click-through rate by 38%; and for Amazon, 35% of sales come from recommendations" [7]. However, this level of intervention has also led users to develop strategies to circumvent algorithmic control: for examples, workers use workarounds to avoid undesirable assignments given by algorithmic managerial systems [8, 9]. But since algorithms are unexplainable black boxes to the users, folk theories are developed, tested and shared between users to get a better understanding of how the algorithm works and how to strategize around it [10–12].

And so, it is worth taking a closer look at how recommendations and filtering can affect our romantic and sexual behavior. The first aim of this paper is to identify folk theories that users develop to better understand algorithmic filtering on dating apps. This will be a unique contribution to the growing literature on folk theory formation since, as far as we are aware, folk theories around dating apps are yet to be identified. The second aim of this paper is to understand how those folk theories are used to deploy strategies that allow users to be more successful on dating apps. With this, we can identify concerns users are facing with algorithmic matchmaking by seeing which features they are trying to circumvent. Folk theories are developed with specific goals in mind and are especially useful to users who believe the algorithm is working against them. Our research can serve as a first step to studying how algorithmic filtering can be improved to enhance user experience.

2 Theoretical Backgrounds

2.1 Algorithmic Pairing and Algorithmic Filtering

The current research on algorithmic matchmaking has focused on algorithms that run on the foreground of dating apps. In those cases, the user is presented with a matching score or a selection of profiles that are explicitly presented as good matches [13]. Dating apps also highlight their unique algorithm when marketing their products, promising the user that they will help them find their 'perfect match.' There is extensive research on compatibility scores and how they affect dating app users [14–16], even when compatibility scores cannot predict the long-term success of a relationship [17, 18].

Compatibility scores are not commonly used by location-based mobile apps that prefer a swiping system. On those apps, the user is given a set of profiles to look at one by one. I will refer to this set of profiles as a "deck." If they are interested in the profile they see, they can swipe right and if they are not, they can swipe left. If two users swipe right on each other, they match and can start a conversation. The algorithm is working in the background: the user is given no indication that the profiles they see are preselected by an algorithm.

While some research has pointed out algorithmic matchmaking can work in the background of dating apps [5], no effort is made to preserve this distinction in selecting users or analyzing data. For example, a 2020 study on dating app algorithms and relational filter bubbles interviews 20 dating app users who use a mix of eleven different apps (including Tinder, Happn and Grindr) [15]. Each of these apps has a unique algorithm and user interface and gives different levels of autonomy to the user. It is challenging to pinpoint how users respond to algorithmic matchmaking over a wide range of different matchmaking methods. And so, we propose the following distinction between two methods of algorithmic matchmaking:

- **Algorithmic pairing** explicitly presents users with other profiles that are determined to be compatible with one another. And so, users are aware of the algorithmic matchmaking that happens at the foreground of the application.
- **Algorithmic filtering and sorting** are used to select a set of profiles for users to browse through. And so, users are not always aware of the algorithmic matchmaking that happens in the background of the application.

2.2 Folk Theory Formation on Social Platforms

Other than simple anecdotal reports from dating app users, there is little understanding of how algorithmic matchmaking really works. There is a lack of transparency about matching criteria which leaves users with no clear understanding of what is included in their feed [19]. Most dating app users have "uncritical understanding of [the] dynamics" of filtering algorithms on dating apps [15]. Even outside of dating platforms, algorithmic filtering is widely misunderstood [10, 20], which leaves users with less agency and less opportunities to manage their experience on the platform [10].

Because of the opacity of dating app algorithms, users need to form their own theories about how the algorithm works to get the most of their experience on dating apps. Folk theories are "intuitive, informal theories that individuals develop to explain the outcomes, effects, or consequences of technological systems" [11]. Users generally build complex theories to make sense of filtering on social platforms [10, 11]. Folk theories are helpful to understand user response to algorithmic change [11] and to analyze affordances and self-presentation goals [12, 21]. On dating apps, user activity is private. Without a public audience to speak of, user behavior, goals and concerns on dating app is very different than on social media platforms. Dating apps can thus provide us with a unique perspective on folk theory formation. To our knowledge, this research would be the first to identify folk theories that mediate user experience on dating apps.

RQ1: What are the common folk theories about algorithmic filtering on dating apps?

2.3 Strategizing Around the Algorithmic

Folk theories allow users to reach their goals by giving them an understanding of how opaque algorithms curate social media feeds [11]. Folk theories are utility-driven meaning that each theory's potential in helping a user achieve their goal is what makes the theory good. And so, it matters less if the theory is descriptively correct as long as it is able to increase utility for users. This is done by testing various prescriptive strategies. Users gather information and build folk theories with the goals of creating strategies that work with the algorithm in reaching their goals [21]. Workers use similar methods when working with algorithmic managerial systems [8, 9]. For example, workers use their knowledge of the algorithm to avoid undesirable work assignments that would automatically be given to them by the algorithm [8]. It would not be surprising if dating app users develop similar strategies and use their folk theories about algorithmic matchmaking to improve their success on the app.

Those strategies can also address ethical worries that users might have around algorithmic control. Mainstream media reports on dating app users only seeing profiles from their own race [22] and on the bias that could result from algorithmically filtering sexual and romantic partners [23, 24]. Outside of dating apps, those biases can become harmful. Lack of user control over filtered content leads to a gatekeeping process that allows tech giants to control what information a user is exposed to [25]. Additionally, technical biases and societal biases within computer systems can create further marginalize certain communities [26]. The same worries should be raised when it comes to algorithmic filtering on dating apps. For example, queer and feminist theories of Human-Computer Interaction challenge the boundaries that algorithmic matchmaking might place on our intimate relationships since they rely on filtering that reflects mainstream sexual and romantic interests [27, 28].

The research on dating apps focuses on how users interact with other users [5, 16, 29], but little research is conducted on the user's interaction with the algorithm. To see how users strategize around the algorithm, we must understand how descriptive folk theories about the algorithm are deployed and developed into prescriptive strategies that can inform user behavior. We will do so by identifying the specific goals that a user might have on a dating app and seeing how different strategies can address different goals. This will also allow us to identify user concerns by seeing what algorithmic features users are trying to circumvent.

RQ2: What are the goals of dating app users on the platform?
RQ3: How do folk theories allow users to reach their desired goals on dating apps?

3 Methods

We used a mixed method approach to gather our data. First, we analyzed Reddit posts from users sharing information about the Tinder algorithm. Second, we confirmed the folk theories and strategies that we identified in the first step through a survey.

3.1 Research Context: Tinder

Tinder is a location-based swiping mobile dating app. Users build a profile with pictures, basic information such as employment and education and a short bio. Users can then "swipe" through a set of different profiles, one by one. A swipe right means that the user is interested in the profile and a swipe left means that they are not. If two users like each other, they match and can start a conversation. Tinder has a "Top Picks" section that recommends ten different profiles to the user each day. Those are algorithmically selected to be good matches with the user.

Our research focuses on Tinder because it is the most widely used mobile dating app. There is no information on how the algorithm works, making it ideal to understand how different levels of awareness and understanding affect user behavior. The "Top Picks" section makes is even more interesting since it allows the user to directly see what kind of profiles the algorithm is selecting as desirable. Finally, since the user is only able to filter profiles by distance, age and gender, user's autonomy is extremely limited in comparison with other dating apps that allow for various filters such as race, drinking and smoking habits, or religious beliefs. The current research on Tinder has focused on user psychology and user-to-user interaction [5, 16, 29]. As far as we are aware, the research on Tinder so far ignores how the user navigates the algorithmic aspect of the platform.

3.2 Questions, Tips and Sensemaking on Reddit

Reddit is a social discussion website where users can share links, texts, or images. The posts are organized in different subreddits, each focusing on a specific topic of interest. Subreddits such as r/Tinder, r/SwipeHelper, and r/Seduction usually feature posts from users who share tips and concerns from their personal experiences on Tinder.

Some use the subreddits to share their knowledge of the algorithm, using shared experience to determine how specific features of the algorithm might work. Others share tips for others to maximize their matches and have more meaningful connections on the app. Finally, some use the subreddit to vent their frustrations and concerns about the algorithm mediating their romantic and sexual life.

To find relevant posts, we used keywords such as "algorithm," "filtering," "Top Picks," and "increase matches" to search for relevant posts. We found 39 threads that explicitly mentioned the Tinder algorithm in the title. We excluded 4 threads where the discussion was focused on non-algorithmic methods such as "use better pictures," or "write more details in your bio." The remaining 35 threads were grouped in two categories: one category for users who were asking a question or raising a concern (25 threads), and one category for users who were giving out answers or tips (10 threads). We limited ourselves to posts from the past two years since Tinder constantly goes through substantial changes that would affect the user's perception of the algorithm.[1] The resulting 35 threads led to 73 relevant posts since each thread had replies from other

[1] Reddit does not show the exact time stamp of each post but shows an approximate time stamp such as "1 year ago." While the two-year limit might seem like a strict cutoff, the changes that Tinder went through before our cutoff are too substantial to have any relevant data before then.

users. The posts were analyzed and coded to reveal common concerns and popular folk theories and strategies. The categories that came up in our review were collapsed into themes through a comparative analysis [30]. Our final codes correspond to specific folk theories or strategies that emerged during our analysis, and correspond to the subsections of the Findings for RQ1 and RQ3: ELO scores (4 posts), new profile (15 posts), broader filters (5 posts), and swipe ratios (14 posts).

3.3 Survey

Since Reddit users only represent a narrow set of Tinder users, and since the posts were limited due to our strict search criteria, we designed a survey to confirm the trends that were identified in the initial data. The survey questions were written to ask participants specifically about the strategies and concerns that were commonly discussed on Reddit.

Participants were recruited on Amazon Mechanical Turk using CloudResearch [31]. To take the survey, workers must be CloudResearch approved participants with a 95% approval rate or above and at least 100 HITs approved. We collected 558 responses. 260 respondents did not pass the qualification check at the beginning of the survey that asked them to identify Tinder gestures and features (e.g. swiping right, swiping left, Top Picks), or failed the attention checks within the survey to assure a high quality of responses. This left us with 298 responses (105 females, $M_{age} = 32.13$, $SD = 7.16$). All respondents live in the United States. The median completion time was 7 min and 12 s.

Respondents were asked if they knew of different folk theories and if they employed any of the strategies we identified from our Reddit data. To see if the rationale of the respondents matches what we saw on Reddit, the survey also collected qualitative data by asking participants about why they employ each strategy. Then, respondents were asked to tell us about their goals on Tinder since different users understand success on Tinder differently. Additionally, respondents were asked specific questions about filtering options available on Tinder to gage their preferred level of control. Finally, respondents were asked about attractiveness metrics that might be operating behind dating apps.

Since our main goal was to confirm data gathered from Reddit, we analyzed the quantitative data by looking at the percentage of users who knew about and employed specific folk theories and strategies. The qualitative data was coded to distinguish between algorithmic and non-algorithmic justifications at first, and when more fine-grained results were relevant, a second round of coding was conducted to find further trends [30]. For any survey question in which respondents could select more than one answer, the frequency or number of times an answer was selected is reported. For any survey question in which a respondent could only select one answer, the percentage for how many times that answer was selected is reported.

4 Findings

4.1 RQ1: Identifying Folk Theories

ELO Scores. Users believe that they are given an attractiveness score once they have been active on the app for long enough. This is sometimes referred to as a desirability score by Tinder executives, or an ELO score by users in reference to the ELO rating system used for ranking chess players. One Reddit user tested the hypothesis and shared his results: "*I posted a really hot model pic just to do an experiment: and of course, sure enough you get 30 likes in an hour. But then I changed back to my not so hot photos, and one thing that I noticed: I'm now being shown to the hot ladies. And many of my potential matches are 9 s and 10 s.*"[2] This experiment shows that with more "likes" on their profile, they were able to get a higher attractiveness score from the algorithm and the profiles that the algorithm selects for them are also ranked higher on a conventional attractiveness scale.

Users believe that ELO scores also determine the profiles in their Top Picks sections. The Top Picks section includes 10 profiles that are recommended to a user each day. Tinder writes that Top Picks are meant "to zero in on the [profiles] that suit [each user's] taste and are most interesting to [them]" [32]. However, 4 different Reddit users wrote that their Top Picks section, which should show them profiles that they would be most interested in, only features conventionally attractive people: "*Every single day I literally only see white girls and only once in a while a Hispanic girl that has light enough skin to pass as white. I wouldn't see this as a problem if Tinder's algorithms saw that I swiped right on this type of demographic. However, that's not the case for me.*" Instead of learning the preferences of each user, users believe that the algorithm resorts to popular profiles that exhibit conventionally attractive features.

Most survey respondents (64.8%) believe they somewhat understand why certain profiles are included in their fields and other are not, with 27.2% saying they have a good understanding and 5.7% saying they do not understand at all. Out of our survey respondents, 45.0% agreed with the statement that that Tinder groups profiles together based on an attractiveness score, 16.4% disagree with the statement and 38.6% neither agreed nor disagreed. 79.5% respondents believe that Tinder can know who they are attracted to based off their activity on the app, which shows that even if some respondents did not believe in an attractiveness score, they were still aware of some algorithmic intervention happening in the background.

4.2 RQ2: Identifying User Goals

It is hard to identify one shared goal among all Tinder users. Even though dating apps are usually seen as a mean to find romantic relationships, many users have found more casual relationships and friendships on Tinder: out of our 298 survey respondents, 195 indicate they use Tinder to find a serious relationship, 119 use Tinder for casual hook-ups, 91 use Tinder to find friends and 42 to chat with people online without meeting them. And so, users will vary immensely in their goals. However, when thinking about algorithmic filtering, we can identify two high-level aims that are shared between users:

Boosting ELO Scores. On one hand, 21.7% of survey respondents prefer to get as many matches as possible instead of having fewer matches of good quality. To get more matches, many users believe that they can artificially inflate their ELO score since users believe that profiles with a higher ELO score are shown to more people.

[2] The user is referring to "9 s and 10 s" to describe the attractiveness of their potential matches, i.e., 9/10 and 10/10.

Reddit users associate having a higher ELO score with higher visibility: "*The higher the score, the more visibility you get to others.*" If their profile is seen by more people, users have better chances of matching. Another user writes that they ran experiments trying to lower a profile's ELO score and that "*eventually you'd start seeing the more unattractive people.*" And so, another advantage of artificially increasing a profile's ELO score is to be exposed to profiles that are more conventionally attractive.

More Filtering and Control. On the other hand, some Tinder users prefer to have more control over the profiles that they see so that they do not need to endlessly swipe through profiles that they might not be interested in. 78.3% of survey respondents said they preferred to get fewer matches of good quality rather than as many matches as possible. This was especially true for users who did not have conventional preferences and were worried that the algorithm could not learn what they are looking for.

To illustrate, one user worries that their specific preference might make the algorithm think they are too picky: "*if the algorithm punishes the user for 'being too picky' […] and GNC [gender-nonconforming] isn't a filter option, what's a butch4butch to do?*" Another user worries that the type of women they are attracted to would not usually be considered conventionally attractive by the algorithm: "*if I wanna match with chubby girls will selecting only chubby girls work best? or will it just mark my score as high and I get matched only with higher score women?*".

4.3 RQ3: From Folk Theories to User Strategies

In Sect. 4.1, we identified folk theories that track users' beliefs about how the Tinder algorithm functions. In Sect. 4.2, we identified two goals that guide the behavior of different users. In this section, we bring the two together and ask: how do users employ folk theories to develop strategies that allow them to reach their specific goals on dating apps? The strategies that we identify below are application of the folk theory around ELO scores. In general, we take folk theories to be descriptive, and strategies to be prescriptive. However, many different folk theories might emerge in our results below.

Creating a New Profile. Users believe that their profile gets a boost when it is first created. This could be because profiles that are not assigned an "attractiveness score" are shown to more users. After Tinder learns the user's preference, their dating deck will be filtered: "*When you first create the account, the app pushes you in the faces of everyone around you. Then it determines your 'value' and mostly just shows it occasionally to people with about equal value.*" According to other users, the noob boost might also allow new users to have a favorable first experience with the app and play a role in monetization strategies.

On Reddit, creating a new profile was one of the most discussed method to maximize the number of matches a user gets. 15 different users on Reddit indicate that creating a new profile has allowed them to receive more matches. Since many people believe that they get a new profile boost, and since creating a new account requires very little effort, it was the preferred strategy of many Reddit users: "*So I thought, I can exploit that 'new user boost' and what I've been doing is create an account, feed on the new user boost, then after 2–4 weeks delete the account and start over.*" This method was less popular in the survey: only 14.1% of respondents indicated creating a new profile. Most of them did so because they needed a fresh start, but 8 respondents explicitly mention the new profile boost as a reason for starting a new profile.

Expanding Filters. Another popular algorithmic strategy is changing location and age settings to include more potential profiles in the user's swiping deck. This was the most popular strategy for survey respondents with 45.0% expanding their location filter and 34.9% expanding their age filter. Most people (n = 120) indicated that they did so to increase the potential for a match by playing the numbers game: more people equal more matches. But 8 respondents mentioned the algorithm explicitly saying that their profile gets a better score by expanding filters in this way.

On Reddit, 5 users wrote that by being more inclusive in their age and distance filters, they can be shown to more profiles so that the algorithm classifies them as more active *and* more attractive. Users even expanded their filter beyond their interests. For example, by including areas they are unlikely to travel to and meet someone: "*A match with someone far away has almost no value because it's super unlikely we'll ever get around to meeting up. But if expanding the range also indirectly helps with getting more matches close by then it's obviously worth it.*" One survey respondent makes a similar point with age, writing that he includes older women even though he is not necessarily interested in people in that age range.

This method is even applied to gender as some users switch their preference to include genders that they are not attracted to, simply to get more users to swipe on their profile. One Reddit user explains why this would work: "*I came to the conclusion that gay men swipe on everything. I put my profile on gay and got a ton of likes. I now have 99+ likes and the algo has deemed that my ELO is high. I switched back to straight and it only shows me 10 s.*" 2 Reddit users mention this strategy. 4.4% of survey respondents indicate changing their gender setting, but all of them also indicate that they are attracted to multiple genders.

Swipe Ratios. Remember that Tinder presents users with a deck of profiles that they can see one by one. By swiping right, the user indicates that they are interested in the profile and, if there is a match (i.e., both users swipe right on each other), they can start a conversation. By swiping left on a profile, the user indicates that they are not interested and there is no possibility to chat with the profiles that they swiped left on. There is also no way to skip one profile and go to the next without swiping either left or right. 31.2% of survey respondents said that they changed the way they would swipe on a profile with 22.5% saying that they swipe right on profiles they are not interested in and 12.1% saying they swipe left on profiles they are interested in. 14 Reddit posts mention swipe ratios and how they affect algorithmic filtering; however, the advice given varies. Some users believe that the app "punishes" them for being too picky and some users believe that the app "punishes" them for being too inclusive. Let's consider each possibility.

On one hand, if a user swipes too many profiles left, then they will not be shown to as many users. This is because a user's profile is prioritized when there is a chance of matching. The user's profile will not be as visible to others: "*I tend to be very selective on Tinder as a guy and I definitely swipe left on the majority of profiles and only swipe right on a few. […] This would lead to me getting less matches although they are higher* *quality matches. However, because I get less matches would I be put as lower priority in the algorithm due to having less matches?*" This user is trying to have fewer matches but worries that his strategy is counterproductive. It is possible that the algorithm assigns a lower ELO score to this profile since they are being too picky and not receiving as much exposure and activity as other profiles. The solution then is to swipe more people right, even if the user is not necessarily interested in them. Out of the 22.5% of survey respondents who indicate swiping right on people they are not interested in, a majority (n = 57) indicated being more inclusive simply because they wanted more matches. Many say that there is an advantage in "*casting a wider net*" and that they "*can save time and increase efficiency because [they] only have to look at the ones who have already liked [them] instead of evaluating everyone.*" Others (n = 6) say that the algorithm learns that they have varied preferences and so learns to include many people in their recommendation.

On the other, if a user swipes too many profiles right, then Tinder might consider them to be fake or spam: "*Tinder does have this algorithm apparently that makes you less visible the more you swipe right, presumably it's because they know somebody who swipes right on everyone is just a bot who is trying to spam users*" And so, according to this Reddit user, someone who is not picky enough might similarly hurt their potential to match with other users. Generally, it might be best to be a little pickier and swipe left on profiles that one might be interested in. 10 respondents write that by being pickier, the algorithm will work harder to find them a good match. For example, one writes that "[swiping more people left] *makes Tinder use their algorithm to send me to more people to keep me using the app.*"

Manual Filtering. While there is no way to add filters to Tinder, many users on Reddit indicated that they would prefer more filtering options, and this was reflected in our survey results: 86.2% of respondents either strongly agree or agree that they prefer a dating app that allows them to filter profiles that they see and only 1.0% disagree. When asked which filters they would prefer, out of 298 respondents, 127 respondent checked drinking or smoking habit, 115 checked political belief, 85 checked race, 83 checked religious belief, and 78 checked educational level. Some wrote down other options such as hobbies. When asked about how they could narrow down their dating pool, no respondent had an algorithmic strategy or solution. Most people (n = 86) said that the best way to get matches that meet their criteria is to carefully read each profile to get as much information as possible (such as interests, social media links, etc.) before swiping. 4 respondents said they just use another app that gives them more filtering options.

5 Discussion

5.1 Playing the Numbers Game

We have identified folk theories and strategies that users employ to maximize their success on Tinder: creating new profiles, carefully attending to their swipe ratio, and expanding ranges of different filters. However, all of those strategies help a user maximize the number of matches that they receive, and none can help the majority of users who are looking for quality instead of quantity. The Tinder experience seems to have become gamified: some users want to receive as many matches as possible without thinking about the possibility of meeting those users in real life and this becomes clear when we take a closer look the strategies we identified. Some users indicate that they are playing a numbers game: match with as many people as possible by swiping right generously and expand every available filter to include as many profiles as possible. As a result, users will match with users that they have no interest in meeting at all. For example, some users match with users that are too far away and even with users of genders that they are not attracted to. This shows that playing the numbers game is more important than the outcome of meeting other users.

On the other hand, most users choose to be picker and get higher quality matches instead of as many matches as possible. Nevertheless, they worry that this strategy is lowering their chances of meeting new people since their profile might be "punished" by the app. This shows that some design choices make the users believe that Tinder is *meant* to be played as a numbers game: different paid features that boost your profile and the focus on increased match rate can ostracize users who are looking for more meaningful connections. Those users are left with no strategy to teach the algorithm about their preferences. This was especially true for users that have preferences that do not reflect conventional standards such as gender-nonconforming people. Since empirical research shows that it is unlikely that an algorithm can learn personal romantic and sexual preferences, algorithmic filtering tends to reflect conventional beauty standards instead of learning from user preferences. Because of this, users indicated that they prefer control over filtering options. User-set filters could also allow users who prefer only matching with a few people to avoid swiping through many profiles that they are not interested in, without the risk of being assigned a lower ELO score because they are seen as "picky."

5.2 Folk Theories, Sensemaking and Self-worth

Our research builds on prior work that links folk theories to algorithms on social feeds [12, 21]. Tinder users who seek to increase their number of matches look for information about the algorithm to see if they can manipulate it for their benefit. Both exogenous and endogenous sources of information are used to collect this data: users can turn to platforms like Reddit or run their own tests with different photos, fake profiles, or by changing specific settings on their apps. Subreddits like r/Tinder and r/SwipeHelper are great forums to aggregate multiple sources of information to help users make sense of their own experiences: many turn to Reddit to vent about their low success, while others share tips to help them. Those collective efforts yield interesting folk theories about algorithmic filtering on dating apps. Users then employ those folks theories to develop and deploy strategies themselves, hoping to get more matches and better connections. Our study is then a great illustration of the folk theory formation process that has been studied on other social platforms and confirms many theoretical underpinnings of those research projects [10, 11].

One interesting theme that came out from our results is that many users use folk theories to make sense of their own negative experiences and that those theories can help users avoid damaging their own self-worth. One user points out that people can have vastly different experiences because of what the algorithm learns about them through their activity: "*I noticed this when my roomie and I were both on. Both ladies. I'm a chubby cute girl, and she is a gorgeous girl who men have historically lost their shit over. We have the same taste in guys, and we never ever ever even had the same pool of men to look at.*" Another Reddit user writes that they have "*lost so many nights thinking [they are] fucking worthless and pathetic to a shitty algorithm.*" Even though empirical research shows that algorithms cannot predict a user's romantic and sexual preference, algorithmic filtering is shaping the user's intimate life which can have effects on their mental health and self-worth. And so, folk theories can allow users to make sense of their negative experiences and resist the harming of their self-image that results from algorithmic filtering on dating apps.

5.3 Limitations and Future Work

We hope future research can take this conversation forward, especially considering the limitations of our study. We grouped users into two categories: those who want to match with as many people as possible and those who want a high quality of matches. However, in each category, there are those who are interested in casual hook-ups, serious relationships, or friendships. To simplify our study, we have collapsed many motivations together, but a more in-depth analysis should take those into consideration. Another limitation of our study is the amount of qualitative data that we gathered from Reddit. We limited ourselves to the most recent posts to have more accurate results. Future work could investigate other sources of qualitative data to form a more robust understanding of folk theories that might arise from shared experiences.

6 Conclusion and Design Recommendation

Whether your goal is to match with as many people as possible or carefully match with a select few, algorithmic filtering is becoming an obstacle. For those who want as many matches as possible, different strategies based on folk theories allow users to artificially boost their profiles and maximize their matching potential. But for those who want to see profiles that match their criteria, there seems to be no strategy available. One commonality between those two groups is that they would both prefer more control over the filters that are available to them, and so, apps with more options such as political belief or drinking habit might be a better choice. One might think that applying user-set filters to a dating app might not be a desirable design choice. First, this would severely limit the number of profiles that a user can see daily and therefore, their activity on the app. Second, by filtering certain demographics, user activity might raise ethical concerns such as exclusive sexual and romantic preferences that reflect patterns of injustice. However, both of those concerns can be answered.

First, as we have seen, user-set filters such as age and location are fluid and users constantly change them depending on their goal. If users want to browse through new profiles, they will expand their filters and so the profiles they see and their activity on the app will not necessarily be limited. User-set filters can ultimately be less limiting than algorithmic filters that cannot be turned off or expanded by the user. Second, any ethical concern that arises from user-set filters will also be mimicked by algorithmic filtering since algorithmic filtering learns from user activity. All in all, the concerns that arise from filtering will be the same, whether the filters are set by the user or by an algorithm. And so, whether the user has control over their filtering or whether the algorithm decides who would be a good match to the user, the fair and responsible design choice would be to give the user control to allow them to explore their interests and attractions. It is worth noting that our recommendation are in line with Hutson et al. [27]: dating apps that use a matching algorithm should encourage people to look beyond what the algorithm believes is a safe choice. But since our research shows that users naturally look beyond their explicit preferences, we believe that giving control to the user, instead of introducing diversity into the algorithm (as Hutson et al. argue), is a better way to go forward that preserves user autonomy.

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