FINDING LOVE IN THE BLACK BOX

THE ROLE OF ALGORITHM AWARENESS IN DATING APPS

Student name: Doris Bukman
Student number: 485169
Supervisor: Dr. Elisabeth Timmermans

Media, Culture and Society
Erasmus School of History, Culture and Communication
Erasmus University Rotterdam

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ABSTRACT

Most popular dating apps incorporate artificial intelligence (AI) to match users to one another. However, these platforms are not fully transparent about how their recommender systems work. In turn, users have varying degrees of awareness of matching algorithms. Unfortunately, little is known about how insight into algorithmic functioning affects the online dating experience. This research examined the relationship between algorithm awareness, self-perceived attractiveness, and satisfaction with the quality of matches. Firstly, it was theorized that a higher awareness of the recommender system will lead to more success on dating apps in terms of matching, making users feel more positive about their own attractiveness. Secondly, awareness was expected to increase the trust that users have in the abilities of matching algorithms, which consequently would enhance satisfaction with the matches that they come across on dating apps. A survey was conducted among 500 online daters in collaboration with the Dutch dating app Breeze. The data were analyzed with the use of structural equation modeling. It was found that while there was no apparent relationship between algorithm awareness and success, being more successful on dating apps was associated with higher self-perceived attractiveness. This effect appeared to be stronger for male than for female users. Importantly, higher algorithm awareness was correlated with more trust in the recommender system, which in turn positively related to the ease by which users could find matches that they are interested in. The presence of this fully mediated effect between awareness and satisfaction with matches suggested that knowledge of matching algorithms can affect both the evaluation of the recommender system as well as the results achieved on dating apps. Despite limitations, this research contributed to the relatively limited literature on human-AI interaction in online dating. Overall, the results indicated that increasing the awareness that users have of algorithm functioning could improve the experience of using dating apps.

Keywords: *Dating apps, Algorithms, Algorithm awareness, Trust, User experience*

Word count: 13781

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1. INTRODUCTION

Already in 1965, Harvard student Jeffrey Tarr launched his company *Operation Match*, a computer-assisted dating service (Cole, 2024, para. 4). Applicants had to fill in a 75-question pamphlet twice, about their own characteristics such as beliefs and lifestyle, and the same questions about their ideal mate (Chen, 2018, para. 9). After respondents mailed the questionnaire, each pamphlet was converted to a punch card and run through a room-sized IBM computer to find the most optimal partner (Wang, 2023, p. 261). The mysticism of the machine's mechanisms created a sense of legitimacy, according to Tarr: 'The great God computer must know something we don't' (Cole, 2024, para. 8). The real process was not so sophisticated. The cards were sorted by a few criteria such as location and age, and were then matched at random (Cole, 2024, para. 7). Tarr later admitted: 'The idea that we were matching based on compatibility was purely a marketing thing. It was always more art than science' (Cole, 2024, para. 9).

It was not until the mid-1990s that online dating took off with the arrival of *Match.com* (Sharabi, 2022, p. 3). Singles scrolled through a grid of profiles and could send a message to any 'personal ad' (Sprecher et al., 2018, p. 3). Throughout the early 2000s corporations such as *eHarmony* began to experiment with compatibility matching based on questionnaires, similar to Operation Match four decades earlier (Sharabi, 2022, p. 3). Eventually, online dating became revolutionized after the development of mobile dating applications (Wang, 2023, p. 262). Dating apps run on smartphones and utilize GPS services to pair strangers (Wu & Trottier, 2022, p. 91). Their interfaces are simple and appealing, leading to a 'gamified' dating experience (Berger, 2023, p. 3). Typically, two users are shown each other's profiles, and if both indicate interest, they are 'matched' and can begin a conversation (Wu & Trottier, 2022, p. 91). This format was first popularized by Tinder in 2012, allowing users to swipe either left or right on another profile (Albury, 2017, p. 83). Since then, various alternative dating apps have emerged that use a similar format (Holtzhausen et al., 2020, p. 2). These apps can target certain demographics, such as *Her* for queer women, or they offer distinctly different features (Wu & Trottier, 2022, p. 94). For instance, *Breeze*, a dating app based in the Netherlands, does not allow users to chat with one another but immediately sets up a date after a match has occurred (Breeze, n.d.-a, para. 6).

Most mobile dating platforms use artificial intelligence (AI) to improve the app's functioning (Paul & Ahmed, 2023, p. 2). *Algorithms* are the backbone of this system: computational 'rules' that govern the processing, sorting, and analysis of digital data to make automated decisions (Berger, 2023, p. 3). Dating apps use data such as location, interests, and previous interactions to pair users with one another (Wang, 2023, p. 2). Furthermore, through a process of collaborative filtering, users receive recommendations based on the behavior of users with similar tastes (Sharabi, 2022, p. 5). Dating app algorithms promise that they wield behavioral data to find users a good 'match' (Bandinelli & Gandini, 2022, p. 429). This recommender system is supposedly efficient, effective, and scientific (De

Ridder, 2022, p. 549). For instance, the dating app *Hinge* brands itself with its implementation of the 'Nobel prize-winning' Gale-Shapley algorithm, developed by economists to find stable matches (Voll, 2023, p. 17). In an interview with *Vice Magazine*, Logan Ury, Hinge's Director of Relationship Science, explains that Hinge's selection of who is 'most compatible' may be a better choice than the partners users would pick for themselves (Baah, 2020, para. 4). In response to the question why users may not like profile recommendations, Uly answers: 'perhaps who you thought was your type wasn't serving you' and if Hinge seems to think two profiles are a match 'perhaps it's a good nudge' (Baah, 2020, para. 4).

Dating app owners are generally secretive about how their recommender systems operate, making matching algorithms somewhat of a 'black box' to outsiders (Courtois & Timmermans, 2018, p. 12). Generally, applications do not explain to users why a certain profile has been recommended to them (Nader & Lee, 2022, p. 446; Wang, 2023, p. 261). Published information about how the matching system works tends to be vague and superficial (Parisi & Comunello, 2020, p. 68). For example, Breeze's website only mentions that users are matched 'based on [their] profile information, [their] preferences and behavior in the app' (Breeze, n.d., para. 5). Consequently, users navigate dating apps with varying understandings of how the recommender system operates (Huang et al., 2022, p. 2). Some users may be minimally aware of the existence of algorithms on dating apps but have little insight into their influence on profile selection. Others may have a more sophisticated knowledge of processes such as collaborative filtering, and are thus more aware of the effects of their own input on dating apps' output (Huang et al., 2022, p. 1).

Increased awareness of algorithms may affect the online dating experience. For instance, it can prompt users to change their swiping behavior and settings, influencing how successful they are on the app (Hu & Zhan, 2024, p. 3; Nader & Lee, 2022, p. 450). Consequently, users will be more positive about their own 'value' on the dating market (Heino et al., 2010, p. 436). Furthermore, developing an understanding of how the recommender system works could change the degree of faith that users have in matching algorithms (Sundar, 2020, p. 79), leading to a more positive experience overall (Sharabi, 2021, p. 941). Therefore, this project focused on the role of algorithm awareness in dating apps. Specifically, it addressed the following research question: *Among Breeze users, what is the relationship between awareness of dating app algorithms with users' self-perceived attractiveness and satisfaction with the quality of matches?*

The rise of artificial intelligence is accompanied by a growing body of literature that focuses on individuals' perceptions of algorithms (Oeldorf-Hirsch & Neubaum, 2023, p. 2; Shin et al., 2022, p. 1). Research has shown that algorithm awareness influences user behavior on various social media platforms (DeVito, 2021, p. 2; French & Hancock, 2017, p. 3). However, studies conducted on this phenomenon in the context of dating apps are sparse (Hu & Zhan, 2024, p. 2). This is unfortunate, given that dating app use has been connected to adverse emotional outcomes (Breslow et al., 2020, p. 25; Her & Timmermans, 2021, p. 1315; Strubel & Petrie, 2017, p. 34). In particular, a failure to be successful can negatively affect well-being (Her & Timmermans, 2021, p. 1314). Whether the perception of matching algorithms affects the results of dating app use is largely unclear (Hu & Rui, 2023, p. 3). By focusing on algorithm awareness, this research added to the knowledge of the user experience in the process of online dating, as well as to the literature on human-AI interactions on social media (Albury et al., 2017, p. 8; Oeldorf-Hirsch & Neubaum, 2023, p. 2).

Apart from this project's scientific contribution, an inquiry into the role of algorithm awareness also has a broader societal relevance. The use of dating apps has intensified over the last decade and has become normalized (Castro & Barrada, 2020, p. 1; Degen & Kleeberg-Niepage, 2022, p. 180). Market leader Tinder has been downloaded over 530 million times globally, followed by Bumble (100 million) and Badoo (100 million) (Brooks, 2023, para. 8). They have become powerful social intermediaries in the process of matchmaking, functioning as alternatives for finding a partner in traditional ways, such as through mutual friends or in bars (Hobbs et al., 2017, p. 272). Some singles even feel that using dating apps is inevitable because there are no viable alternatives (Hu, 2024, p. 1171; Narr, 2022, p. 5350). While the popularity of dating apps has dropped slightly in the last few years (Brink, 2024, para. 2; Parham, 2023, para. 8), the formation of intimate relationships is now partially dependent on matching algorithms (De Ridder, 2022, p. 594). Given that dating apps are currently often employed to find romantic or other connections, understanding the mechanisms and effects of algorithmic matchmaking is crucial (Narr & Luong, 2023, p. 3). If improving algorithm awareness does improve users' self-evaluation and their dating success, increasing transparency of recommender systems may be beneficial (Zarouali et al., 2021, p. 2).

The research question was addressed with a digital survey distributed among Breeze users, the results of which were analyzed using structural equation modeling. The following section will first detail more information about Breeze, and set out how the relevant concepts are situated in the literature. This is followed by an explanation of the research design and the results of the statistical models. Lastly, the main findings, their implications, and important limitations will be discussed.

2. THEORETICAL FRAMEWORK

2.1. Affordance structure of the Breeze dating app

Before discussing the literature on algorithm awareness, it is important to consider differences in the *affordances* of dating apps: ‘the perceived range of possible actions linked to the features of the platform’ (Pruchniewska, 2020, p. 2425). While most of the literature has focused on Tinder (Castro & Barrada, 2020, p. 4; Menon, 2024, p. 3), other dating apps have emerged with distinct features. As each has a unique recommender system, perceptions of matching algorithms cannot be considered uniform across different platforms (Albury et al., 2017, p. 3). This research focuses on Breeze, which markets itself as ‘the simple, safe and serious dating app’ (Breeze, n.d.-a, para. 1). Breeze was created in the Netherlands by a group of students from Delft University (Bruma, 2022, para. 7). At first, the app launched in large Dutch cities, but it has since spread to Belgium and recently the UK (Breeze, n.d.-a, para. 1; De Leeneer, 2023, para. 2).

Breeze differs from other popular dating apps in two ways. First, after two users match, they are unable to chat. Instead, after both indicate their availability, the app will automatically plan a date and ask users to pay a fee of €9. This amount covers administration costs, as well as the first drink at the location where the date takes place (Breeze, n.d., para. 6). By automating the planning process and demanding an investment fee, Breeze incentivizes individuals to meet up and build connections. In contrast, Timmermans and Courtois (2018) found that less than half of Tinder users have ever had an offline encounter with another user (p. 13). Second, while dating apps such as Bumble allow endless profile scrolling, Breeze provides only a handful of potential matches every day, at 7 AM and 7 PM (Breeze, n.d.-b, para. 1; Ward, 2017, p. 1647). This feature attempts to overcome choice overload: if people are presented with more choices, they end up becoming less satisfied with their eventual selection (D’Angelo & Toma, 2017, p. 4). Furthermore, having many options makes daters more likely to reject others, leading to fewer matches overall (Pronk & Denissen, 2020, p. 388). If Breeze users have fewer options, they will thus more often accept a date. By avoiding ‘endless swiping and chatting’ Breeze also discourages compulsive use (Breeze, n.d.-b, para. 1; Hu & Rui, 2023, p. 3).

Breeze is an intriguing case for the exploration of algorithm awareness on dating apps. Firstly, users only receive a small number of recommendations and immediately commit to a date after matching. If the matching algorithm works very poorly, users will quickly be dissatisfied, given that there are only a limited amount of opportunities to connect with others. Therefore, Breeze’s recommender system arguably holds a higher significance than in other ‘unlimited’ dating apps. Secondly, as mentioned above, most academic research has focused on Tinder, or on other popular dating apps such as Bumble or Grindr (Corriero & Tong, 2016, p. 121; MacLeod & McArthur, 2019, p. 822; Van De Wiele & Tong, 2014, p. 619). While these apps are employed internationally, they were developed in the United States (Menon, 2024, p. 2; Wise, 2019, para. 2). As the national context partially determines the landscape of online dating, it is beneficial to also study dating apps such as Breeze which were created for a non-American audience (S. Wu & Trottier, 2021, p. 2).

2.2. Success mediates the relationship between algorithm awareness and self-perceived attractiveness

The term algorithmic imaginary refers to how people imagine, perceive, and experience algorithms (Bucher, 2017, p. 31). In other words, the perception of social media algorithms affects how they are used, and in turn, how they affect users. In her study about Facebook, Bucher (2017) showed that users develop their own understanding of algorithmic functioning through interactions with the platform (p. 31). This leads users to engage with the recommender system in different ways, for instance clicking on content randomly to ‘confuse’ the algorithm and inhibit its operations (Bucher, 2017, p. 37). Because little is known about how social media algorithms work, users rely on *folk theories*: ‘intuitive, informal theories that individuals develop to explain the outcomes, effects, or consequences of technological systems’ (Nader & Lee, 2022, p. 447). In the context of dating apps, researchers such as Nader and Lee (2022, p. 445) and Parisi and Comunello (2020, p. 66) studied commonly held perceptions of algorithms and different user strategies. They found that online daters adjust how they use the app based on their algorithmic imaginary and folk theories (Nader & Lee, 2022, p. 445; Parisi & Comunello, 2020, p. 86). For instance, a common conception is that potential matches are shown based on one’s own attractiveness, understood as the amount of positive feedback the profile receives (Nader & Lee, 2022, p. 450). There is some indication that this is true, at least in the case of Tinder (Courtois & Timmermans, 2018, p. 6).

The *awareness* that users have of the recommender system is part of the algorithmic imaginary (Zarouali et al., 2021, p. 2). Algorithm awareness can be defined as individuals’ awareness of the presence of algorithms and how they work (Dogruel et al., 2022, p. 1315). As mentioned above, this definition is complicated by the fact that the exact functioning of algorithms is typically unknown. However, users may not be aware of the presence of an algorithm at all. For instance, Gran et al. (2021) found that more than half of Norwegian participants had no or low awareness of the existence of personalized recommendations on YouTube or Spotify (p. 1785). An entirely different result was obtained by Rader and Gray (2015) in a study on Facebook users, where approximately 75% of respondents had at least a basic awareness of algorithmic curation on their timelines (p. 177). If users are aware that a recommender system is active, they may have varying understandings of the basic workings and limitations of algorithms. Examples are being aware that algorithms filter content in a personalized manner, that they serve to influence users’ behavior, and that they utilize users’ direct and indirect input on the platform to generate recommendations (Zarouali et al., 2021, p. 2). Overall, algorithm awareness is affected by factors such as age, gender, and education (Gran et al., 2021, p. 1785; Siles et al., 2022, p. 3), and it has been shown to influence behavior on social media platforms (DeVito, 2021, p. 2; French & Hancock, 2017, p. 3).

Little is known about the level of algorithmic awareness among the user base of dating apps

(Hu & Zhan, 2024, p. 2). It has been observed that some users are not aware of the presence of matching algorithms at all (Huang et al., 2022, p. 1; Parisi & Comunello, 2020, p. 81). Knowledge of algorithms could change how users employ dating apps, and in turn their success on them. Hu and Zhan (2024) found that algorithm awareness is negatively associated with mate-searching difficulty (p. 6). They theorized that this is due to the practice of calibrating algorithms, whereby users try different strategies on the platform, compare the results, and make decisions accordingly (Hu and Zhan, 2024, p. 3). Users 'boost' the algorithm by expanding filters, for instance by including a bigger age range of potential matches, so that their profiles are liked more often, thus improving their 'attractiveness score' on the app (Nader & Lee, 2022, p. 453; Myles & Blais, 2021, p. 2). Another example is deleting and recreating one's profile to enjoy the increased visibility that the app gives to new users (Nader & Lee, 2022, p. 452). These algorithm hacks have been studied primarily in the context of Tinder (Albury et al., 2017, p. 6). However, studies of other apps also show that users can build an understanding of the recommender system and adjust their strategies accordingly (Pidoux, 2023, p. 204; Wang, 2020, p. 182).

In short, algorithmic awareness leads users to implement strategies to boost dating app's functioning, which could lead to more success on the dating app in terms of metrics. If online daters adjust their swiping behavior and settings, they are seen more by other users, thus increasing the chances of getting a match (Hu & Zhan, 2024, p. 3). They may also leverage the algorithm to find the profiles that they are most compatible with, therefore enhancing the chances of getting a match as well as finding a satisfying connection (Nader & Lee, 2022, p. 455). These strategies depend on the specific affordances of each app (Pidoux, 2023, p. 205). For instance, Breeze users could adjust their filter settings, profile descriptors or change their answers on the prompts to influence the matching algorithms. Because all matches lead to a date, changing swiping behavior is likely employed less than on apps such as Tinder.

However, whether these strategies are effective remains largely unexplored (Nader & Lee, 2022, p. 448). Because there is no way to see others' metrics, the amount of matches that is considered a lot differs between individuals (Her & Timmermans, 2021, p. 1308). Thus, it is difficult to verify whether a change has actually been successful. An alternative explanation would be that those who implement such algorithm-boosting strategies simply perceive themselves to be more successful due to a false sense of control (Hu & Zhan, 2024, p. 11). This *illusion of control* can be understood as 'the tendency to be over-confident in one's ability to attain outcomes that are chance determined' (Tong et al., 2016, p. 647). This leads users to believe that they are getting more matches after undertaking actions to manipulate the algorithm, even though this might not be the case. This effect was explored by Tong et al. (2016) who found that increased perceived control on dating sites was associated with more satisfaction with the matching process (p. 659). These two explanations lead to the first hypothesis:

H1: Algorithm awareness is positively associated with perceived matching success on dating apps

The use of dating apps has been connected to more negative perceptions of one's body and face (Breslow et al., 2020, p. 21; Strubel & Petrie, 2017, p. 34), which can be explained by the fact that failing to get matches may lead to feelings of being rejected (Castro & Barrada, 2020, p. 14; Kallis, 2021, p. 84). Research on online dating has shown that physical appearance is key to the choice of accepting another profile (Fiore et al., 2008, p. 2; Roshchupkina et al., 2023, p. 175). Mobile dating applications tend to have a photo-centric layout. For instance, on Breeze, the profile pictures are featured prominently and cover most of the screen (Jenny, 2021, para. 3). Users can answer only a few question prompts, and biographic information tends to be limited (De Graaf, 2023, para. 13). These affordances of dating apps hyperbolize the importance of physical attraction, given that users only have access to visual and minimal textual cues (Arias & Punyanunt-Carter, 2018, p. 7072). Therefore, users quickly assess others based on their appearance (Strubel & Petrie, 2017, p. 37). If users' efforts to post pictures that conform to beauty standards are not approved by other users, this may lead to increased self-objectification and lower self-perceived desirability (Strubel & Petrie, 2017, p. 37).

Similarly, online dating can have a positive effect on users' self-image if they feel validated by their experiences on the app (Holtzhausen et al., 2020, p. 9). Matching success is associated with improved self-worth assessment (Her & Timmermans, 2021, p. 1315). This is supported by the finding that 'boosting confidence' is a common motivation for using dating apps (Sumter et al., 2017, p. 30; Timmermans & De Caluwé, 2017, p. 349). In research by Ward (2017), one interviewee describes how she used Tinder to improve her confidence after a painful breakup: 'I was lying in bed crying for my ex and then whenever I had a match I was like, 'Yes! There are still men out there that like me!' (p. 1650). Thus, the effect of dating app use on self-perceived attractiveness is determined by the success that users feel they have on the app.

Examining the effect of dating app use on self-perceived attractiveness is important as dissatisfaction with one's appearance is associated with multiple adverse outcomes. Importantly, feeling unattractive can lead individuals to believe that they cannot achieve satisfying romantic or sexual partnerships (Bale & Archer, 2013, p. 69; Thomas et al., 2022, p.6). A lack of self-perceived romantic desirability negatively affects psychological outcomes (La Greca & Lopez, 1998, p. 89). According to *Sociometer theory*, feeling unwanted can negatively impact self-esteem, as self-esteem is an internal measure of how much people feel valued in interpersonal relationships (Leary & Baumeister, 2000, p. 2). Low self-esteem is associated with lower well-being, for instance, depression and an inability to cope with stress (Abdel-Khalek, 2016, p. 127; Heatherton & Wyland, 2003, p. 219). Furthermore, lower self-perceived attractiveness as a result of rejection can also incentivize detrimental behaviors. For instance, Tran et al. (2019) found that dating app users were more likely to use unhealthy weight loss strategies, which could be explained by the emphasis on physical attractiveness on the apps (p. 10). Therefore, it is worthwhile to investigate the effect of success on dating apps on satisfaction with one's appearance. It is theorized that:

> H2: Self-perceived matching success on dating apps is positively associated with self-perceived physical attractiveness

However, the effect of success on self-perceived attractiveness may differ depending on other factors. Firstly, motivation for using dating apps can play a role. According to *Uses and Gratification theory (UGT)*, individuals seek out media to satisfy specific needs (Bryant & Sheldon, 2017, p. 2). This framework assumes that individuals are aware of their own needs, and actively seek them out, which leads to differing patterns of media use (Van De Wiele & Tong, 2014, p. 650). While needs guide the search for gratifications, whether and how these gratifications are obtained also influences consumers' needs reciprocally (Van De Wiele & Tong, 2014, p. 651). UGT has been used to map different common motives for using new media such as Instagram or Pinterest (Bryant & Sheldon, 2017, p. 2). Similarly, research has also identified a variety of possible motivations for online dating (Ranzini & Lutz, 2017, p. 85). Estimates of the number of different motivations for using dating apps range from six (Menon, 2024, p. 7; Sumter et al., 2017, p. 2; Van De Wiele & Tong, 2014, p. 619) to 13 (Timmermans & De Caluwé, 2017, p. 349). Apart from looking for a long-term romantic partner or sexual encounter, dating apps can be used for the sake of entertainment, to pass the time, or to gossip about profiles with a group of friends (Ranzini & Lutz, 2017, p. 84).

Importantly, some individuals use dating apps as a means to boost their self-confidence (Timmermans & De Caluwé, 2017, p. 344). As dating app affordances revolve heavily around physical appearance, getting a match can serve as a validation of one's self-worth (Sumter et al., 2017, p. 16). A person can create an online dating profile to assess the number of matches he gets, to get a sense of how attractive others find him (Timmermans & De Caluwé, 2017, p. 344). These users may be paying more attention to the amount of matches they get, rather than getting to know other users for the sake of connecting with them offline, for instance. Research by Sumter et al. (2017) revealed that while Tinder users motivated by self-validation tended to use the app significantly more, they were not more likely to go on dates with others offline, and less likely to have sexual relations with other users (p. 14). Because these users aim to get a sense of how valued they are on the dating market based on the amount of positive feedback they get from other users, it can be expected that the effect of matching success on self-perceived attractiveness will be stronger. While it appears that this sensitivity has not been tested directly, research on other social media platforms indicates that this could be true. For instance, individuals with a higher appearance-comparison tendency experience lower body satisfaction after Facebook use (Fardouly et al., 2015, p. 43). Among dating app users, Blake et al. (2022) found that an increased motivation for self-worth validation was associated with a higher likelihood of disordered eating (p. 7). Thus, users who are largely motivated by the search for an ego boost will likely hold more value to the amount of matching success that they perceive to have.

H3: The association between perceived matching success on dating apps and self-perceived physical attractiveness is greater among users with an ego boosting motive

Secondly, gender may affect the association between success and self-perceived attractiveness. Research has found that validation of physical appearance is more important for women than men (Park et al., 2009, p. 116; Schmidt & Martin, 2019, p. 579). Thus, one would expect that female dating app users will experience a stronger self-evaluative reaction to rejection or acceptance when it comes to matching. Interestingly, however, it appears from the literature that male users experience more negative appearance validation when using dating apps. Rodgers et al. (2020) observed that among men, frequent checking of dating apps was positively correlated with body shame, which did not emerge among women (p. 1472). Similarly, Strubel and Petrie (2017) conclude that self-esteem is generally lower for Tinder users than non-users, but only among men (p. 37). However, these studies only looked at overall self-evaluative outcomes, passing over the role of success on the app. Lower self-worth assessment after use among men may be explained by the fact that male users on average tend to receive fewer matches than women, and tend to be the ones initiating conversations in chat in heterosexual interactions (Timmermans & Courtois, 2018, p. 14). Therefore, it is worthwhile to compare the effect of matching success on self-perceived attractiveness between men and women.

H4: The association between perceived matching success on dating apps and self-perceived physical attractiveness is greater among male users

Through combining the first and second hypotheses, a fully mediated effect of algorithm awareness on self-perceived attractiveness is tested. The theoretical framework of the first model can be found below.

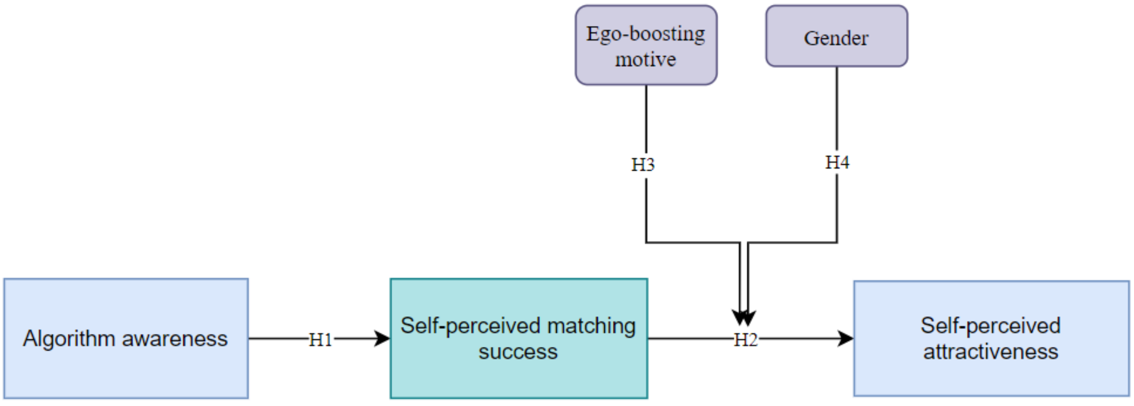

Figure 1.

Visualization of the relationship between algorithm awareness and self-perceived attractiveness

2.3. Awareness relates to satisfaction with matches through trust in matching algorithms

Algorithm awareness may also affect perceived success through *trust* in the recommender system. According to Rousseau et al. (1998), trust is ‘a psychological state comprising the intention to accept vulnerability based upon positive expectations of the intentions or behavior of another’ (p. 385). Although there is a lack of consensus about an exact definition, a situation that involves trust generally encompasses three components: someone who gives trust, here the online dater, an individual or thing to be trusted, the algorithm, and something at stake (Hoff & Bashir, 2015). Dating app users invest time and resources to use the platform and possibly go on dates, as well as risk emotional pain due to disappointment or rejection (Her & Timmermans, 2021, p. 1314; Timmermans et al., 2021, p. 796). In the case of Breeze, users also have to invest a monetary fee. Some authors conceptualize trust in algorithms similarly to interpersonal trust, measured with concepts related to fairness, accountability, and transparency (Shin et al., 2022, p. 1; Shin & Park, 2019, p. 277), which is termed ‘human-like’ trust (Cabiddu et al., 2022, p. 686). Contrarily, this project will focus on ‘system-like’ trust in dating app algorithms. This conceptualization revolves around the perceived reliability or usefulness of technological artifacts and assumes that trust in technologies is distinct from trust in other people (Mcknight et al., 2011, p. 2). Trust then refers to the belief that the algorithms have desirable attributes that satisfy the users’ expectations (Cabiddu et al., 2022, p. 686). In the context of dating apps, this means that users believe that their investments will lead to satisfaction of their specific needs.

According to Eszter (2021) an increase in algorithm awareness, called algorithmic literacy, increases the faith that users have in the accuracy and reliability of recommender systems (p. 353). Following Sundar's (2020) application of the *Theory of Interactive Media Effects* to the human-AI relationship (*HAII-TIME framework*), such a relationship can be partially explained by cue effects (p. 79). If a user understands a recommendation has been generated by AI, this ‘symbolic cue’ triggers cognitive heuristics based on existing knowledge or beliefs (Sundar, 2020, p. 80). This in turn affects the perception of the technology. Consumers tend to consider algorithmic decision-making to be more accurate and objective, because of the idea that automation eliminates human error and prejudices (Jang et al., 2022, p. 4). Consequently, if users have less knowledge about AI, being aware of the presence of a recommender system will trigger fewer positive heuristics, thus leading to a lower level of trust overall (Jang et al., 2022, p. 5). These users will have less belief in the ability of matching algorithms to satisfy their desires.

The relationship between awareness and trust in algorithms is supported by empirical research in various fields. For instance, Jang et al. (2022) found that users with more knowledge of algorithm functioning exhibited more trust in AI-generated news articles (p. 9). Similarly, according to Shin et al. (2022), higher awareness of algorithms is associated with more faith in algorithmic-decision decision-making (p. 9). In a sample of Romanian students, more expertise in recommender systems was also related to more trust in AI in e-commerce (Teodorescu et al., 2023, p. 11). However, it has not been thoroughly explored whether this association also exists for dating apps. Humans tend to judge algorithmic decision-making as less trustworthy when it comes to tasks that require social skill or ‘human intuition,’ rather than mechanical tasks (Lee, 2018, p. 9). Thus, the relation between awareness of an app’s recommender system and trust in algorithmic matchmaking may differ. One assessment of this mechanism among online daters was conducted by Hu and Wang (2023) among users of *Tantan*: a Chinese dating app that resembles Tinder (p. 6). Their findings showed that more knowledge of dating app algorithms increases users’ trust, as it reduces negative perceptions of the system (Hu & Wang, 2023, p. 9). However, the authors conceptualized trust as human-like (Hu & Wang, 2023, p. 8), and it is unclear whether the same mechanism applies to system-like trust. Furthermore, there appears to be no literature that explores the relationship between awareness and trust in other dating apps. Therefore, for Breeze users, it is hypothesized that:

H5: Algorithm awareness is positively associated with trust in dating app algorithms

The level of trust that users have in the recommender system may affect their experiences on a dating app. Specifically, if online daters believe that the matching algorithms work well, they may end up being more content with the profiles that are recommended to them. Finkel et al. (2012) attributed this to expectancy effects (p. 27). If users expect that a dating app’s algorithm is effective at providing compatible potential matches, they are likely happier with the recommended profiles (Finkel et al., 2012, p. 27). Sharabi (2021) explored this effect in a longitudinal study among users of different online dating platforms (p. 936). Participants who believed that algorithms were effective were more successful in finding a partner online that they wanted to continue dating offline (Sharabi, 2021, p. 941). This can be the result of a placebo effect: if users believe that a match has been determined as compatible by a seemingly valid authority, the algorithm, they are more likely to believe these matches are actually compatible (Finkel et al., 2012, p. 27). Users experience a greater certainty about matches both online and during offline dates and interpret negative experiences more positively (Hu & Rui, 2023, p. 2; Sharabi, 2021, p. 937). Similarly, the effect may be upheld by *confirmation bias*: the tendency to act in ways that confirm pre-existing beliefs (Finkel et al., 2012, p. 27). Sharabi (2021) posed that algorithm-trusting individuals will self-disclose more to potential partners (p. 937). Similarly, Hu and Rui (2023) theorized that a higher belief in algorithms leads users to invest more effort in communicating with matches (p. 2). Thus, trust in algorithms prompts users to engage more with matches, and leads to more satisfaction about the potential partners that are met on the app (Hu, 2023, p. 1167). In the case of Breeze, where users are unable to chat beforehand, confirmation bias could manifest differently. Users may be more likely to accept a potential date or to put more effort into building a connection during the offline interaction.

As a result, users will feel more satisfied with the potential matches offered by the algorithm. They feel as though the profiles that they come across are attractive, interesting, and seemingly compatible. This conceptualization of online dating success is different from success in terms of the number of matches and conversations. Matching quantity and matching quality can be correlated, given that one needs matches to be satisfied with them, but they do not necessarily correspond. A user may receive many matches, but none that translate to the connection that the user is looking for (Gibbs et al., 2006, p. 168; Hobbs et al., 2017, p. 278). Similarly, users may receive a low number of matches but can be very interested in the few that they are in contact with. Satisfaction with the quality of matches is an important outcome of dating app use. According to research by Courtois and Timmermans (2018) coming across appealing profiles on Tinder enhances user satisfaction with the app overall, which consequently is associated with a better mood after swiping (p.10). Hence, it is worthwhile to investigate whether satisfaction with match quality is influenced by beliefs about the recommender system. Expectations about the functioning of the matching algorithm could affect how online daters evaluate the profiles that they come into contact with. Therefore:

H6: Trust in dating app algorithms is positively associated with satisfaction with matches

The relationship between trust in dating app algorithms and users' satisfaction with who they match with may be impacted by their motivations for use. As posed by UGT, individuals' motivations for online dating shape the type of connections that they seek out (Sumter et al., 2017, p. 9; Van De Wiele & Tong, 2014, p. 650). While dating apps tend to be stereotyped as 'hook-up apps' (Hobbs et al., 2017, p. 278; Ranzini & Lutz, 2017, p. 81), they are often employed to find romantic relationships: connections that are 'serious, meaningful and long-term oriented' (Chan, 2017, p. 247). If, as theorized above, the relationship between trust and interest in matches is partially explained by confirmation bias, this effect will be stronger for those who are looking for a romantic partner. In pursuit of their relational goals, these users can improve their communication with potential partners, for instance by disclosing more or being more authentic (Ranzini & Lutz, 2017, p. 88). Research on Tinder has found that those with a relationship-seeking motive are more likely to meet other users offline (Sumter et al., 2017, p. 14). On the other hand, if users are only using dating apps to get an 'ego boost' or to entertain themselves, whether they match with potential partners who they are interested in is not particularly relevant (Corriero & Tong, 2016, p. 126). In other words, a higher belief in matching algorithms will not incentivize individuals to engage more with other users, as these individuals are not as concerned with getting to know their matches (Sharabi, 2021, p. 936). Consequently, users who are motivated to build stronger connections with matches, such as forming a serious romantic relationship, may experience a stronger effect of algorithm trust on satisfaction with matches.

H7: The association between trust in dating app algorithms and satisfaction with matches is greater among users with a relationship motive

The theoretical framework for the mediation effect of awareness on satisfaction with matches is visualized in Figure 2.

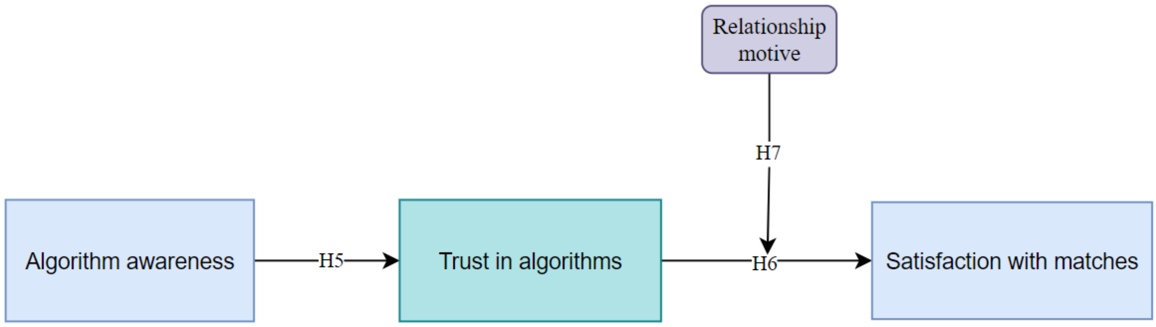

Figure 2.

Visualization of the relationship between algorithm awareness and satisfaction with matches

3. RESEARCH DESIGN

This study empirically assessed the relationship between awareness of dating app algorithms, self-perceived attractiveness, and satisfaction with matches. To do so, data was collected with the use of a digital survey, targeted at individuals who are currently using dating apps. Surveys are suitable to quantitatively assess the characteristics, emotions, or opinions of a given population (Coughlan et al., 2009, p. 7). Furthermore, as filling in a survey is done anonymously and takes relatively little effort, more participants can be reached (Wright, 2005, p. 1035). The survey was designed with the Qualtrics online survey tool. Because data about dating is sensitive, the survey was anonymous to comply with ethical research standards and to respect participants' privacy. Data was securely stored and not shared with third parties. Before participants gave their consent, they were informed about their anonymity, the overall purpose of the research, as well as their right to withdraw their participation at any moment. The target population consisted of adults who used Breeze in the previous 31 days. If participants did not meet these qualifications, they were filtered out of the survey. The list of questions can be found in Appendix A.

3.1. Sample

The sample for this research was collected in collaboration with Breeze among its userbase. To boost the response rate, Breeze selected 5000 users who were often active or who participated in surveys in the past. These users received a pop-up on the app with a link to the survey. This is a form of convenience sampling, and it is non-probabilistic as not every Breeze user had an equal chance of participating (Fricker, 2017, p. 8). Therefore, the sample was possibly biased by the fact that these respondents used the app more than others. The pop-up was active for two days, after which sufficient data was collected. In total, the survey received 688 responses. Of these, 23 respondents did not qualify due to not having used Breeze in the previous month, and 165 respondents did not finish the survey. As a result, 500 complete responses remained in the final sample. Because only complete responses could be used in the analysis, there were no missing data that could be addressed or imputed. Table 1 shows a breakdown of important descriptors. Most respondents were Dutch (79.2%) and heterosexual (91.2%). The majority of respondents were male (62%). Most users obtained a bachelor's degree (43%) followed by a master's degree (28%) and vocational education (17.4%). They most often created their accounts less than half a year ago (43%). The mean age of the sample was 36 (*SD* = 10.67).

Table 1.

Demographic descriptors of complete sample

Variable	Number of observations	Percentage
Gender		
Male	309	62%
Female	189	38%
Non-binary/other	2	0%
Sexuality		
Heterosexual	456	91.2%
Homosexual	24	4.8%
Other (bisexual, pansexual, asexual, unsure)	20	4%
Nationality		
Dutch	391	79.2%
Belgian	101	20.2%
Other	3	0.6%
Highest obtained education		
Less than high school	0	0%
High school	47	9.4%
Vocational	87	17.4%
Bachelor's degree	215	43%
Master's degree	140	28%
PhD	6	1.2%
Other	5	1%
How long ago was the account created?		
Less than half a year ago	215	43%
More than half a year ago	116	23.2%
More than a year ago	169	33.8%

3.2. Measures

This section sets out the operationalizations of the various used concepts, along with the control variables. For each scale, a confirmatory factor analysis (CFA) was used to test whether the items appropriately measured the same *latent* variable: the unobserved construct that each scale aims to assess (Brown & Moore, 2012, p. 381). CFA is typically conducted using *maximum likelihood* (ML) estimation, but as this assumes a continuous distribution, ML might be problematic for ordinal Likert scales, especially if there are only a few answer options (Li, 2016, p. 937). Instead, CFA was carried out with the *weighted least square mean and variance-adjusted* (WLSMV) method, which was designed for ordinal Likert scales (Park, 2023, p. 86). The standardized factor loadings for all measures can be found in Appendix B. If the scale was altered for this research, CFA outputs are also discussed below. An item was removed if it yielded a factor loading of below .600, and removing the item substantially improved Cronbach's alpha. All mean values and standard deviations can be found in Table 3.

Algorithmic awareness. Algorithmic awareness refers to the self-reported knowledge that dating app users have about algorithm functioning. According to Hamilton et al. (2014), this is measured best by presenting respondents with a particular algorithmic feature, such as news feed filtering on Facebook, and asking them whether they are familiar with it (p. 638). This is difficult in the case of dating apps, given that there is little certainty about their exact features, and they may differ widely between apps (Courtois & Timmermans, 2018, p. 6; Iovine, 2021, para. 3). This research used the Algorithmic Media Content Awareness (AMCA) scale developed by Zarouali et al. (2021), which focuses on four dimensions that can be used as a single measure as well: content-filtering, automated decision-making, human-algorithm interplay, and ethical considerations (p. 6). This scale was developed for recommender systems such as Spotify and Facebook. Therefore, the phrasing was changed to suit the dating app context. The scale consisted of questions such as 'Algorithms are used to recommend profiles to me on Breeze' or 'It is not always transparent why algorithms decide to show me certain profiles on Breeze.' Answer options were based on a 5-point Likert scale, ranging from 'completely not aware' to 'completely aware.' The average value was 3.06 (SD = 0.84), indicating that participants tend to lean towards higher awareness. The Cronbach's alpha was high (α = .93), indicating good internal consistency.

Matching success. Matching success was adapted from the Subjective Online Success scale by Her and Timmermans (2021). This is a four-item Likert scale with statements such as 'I think that I have many matches on dating apps' with answer options ranging from 1 ('completely disagree') to 5 ('completely agree'). Two items revolve around receiving and sending messages, such as 'I think that I receive many conversations initiated by other users' (p. 1310). This does not apply to Breeze, given that users are unable to chat with each other before going on a date. Therefore, these two items were replaced with the item 'I think that many other users want to go on a date with me on Breeze,' turning the measure into a three-item scale. The obtained mean value of 2.10 (SD = 0.98) was slightly below the middle of the answer range, meaning that self-reported success tended to be moderately low. The scale yielded a good Cronbach's alpha (α = .85). The factor loadings all exceeded .800. Note that because the scale only had three items, the model fit indicators were unreliable and therefore not taken into account (Kline, 2023, p. 201).

Self-perceived attractiveness. Self-perceived attractiveness was measured using the ‘physical appearance’ subscale of the Personal Evaluation Inventory (PEI) by Shrauger and Schohn (1995). This seven-item Likert scale measured one’s overall self-perceived attractiveness. Three items estimated participants’ positive conception of self-perceived attractiveness, for instance ‘I am pleased with my physical appearance.’ The remaining items were negatively phrased, with statements such as ‘most people would probably consider me physically unattractive’ (Shrauger & Schohn, 1995, p. 277). Answer options ranged from 1 (‘strongly disagree’) to 4 (‘strongly agree’), and responses were recoded so that higher responses indicate higher self-perceived attractiveness. Participants tended to report themselves as having relatively high attractiveness (M = 2.76, SD = 0.64). The scale yielded good internal consistency (α = .85).

Algorithm trust. Algorithm trust was assessed using Sharabi's (2021) algorithmic beliefs scale, consisting of seven Likert-scale items (e.g. ‘I would trust matching algorithms to find me a partner’) (p. 938). Answer options ranged from 1 (‘strongly disagree’) to 7 (‘strongly agree’). However, three out of seven items on this scale revolved around participants’ faith in the app’s ability to find them a romantic partner. Users may have different motivations for using online dating, such as finding casual sex or passing time (Timmermans & De Caluwé, 2017, p. 348). These users have other conceptions of dating success, and the original scale might not be relevant to them. Therefore, the phrasing of the scale items was altered to make it applicable to various dating goals. For instance, ‘matching algorithms lead to more successful relationships’ was changed to ‘Breeze algorithms lead to more successful connections’ (see Appendix A for the full list). The average value converged towards the middle of the scale range (M = 3.36, SD = 1.05). CFA factor loadings exceeded .600 except for one item: ‘A mathematical formula can predict who I will be attracted to’ (.469). However, this was not removed as doing so did not substantially improve the Cronbach’s alpha of .86.

Satisfaction with matches. Whether users were satisfied with the quality of matches that they received was measured using mate-searching difficulty, developed by Hu and Zhan (2024, p. 6). Respondents were asked how difficult it is to find people who, for instance, ‘You are physically attracted to’ or ‘Seem like someone you would want to meet in person.’ Answer options ranged from 1 (‘very easy’) to 4 (‘very difficult’) (M = 1.99, SD = 0.66, α = .84). The mean value of satisfaction with matches was situated very closely to the middle of the answer range. This scale was applicable regardless of the type of relationship users were looking for.

Motivation of use. The motivation of use measure assessed the presence of two motives for using dating apps, chosen from the Tinder Motivates Scale (Timmermans & De Caluwé, 2017, p. 349). These two were relationship-seeking (M = 5.92, SD = 0.87, α = .83) and ego boost-seeking (M =2.52, SD = 1.28, α = .89). These featured items such as ‘I use Breeze to fall in love’ or ‘I use Breeze to get compliments’ with answer options ranging from 1 (‘totally disagree’) to 7 (‘totally agree’) (p.

1310). After conducting CFA, one item in the relationship-seeking motive, ‘I use Breeze to date,’ yielded a low factor loading (.360) and was removed. This boosted the Cronbach’s alpha from acceptable (.77) to good (.83) and resulted in a total of ten items. Interestingly, the average value of relationship-seeking among the sample was more than twice as high as ego boost-seeking. A paired samples t-test showed that these estimates were significantly different, $t(497) = 47.08$, $p < .001$.

Self-esteem. Self-esteem was used as a control variable, and measured with the Rosenberg scale, which has high reliability and correlates significantly with other self-esteem scales (Rosenberg, 1979, p. 61; Zervoulis et al., 2020, p. 13). This Likert scale ranged from 1 (‘strongly disagree’) to 4 (‘strongly agree’) and incorporated both measures of positive self-esteem (e.g. ‘I feel that I’m a person of worth’) as well as negative self-esteem (e.g. ‘I feel I do not have much to be proud of’). Reliability in this sample was also quite high ($\alpha = .89$). The average value of 3.19 ($SD = 0.51$) indicates that respondents tended to have higher self-esteem scores.

Along with measuring the concepts above, the survey collected other (demographic) data that are associated with dating app outcomes: age (Hu & Rui, 2023, p. 5) and gender (Bale & Archer, 2013, p. 70; Strubel & Petrie, 2017, p. 35). The survey incorporated a measure of time spent on the dating app. Users were asked about their frequency of use, ranging from 1 (‘almost never’) to 7 (‘multiple times a day’) ($M = 5.43$, $SD = 1.18$). Note that the average value of frequency was quite high, indicating that respondents tended to check Breeze often.

As the research population was dating app users from the Netherlands and Flanders, the items had to be translated into Dutch. For the Tinder Motivates Scale, a Dutch translation was provided by the authors (Timmermans & De Caluwé, 2017, p. 349). Similarly, a pre-translated version of the Rosenberg scale was used (Vervloed, n.d., para. 5). The other items were translated using the forward-backward method (Maneesriwongul & Dixon, 2004, p. 180). After first translating the items into Dutch, a student who was not involved in the research translated these back into English to ensure the meaning remained consistent.

3.3. Statistical analyses

To test the relationships between variables, *structural equation modeling* (SEM) was employed, using *lavaan 0.6-17* in R 4.2. SEM is particularly useful when investigating multi-faceted constructs that are related in a more complex causal system, for instance when looking at a mediated effect (Ullman & Bentler, 2012, p. 38). In the first model, the relationship between algorithm awareness and self-perceived attractiveness was tested, mediated by self-reported success on Breeze. The direct effect of awareness on self-perceived attractiveness was also estimated. Age and gender were used to control for possible confounding, given that both have been shown to affect algorithm awareness as well as success on dating apps (Castro & Barrada, 2020, p. 15; Gran et al., 2021, p. 1785; Timmermans & Courtois, 2018, p. 14). Similarly, individuals who use Breeze often might be more aware of algorithm functioning, and frequency of use could also impact the level of matching success (Alexopoulos et al., 2020, p. 174; Brodsky et al., 2020, p. 44). Therefore, frequency of use was also used as a covariate. It needs to be noted that while this latter measure is technically categorical, it was deemed appropriate to use as continuous given its distribution (Rhemtulla et al., 2012, p. 370). It was hypothesized that the effect of success on attractiveness is moderated by both gender and an ego boosting motive. Therefore, these variables were included as interaction terms. Self-esteem was also controlled for as it possibly confounds the relationship between self-perceived success and self-perceived attractiveness (Bale & Archer, 2013, p. 74), as does age (Brase & Guy, 2004, p. 477). The second model used SEM to test the associations between algorithm awareness, trust, and satisfaction with matches on dating apps. Again, this also included testing the direct effect of awareness on satisfaction. The same set of covariates (age, gender, and frequency of use) was used in the pathway between awareness and trust, as well as between trust and satisfaction, given that they have been shown to affect all variables (Alexopoulos et al., 2020, p. 174; Cabiddu et al., 2022, p. 692; Hu & Wang, 2023, p. 6). The relationship motive of use was tested as a moderator between algorithm trust and satisfaction with matches.

Both models included interaction terms made up of two latent variables. Such constructs are rarely implemented in SEM because they require more complex non-linear specifications (Marsh et al., 2004, p. 276). Luckily, new approaches have been developed that allow for a more simple execution for applied researchers (Lin et al., 2010, p. 375). The approach used in this research, *double-mean-centering*, consisted of first centering the indicators, creating the interaction terms by multiplying these with the predictor variable, and finally centering the interaction terms again. This method is less complicated than alternative approaches and shown to be superior when the normality assumption is violated (Lin et al., 2010, p. 386). This technique is easily accessible in the *semTools* package in r. Because there are currently no appropriate methods to estimate goodness-of-fit for models that include latent interactions, these indicators were gathered by first fitting the models without interaction terms (Schoemann & Jorgensen, 2021, p. 327). There are various indices for assessing model fit, which can show substantial variability depending on the model's characteristics (Stone, 2021, p. 2). Based on the recommendation by Kline (2023), four indices were reported: model chi-square test, root mean square error (RMSEA), the comparative fit index (CFI), and the standardized root mean square error (SRMR) (p. 289). For each path, the R-squared was reported as well.

Similarly to the CFA, fitting the SEM models would be most appropriate using the WLSMV estimator given that the measurement items were categorical rather than continuous. However, lavaan was unable to perform this operation due to the high number of categories resulting from the double-mean-centering procedure. Instead, the model parameters were estimated using ML with the nonparametric bootstrap with 2000 iterations based on recommendations by Lai (2018, p. 617). This approach does not assume normally distributed data (Lai, 2018, p. 601), which is advantageous in the case of the collected sample, as will be shown in the following section.

3.4. Assumptions tests

Before conducting the analyses, several tests were used to assess whether the data distributions met the assumptions for regression, the results of which are summarized in Table 2 below. Linearity was assessed by inspecting a plot of the residuals against the fitted values. When these plots appeared to deviate from linearity, this was examined using a Durbin-Watson test. Similarly, homoscedasticity and the absence of influential outliers were confirmed with a scale-location plot combined with the Breusch-Pagan test and a plot of the residuals versus leverage respectively. VIF scores of below 2 for all models showed that multicollinearity was not an issue for the analyses. Normality, however, proved to be somewhat problematic. Density plots of self-perceived success especially, as well as satisfaction with matches, appeared to be substantially non-normal, which was confirmed with the Shapiro-Wilkins test. Because, as explained above, bootstrapping was used to estimate SEM, no action was undertaken to address this non-normality. Table 3 shows the correlations between all variables used in the two models, as well as the means and standard deviations.

Table 2.

Assumption checks of statistical models

Outcome variable	Linearity	Normality	Homoscedasticity	Absence influential outliers	Multicollinearity
Model 1					
Success	Met	Not met	Met	Met	Met
Self-perceived attractiveness	Met	Met	Met	Met	Met
Model 2					
Trust	Met	Met	Met	Met	Met
Satisfaction with matches	Met	Not met	Met	Met	Met

Table 3.

Descriptive statistics and correlation matrix for continuous variables

Variable	Mean	*SD*	Range	1	2	3	4	5	6	7	8	9	10
1. Age	35.52	10.67	19-69										
2. Frequency of use	5.43	1.18	1-7	-.09*									
3. Algorithm awareness	3.06	0.84	1-5	-.14**	.06								
4. Trust in algorithms	3.35	1.05	1-7	-.03	-.02	.27***							
5. Self-perceived success	2.10	0.98	1-5	-.06	-.19***	.03	.26***						
6. Self-perceived attractiveness	2.76	0.64	1-4	.12*	-.08	-.04	-.09*	.37***					
7. Satisfaction with matches	1.99	0.66	1-4	-.13**	-.18***	.10*	.29***	.51***	.041				
8. Ego boosting motivation	2.52	1.28	1-7	-.11*	-.02	.06	.16***	.07	-.10*	.06			
9. Relationship-seeking	5.92	0.87	1-7	.04	.09	.01	.11*	-.03	-.06	-.02	-.09*		
10. Self-esteem	3.19	0.51	1-4	.14**	-.00	-.02	-.06	.11*	.50***	-.01	-.27***	.03	

Note: significance levels: p <.001***, p <.01 **, p <.05
N = 500
Descriptives are based on composite rather than latent scales

4. RESULTS

4.1. Model 1: Algorithm awareness, success and attractiveness

The first model explored the relationship between Breeze users' algorithm awareness, self-perceived success in terms of matching and going on dates, and their self-perceived attractiveness. The results of SEM can be found in Table 4. Here the unstandardized and standardized coefficients, as well as the accompanying standard errors and significance levels are reported. The interpretation focused mainly on the unstandardized estimates. The main effects are visualized in Figure 3.

First, it is important to consider the goodness-of-fit indicators of the model to assess the overall appropriateness of the analysis. Both the RMSEA (.051) and SRMR (.062) stayed below the thresholds of .06 and .08 respectively, suggesting a reasonable fit (Hooper et al., 2007, p. 54). During the first run of the model, the CFI score did not exceed the minimal acceptable value of .900. This was improved by modeling error covariances between two items for the algorithm awareness scale and two items in the attractiveness scale, after an inspection of the modification indices. Unfortunately, the chi-square test yielded a significant result, indicating a poor model fit. However, it needs to be noted that this test is very sensitive to sample size, and as *N* increases, the null hypothesis is likely to be rejected based on small discrepancies (Peugh & Feldon, 2020, p. 19).

The first part of the model equation concerned the relationship between algorithm awareness and self-perceived success, the mediator. The path explained a quite small proportion of variance in the outcome variable ($R^2 = .103$). Here, there was a small and non-significant effect ($b = 0.081$, $p = .111$). Therefore, the first hypothesis (H1) could not be supported. Gender had a strong significant effect on self-perceived success ($b = 0.502$, $p < .001$), meaning that female users found it easier to get matches and go on dates. Interestingly, frequency of use had a small negative effect on self-perceived success ($b = -0.091$, $p = .023$). The path between self-perceived success and attractiveness did show a substantial significant positive relation ($b = 0.212$, $p < .001$). This indicated that users who considered themselves to be more successful on Breeze also considered themselves to be more attractive, after controlling for general self-esteem. This offered support for H2: matching success is positively related to one's assessment of their attractiveness. Furthermore, the variance explained by the model was relatively high (.438), indicating that it fit the data somewhat well. There was no evidence for the existence of an interaction effect between ego boosting motivation and self-perceived success (H3) ($b = -0.009$, $p = 0.729$). For gender as a moderator, on the other hand, there was a significant negative effect on self-perceived attractiveness ($b = -0.140$, $p = .027$), meaning that the association between success and attractiveness was weaker among women (H4).

With regards to the direct estimated effect of algorithm awareness on self-perceived attractiveness, the estimate was negative and non-significant ($b = -0.033$, $p = .290$). The indirect estimated effect was also non-significant ($b = 0.071$, $p = .122$).

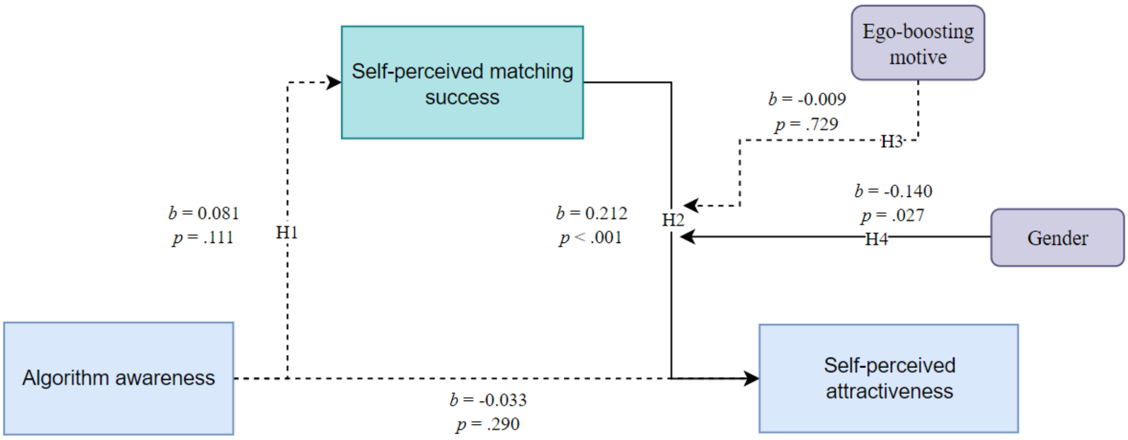

Figure 3.

Visualization of results of first model

Note: dashed lines indicate non-significant relationships

Table 4.

SEM results for the first model

	Self-perceived success (mediator)				*Self-perceived attractiveness (outcome)*			
	Unstandardized		Standardized		Unstandardized		Standardized	
	Coeff.	*SE*	Coeff.	*SE*	Coeff.	*SE*	Coeff.	*SE*
Main effects								
Algorithm awareness	0.081 (*H1*)	0.051	0.076 *(H1)*	0.047	-0.033	0.031	-0.044	0.041
Success	---	---	---	---	.212*** (*H2*)	0.038	0.302*** *(H2)*	0.044
Ego boost motive	---	---	---	---	0.009	0.026	0.016	0.044
Ego boost motive x success	---	---	---	---	-0.009 *(H3)*	0.027	-0.016 *(H3)*	0.045
Gender (1 = female)	0.502***	0.098	0.257***	0.048	0.009	0.058	0.007	0.042
Gender x success	---	---	---	---	-0.140* *(H4)*	0.063	-0.096* *(H4)*	0.043
Covariates								
Age	-0.009*	0.004	-0.101*	0.046	0.004	0.003	0.066	0.040
Self-esteem	---	---	---	---	0.893***	0.088	0.585***	0.038
Frequency of use	-0.091*	0.036	-0.113	0.049	---	---	---	---
Measures of fit								
*R*²	.109				.438			
RMSEA	.051							
SRMR	.062							
CFI	.900							
χ2	1835.335***, df = 804							
Effect sizes								
Direct effect	-0.033	0.031	-0.044	0.040				
Indirect effect	0.071	0.011	0.023	0.015				

Note: Significance levels: *p* < .001***, *p* < .01 **, *p* < .05 *
N= 498 (two respondents who identified as neither male nor female were removed)

4.2. Model 2: Algorithm awareness, trust, and satisfaction with the quality of matches

The second model explored the associations between algorithm awareness, trust in dating app algorithms, and users' satisfaction with the quality of their matches. The results can be found in Table 5 and a visual representation in Figure 4. Compared to the first model, the fit indices were slightly better, with an RMSEA and SRMR of .047 and .053 respectively, and a CFI above .900. The chi-square test, however, was again highly significant, possibly indicating a poor model fit.

The fifth hypothesis revolved around the path between algorithm awareness and trust. Here, a strongly significant and moderately large positive association was found while controlling for age, gender, and frequency of use (b = 0.342, p < .001). Users who were more aware of algorithm functioning were thus also more trusting of Breeze's algorithms. Therefore, the results offered support for H5. However, the variance in trust explained by awareness, frequency of use, and age was quite low (R^2 = .086). The subsequent path between trust and satisfaction with matches also yielded a positive and significant estimate (b = 0.213, p < .001), which confirms H6: users who have more faith in the dating app's abilities are also more likely to be interested in the people that they match with on the app. The explained variance of this equation on satisfaction with matches was bigger than the first path, but still relatively small, with an R^2 of .224.

Age (b = -0.008, p = .001) and frequency of use (b = -0.075, p = .002) negatively impacted satisfaction with matches, although these effects were small. Being female again had a positive effect on being satisfied with matches (b = 0.145, p = .013). However, this effect was both smaller as well as less significant than the effect of gender on self-perceived success in model 1. The hypothesized interaction between relationship-seeking and trust was non-significant (b = 0.055, p = .082), meaning that there was no support for H7: users who are more interested in establishing a romantic relationship will have a stronger association between trust in algorithms and satisfaction with matches. While the direct effect was essentially zero and highly non-significant (b = 0.001, p = .980), the total indirect effect was positive and significant (b = 0.073, p < .001), indicating that we are dealing with a full mediation effect (Gunzler et al., 2013, p. 392).

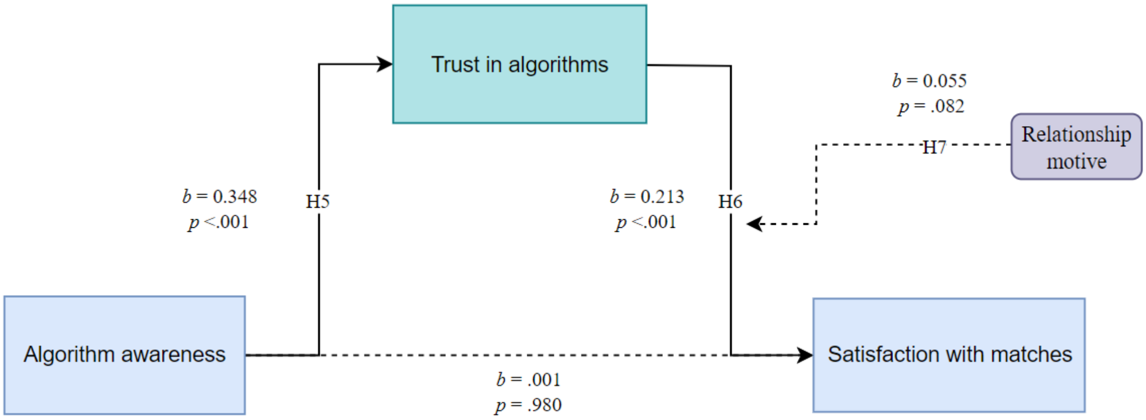

Figure 4

Visualization of results of second model

Note: dashed lines indicate non-significant relationships

Table 5.

SEM results for the second model

	Trust (mediator)				*Satisfaction with matches (outcome)*			
	Unstandardized		Standardized		Unstandardized		Standardized	
	Coeff.	*SE*	Coeff.	*SE*	Coeff.	*SE*	Coeff.	*SE*
Main effects								
Algorithm awareness	0.342*** (*H5*)	0.059	0.287***(*H5*)	0.046	0.001	0.032	0.001	0.048
Trust	---	---	---	---	0.213*** (*H6*)	0.030	0.381*** (*H6*)	0.047
Relationship-seeking	---	---	---	---	-0.021	0.037	-0.028	0.048
Relationship-seeking x success	---	---	---	---	0.055 (*H7*)	0.032	0.086 (*H7*)	0.049
Covariates								
Age	-0.001	0.005	-0.002	0.047	-0.008**	0.002	-0.153**	0.044
Gender (1 =female)	-0.082	0.108	-0.038	0.050	0.145*	0.058	0.120*	0.048
Frequency of use	-0.059	0.044	-0.066	0.050	-0.075**	0.024	-0.152**	0.047
Measures of fit								
R^2	.086				.223			
RMSEA	.047							
SRMR	.053							
CFI	.934							
$\chi 2$	832.018***, df = 394							
Effect sizes								
Direct effect	0.001	0.032	0.001	0.048				
Indirect effect	0.073***	0.016	0.109***	0.023				

Note: significance levels: $p < .001$***, $p < .01$ **, $p < .05$ *
N= 498

Table 6 below shows an overview of the hypotheses, and whether or not they are supported by the analyses. The implications of these results will be discussed further in the discussion section.

Table 6.

Summary results for hypotheses

	Hypothesis	Supported
Model 1		
H1	Algorithm awareness is positively associated with self-perceived matching success on dating apps	No
H2	Self-perceived matching success on dating apps is positively associated with self-perceived physical attractiveness	Yes
H3	The association between perceived matching success on dating apps and self-perceived physical attractiveness is greater among users with an ego boosting motive	No
H4	The association between perceived matching success on dating apps and self-perceived physical attractiveness is greater among male users	Yes
Model 2		
H5	Algorithm awareness is positively associated with trust in dating app algorithms	Yes
H6	Trust in dating app algorithms is positively associated with satisfaction with matches	Yes
H7	The association between trust in dating app algorithms and satisfaction with matches is greater among users with a relationship motive	No

5. DISCUSSION

Today, dating apps play a pivotal role in matchmaking (Berger, 2023, p. 3; Hobbs et al., 2017, p. 272). These platforms leverage AI to present users with potential matches and market these algorithms as effective and convenient (Paul & Ahmed, 2023, p. 1). Nonetheless, they do not fully disclose how their algorithms calculate compatibility, leading users to navigate online dating with varying levels of awareness of the recommender system (De Ridder, 2022, p. 549). Unfortunately, little is known about how users' understanding of these algorithms affects how they experience dating apps (Paul & Ahmed, 2023, p. 1). Therefore, this research explored the role of awareness of matching algorithms among users of the dating app Breeze. In particular, it examined the relationship between algorithm awareness and users' self-perceived attractiveness and satisfaction with matches.

In the first analysis, it was theorized that a higher awareness of algorithm functioning would enhance matching success (Hu & Zhan, 2024; Nader & Lee, 2022, p. 455), thereby boosting users' self-perceived attractiveness. However, no support was found for this mediation effect. Awareness of the recommender system did not significantly improve users' success in matching with others, contradicting findings by Hu and Zhan (2024) that algorithm awareness positively impacts users' chances on dating apps (p. 10). In contrast to expectations (Vera Cruz et al., 2023, p. 607), users who reported more frequent use of Breeze also reported lower matching success. This small negative effect of use frequency may be explained by Breeze's affordances. Users immediately commit to going on a date after matching, and obtaining many matches is thus unpractical. Conversely, users who have not found a match will continue to use the app longer. The relationship between success and use time may differ for other dating apps. For instance, in a study among Tinder users, Courtois and Timmermans (2018) found a positive but nonsignificant effect of use frequency on perceived success (p. 175).

SEM analysis did reveal a strong positive relationship between self-perceived success and self-perceived attractiveness. Such an association is not very surprising, as mobile dating applications such as Breeze have a photo-centric layout and physical appearance largely determines swiping decisions (Fiore et al., 2008, p. 2; Kallis, 2021, p. 81). Consequently, failure to match with others might negatively affect one's assessment of their own attractiveness (Castro & Barrada, 2020, p. 14). This aligns with the finding that outside of online dating, romantic rejection also decreases individuals' self-perceived mate value (Zhang et al., 2015, p. 4). However, alternative causal mechanisms cannot be ruled out. For instance, while self-perceived attractiveness and externally rated attractiveness are different concepts, they are highly correlated (Teng et al., 2022, p. 539). Therefore, attractive users may receive more matches and simultaneously be more satisfied with their appearance. As it was not possible to control for 'actual' attractiveness, this may confound the relationship between dating app success and self-perceived attractiveness.

Notably, the research found that the relationship between self-assessed attractiveness and success is stronger among men. This corroborates the observation that male users face more negative appearance feedback on dating apps (Rodgers et al., 2020, p. 1472; Strubel & Petrie, 2017, p. 37). Male users generally have much less matching success (Timmermans & Courtois, 2018, p. 14; Tyson et al., 2016, p. 4). However, it is surprising that success impacts self-perceived attractiveness more among men, given that women tend to be more sensitive to appearance-based rejection (Bale & Archer, 2013, p. 71; Park et al., 2009, p. 116). Furthermore, it was hypothesized, following Uses and Gratification theory, that user motivations would impact the relationship between reported matching success and self-perceived attractiveness. However, when using the ego boost motivation as a moderator, no significant effect was found.

In the second analysis, it was found that algorithm awareness was associated with more satisfaction with the quality of the people that users match with, in terms of attraction and compatibility. This effect was mediated by trust in Breeze's recommender system. Users who reported being more knowledgeable about algorithms also exhibited more trust in the matching abilities of the system. The results suggested that awareness of the recommender system tends to be accompanied by faith that the dating app can offer suitable potential partners. This association can be explained by cue effects, consistent with the HAII-TIME framework (Jang et al., 2022, p. 4). If online daters recognize that algorithms are in effect, this triggers cognitive heuristics based on the belief that AI is accurate and objective (Sundar, 2020, p. 80). As a result, these users will evaluate the system more positively, exhibiting more trust in Breeze's ability to find compatible matches (Jang et al., 2022, p. 6).

Lastly, trust in the recommender system was positively related to satisfaction with matches. Users who had more faith in Breeze's matching algorithms also found it easier to match with people that they were interested in. This can be attributed to expectancy effects: if online daters expect to receive favorable profile recommendations because they believe that the matching algorithm works well, they will also be happier with the outcomes (Finkel et al., 2012, p. 27). Simultaneously, users' behavior could also change if they believe that a match is compatible. For instance, if this conviction prompts them to invest more effort in communicating (Hu & Rui, 2023, p. 2). Alternatively, if users have good experiences with the matches that they come across, they are also more likely to reflect more positively on the abilities of the system. However, given Sharabi's (2021) experimental evidence that belief in algorithms positively affects date evaluations, it is plausible that trust in the recommender system does influence satisfaction with matches (p. 941). This association appeared to be unaffected by whether or not users were seeking a romantic relationship.

Overall, it appeared that awareness of algorithms affects the degree to which users are interested and satisfied with their matches on dating apps, mediated through the trust they have in the abilities of the recommender system. Breeze users who reported a higher understanding of the functioning of matching algorithms also found it easier to match with potential partners that they considered attractive or were interested in meeting in person. While there was no relationship between awareness and success in terms of matches, having more knowledge about algorithmic functioning was associated with a more positive experience on dating apps.

5.1. Limitations and future research

Several shortcomings of the research need to be noted. Importantly, it is impossible to establish causality based on cross-sectional and observational data (Savitz & Wellenius, 2023, p. 514). Especially the paths between success and attractiveness, as well as between trust and satisfaction with matches, could be better investigated with longitudinal or experimental methods. Concerning the statistical analyses, the goodness-of-fit indicators signaled possible issues. Firstly, the R-squared of the paths between algorithm awareness and success, and between algorithm awareness and trust, were remarkably low, both below .110. This indicates that the model equations had little explanatory power for the values of success and trust. While models with low R-squared can still be valid if some predictors are shown to be significant (Ozili, 2023, p. 8), it needs to be kept in mind that the specified regressions captured only a small proportion of variance. Secondly, while most global fit statistics were adequate, the chi-square test was significant for both models. Because significant chi-square statistics are common in empirical research and the metric is sensitive to large sample sizes, this was not considered a major threat to the validity of the results (Kline, 2023, p. 271; Peugh & Feldon, 2020, p. 19).

A further limitation relates to the operationalization of algorithm awareness. The used AMCA scale was developed by Zarouali et al. (2021) to address the scientific lack of consensus about how to measure awareness of algorithms on social media platforms (p. 2). While this scale was shown to be reliable and valid, its use in the context of this study introduced three possible issues (Zarouali et al., 2021, p. 8). Firstly, the scale tested to what degree users consider themselves aware of certain features of recommender systems, for instance, content filtering or automated decision-making (Zarouali et al., 2021, p. 2). However, users' perceived awareness may not fully correspond to their actual awareness of these features (Radecki & Jaccard, 1995, p. 129). Secondly, the AMCA scale was initially created for platforms such as Facebook and Netflix (Zarouali et al., 2021, p. 4). Therefore, it did not account for a unique feature of online dating: that profiles are not only shown to the user but the user is also shown to other profiles. As research on algorithm awareness in the context of dating apps is scarce (Paul & Ahmed, 2023, p. 1), it could not be confirmed that the AMCA scale is suitable for matching algorithms. Lastly, because the exact functioning of dating app algorithms is unclear, the five dimensions tested by the AMCA scale may not all be applicable (Courtois & Timmermans, 2018, p. 12). Ideally, future research would critically examine the operationalization of algorithm awareness, potentially developing a metric for the online dating context.

The results of this research were also possibly influenced by the sampling population. The affordances and marketing strategies of dating apps can attract userbases with different characteristics and interests (Wu & Trottier, 2021, p. 3). Breeze differentiates itself from popular apps such as Tinder by skipping the chatting stage and providing a limited amount of recommended profiles (Breeze, n.d.-b, para. 1). As a result, Breeze users quickly commit to meeting up with someone in person. These features might attract particular types of users, for instance, daters who are looking for more serious connections. In the used sample, the relationship-seeking motivation was present to a high degree (*M* = 5.92). In comparison, studies that apply the motivations scale to groups of Tinder users typically found mean values close to 4 (Barrada & Castro, 2020, p. 9; Degen & Kleeberg-Niepage, 2022, p. 185; Timmermans et al., 2018, p. 132; Timmermans & De Caluwé, 2017, p. 347). Furthermore, the average age of the sample was relatively high, approximately 36. This is somewhat unexpected as the user base of dating apps typically consists of young adults (Sumter & Vandenbosch, 2019, p. 655). These sample characteristics, along with possible differences in unobserved variables, might result in different estimates if applied to another population.

Similarly, it is unknown whether the affordances of Breeze themselves affected the identified mechanisms. For instance, because there are fewer opportunities for matches, users may pay more attention to the recommender system compared to dating apps that offer endless partner suggestions. This in turn could affect how users view the functioning and abilities of algorithms. As there appears to be no literature focused on the perceptions of ‘finite’ dating app algorithms such as Breeze’s, this remains speculative. Regardless, caution is warranted when generalizing these results to the entire population of dating app users. Through replicating this study among different populations, future research could explore whether the role of algorithm awareness differs between dating apps. Furthermore, it needs to be noted that 90% of the sample identified as heterosexual, and online dating dynamics may differ among populations of Queer users. For instance, the finding that the effect of success on self-perceived attractiveness is stronger for men might disappear when focusing on same-sex interactions (Tyson et al., 2016, p. 4). Therefore, extending the analysis with an examination of non-heterosexual people might be beneficial.

Lastly, future studies should aim to provide a nuanced understanding of the effects of algorithm awareness. Firstly, while algorithm awareness did not appear to influence matching success, it is unclear whether it affects behavior. In particular, while several scholars have qualitatively mapped users’ strategies to boost algorithmic functioning (Huang et al., 2022, p. 1; Myles & Blais, 2021, p. 1; Nader & Lee, 2022, p. 455), it is unclear whether algorithm awareness actually triggers these actions (Hu & Zhan, 2024, p. 11). Future studies could empirically test an association between awareness and algorithm-boosting strategies, possibly developing a metric that assesses the latter. Secondly, as explained above, the positive relationship between awareness and trust can be explained by cue effects. However, it is yet to be establish that awareness of matching algorithms does actually produce positive heuristics (Hu & Wang, 2023, p. 10). Research could benefit from exploring how awareness interacts with specific attitudes towards AI. For instance, *algorithm aversion* refers to the reluctance to engage with methods because they are based on AI (Burton et al., 2020, p. 220). This can for example occur if individuals are critical of the intransparency surrounding these programs. Research has shown that algorithm aversion can exist alongside high trust in the abilities of AI, further complicating the relationship between attitudes and acceptance of recommender systems (Wu et al., 2024, p. 8).

5.2. Implications

Implementations of artificial intelligence are rapidly gaining ground, for instance in education, entertainment, and journalism (Shin et al., 2022, p. 1). While these algorithms are often presented as neutral and unbiased, they have profound power to shape social processes, by for instance reinforcing prejudices or influencing public opinion (Oeldorf-Hirsch & Neubaum, 2023, p. 2; Parisi & Comunello, 2020 p. 86). Similarly, the proliferation of matching algorithms in the world of dating can impact the formation of romantic connections (Nader, 2020, p. 248). As shown by this study, the effects of these algorithms may depend on the knowledge users possess about their mechanisms. It is therefore a key addition to research on how users' perceptions shape algorithmic mediation on dating apps (Myles & Blais, 2021, p. 3).

Theoretically, this study contributed to the literature on human-AI interactions (Sundar, 2020, p. 83). It added to the scholarly understanding of the meaning and effects of algorithm awareness. The results offered support for the hypothesis that users' understanding of the recommender system can have positive effects on the online dating experience. This corroborated findings from scholarly work, particularly on the relationship between awareness and trust in recommender systems. Research has shown that more knowledge is associated with more faith in algorithmic decision-making in various fields (Jang et al., 2022, p. 9; Teodorescu et al., 2023, p. 11). The current study extended these conclusions to the context of dating apps and showed that matching algorithms therefore may share similarities with other recommender systems. This finding is especially interesting given that users tend to judge algorithms as less trustworthy for tasks that emulate 'human intuition' such as matchmaking (Lee, 2018, p. 9). It demonstrated that users' understanding of how the recommender system operates can be an important influence on how they perceive and experience dating apps. Furthermore, previous empirical studies on dating apps relied on a self-made one-item measure to assess algorithm awareness (Hu & Wang, 2023, p. 7; Hu & Zhan, 2024, p. 7). Based on the found literature, this study appears to be the first that employs the AMCA scale for online dating. While, as discussed in the limitations above, it is not entirely certain that this scale is suitable for matching algorithms, it did prove to have good internal consistency in the sample.

If awareness of matching algorithms improves the online dating experience, this implies that improving transparency can be beneficial for users. This takeaway is consistent with the call for transparency that can be heard in scholarship (Grimmelikhuijsen, 2023, p. 243), as well as in new legislation on algorithms, such as the EU's Artificial Intelligence Act (Söderlund et al., 2024, p. 2). Allowing users to 'look into the black box' by making computer code publicly available is not enough, as this does not guarantee that the recommendation mechanism is understandable (Blacklaws, 2018, p. 2). Some dating platforms are trying to inform users about how their algorithms work (Paul & Ahmed, 2023, p. 1004). For instance, Tinder, Hinge, and Breeze all incorporate a 'how does our AI work' section on their websites (Breeze, n.d., para. 5; Hinge, n.d., para. 4; Tinder Newsroom, n.d., para. 5). For users, consuming this information to learn more about algorithm functioning may enhance their faith in the app's abilities, and in turn improve their chances while online dating. However, the materials provided by data apps tend to stay superficial and may offer little substantial benefits (Parisi & Comunello, 2020, p. 68).

Apart from complying with legislative pressures, dating app owners may find it worthwhile to increase algorithm awareness to retain their user bases. Users report frustration and cynicism about the online dating process, even leading to 'dating burnout' (Redling, 2024, p. 86). Recent news coverage suggests that younger daters in particular are gradually turning away from dating apps, causing *Match Group*, the owner of 40 different dating platforms to experience an 80% plunge in stock value from 2021 to 2024 (Brink, 2024, para. 2; Parham, 2023, para. 8). If improving transparency about matching algorithms can cause users to gain faith in the app's abilities, in turn advancing the online dating experience, this could help turn the tide. However, it is questionable whether it is truly in the interest of platform owners to fully inform their user bases. Recommender systems are protected intellectual property to avoid imitation by competitors or manipulation by users (Sharabi, 2021, p. 933). Furthermore, Myles and Blais (2021) argue that 'the mystique surrounding Tinder's algorithm […] is as productive for the matchmaking industry as the actual technical operations they perform' (p. 1). As Jeffrey Tarr already recognized in the 1960s, the enigmatic knowledge of the 'great God computer' brings a great sense of legitimacy. As a result, dating apps must balance transparency and appeal, carefully considering when to open the black box.

5.3. Conclusion

Despite several limitations, this study demonstrated among a sample of Breeze users that a higher awareness of the functioning of matching algorithms was associated with more trust in their abilities. Consequently, when Breeze users had more trust in the recommender system, they found it easier to match with profiles that they were attracted to and interested in. This offered support for the hypothesis that trust mediates the relationship between awareness and satisfaction with matches. Simultaneously, algorithm awareness was not associated with improved success in terms of matching with more Breeze profiles, nor with improved self-perceived attractiveness. However, a higher self-reported success rate was positively related to self-perceived attractiveness, a relationship which was stronger among male Breeze users. Overall, these findings shed more light on the role of algorithm awareness in online dating processes and suggest that enhancing users' understanding of matchmaking algorithms could improve the experience of using dating apps.

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APPENDIX A

Table A1

Full survey

Consent form		
Dear respondent, thank you for your interest in this research. You are invited to participate in a questionnaire about your experiences with Breeze. The questionnaire will take around 7 minutes to fill in. Please answer each question carefully and honestly. Your personal opinions are very important, and there are no right or wrong answers. CONFIDENTIALITY OF DATA All research data remain completely confidential and are collected in anonymous form. We will not be able to identify you. There are no risks or discomforts associated with participating in this research. Results will only be used for academic purposes. Participation in the survey is voluntary, and you can decide to end your cooperation at any time. MORE INFORMATION If you have any questions about this survey, you can contact the researcher: Doris Bukman, email: […] This research is under supervision of dr. Elisabeth Timmermans, author of *Liefde in tijden van Tinder* (Love in Times of Tinder)		
If you understand the information above and agree to participate in the study, select 'I consent' to start the questionnaire 1. I consent 2. I do not consent		
Variable	Source	Questions
Use		In the last 31 days, have you used Breeze? 1. Yes 2. No
Account creation	Timmermans and Courtois (2018)	How long ago did you create your Breeze account? 1. Less than half a year ago 2. More than half a year ago 3. More than a year ago
Frequency of use	Alexopolous et al. (2020)	Approximately, how often do you use Breeze? 1. Almost never 2. Once a month 3. Multiple times a month 4. Once a week 5. Multiple times a week 6. Every day 7. Multiple times a day
Demographic variables		
Age		What is your age?
Nationality		What is your nationality? 1. Dutch 2. Belgian 3. Other …
Gender		What is your gender identity?

		1. Male 2. Female 3. Non-binary 4. Other/prefer not to say
Sexuality		What option describes your sexuality best? 1. Homosexual 2. Bisexual 3. Heterosexual 4. Asexual 5. Pansexual 6. Other/prefer not to say
Education		What is the highest level of education you have completed? 1. Less than high school 2. High school 3. Vocational degree or equivalent 4. Bachelor's degree (university or professional) 5. Master's degree (university or professional) 6. PhD 7. Other ….
Main predictors		
Motivations	Timmermans en De Caluwé (2017)	Please indicate for the following statements how much you agree or disagree I use Breeze.. [Romantic subscale] 1. To find someone for a serious relationship 2. To fall in love 3. To meet a future husband or wife 4. To build an emotional connection 5. To find someone to date [Ego boosting subscale] 12. To get an 'ego boost' 13. To see how desirable I am 14. To get self-validation from others 15. To get compliments 16. To be able to better estimate my own attractiveness 17. To get attention (1) Strongly disagree (2) Disagree (3) Somewhat disagree (4) Neither agree nor disagree (5) Somewhat agree (6) Agree (7) Strongly agree
Algorithm awareness	Zarouali et al. (2021)	Please indicate to which extent you are aware of the following statements about algorithms in Breeze 1. Algorithms are used to recommend profiles to me on Breeze 2. Algorithms are used to prioritize certain profiles above others 3. Algorithms are used to tailor a profile selection to me on Breeze 4. Algorithms are used to show someone else different profiles than I get to see on Breeze 5. Algorithms are used to show me profiles on Breeze based on automated decisions 6. Algorithms do not require human judgments in deciding which profiles to show me on Breeze 7. The profiles that Breeze shows me depend on my behavioral data 8. The profiles that algorithms recommend to me on Breeze depend on my online behavior on this dating app

		9. The profiles that algorithms recommend to me on Breeze depend on the data that I make available online 10. It is not always transparent why algorithms decide to show me certain profiles on Breeze 11. The selection of profiles that algorithms make on Tinder can be subjected to human biases such as prejudices and stereotypes 12. Algorithms use my personal data to recommend certain profiles to me on Tinder, and this has consequences for my online privacy 13. Breeze algorithms are used to show me profiles based on automated decisions (1) Not at all aware (2) Slightly aware (3) Somewhat aware (4) Moderately aware (5) Completely aware
Algorithmic trust	Sharabi (2021)	Please indicate to which extent you agree with the following statements 1. Breeze algorithms really work 2. I would trust Breeze algorithms to find me a romantic or sexual partner 3. Breeze algorithms lead to more successful connections 4. A mathematical formula can predict who I will be attracted to. 5. Breeze algorithms are better than I am at finding me a romantic or sexual partner 6. Breeze algorithms provide me with better quality connections 7. Breeze algorithms are more effective than traditional ways of meeting people (1) Strongly disagree (2) Disagree (3) Somewhat disagree (4) Neither agree nor disagree (5) Somewhat agree (6) Agree (7) Strongly agree
Perceived matching success	Her and Timmermans (2020)	Please indicate to which extent you agree with the following statements 1. I think that I have many matches on Breeze 2. I think that many other users want to go on a date with me on Breeze 3. I consider myself being successful on Breeze (1) Strongly disagree (2) Somewhat disagree (3) Neither agree nor disagree (4) Somewhat agree (5) Strongly agree
Satisfaction with matches	Hu and Zhan (2024)	When you use Breeze, how easy or difficult is it for you to find people who … 1. You are physically attracted to 2. Are looking for the same kind of relationship as you 3. Seem like someone you would want to meet in person (1) Very difficult (2) Difficult (3) Easy (4) Very easy
Self-perceived attractiveness	Shrauger and Schohn (1995)	Please indicate to which extent you agree with the following statements 1. It bothers me that I am not better looking. 2. I am pleased with my physical appearance. 3. I am better looking than the average person. 4. I am fortunate to be as good looking as I am. 5. Most people would probably consider me physically unattractive. 6. I wish I could change my physical appearance. 7. I would be a lot more successful in dating if I were better looking. (1) Strongly disagree (2) Somewhat disagree (3) Somewhat agree (4) Strongly agree
Self-esteem	Rosenberg (1979)	Please indicate to which extent you agree with the following statements 1. On the whole, I am satisfied with myself. 2. At times I think I am no good at all. 3. I feel that I have a number of good qualities 4. I am able to do things as well as most other people.

	5. I feel 1do not have much to be proud of. 6. I certainly feel useless at times. 7. I feel that I'm a person of worth. 8. I wish I could have more respect for myself. 9. All in all, I am inclined to think that I am a failure. 10. I take a positive attitude toward myself. (1) Strongly disagree (2) Disagree (3) Agree (4) Strongly agree
End of survey	
Thank you for participating in this survey If you have anything to add that you feel is important to the research, please write below:	

APPENDIX B

Table B1.

Standardized factor loadings and fit indices CFA

	Variable							
Item number	Algorithm awareness	Self-perceived success	Self-perceived attractiveness	Algorithm trust	Satisfaction with matches	Self-esteem	Relationship seeking	Ego boost motive
1	.833	.902	.772	.811	.871	.738	.906	.856
2	.800	.887	.793	.718	.809	.854	.848	.819
3	.886	.801	.704	.790	.882	.671	.853	.836
4	.793		.716	.469		.638	.642	.827
5	.840		.723	.611		.787	.360	.846
6	.706		.769	.798		.824		.775
7	.746		.724	.727		.788		
8	.789					.653		
9	.667					.867		
10	.476							
11	.608							
12	.573							
13	.852							
Fit measures								
RMSEA	.108	.0	.159	.052	.0	.116	.0	.087
SRMR	.047	.0	.092	.036	.0	.067	.023	.035
CFI	.996	1	.970	.997	1	.998	1	.997
$\chi 2$	34925*** df = 78	3870*** df = 3	5895*** df = 21	6761*** df = 21	2376*** df = 3	14971*** df = 36	5253*** df = 10	11645*** df = 15

Note: significance levels: p <.001***, p <.01 **, p <.05 *
N= 498
Item 5 was removed from the relationship seeking scale as the factor loading was smaller than 0.