When the “Matchmaker” Does Not Have Your Interest at Heart: Perceived Algorithmic Harms, Folk Theories, and Users’ Counter-Strategies on Tinder

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On online platforms, algorithms help us build and manage our relationships. However, their invisible interventions might also pose harm to these connections. Dating platforms offer a prime example where, despite extensive research on human-inflicted harm, the potential harm from the algorithms themselves, and user strategies for mitigating them, remains largely unexplored. In our analysis of 7,043 reviews and interviews with 30 Tinder users, we unveiled how users perceive algorithmic harm as damaging self-esteem, sabotaging potential relationships, encouraging antisocial behavior, and misrepresenting or marginalizing certain identities. We introduce a new algorithmic folk theory, the "*conflict of interest*" theory, perceived to perpetuate these harms. This theory encapsulates users’ sense of a contradiction between the dating platform’s promise of finding the perfect partner (leading to discontinued use of Tinder) and its commercial interest in retaining users to increase revenue. Users suspected various algorithmic processes pursuant to this theory, such as (a) throttling profile visibility, (b) manipulating users’ matches, and (c) recommending large quantities of profiles that will not lead to matches. They also described various strategies in resistance or defense of these suspected algorithmic processes, such as engaging in counter-intuitive behaviour to disrupt the unfavorable algorithmic processes or leveraging location based filtering for match variety and safety. We conclude by discussing how the perceived algorithmic harms can inform the development of new algorithmic implementations that balance both user and company interests.

CCS Concepts: • **Human-centered computing** → Empirical studies in HCI.

Additional Key Words and Phrases: algorithmic harms, online dating, folk theories, relationship building, users’ strategies, algorithmic resistance, automated decisions, transparency, explanations

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1 INTRODUCTION

Algorithms can shape and mediate relationships on a variety of online platforms, such as social media and messaging apps [6, 43, 55, 114], online marketplaces [8, 61], and dating platforms [26]. While such algorithms offer opportunities to maintain old relationships and build new ones, they can also introduce harm to people's social relationships [43, 55, 57].

A context in which algorithmic harms to individuals and their social relationships remains under-explored is online dating - barring early reflections on racial and sexual biases amplified by matching algorithms [59, 79]. This is a conspicuous gap given the extensive use of algorithms in dating apps for user recommendation, and extensive research into *human-inflicted* harms through online dating such as sexual violence [3, 74, 107] and harassment [18, 35, 47, 60, 88].

In this paper, we use the lens of algorithmic "folk theories," i.e., the theories that users of algorithmic systems develop to make sense of the system's operation [31, 42], to understand users' perceptions of algorithmic harms and their strategies for mitigating associated algorithmic processes in the context of Tinder, the most popular dating platform [100]. In recent years, research has explored how users of dating apps develop algorithmic folk theories to make sense of what they experience on the platform [77], to explain how matching algorithms work and increase their attractiveness rating [58, 77], and even to manage the subsequent stages of relationship formation [90, 105]. Yet users' perceptions of the harms that algorithms cause on dating platforms have not been directly studied. Such an exploration is essential for a more complete understanding of the harms that users perceive themselves to be at risk of in online dating - whether from humans or machines - and for informing future designs to mitigate threats from diverse sources. Therefore, we ask:

- **RQ1.** What potential harms do users think Tinder dating algorithms might cause to themselves and their relationships?
- **RQ2.** What are users' perceptions, beliefs, and folk theories about how algorithms instigate such harms?
- **RQ3.** How do users alter their usage strategies of dating apps to reduce the perceived harms of Tinder dating algorithms and regain control of their dating experiences?

To answer these questions we conducted a two-stage study. In the first stage, we analyzed 7,043 Tinder reviews to get an overview of the harms that users perceive Tinder dating algorithms to cause to their relationship building process. In the second stage, we conducted semi-structured interviews with 30 Tinder users to understand their folk theories and sense-making of such harms and the nuances of their app-usage strategies to mitigate undesirable algorithmic processes and regain a sense of agency and control.

Our findings reveal several algorithmic harms perceived by users such as damaging self-esteem, sabotaging potential relationships, encouraging anti-social behavior, and misrepresenting/ marginalizing certain identities. Participants collectively suggested a new overarching folk theory of dating algorithms that perpetuate these harms, which we call the "*conflict-of-interest*" theory: the perceived contradiction between the dating platform's main promise of finding the perfect partner (which would result in discontinued use of Tinder), and the platform's commercial interest in keeping users on the platform and increasing premium membership subscriptions. Users suspected various algorithmic processes pursuant to this theory, such as (a) throttling profile visibility, (b) manipulating users' matches, and (c) recommending large quantities of profiles that will not lead to matches. Users described various strategies in resistance or defense of these suspected algorithmic processes, some of which would appear directly counterproductive such as not "liking" profiles that one actually finds attractive. The findings also show that users perceive algorithmic processes to *enable* human-inflicted harm, such as the belief that accounts are automatically banned when one's profile is reported to the app, which can be abused by a user in retaliation for being romantically rejected. This suggests that algorithmic and human-inflicted harms may be intertwined, necessitating that future research on computer-mediated harm mitigation take both human and machine entities into account.

2 RELATED WORK

2.1 Interpersonal Harm through Online Dating

Interpersonal harms are well studied in HCI, including those that manifest online (e.g., harassment [18, 35, 47, 60, 88], cyberbullying [66]) and in the physical world (e.g., cyber-grooming [70, 72] to coerce victims into sexual abuse [74] or sex trafficking [12]). A context through which computer-mediated interpersonal harm often occurs - and is often studied - is online dating because such apps are designed for users to traverse their interactions into the physical world, thus putting them at risk of harm across virtual and physical modalities. Harassment through messaging interactions in dating app interfaces is well documented [5, 11, 91], and dating apps are also a well known facilitator of physical sexual harm [3, 107]. For example, research has connected dating app-use with increased likelihood of sexual violence victimization [22, 51], and other work has found dating apps to be a common method of introduction between perpetrator and victim of sexual assault - accounting for 10% of overall rape cases in some samples [83, 87].

The literature has elucidated various ways in which interpersonal harm manifests in online dating, including both intentional acts and those that are unintentional (without a deliberate intent to cause harm). For example, research has explored intentional harm through deceptive practices like the creation of fake profiles for scams [113], as well as harassment stemming from romantic rejection [91]. There is also extensive research on targeted harm towards users from marginalized groups, such as online bullying and discrimination [38, 40], as well as ‘identity-based harms’ [39]. Identity-based harms refer to harms that specifically target users based on aspects of their identity, such as their sexual orientation, gender identity, race, or religious beliefs. For instance, Duguay et al. have documented how queer women on dating platforms frequently encounter sexually aggressive “homophobic” users, including instances of receiving unsolicited explicit images or being pressured into sexting [39]. Several studies have also explored the outing of gay users in culturally conservative areas, revealing the complex and often dangerous challenges they face [16, 17, 25]. Interpersonal harms in online dating can occur unintentionally as well, often influenced by sexual scripts [24, 84] and consent practices [116] that lead to misinterpretations of consent through dating app interfaces.

Technical solutions developed in response to these risks include improved interaction interfaces for better impression formation [48, 119], AI-based detection of harassment and unwanted images [93, 99], and concepts for mediating consent [115], addressing the challenges in practicing harm-mitigative consent [116]. Online daters have also developed their own safety strategies while using dating apps. Users, especially women and LGBTQ+ individuals who are at higher risk of dating-related harm [5, 9, 45], often manage safety by selectively disclosing personal details and engaging in impression management [41, 117]. This includes strategies like masking casual sexual interest to avoid “slut shaming” [17, 118] and carefully evaluating potential partners through their profiles and messaging [50] to reduce the risk of physical harm [119]. Woman-identifying users also use safety check-ins with friends and family during face-to-face dates [9].

2.2 Algorithmic Harm through Social Platforms and Users’ Folk Theories

It has become clear through the literature that the way users perceive risk of interpersonal harm significantly influences how dating apps are used, and knowledge of that use has in turn influenced how they are designed. Yet there is relatively limited knowledge of how users perceive harm inflicted or facilitated by dating app *algorithms*, and the strategies employed for mitigating these perceived risks.

The term *algorithmic harm* has been used in a variety of ways, dealing inter alia with aspects of racial, gender, and identity bias (e.g., [21, 49, 54, 78]), discrimination [23, 63], privacy violations, surveillance, news filtering, and electoral impacts [106], and so on. Attempts have been made to categorise these numerous and diverse forms of harm. These include the distinctions made by Barocas and Crawford [13] between two specific forms of algorithmic harm: allocational and representational. In short, allocational harm occurs when resources or opportunities are unfairly distributed or withheld. Representational harms, on the other hand, pertain to the misrepresentation or marginalization of social groups, as highlighted in studies by [10, 64, 65]. Further classification is provided by Saurwein and Spencer-Smith, who defined roles for algorithms in harm on social media platforms [89], comprising (1) deficient tools that lead to errors, (2) instruments that serve manipulation, (3) amplifiers of problematic content, (4) enabling structures for problematic behaviour, and (5) instruments of platform power. The AI, Algorithmic, and Automation Incidents and Controversies (AIAAIC) maintains a repository of over 1000 algorithmic harms and has produced a consequent taxonomy of harms [4].

Social media platforms have been a popular context for studying the adverse impacts of algorithms due to their proliferation for curating and moderating user-generated content. Researchers have shown that sometimes users are not consciously aware of algorithmic processes on social platforms, which can have negative impacts on human relationships (e.g., [42, 44, 61, 86]). For instance, studies on Facebook's news feed curation algorithm have revealed that users frequently do not realize the algorithmic influence at play. This lack of awareness leads them to mistakenly blame their friends and family for the disappearance of posts, rather than recognizing it as a result of algorithmic selection [42].

Conversely, in some cases users do perceive algorithmic harm and construct *folk theories* to explain how algorithms work (e.g., [7, 30, 31, 64, 68, 92, 103]). These folk theories, which are intuitive, informal explanations that individuals develop to make sense of technological systems, have been found to guide user behavior and resistance to algorithmic changes [31]. Devito et al. conducted several studies on the interplay between folk theories and self-representation practices on social media to explore how folk theories help guide users' behavior in managing impressions to others [28, 30, 31]. Karizat et. al. [64] applied Identity Strainer Theory to refer to users' beliefs that "an algorithm filters out and suppresses certain social identities" (e.g., LGBTQ+ identity). The study also illustrated that users changed their behavior to resist the perceived algorithmic suppression and associated harm. An analysis of 102,827 tweets of a hashtag (i.e., #RIPTwitter) in a Twitter timeline revealed that users' folk theories influence their resistance to algorithmic change [31]. Overall, the body of literature on algorithmic harm and folk theories - particularly in regards to social platforms - makes clear that the user experience is significantly impacted by users' perceptions of adverse impacts of algorithms because they employ strategies to resist, mitigate, or adapt to algorithmic processes.

2.3 Online Dating Algorithms and their Impact on User Experience

Dating apps are a conspicuously understudied context for how users perceive and attempt to mitigate algorithmic harm given 1) the extensive body of knowledge into user strategies for perceiving and mitigating risk of *interpersonal* harm and 2) the extensive use of algorithms in dating apps. Today's leading dating apps employ algorithms for processes ranging from bot detection [2], user verification [40], detection of interpersonal harm [93, 99], and most importantly: user recommendation (also called matchmaking). Extensive attention has been given to Tinder's matchmaking algorithm in particular (e.g., [14, 26, 27, 62, 67, 69, 73, 77]) given the general popularity of the app and the centrality of its user recommendation/matchmaking algorithm to the user experience. Tinder users view profiles one at a time in an order determined by the recommendation algorithm [1, 109]. The ability to message another user depends on both partners establishing a “match” by “liking” each other’s profile when it appears in the recommendation interface [80]. This makes one’s visibility to other users through the recommendation algorithm a crucial factor to their dating success - Sharabi’s work demonstrated that simply believing in the effectiveness of matching algorithms impacts real-life first-date experiences [90]. Users reported better first dates to the extent that they believed in the algorithmic matching process.

While there is no work to our knowledge that has studied online daters’ perceptions of algorithmic harms and associated mitigation strategies, attention has been given to folk theories of how Tinder’s matching algorithm operates and how users adapt their usage strategies to maximize dating success. Tinder has long been speculated to base its matching algorithm on “Elo scores” [62, 96] - a measure of one’s attractiveness based on the number of “likes” they receive in conjunction with how selective they are in giving out “likes” themselves (the most attractive users would therefore receive the most likes while giving out the least likes). In March 2019, the company announced they had abandoned the Elo score; however, users are still in the dark about how the algorithm works [101]. Courtois and Timmermans used an experience sampling method to measure users’ swiping and liking ratio, along with resultant number of matches, to infer the inner workings of the matching algorithm [26]. The study concludes that Tinder “prohibits its major assets of attractive profiles and liked profiles to run out too soon” in order to convert non-paying users to premium subscription plans (p. 13). Nader and Lee [77] observed that users’ belief in a desirability score (similar to the Elo score speculation) led to various strategies to increase one’s score, such as creating new profiles or adjusting search filters. Abel et al. [1] built upon this by conducting 22 in-depth user interviews. Their findings revealed diverse theories among users about how Tinder’s algorithms operate. They attributed Tinder’s profile curation not only to desirability scores but also to factors like user feedback, romantic compatibility, and the profitability of choices [1]. Similarly, in their interview study, Huang et al. [58] identified folk theories surrounding the Tinder matching algorithm. They noted perceptions of the algorithm as facilitating a form of “shopping”, being subject to chance and randomness, and functioning as a bracket system for scoring users.

Despite these insights, user perceptions of algorithmic harms in dating apps and associated coping strategies have not been an *explicit* research focus. This paper aims to fill this gap by delving into the nature of algorithmic harm on Tinder, users’ theories, and mitigation strategies for such harm. We extend our focus beyond Tinder’s matchmaking algorithms to encompass all types of algorithms used on Tinder that can mediate or influence user relationships. For the sake of simplicity, we will refer to these collectively as the ***Tinder dating algorithms***.

3 METHOD

This study was conducted in two stages to explore algorithmic harms in relationship building on the Tinder platform and how users perceive and cope with these harms.

3.1 Stage 1: Analyzing Tinder App Reviews

Considering that application reviews contain rich, contextual information about how users perceive an app [110], we first conducted a qualitative analysis of 7,043 Tinder app reviews from the Google Play Store, focusing on the types of algorithmic harms experienced during interactions with the platform.

3.1.1 Data collection. We collected the data using a Python script based on BeautifulSoup [34], a package for web scraping and parsing HTML files. The dataset consisted of 7,043 user reviews from the Google Play Store on the Tinder app [58]. Each user review included a rating indicated by the number of stars (0–5), a timestamp, the review text, and the number of likes. The average review was 23.5 words long. Reviews were collected over a year, from March 27, 2020, to March 27, 2021, a period marked by a surge in Tinder's user base and its highest interaction rate to date [97]. This time frame offered a comprehensive dataset for our analysis. In compliance with ethical research practices [46, 81], usernames were anonymized despite the public availability of this data.

3.1.2 Data analysis. Our data analysis of the Tinder reviews, conducted through reflexive thematic analysis [19], involved the following steps to ensure a thorough understanding:

(1) Creating Initial Themes through Thematic Analysis: Two coders started by conducting a line-by-line open coding of 900 reviews using reflexive thematic analysis. This initial phase involved each coder independently analyzing a different set of 200 random reviews to identify potential themes. The authors then discussed the identified categories and subcategories of themes, culminating in a preliminary codebook based on 400 reviews. To validate the comprehensiveness of these themes, both coders independently coded another set of 500 reviews. This process resulted in a codebook encompassing five categories and eleven subcategories of themes.
(2) Filtering Irrelevant Reviews Using Keywords: To refine the focus on reviews that discussed algorithmic harms to relationship building, two coders extracted 90 keywords indicative of such harms (e.g., 'self-worth', 'confidence', 'ugly', 'fake', 'unreal', 'ban', etc.). These keywords were manually chosen based on their occurrence frequency in the manually coded reviews, in a manner akin to feature selection in [110]. We then utilized MAXQDA's automatic coding function to filter the dataset, retaining only the reviews containing these keywords. This step narrowed down the review corpus to 1,658 relevant entries.
(3) Expanding and Revising Themes: With the refined dataset, we further applied thematic analysis using the automatic coding function to assign and expand themes across the remaining reviews. We rigorously reviewed the codebook for relevance and redundancy, focusing exclusively on problem statements that directly referenced 'algorithm', 'system', or 'automatic' issues. Reviews unrelated to the dating algorithm, such as those mentioning technical difficulties (e.g., installation or verification) or general complaints (e.g., about age restrictions, expensive subscriptions, or advertising), were excluded. This resulted in a structured thematic schema with three primary categories of harm and their respective subcategories.

3.2 Stage 2: In-Depth Interviews

Although the reviews provided us with a general understanding of the ways users perceive Tinder dating algorithms to damage users' intrapersonal and interpersonal relationships, in many cases these reviews were brief and did not offer a nuanced understanding of users' folk theories and mitigation strategies. To deepen our understanding from the reviews, we conducted 30 in-depth interviews focusing on users' interpretations of algorithmic harms, their mitigation strategies, and overall behavior on Tinder. This approach provided a richer and more balanced view of users' experiences, compared to the typically negative skew of app reviews [110].

3.2.1 Sampling. When examining users' algorithmic folk theories and their motivations for using a dating application, users' technical and cultural backgrounds, as well as their ethnicity, are of critical importance [42]. Therefore, we recruited our participants via multiple channels (i.e., 40% through Instagram ads targeting users in different countries, 30% via Telegram channels with international members, 20% through university mailing list announcements across various faculties, and 10% through Tinder app ads). This allowed us to target users with different backgrounds and to assemble a relatively balanced group of participants from Western and non-Western cultures (e.g., German, Albanian, Nigerian, Indian, Pakistani, Iranian). Since Tinder is mainly used by younger adults [98], our sample also consisted of users between the ages of 23 and 44 (average age 30). Our participant gender distribution included 13 cisgender women, 14 cisgender men, and 3 non-binary individuals. Regarding sexual orientation, 24 identified as heterosexual, while 6 were members of the LGBTQ+ community, comprising 2 gay, 2 bisexual, 1 pansexual, and 1 queer participant. The range of Tinder usage varied from 3 months to 5 years among participants, averaging approximately 1 year and 9 months. All participants had actively used the app in the weeks leading up to the study and had been on the platform for a minimum of two months. They were all located in the rural and urban areas of Germany. For a detailed breakdown of participant demographics, refer to Table 2 in the Appendix.

3.2.2 Procedure and Analysis. Employing a semi-structured interview approach [36], we developed a guide covering: (a) users' understanding and theories about Tinder's dating algorithms and how they generate and prioritize recommendations, (b) potential challenges associated with these algorithms, (c) their impact on users' online and offline relationships, and (d) strategies users employ to overcome related challenges. Although our research primarily focused on potential algorithmic harm rather than real-life physical harm, we took several precautions to protect participants from potential stress or discomfort. We gave participants the option to select between a video conference or an audio call for the interview, and informed them that they could choose to end or pause the interview at any point. Conducted online via Zoom and WhatsApp, these sessions were audio-recorded with consent and lasted 40 to 50 minutes. Participation was voluntary without compensation.

In the analysis phase, we began by transcribing the interviews, anonymizing the data by removing personal details, and assigning each participant an index (P#). Applying inductive thematic analysis [19], two researchers independently coded each interview in Nvivo. We focused on primary categories including nuances of perceived algorithmic harms and the conflict of interest theory alongside users' countermeasures. This iterative analysis allowed us to identify and define subcategories within these main themes. For instance, under the 'conflict of interest theory,' we cataloged specific descriptions of the theory and gathered supporting evidence. After completing this initial phase, we achieved a consensus and laid the groundwork for structuring, discussing, and interpreting the data. In the next phase, we utilized MAXQDA Analyzer to methodically map all statements from the interviews onto our established categories and subcategories. The final phase involved a series of online meetings where we systematically refined our understanding of the relationships between the themes we had identified.

4 FINDINGS

Our analysis from both stages yields insights into the types of algorithmic harms perceived by Tinder users, along with their folk theories and response strategies. The reviews enabled us to outline three main categories of algorithmic harms, addressing RQ1. The interviews not only provided depth and nuance to our understanding of these harms but also helped us to associate these harms with users' folk theories about the algorithms' underlying motivations. Furthermore, the interviews revealed users' strategies for mitigating harm and interacting with the Tinder dating algorithms. Table 1 summarizes our findings, showcasing the types of perceived algorithmic harms (Section 4.1), the algorithmic processes discussed in reviews and interviews indicative of users' folk theories (Section 4.2), and their mitigation strategies (Section 4.3). The following section will

Table 1. An overview of the perceived algorithmic harm, perceived algorithmic processes, users' folk theory, and users' counteracts

Perceived algorithmic harm	**Example**
Damaging Self-esteem	The algorithm is perceived to damage users' self-esteem by limiting the number of matches and likes: "*I didn't have many matches or likes. You might think okay, that's not the algorithm's fault that people don't like me. But what if it is? What is this going to do to my self-worth?* " (P19).
Sabotaging Potential Relationships	The algorithm is perceived to sabotage the potential relationships by suddenly removing the matches from the matchlist: "*I was texting with a guy for some time now and we were planning to go on a date, but Tinder removed all my matches and he was removed too* "(P29).
Encouraging Anti-Social Behaviour	The algorithm is perceived to urge the users to block and report other users by repeatedly recommending the rejected profiles: "*Tinder kept suggesting a friend of mine and I had to block the profile so I wouldn't see her ...* " (P13).
Identity-based Harm	The algorithm is perceived to misrepresent certain gender identities: "*The binary nature of Tinder algorithms, representing users exclusively as either male or female, [...] imposes unnecessary pressure on us*" (P12).
Perceived algorithmic processess	**Example**
Throttling Profile Visibility	The algorithm is perceived as intentionally not recommending a profile to others:"*No matches or likes after a while, not even after a premium membership. The algorithm is crap*" (R4511).
Manipulating Users' Matches	The algorithm suddenly deletes the matches from the matchlist: "*Matches disappear, and it's not because people unmatch you. Do you know why? Because they reappear after some time*" (P17).
Recommending Large Quantities of Profiles that Will not Lead to Matches	The algorithm is perceived as recommending overly attractive profiles rather than those that fit: "*Tinder isn't where everyone finds their soulmate. It seems more like a showcase of attractive people [...] not those who might be perfect for each other...*" (P1).

The "Conflict-of-interest" folk theory: There is a contradiction between the main promise of dating apps to help users find the perfect partner, and these apps' commercial interests in retaining users on the platform:
"*The Tinder algorithm doesn't genuinely aim to connect people, as it contradicts their business model*" (P23).

Counteracts	**Example**
Optimizing Profile/Search Strategy	Users change the distance range to get better recommendations: "*I changed the filters and chose a broader range to have more recommendations* " (P26).
Knowing Your Competitors	Users observe and analyze the competitors by setting up a fake: "*I created a fake male account to see my competitors in the neighborhood and to evaluate myself* "(P10).
Engaging in Counter-intuitive Behaviors to Disrupt Unfavorable Algorithmic Processes.	Users "like" the repeatedly recommended profiles they do not genuinely like to let the person know they are not interested themselves: "*There was a guy who kept being suggested to me no matter how many times I swiped left [...] To get rid of him, I liked the man's profile and sent him a message myself*" (P3).
Leveraging Location-based Filtering for Match Variety and Safety	Users use VPN to manipulate their location based filtering: *"Many start using VPNs to change their location. Sometimes, you match with them only to discover they're actually somewhere like Izmir"* (P5).
Bypassing the Algorithm by Moving to Other Platforms	Users move to other social media platforms to check the authenticity of a recommended profile: *"I just ask for the Instagram and Whatsapp account at the very beginning to see if the person is real"* (P20).

present our findings in detail, reporting the themes extracted from both reviews and interviews, with N_r indicating the number of statements related to a theme from reviews and N_p for those from interview participants.

4.1 The Perceived Algorithmic Harms to Intra- and Inter-Personal Relationships (RQ1)

Our analysis of online reviews uncovered various types of relationship harms, both at the intrapersonal level, a) damaging users' self-esteem and at the interpersonal level, b) sabotaging potential relationships, and c) encouraging antisocial behavior. The findings from our interviews not only confirmed and enriched the insights from the reviews about the types of perceived algorithmic harm but also broadened the spectrum of harm. In particular, the interviews revealed d) algorithmic identity-based harm, specifically pertinent to our LGBTQ+ participants. This aspect was particularly valuable, given the lack of demographic information about the reviewers in Stage 1.

4.1.1 Damaging Self-esteem: A common form of perceived intrapersonal harm that emerged from the reviews was self-esteem damage, primarily attributed to a lack of matches or likes (N_r=51). One review encapsulated this by lamenting, "*Tinder algorithm leads to competitive pressure, lack of self-confidence, frustration, and thereby destroys the dating world*" (R3962). While the low number of likes and matches could be attributed to a profile's lack of appeal to other users, many reviewers pointed the finger at Tinder's dating algorithms, suggesting that the system intentionally did not recommend their account to other users sufficiently. Review 2809 provided a succinct example of this sentiment, stating, "*When I newly registered a while ago, there were likes in the first few days, but nothing has happened for weeks. Tinder can't convince me that everyone here finds me so ugly*" (R2809). These abrupt shifts in match rates led many reviewers to the conclusion that Tinder's algorithms were designed to incentivize them to upgrade to a premium account. Review 6396 put it starkly, questioning, "*Can it be that you have massively limited the matches in the free version lately, or did I turn ugly in one fell swoop? I used to have regular matches; now, none at all.*"

Reviewers suspected that Tinder's algorithms were burying their profiles, making it hard for others to see them, and resulting in fewer matches. Review 5688 shared these frustrations: "*I'm getting zero matches after multiple days of swiping on 200 people a day!... I don't know what the heck is wrong with the algorithm, but I suspect my profile just got buried in oblivion, so no one ever sees me.*" Review 1843 criticized Tinder for exploiting users' insecurities to increase their revenue, expressing, "*Please, don't let anyone tell you you're unsuitable! This app thrives on your self-doubt so that you sign up for expensive subscriptions and Tinder makes money! Then I'd rather be single, but rich and happy*!" Reviews often interpreted this decreased visibility and subsequent decrease in matches as a hit to their self-esteem: "*If the algorithm is working great, then I'm too ugly*" (R2859).

In the interviews, as with the reviews, the harm to self-esteem due to a limiting number of recommendations and matches on the platform was a recurring theme (N_p=12). P8 experienced such significant frustration that they chose to leave Tinder entirely, feeling it was damaging their self-esteem. He shared, "*I compared my recommendations to my roommate's. Her suggestions were endless, and she would get a multitude of matches. I couldn't understand what was happening. It felt like it was undermining my self-esteem. So, I stopped using Tinder*" (P8).

Participant 19 also voiced a similar sentiment, "*I didn't have many matches or likes. You might think okay, that's not the algorithm's fault that people don't like me. But what if it is? Nothing hurts me more than when the algorithm pairs me with someone who has explicitly stated 'No BLACK PEOPLE' in their bio. What is this going to do to my self-worth?*". This sentiment suggests that due to a clear mismatch between the preferences of the recommended profiles and P19's profile, they concluded that the algorithm may not be presenting their profile to the right audience, leading to a low number of likes and matches.

4.1.2 Sabotaging Potential Relationships: This type of perceived algorithmic harm emerges once a match is established, and users are poised to initiate a relationship. Many reviewers (N_r=229) have voiced their frustrations, pointing to a common issue - matches mysteriously disappearing from their list of messaging interactions. R431 lamented, "*Another match disappeared (so far #8) in the middle of a really nice get-to-know-you [messaging interaction] and supposedly no chance to recover it... Honestly, I am starting to feel like Tinder is doing this on purpose to keep me as a paying customer.*" This concern highlights a problematic scenario where users lose the opportunity to connect with potential partners due to communication channel failures. R513 refers to these algorithmic processes thwarting their chance of building a potentially successful relationship as anti-social, stating, "*Oddly enough, every time I get matched with a very pretty girl and she even texts me first, which has happened more than 10 times now, Tinder algorithm says no, that cannot be. The match disappears and so does the message. No matter how fast I reply, really antisocial.*"

Although a match's disappearance from the list can occur when the other user unmatches, reviews presented various reasons to believe this was a result of algorithmic processes, not human actions. Many cited the instantaneous nature of the disappearance, which happened too quickly for a human to react. R1528 noted, "*Many matches disappear within seconds. The other person couldn't have possibly unmatched so quickly.*" Some even observed the simultaneous vanishing of all matches, with R3210 expressing frustration: "*I just opened the app, and ALL my messages and matches are just gone... Are you kidding me? I haven't exchanged numbers with anyone yet, and now I'm sure I can't find them again.*"

Most significantly, the sporadic reappearance of matches led users to believe that Tinder's algorithms were sabotaging their potential relationships. R2565 remarked, "*Unfortunately, Tinder controls your matches because matches disappear and reappear.*" R400 shared a peculiar incident: "*I was texting a person, but suddenly they were no longer on my match list. Later, I received a message from that same person on Instagram asking why I had unmatched them, which I hadn't. How would you interpret that? Neither of us ended the match, so was it the algorithm? Why did you do that to us?*"

Sabotaging potential relationships was also underscored by interview participants (N_p=9). They offered more examples of perceived algorithmic harms and gave insights into why they believe these problems stem from the dating algorithms. For instance, P17 noted a peculiar pattern of disappearing and reappearing matches, stating, "*Matches disappear, and it's not because people unmatch you. Do you know why? Because they reappear after some time... Tinder wants to keep you engaged, but you have no control over the situation [...] It happened to me several times. The worst part is, they are going to think you were a b**ch and just unmatched them*" (P17).

Expanding on this theme, P30 referred to another facet of this perceived sabotage and added a layer of complexity, pointing out that the harm created might be reciprocal and detrimental to other users' self-esteem, depending on the circumstances of the conversation. They said, "*I was texting with a guy for some time now and we were planning to go on a date, but Tinder removed all my matches and he was removed from my match list too. I feel sorry because he was so insecure and also younger than me, I don't want him to think he has been rejected*" (P29). Further voicing distrust, P24 added, "*I don't trust the algorithm there, it's so arbitrary. I'd rather stick to other communication platforms where at least you have the person's phone number and won't lose touch completely if something goes wrong. With this, you're just left hanging with nothing.*"

These accounts suggest that users perceive the algorithmic processes as manipulative, jeopardizing their prospects of forming meaningful relationships. Notably, as emphasized by P29, the perceived impact extends beyond individual users to potentially affect their conversation partners on the platform, underscoring a mutual potential for harm.

4.1.3 Encouraging Anti-Social Behaviour: Reviews have brought to light how Tinder's algorithms might inadvertently encourage antisocial behavior by repeatedly recommending the same unwanted profiles and enabling the abuse of reporting mechanism. The former is represented by the repetitious recommendation of profiles that users have already swiped left on or rejected. This may leave users with little choice but to block or report others on the platform as a way to avoid seeing those profiles again. For instance, R6938 stated: "*The same people are always shown, whether you swipe left or right! The user is urged to block the account so that it is no longer displayed*".

In addition, a significant number of reviews (N_r=205) have raised concerns about the potential misuse of Tinder's reporting feature and the perceived lack of adequate algorithmic intervention to validate and mitigate baseless reports. Some reviewers believed that the platform automatically bans users based on unverified reporting, which could easily be exploited. R1846 shared a personal account of being reported and subsequently banned for merely refusing an in-person meeting, asserting that "*the developers*" do not authenticate the reports: "*I was just chatting with a guy, and I guess he got upset because I wouldn't meet him, and reported me. The developers don't even check if there is a valid reason. It feels like I'm forced to meet anyone who asks, or else they could report me...*" (R1846). This sentiment resonates with R6007, who suspects they were reported by a match they had rejected, resulting in an immediate ban without any verification: "*I was instantly blocked because I turned down a guy. Nothing was checked, and I simply couldn't log into my account afterwards.*"

Similarly, R3032 believes the report feature was abused by an ex-partner for personal vendetta: "*After my recent breakup, I reactivated my Tinder account and it was banned after a short time. I know that my ex-girlfriend and her friends reported me for personal reasons. Unfortunately, the support is not responding and will not tell me how I am supposed to have violated the terms of use!*" (R3032). Moreover, R5922 highlighted the potential misuse of the automatic banning process, stating that it could be exploited by anyone bearing a grudge: "*Theoretically, anyone who doesn't like you can automatically ban you; even if you had done nothing wrong to them, they will find your profile and just report you along with their friends*".

The interviews further elucidated the nuances of the algorithmic harm related to encouraging anti-social behavior, such as blocking other users on the platform (N_p=10). P9 elaborated on this effect: "*The only option to avoid being recommended to unwanted people is by either blocking or reporting them. [...] People often resort to reporting others as soon as they find something they don't like.*" (P9). The interviewees also suggested that this anti-social behavior extends beyond the digital confines of the platform, leading to real-world bullying and harassment. This harm can occur simply from being recommended to nearby profiles that users wish to avoid. P25, for instance, recounted an experience where his classmates bullied their teacher after her profile appeared as a recommendation on their Tinder feed: "*She (the teacher) was suggested to one of my classmates; she wasn't unattractive, but my classmates circulated her pictures in public social networks and started bullying her*" (P25). P28 shared a personal ordeal related to workplace discomfort due to her Tinder profile still being active and recommended to others, even though she was banned on the platform: "*Unexpectedly, I found myself logged out and unable to log back in; I was blocked, yet my profile was still visible and being recommended to others. I discovered this when some colleagues started making me uncomfortable at work. They had seen my profile on Tinder and thought I was available, but now I'm in a relationship now, so this gave them a misleading impression*" (P28). P29 resonated with P28's account, adding: "*It's really annoying when your profile is recommended to men in your social circle and they assume you're desperate for a relationship and are making yourself available for them. They approach you in real life and harass you. I've already had two such cases.*"

These narratives emphasize that some users interpret algorithmic recommendations on Tinder as an indication of the profile owners' availability and may approach them in real life based on this presumption, potentially leading to harassment.

4.1.4 Identity-based harm: Insights gathered from our interviews underscored a distinct form of harm from the ones mentioned in the online reviews: This harm, labeled as identity-based harm, was particularly salient to the LGBTQ+ participants, representing the damage resulting from misrepresentation or misclassification of certain identities such as gender and sexual orientation.

All of our LGBTQ+ participants mentioned feelings of being marginalized and excluded on the platform due to this problem. For example, P2 shared their frustration, saying, "*I feel marginalized* *on Tinder because it's literally like 'you're a man' or 'you're a woman.' There is no in-between. There is no space for others to express themselves if they don't fit into this binary*". P19 echoed this sentiment, stating, "*In society, we often feel like we don't belong, and I believe Tinder plays a nasty role in perpetuating these biases. I have a mustache, wear very masculine clothing, and am typically perceived as a man. However, in intimate situations like dating, I don't want that stereotype. Yet, Tinder presents me as male to others*" (P19).

P12 succinctly encapsulated the harm caused by misrepresentation of identity on Tinder: "*As a member of the LGBTQ+ community, our self-assurance can be fragile, often disrupted by seemingly minor incidents. Personally, being perceived strictly as a man or woman triggers feelings of gender dysphoria, an experience that generates insecurity, creates anxiety, and impairs my sexual arousal. The binary nature of Tinder's algorithm, representing users exclusively as either male or female, contributes to this issue by inaccurately representing our identities and imposing unnecessary pressure on us*" (P12). P22 also expressed discomfort with the platform's lack of nuance: "*I always have to double-check everything with others to avoid misunderstandings: 'are you really gay? are you really into me?'*" (P22).

Our queer participants have reported incidents where such harm transcends virtual interactions. P2 explained, "*Heterosexual men can make queer men feel very threatened, you know, we've been usually bullied by them as kids in school because we are a little effeminate or whatever. They are the ones who normally create this power imbalance and we feel uncomfortable in their presence. And Tinder algorithm is making this worse. Because we can't avoid heterosexuals seeing our profiles. I have friends who even got physically hurt by straight people*" (P2). P5 also shared, "*This is happening in India and also my friends from Pakistan have told me similar stories about religious folks targeting gay guys with fake profiles. They bait them with promises of a party, but the reality is way different—they either harm them or publicly out them at local religious places. With no way to verify profile authenticity, the whole thing becomes a big mess, leading to serious issues and potential harm for us*"(P5). As these experiences illustrate, the perceived harm of the algorithm on dating platforms does not stop at misrepresentation; it potentially perpetuates harm inflicted by others through recommendation of profiles made for nefarious purposes, leading to serious physical and emotional consequences for this already vulnerable group.

4.2 The "Conflict-of-Interest Theory": Competing Interests and Clashing Values Between the Dating Algorithms and Users (RQ2)

Throughout the interview process, a theory repeatedly emerged among participants (N_p=16) to explain the root of the perceived harms by Tinder's dating algorithms. We termed this the "conflict-of-interest" theory, which underscores a contradiction between the perceived *"promise"* of Tinder's algorithms to help users find the right partner, and the app's *"business strategy"* of retaining users on the platform. This theory carried the assumption that Tinder's matching algorithm knows the *´´right"* matches, yet intentionally sabotages them in order to retain users on the platform and spur them into paid memberships. For instance, P14 said: "*I don't think the algorithm wants to show the user the right matches. They want us to stay on the platform by deceiving us with so many matches, none of which truly match. This encourages users to continue swiping*" (P14).

Participants across the interviews and reviews considered several perceived algorithmic processes as tangible evidence in support of their conflict-of-interest theory, which we describe in the following subsections (also listed at Table 2).

4.2.1 Throttling Profile Visibility. Some users believed that Tinder's algorithm intentionally does not show one's profile to nearby users after a certain period of time in order to persuade users into paid memberships to sustain their prior level of visibility (N_p=10). Some participants claimed to have proved this algorithmic process by creating new accounts and comparing recommendations with their older account. Per P14: “*It’s clear that after a while, they don’t show your profile to others anymore. You can create a new account and check. The number of recommendations changes a lot. Maybe that’s a payment strategy.*” P20 echoed a similar sentiment:“*They don’t show your profile to others after a while. I know because I created new profiles and then I had better recommendations. People started seeing my profile again. I guess it’s to push you to pay.*” Some participants did end up paying for a premium membership, yet remarked that the quality of their profile recommendations did not improve, furthering the perception that the algorithm intentionally avoids matching compatible users. This sentiment was also reflected in the online reviews. Reviewer 4511 wrote, “*Stay away from Premium! Pure rip-off. The algorithm is simply unsatisfactory; its main goal is to keep you engaged without delivering on its promise.*”

4.2.2 Manipulating Users’ Matches. Some users alleged manipulation and sabotage of their match lists by Tinder’s algorithms (N_p=7), with the suspected intent of either coaxing users back onto the app with non-existent matches or deleting already-established matches that could have manifested into real relationships and eventual account deletion. For example, P7 stated: “*Matches are added to your match list that you don’t remember swiping right on, and then some just disappear and pop up again. Tinder just wants you to be on the app. Nothing else matters to them.*” P23 echoed a similar sentiment: “*I lost some of my matches. You just open your match list and they are not there. Maybe it seems like a punishment for not having a premium account.*” As P23 alludes to, these supposed algorithmic manipulations of match lists were interpreted by some users as subtle prodding by the platform to purchase a premium membership so their matches are not further tinkered with. Per R1371, “*The algorithm is so annoying. I get notifications that I have matches but nothing is there. Or they have vanished in thin air. The app wants to tell me that I need a subscription... A huge disappointment; they only want your money*”. Yet other users believed match list manipulation still occurs with paid memberships to ensure that users do not successfully start a relationship and leave the platform: “*Tinder intentionally removes the matches to keep you paying... Rip-off appears to be part of their business model*” (R6332).

4.2.3 Recommending Large Quantities of Profiles That Will Not Lead to Matches. Users across interviews and reviews spoke to a suspicion that the matching algorithm prioritizes profile recommendations that are unlikely to result in a romantic connection so that users are kept active on the platform.

There were three related algorithmic processes that users identified: recommending profiles that are too attractive for the target user, repeatedly recommending the same users - including fake profiles, and ignoring recommendation preferences. Many found the profiles they were presented with to be “*too good to be true*” (P3) or “*overly attractive*” (P29), thus making it unlikely that recommended users would reciprocate their interest and establish a match (N_p=15). P1 encapsulated this feeling: “*Tinder isn’t where everyone finds their soulmate. It seems more like a showcase of attractive people with long waiting lists, not those who might be perfect for each other. It’s their business strategy to keep you on the app*”(P1). Similar sentiments were reflected in reviews, with one reviewer questioning: “*For a while now I seem to only get to see profiles from the absolute most attractive users who probably have hundred matches anyway. Is this a new marketing strategy?*” (R2757).

Some users described repeated recommendations of the same profiles, seemingly as a way to pad the quantity of profiles shown without bringing the user closer to establishing a legitimate match. As P10 described, “*It’s always the same profiles they show you over and over, that’s their business model—to show you some recommendations rather than nothing*” (P10). This issue was particularly frustrating when users were shown profiles they had previously rejected. Relatedly, participants (N_p=7) expressed concerns about the prevalence of fake profiles, with some asserting that Tinder intentionally does not want to remove these profiles so that it can inflate the number of recommendations to a user. They identified profiles as potentially fake based on suspicions of photoshopped pictures, blank profile photos, and inauthentic behavior. P21 observed: "*Some profiles are obviously faked. For example, with a photoshopped or blank profile picture. But Tinder doesn't remove them. They seem to want these profiles to exist to increase the number of recommendations*" (P21). This perception of fake profiles contributing to user retention was echoed in online reviews as well: "*Constant matches... but you get NO ANSWER from the profiles!!! Or just one reply, then none for days... Either they are fakes or they're simply incapable of writing. I feel rather fooled... They only want you to keep paying them*" (R1340).

Others suspected that the rash of unfit profiles they were being shown was due to the algorithm purposely disregarding explicit preferences for profile recommendations (N_p=22).

For example, P18 described their age preferences being ignored: "*They regularly suggest women outside of my specified age range. It seems they prioritize keeping the number of profile recommendations high, rather than ensuring they meet my criteria*" (P18). Users were also frustrated when recommendations included profiles far outside their specified distance range, even from other countries or continents. P7 added: "*Sometimes, the recommended profiles were from China or Russia. It's clear that I won't travel around the world to meet someone*". Queer participants, in particular, faced unique challenges and frustrations in setting profile recommendation preferences because several important settings do not exist on the platform. Some users believed such preferences could be inferred by the algorithm through user behavior, yet were being intentionally ignored. P22 expressed such frustration: "*For the LGBTQ+ community, there are specific characteristics that matter a lot, such as whether someone is a top or bottom. But you can't filter for that on Tinder. I get a lot of matches, but they don't align with my preferences. I thought maybe the algorithm would learn from my interactions, but it doesn't. After some swiping, it even starts to suggest female users to me, even though that's not what I want. It's like Tinder has its own agenda to keep me on the platform*" (P22).

4.3 Working With, Through, and Around the Tinder Dating Algorithms to Regain Agency (RQ3)

The perceived harms caused by the Tinder dating algorithms, combined with doubts regarding the alignment between the algorithms' *"promise"* of romantic matches and its financial incentives, led users to engage in a struggle to regain agency and control over their dating experiences. This included working *with* the Tinder dating algorithms to increase the number of suitable matches, working *through* the algorithms to counteract the unfavorable algorithmic actions, and working *around* the algorithms by bypassing their influence altogether. Below, we explain these strategies and how they were applied by users to mitigate, reduce or prevent the perceived algorithmic harms.

4.3.1 Resetting the Algorithm with User Account Changes. Users tried to manipulate their profile (e.g., by adding more photos) or their search strategies (e.g., by expanding the filters) in an attempt to regain control of their profile visibility and possibly get more recommendations. For example, some participants (N_p=13) believed that they could improve the quantity of profile recommendations by selecting a broader distance and age range: "*I changed the filters and chose a broader range to have more recommendations*" (P26). Others (N_p=7) believed that Tinder's algorithms would recommend *"more attractive"* profiles to the users who uploaded more pictures of themselves: "*When I uploaded more photos of myself, I felt that the men who were suggested to me were also more attractive*"(P7). Logging in and out of the platform or creating a new account (N_p=4) were also mentioned as methods to "*reset the algorithm*" and "*obtain better matches*" (P1).

4.3.2 Knowing Your Competitors. One strategy for mitigating algorithmic harm to self-esteem involved being aware of *competitors* in the area - referring to other users in their geographic area who would be interested in the same pool of available daters. Many participants (N_p=15) used the platform to observe and analyze competing users in the neighborhood, and some optimized their accounts accordingly. While Tinder's matching algorithm is designed to only allow recommendation of profiles that match one's preferences, users circumvented this restriction by creating a fake profile of the opposite sex, changing their sexual interests, or using another user's account to view the profiles of nearby users. For example, P10 explained, "*I created a fake male account to see my competitors [other women] in the neighborhood and to evaluate myself, but others' [profiles] were not so good. So I felt reassured. I thought my chances were high*" (P10). P15 mentioned that he created a fake female profile with some of his friends "*to get a better idea of other male profiles*" and even "*texted with them to find out what online dating strategies they had and feel more confident.*"

4.3.3 Engaging in Counter-Intuitive Behaviors to Disrupt Unfavorable Algorithmic Processes. When participants encountered unfavorable algorithmic acts, some engaged in counter-intuitive behaviors to counteract them such as disliking profiles that they find attractive, liking profiles without genuine interest, and blocking users who have not done anything wrong. For instance, P16 mentioned that he never swipes right on profiles that are *"too attractive"* for him, believing that they are unlikely to reciprocate his interest and that his *"ranking will decrease by the algorithm"* as a result.

When the algorithm persistently recommended profiles they had previously disliked, some participants decided to like these profiles and handle the situation themselves by conveying lack of interest via messaging. P3 is a representative example of this group: *"There was a guy who kept being suggested to me no matter how many times I swiped left on him, so I figured he must have a paid account. I took a screenshot of his profile, showed it to my roommate, and asked her if he kept getting suggested to her too, and she said yes. So, to get rid of him, I liked the man's profile and sent him a message myself to let him know I was not interested"* (P3). Other users decided to block these persistent profiles despite the profile owners having done nothing wrong, as a last resort to removing the profile from being continually recommended. As P13 explains: *"Tinder kept suggesting a friend of mine and I had to block the profile so I wouldn't see her and she wouldn't see me. But I'll never know if she saw that I blocked her. Hopefully not, because she was my friend"* (P13). While P3 and P13 both engaged in counter-intuitive behaviours on the platform, P13's action can be perceived as antisocial behaviour, which we previously discussed as a type of harm to other users.

4.3.4 Leveraging Location-based Filtering for Match Variety and Safety. Some participants contended that Tinder's dating algorithms create socioeconomic bubbles. To circumvent these algorithmically constructed bubbles, many participants (N_p=17) opted to use Tinder in different neighborhoods or larger cities. For instance, P11 shared, "*I visited the luxury district with my friends and used Tinder there. It's a fantastic way to meet guys from those neighborhoods*" (P11). P4, a resident of a rural area, also mentioned that he hacks Tinder's dating algorithms' location-based filtering by using the app whenever he is "*in big cities nearby*" in order to "*meet girls from big cities*" (P4).

For queer participants, the harm caused by location filtering could be significantly greater if they found themselves in an environment or country that is not *"queer-friendly."* P2 and P9 mentioned refraining from using Tinder in certain places or during specific periods if they were in a *"toxic environment"* due to the fear of harm or bullying. As P2 explained, "*Being part of the LGBTQ+ community, I've had my fair share of bullying, so I'm really careful with Tinder to protect myself. I was once in a really toxic workplace where I just didn't vibe with the people around me. The thing is, Tinder's algorithm doesn't let you exclude specific people, so I stopped using the app when I was in that situation. I didn't want to give them another reason to target me*"(P2). P5 revealed that it is a common practice for them to use a VPN to circumvent the location filtering of the algorithm, "*The* *location-based filtering in the algorithm can pose a real issue for the queer community. Things can get risky in places like India, Turkey, or Pakistan, where using Tinder can seriously jeopardize people's safety, families, and jobs. That's why many start using VPNs to change their location. Sometimes, you match with them only to discover they're actually somewhere like Izmir. It's fascinating to see how individuals navigate the system for their safety*" (P5).

4.3.5 Bypassing the Algorithm by Moving to Other Platforms. To prevent perceived sabotage to their potential relationships, participants attempted to bypass Tinder dating algorithms by switching communication to other social media platforms or exchanging phone numbers. Although this might happen naturally as users develop relationships with one another, we found some evidence that participants (N_p=13) might do this very early in order to verify an account's authenticity (in part due to distrust that Tinder's algorithms want to remove fake profiles) or to prevent Tinder's algorithms from deleting matches. For example, P20 preferred to manually conduct account verification by finding the respective person on other social media platforms: "*I don't ask for other photos, I don't even care if the account is verified or not; that doesn't help, I just ask for the Instagram and WhatsApp account at the very beginning to see if the person is real*" (P20). P17 referred to authenticity concerns too, but also the fear of Tinder's algorithms sabotaging interactions that occur on the dating app: "*The first thing you do on Tinder is find the person on Instagram and WhatsApp, Instagram because you want to check if the person is real or not, and WhatsApp because there you have control there and you do not have to be afraid of losing contact because the match disappeared or something*" (P17).

5 LIMITATIONS AND REFLECTIONS

This paper builds on existing research about the harms experienced by users on dating apps by highlighting the perceived algorithmic harm to users' relationships and their strategies for mitigating it. However, the study's sample and methodology have inherent limitations. Firstly, we limited our focus to the Tinder dating app. This decision was made because each dating app employs different algorithms [85], and broadening our study across various platforms could have introduced complexity. Secondly, due to legal constraints in Germany regarding data scraping and the requirement to log into a personal account to access App Store data, we confined our review to publicly available data from the Google Play Store. Lastly, we acknowledge that app reviews do not encompass the complete user experience and may reflect a limited range of perspectives, alongside the challenge of inaccessible user demographics.

We aimed to address some of these limitations with the second part of our methodology: semi-structured interviews. These interviews revealed many blind spots not apparent in the reviews, allowed us to engage with iOS users, and ensured a diverse demographic representation. Notably, our inclusion of the LGBTQ+ community led to the identification of a unique type of perceived algorithmic harm specific to these communities, thus enriching our findings. However, we must acknowledge that our sample was predominantly cisgender, meaning the interviews provide only a partial representation of Tinder users. More involvement from trans users, who are highly impacted by algorithmic harm [29] and face unique self-presentation challenges in online dating [45], may yield additional perceived algorithmic harms and should thus be a focus of future work. Additionally, our data does not differentiate between premium and free users of the app. This is due to the lack of user account information in reviews and the tendency of interviewees to switch between account types. Moreover, while gender could play a significant role in the experience of algorithmic harm, our study did not delve into gender-specific impacts, as this was beyond our research scope.

It is also important to note that the algorithmic harms mentioned in this paper are those that users perceive and attribute to the algorithm, and they may not necessarily reflect what is actually happening on the platform. Nevertheless, our research underscores the importance of considering these perceived harms when trying to fully understand user behavior and strategies on these platforms. Therefore, we urge the research community to continue investigating this topic. As dating app algorithms are continuously evolving, new types of perceived computer-mediated harms may emerge over time.

6 DISCUSSION

In this study, we have broadened the existing view of potential harms on dating platforms by examining the algorithmic harms perceived by users at both personal and interpersonal levels. Given the extensive research on human-inflicted harm on dating apps, adopting an algorithmic lens to interpret perceived harms offers a fresh approach. This not only complements existing perspectives but also provides crucial insight into users' behavior and counter-strategies on such platforms. To further illustrate this, we first connect our discovered conflict-of-interest folk theory of Tinder's algorithms to the broader algorithmic folk theory literature to elucidate key differences in how users construct and respond to perceptions of algorithmic processes on dating apps (which users intend to eventually stop using after achieving their goals) and social media platforms that are intended for continual use. We then outline how our findings on algorithmic harms in online dating build upon and broaden existing research on algorithmic harms in other contexts. Subsequently, we explore the interplay between human-inflicted and algorithmically-inflicted harm, demonstrating how algorithmic processes can mediate and perpetuate pre-existing human-inflicted harms and social biases. Finally, we examine current design approaches for harm mitigation to discuss the implications our study may hold for designing user experiences that are mindful of potential algorithmic harm on dating apps.

6.1 The Conflict-of-Interest Theory, Its Implications, and Associated User Behavior

In the face of perceived algorithmic harms, users constructed a folk theory about Tinder's algorithms that we refer to as the conflict-of-interest theory. The theory references two interests: the interest of users in finding a compatible romantic partner, and the the financial interests of Tinder as a company in sustaining an active, paying userbase. Mechanistically, users in our study believed that Tinder's algorithms were capable of computing romantically compatible matches, yet were engineered to deliberately avoid recommending such profiles together, or to otherwise sabotage promising interactions, to coax users into purchasing premium memberships and continuing their use of the application. This theory diverges from prior research into folk theories about Tinder's algorithms, which attributed profile recommendation to romantic compatibility and user feedback [1] (in direct contradiction with our participants' folk theories), as well as pure randomness and desirability scores [58, 77].

When looking at the broader algorithmic folk theory literature, our Tinder users' speculation of financially-driven algorithmic processes draws comparison to an *"economic motivation"* or *"cash grab"* suspected by Twitter users regarding a rumored change to its content curation algorithm [31]. Yet the impetus of this suspicion is quite different - it is not a rumored change to an algorithm that is prompting the conclusion of financial motivation, but a user's own dating failure. This is an important difference because dating apps have a clear win state for many users that would result in discontinued app-use (finding a long-term partner) whereas social media platforms do not. Continued usage is actually desired by users of other social platforms studied in the algorithmic folk theory literature, such as goals of social support and connection on Facebook, Twitter, and Tumblr [28], as well as visibility for the sake of helping LGBTQ+ people on Tiktok [29]. From our findings, suspicion of economically motivated algorithms on Tinder seems to uniquely derive from intent to justify why one's goals for using (and eventually leaving) a dating app have not been achieved.

User behavior on Tinder discovered in response to their conflict-of-interest theory would appear surprising in light of prior algorithmic folk theory literature. Devito used the concept of platform spirit to explain users' decisions to adapt to perceived algorithmic processes on various social platforms [28, 29]. Platform spirit is defined as "*the user's perception of what a platform is and what it is for, as determined by the user's understanding of the platform's stated mission, its values and actions in practice over time, and the functionality which it allows as juxtaposed with the user's understanding of the platform's purpose*" [28] (p. 18). DeVito goes on to explain that positive platform spirit - or algorithmic processes that users consider aligned with the platform's purpose - prompt users to continue platform-use and adapt to its algorithmic processes. Negative platform spirit - or algorithmic processes that users consider to conflict with the platform's purpose - motivate "*decisions to reduce or stop use of a system*" [29] (p. 6).

The perceived platform spirit of Tinder can more aptly be called a platform *promise* - a word that came up multiple times in our data - to connect users with a compatible partner. Users in our study overwhelmingly considered Tinder's algorithms to violate this platform promise, yet we saw little evidence of them leaving the platform or limiting participation, as DeVito's empirical research on social media platform spirit would suggest [28, 29]. Perhaps the only example in line with this prior work is some Tinder users moving their messaging interactions to other social platforms early in the relationship-building process to avoid algorithmic sabotage of their match list. This complements impression management and formation strategies found in prior online dating research, in which users transitioned their interactions to other platforms - sometimes faster than they were comfortable with [117] - as a way to better evaluate compatibility and safety risks with a potential meeting partner [50].

A reason Tinder users may choose to stay, and even continue paying for memberships, is because the perceived platform promise can divest them of personal responsibility for their dating failures and instead attribute that responsibility to Tinder's algorithms. The conflict-of-interest theory is thus not simply an algorithmic folk theory, but a folk theory about why online daters have been unsuccessful at finding their desired partner in a way that places responsibility for that lack of success on the platform's broken "promise" rather than their own actions or attractiveness: it's not me, it's the algorithm. The suspicion of economic motivation can then be understood as a hypothesis for why Tinder's algorithm would intentionally break its supposed promise.

The counteractions that we found Tinder users to engage with on the platform in response to their conflict-of-interest theory can be described as *"unfaithful adaptations"* [28], or behaviors that run contrary to the intended use of the platform. Intentionally "liking" profiles that one is not attracted to and blocking users that have not done anything wrong would be two examples from our study. While practice of unfaithful adaptations in prior work appears to be for "experimentation" purposes [28] (p. 24) to test a revised algorithmic folk theory, we did not find much evidence of Tinder users experimenting or stress testing their perceptions of algorithmic processes - potentially because doing so would risk the conclusion that they, rather than the algorithm, are the reason they are not getting matches or dates.

If not experimentation, the unfaithful adaptations found in our study align with what Velkova and Kaun refer to as "algorithmic resistance," a form of complicit resistance that acknowledges the power of algorithms but operates within their framework for different ends [108]. We see this exemplified with creation of new accounts to sidestep a perceived algorithmic throttling of profile recommendations as well as manipulating the range of profile recommendation filters; two strategies also evidenced in other online dating folk theory research [1, 77, 112].

6.2 Synthesizing Perceived Algorithmic Harms in Online Dating with the Broader Algorithmic Harm Literature

This section synthesizes Tinder users’ perceptions of algorithmic harm, identified in this study at both the intra- and interpersonal levels, with the broader themes found in algorithmic harm research. We particularly discuss the types of harms our study revealed, and how they connect to and expand the algorithmic harm literature.

At the intrapersonal level, the negative impact of dating apps on self-esteem aligns with well-documented effects of these platforms on mental health, self-compassion, and self-worth (e.g., [71, 76, 104]). Furthermore, it draws parallels with “allocational harm” from the algorithmic harm literature, where automated systems inequitably distribute resources or opportunities [10]. This type of harm is exemplified by dating platform algorithms that reduce profile visibility and the number of matches and likes as usage time increases, ostensibly to motivate users to buy premium services [20]. This practice shares similarities with DeVito’s description of how social media platforms manage content distribution, setting criteria for the visibility each piece of content receives [29]. However, in the dating context, users often internalize the scarcity of matches and likes as personal failings, describing themselves as “ugly” or “unsuitable” - a recurring theme in our findings. This internalization forces a dichotomy: remain “single” or spend money on premium features to enhance perceived desirability and self-esteem. This strategy not only damages self-worth but also perpetuates a system that disadvantages certain groups, reflecting broader concerns about unfair resource distribution seen in other sectors like the gig economy [75].

At the intrapersonal level our LGBTQ+ participants overwhelmingly expressed that the Tinder algorithm’s binary filtering and its failure to consider their specific sexual preferences resulted in mental and physical harm. They detailed feelings of marginalization, frustration, anxiety, and insecurity, sometimes manifested in physical side effects. Supporting our observations, the broader social platform literature, including findings by Walker et al., DeVito, Phan, and Duguay [29, 32, 37, 38, 82, 111], demonstrates that LGBTQ+ individuals often face identity stigmatization, invalidation, and erasure. In algorithmic harm literature, this perceived suppression and misrepresentation of specific gender and sexual identities by the algorithm aligns with what Karizat et al. [64] refer to as “algorithmic representational harm”.

Unlike scenarios where LGBTQ+ users reduced their use of platforms, left them, or employed strategies like “*identity flattening*” or “*identity modulation*” [32, 38, 111] to adjust their identity presentation to match platform norms or avoid stereotypes, or even attempted to “*domesticate*” the algorithm [94, 95], our study highlights a different approach. We found that our participants utilized location-based filtering to mitigate harm and enhance safety, an approach that reflects broader usage trends on social media platforms, as discussed in Haimson and DeVito’s work [33, 52]. However, in the context of dating apps, targeting the “*outright*” audience takes on additional significance due to the platforms’ heavy reliance on geographic location and specific user affordances. For example, our participants employed strategies such as using VPN to change their location to less conservative areas or strategically using the app in queer-friendly environments. This is particularly important in areas where there is a risk of physical violence. While previous research [15, 56] has shown the risks associated with location-based filtering, our findings suggest it can serve as a protective measure for LGBTQ+ users to mitigate potential harms.

The countermeasures found in our study to combat these perceived algorithmic harms echoed prior work, such as profile manipulation found by Nader et al. [77], but also revealed seemingly counter-intuitive behaviors, such as disliking profiles one is attracted to or blocking users who did nothing wrong. These actions could indirectly affect other users; for example, if Tinder misinterprets a block as a response to misconduct, it could lead to an account suspension or ban. This possibility extends the discussion beyond the "*latent harm*" concept described by Walker and DeVito [111], which focuses on harms that develop over time due to coping strategies affecting access to support and resources, primarily impacting the mental and physical health of bi+ individuals. Our findings suggest that such behaviors could also inadvertently impact a broader user base, going beyond intrapersonal harm as it can cause interpersonal harm as well; e.g. by potentially restricting other users' access to platforms like Tinder, reflecting unintended consequences of these coping strategies.

6.3 The Interplay Between Human-Inflicted and Algorithm-Facilitated Harm

Prior research on dating apps has documented both intentional interpersonal harm (such as stalking, harassment, and even sexual violence (e.g., [18, 35, 47, 60, 66, 74, 88]) and unintentional interpersonal harm (resulting from sexual scripts [24, 84] and consent practices [116]). Our findings show that perceived algorithmic harms not only portray algorithms as additional "entities" that users feel the need to protect themselves from, but as enablers and facilitators of human-inflicted harms. In other words, humans and algorithms are not distinct sources of harm, but interconnected. There are several examples of this across our study.

Harassment through dating apps is well known [5, 11, 91], yet our study adds a new dimension of understanding harassment through the role that algorithms may play in enabling it. Interview participants recounted several instances of being harassed due merely to discovery of their profile by others in inopportune or inappropriate social contexts. Examples included a teacher being harassed by students who were recommended her profile, a user being judged by colleagues who discovered their profile, and identity-based harassment to LGBTQ+ users in culturally conservative areas. Furthermore, our findings suggest that Tinder's matching algorithm may be *instigating* harassment. For instance, research on hostile masculinity and "incels" finds that men sometimes engage in sexual harassment as retaliation for being "failed men" incapable of dating success [53]. Perceptions in our study that Tinder's algorithms may be throttling profile visibility and sabotaging relationship success could reinforce feelings of inevitable dating failure, which could be directed at other users in the form of harassment (harassment in retaliation for romantic rejection has been found elsewhere [91]).

Our findings also indicate that Tinder's algorithms may be augmenting capabilities for harm by malicious actors. The creation of fake accounts as a vehicle for hate crimes is particularly problematic. While dating apps typically offer some form of user verification (e.g., profile picture verification), use of such features is typically not obligatory and certainly not foolproof as evidenced by our LGBTQ+ participants who reported instances of being coerced into face-to-face encounters by fake profiles. This finding aligns with previous studies examining identity-based harm targeting gay individuals [16, 17, 25] and deceptive practices [113]. Interestingly, protective features like the ability to block or report users were sometimes viewed as tools to be exploited by malicious actors. Users in our study suspected reporting features were being abused to trigger automatic account banning without proper investigation - although we should note that there is no evidence to our knowledge confirming this is actually how Tinder's banning process works.

6.4 Scrutinizing Perceived Algorithmic Harms and Related Algorithmic Processes

Our study focuses on users' *perceptions* of algorithmic harm on Tinder, which could be based on an inaccurate understanding of how Tinder's algorithms really work. While perceptions of algorithmic processes and harms can influence user behavior regardless of their accuracy [29, 30, 94], it is important to scrutinize the veracity of our Tinder users' perceptions of algorithmic processes before considering design implications to combat the supposed harms that follow from them. While Tinder remains relatively opaque about the exact workings of their algorithms, information made available by the company does provide some insight.

Tinder acknowledges that its matching algorithm does rank profiles, but not based on the Elo Score. Instead, profile activity is the key determinant, with the company stating, "We prioritize potential matches who are active, and active at the same time" [101]. However, this claim is contradicted by Courtois et al., who used the Experience Sampling Method with 88 Tinder users to infer algorithmic processes [26]. Their findings suggest that usage frequency does not significantly influence the likelihood of receiving likes or matches. Moreover, they observed a counter-intuitive trend: "the more recurrent the usage of Tinder, the fewer the number of matches." These insights lend credence to users' perceptions of algorithmic allocational harm, particularly those targeted at long-term users of the app, suggesting that algorithmic processes may indeed be throttling a profile's visibility.

Tinder's own website also lends credibility to users' perceptions that their match preferences are ignored by the recommendation algorithm. Tinder acknowledges that its matching algorithm operates not only based on explicit filtering but also machine learning techniques that involve various factors to determine profile recommendations such as users' "likes and nopes" and "anonymized cues from photos" [101]. In other words, users' filter preferences are not treated as absolute requirements for profile recommendation, but one set of several different factors used to determine which profiles to show.

There are alternative explanations for other experiences reported by users that were suspected to be the result of algorithmic processes. A notable one was the perception that Tinder's algorithms sabotage relationship formation by deleting messaging interactions that seem to be going well. This could simply be the result of a lack of interest from other users. Deleted messaging interactions could be due to a messaging partner voluntarily choosing to unmatch, rather than an intentional effort by an algorithm to sabotage relationship success. Relatedly, an absence of matches may really be due to other users finding one's profile unattractive, rather than profile visibility throttling. Another explanation is that Tinder's algorithms could have detected one's messaging partner to be a bot or a sex worker (neither of which are allowed according to Tinder's Terms of Service), and deleted such accounts without informing matched users of this detection. Tinder does acknowledge use of "automated decision-making and profiling" as part of their moderation efforts (for example, removing bots). The platform also employs automated tools such as safe message filters to identify and manage instances of harmful or illegal behavior, thereby preserving user privacy and security [102]. Lastly, human-driven moderation policies and practices could be the cause of what participants believed to be algorithmic sabotage.

One reason users may be quick to attribute negative online dating experiences to algorithmic processes - however outlandish - is as a scapegoat for one's dating failures. In this light, blaming algorithms for dating failures could be understood as a coping strategy - we refer readers back to our reflection on users' decisions to remain on Tinder despite a perceived broken by its algorithms.

6.5 Implications for Designing Algorithmic Processes in Dating Apps

Designing dating apps to mitigate risk of harm is integral to the user experience, especially for individuals such as women and LGBTQ+ users who are at disproportionate risk of dating-related harm [5, 9, 45]. Users' experiences with risk and actualized interpersonal harm in online dating have informed research on a variety of technical solutions to counter such harm (e.g., nude image detectors and harassment detectors [93, 99]). However, there has been relatively little consideration of how dating apps can be designed to mitigate adverse algorithmic processes, largely due to an absence of empirical investigation of perceived algorithmic harms and associated user strategies.

The discovered conflict-of-interest theory may render this a seemingly futile task - can we expect dating app companies to alter design to mitigate algorithmic processes that generate financial returns? Yet we would point out that the algorithmic processes that users *perceive* may not actually be occurring, and so we hesitate to propose counteractions to these supposed (and potentially nonexistent) algorithmic processes regardless of whether companies may be willing to adopt them. Nonetheless, we would argue that user and company interests are not always mutually exclusive, and there are potential modifications or additions to known algorithmic processes that could benefit both parties. Malicious acts enabled by (the absence of) algorithmic processes such as recommendation of fake profiles made by people that want to coerce marginalized groups into face-to-face meetings clearly benefit neither party - a user that leaves the platform due to harmful experiences neither generates profit nor a dating success story. Improving algorithmic detection of fake profiles, and improving matching algorithms to avoid recommendation of users with harmful beliefs against marginalized groups *to* said groups could foster a more enjoyable experience that leads to extended platform-use.

And while we cannot reliably assert that Tinder's algorithms do indeed inflict the harms attributed to them such as self-esteem damage, relationship sabotaging, and identity-based harm, such categories can be used as goals for new algorithmic implementations. For example, algorithms could help remedy negative impacts to self-esteem due to absence of matches through suggestions for profile construction (e.g., users that include a headshot are x% more likely to receive a match). To help users maximize the chances of a successful online interaction that leads to a face-to-face date, users could engage in AI-mediated messaging interactions with suggested conversation topics. To avoid identity-based harm and marginalization, algorithms could provide more granular demographic details to facilitate more relevant profile recommendations.

7 FUTURE WORK AND CONCLUSION

On online platforms, algorithms significantly influence and mediate our relationships. However, the bulk of research on dating platforms has focused on human-inflicted harm, leaving a gap in understanding the potential harm users perceive from algorithmic interventions. To fill this void and provide a comprehensive, empirical understanding of how users perceive algorithmic harm, how they make sense of it, and the strategies they apply to counteract it, we conducted an extensive analysis of 7,043 Tinder reviews. This was complemented by 30 semi-structured interviews with users of the platform.

Our study unveiled various categories of perceived algorithmic harm affecting both personal and interpersonal relationships. The perceived algorithmic harms ranged from damaging users' self-esteem, sabotaging potential relationships, encouraging antisocial behavior, to inflicting identity-based harm. We found that users formulated a conflict-of-interest theory to rationalize these perceived harms, suggesting a contradiction between a dating app's mission of finding the perfect partner and its commercial interests. This theory was supported by several user-perceived algorithmic processes such as throttling profile visibility and manipulating user matches. Additionally, we found that this belief influenced users' strategies to counter algorithmic harm, resulting in counter-intuitive behaviors on the platform or circumventing it altogether.

Our findings also reveal that users perceive algorithmic processes as enabling human-inflicted harm, suggesting that algorithmic and human-inflicted harms can often intertwine. This underscores our advocacy for future research on computer-mediated harm mitigation to consider both human and machine factors in their investigations. We believe this research will lay the groundwork for future studies exploring the potential harms caused by algorithmic processes across various societal platforms from the users' perspective. Furthermore, we encourage future work to build upon this study by considering and testing the design recommendations proposed herein, aiming to better support users in mitigating potentional algorithmic harms, especially those which detrimentally affect users' dynamic relationships.

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A TABLE OF THE PARTICIPANTS

Table 2. An overview of the participants' demographics

PID	Age	Gender	Sexual orientation	Ethnicity	Cultural Background	Tinder usage
P1	29	Cisgender woman	Heterosexual	White	German	2 Years
P2	27	Non-binary	Pan-sexual	Asian	Chinese/American	3 Months
P3	32	Cisgender woman	Heterosexual	White	German	9 Months
P4	29	Cisgender man	Heterosexual	Black	Nigerian	2.5 years
P5	30	Cisgender man	Gay	Asian	Indian	5 years
P6	25	Cisgender woman	Heterosexual	White	German	3 Months
P7	29	Cisgender woman	Heterosexual	White	German	2 Years
P8	27	Cisgender man	Heterosexual	Asian	Indian	1 Year
P9	28	Cisgender man	Bisexual	White	Serbian/German	1 Year
P10	33	Cisgender woman	Heterosexual	Asian	Iranian	3 Months
P11	32	Cisgender woman	Heterosexual	Asian	Pakistani	2,5 Years
P12	27	Non-Binary	Bi-sexual	Asian	Iranian	6 Months
P13	33	Cisgender man	Heterosexual	White	German	2 Months
P14	40	Cisgender man	Heterosexual	White	Albanian	2 Years
P15	30	Cisgender man	Heterosexual	Mixed race	German/Iranian	3 Months
P16	26	Cisgender woman	Heterosexual	White	German	6 Months
P17	30	Cisgender woman	Heterosexual	Asian	Iranian	2 Years
P18	44	Cisgender man	Heterosexual	White	German	3 Years
P19	23	Non-binary	Queer	Black	Nigerian	5 Years
P20	26	Cisgender man	Heterosexual	Asian	Iranian	2 Years
P21	30	Cisgender woman	Heterosexual	Asian	German/Iranian	3 Months
P22	27	Cisgender man	Gay	Asian	Vietnamese	2 Years
P23	37	Cisgender woman	Heterosexual	White	German	7 Months
P24	23	Cisgender man	Heterosexual	Asian	Iranian	3 Months
P25	38	Cisgender man	Heterosexual	White	German	3 years
P26	33	Cisgender woman	Heterosexual	Asian	Iranian	6 Months
P27	25	Cisgender man	Heterosexual	Asian	Chinese	6 Months
P28	24	Cisgender woman	Heterosexual	Asian	Pakistani	6 Months
P29	34	Cisgender woman	Heterosexual	White	German	10 Months
P30	34	Cisgender man	Heterosexual	White	German	1 year

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