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THE CONSTRUCTION OF MATCHES ON DATING PLATFORMS

by Lene Pettersen & Runar Døving

Dating platforms play the role of the traditional village matchmaker when they suggest potential partners that would be a good fit ('match'). This paper reports from an in-depth study of the matching machinery of four dating platforms using a recommendation system based on a matchmaker model to suggest matches. While content-based recommendation systems form suggestions based on the users' behaviour and interaction patterns, a matchmaker model uses information about the user to form recommendations. In the matchmaker model, what the IT system characterises as the ideal formation and a 'good match' is revealed. By using the reverse-engineering method, we find that of the four platforms investigated, three construct and form matches based on the couple's degree of similarities along psychological and personal aspects, while one platform is based on a 'the more similar along all kinds of axes, the better'-model. None of the platforms employs the anthropological hypergamy principle, which refers to the tendency of women to choose partners of similar or higher social status, while men do the opposite, into its matching account. Match value, which we conceptualise as the match score assigned by the platforms to couples, is a key component in the platforms' matching machinery. Match value is a numeric value presented as an objective and scientific score, representing the degree of how well two persons 'fit' together. The platforms reduce individuals and relationships to a numeric value based on a psychological personality model, which ignores the person's wider social network, class and context. The ranked order of matches does not consequently correspond with the match value, which suggests that the platforms provide benefits for paying members.

Keywords: Dating platforms, recommendation systems, hypergamy, digital anthropology, Bourdieu

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Introduction

Twenty years from now, the idea that someone looking for love won't look for it online will be silly, akin to skipping the card catalog to instead wander the stacks because 'the right books are found only by accident'.

Wired Magazine, 2002

Meeting a potential partner has been reshaped with the advent of big data and algorithmic matchmaking. Dating platforms are the most popular way in which couples meet today (Rosenfeld et al., 2019; Nader, 2021). Like the traditional village matchmaker, digital dating platforms and apps construct and recommend formations of people they consider to be a good fit (Evans & Schmalensee, 2016). How platforms calculate matches are characterised by the embedded values and discourses held by the individuals who construct them (Elish & boyd, 2018; Forsythe, 2001). Behind code, algorithms, computer systems and the practices of machine learning, cultural values are embedded into systems (Elish & boyd, 2018; Forsythe, 2001). As Gillespie et al. (2014) noted, algorithms are best conceived as 'socio-technical assemblages' joining the human and the nonhuman, the cultural and the computational. Algorithmic culture refers to the ways in which the logic of big data and large-scale computation (including algorithms) alters how culture is practiced, experienced, and understood (Hallinan & Striphas, 2016).

Dating platforms and applications are recommendation systems because they provide suggestions of potential candidates to the user. Two types of methods are used in recommendation systems to suggest relevant items or content. (1) Collaborative filtering methods, where suggestions and recommendations are based on the users' past interactions with the system (e.g. articles read, pictures liked, films watched, etc.). (2) Content-based methods, where the platform uses self-reported information about users and/or items (e.g. age, gender and preferences) to model their recommendations. The first method builds recommendations based on algorithms that are modelled on characteristics from the users' behaviour. The second method uses information about the user to form recommendations. Furthermore, different forms of dating platforms exist (Schmitz & Zillmann 2016). One kind is those where the users provide brief or limited personal information in the registration process and that browse potential candidates independently (e.g. Tinder). Another type is those using a matchmaking model. Here, the user follows a registration process similar to that in the first model, yet the system requires more information about the user and uses this input when suggesting potential partners in a list of best matches as output (e.g. Match). In the study at hand, we are interested in the latter kind of platform logics. This is because we want to examine the system's ideals or model that operates behind the matching scene and that the platforms use when deciding which candidates they consider to be a good fit. This also reveals how the platform rank combinations of couples. In both kinds of dating platforms and apps, algorithms are at play when recommending matches. Yet in the matchmaker model, we can gain insights into the ideal match according to the system, as platform owners design the architectures and construct the discourses tied to services (van Dijck, 2013). In the first platform type, users, at least indirectly, and probably unknowingly, have a hand in how a platform operates and develops (Courtois & Timmermans, 2018). Nonetheless, both types of dating technologies are variants of recommendation systems whose algorithms sort, classify, hierarchise, and rank people. A key stake in algorithmic culture is the automation of cultural decision-making processes, taking the latter significantly out of people's hands (Flusser, 2011; Nader, 2021). How, then, do dating platforms using a matchmaker model decide what is a 'good match'? And how do these decisions comply with how heterosexual[1] persons choose a partner for a long-lasting relationship or marriage in practice? Social anthropology and sociology point to the importance of formal and informal legal, as well as secular and religious rules when choosing a lifelong partnership. These disciplines also stress that choosing a partner is not a solo project but rather something that involves the wider social context as well as several families. The hypergamy and homogamy principles explain several of these factors. Hypergamy denotes the universal tendency that women choose long-lasting partners of similar or higher social status (e.g. education level, rank, class, income and occupation) compared to themselves, while men do the opposite (Chudnovskaya, 2017; Mohanadoss, 1995). Homogamy denotes marriages in which the heterosexual partners share some key characteristics, such as having shared values, religion and views on life. Homogamy in these factors is important for partner choice and a long-lasting relationship (Kalmijn, 1998; Kalmijn & Flap, 2001).

We want to explore the algorithmic creation of matches made by dating platforms using a matchmaker model to form combinations of couples, and the extent to which they take into account the hypergamy and homogamy principles in their recommendations. Although dating platforms and their users have received considerable attention over the past decades from various academic disciplines, none has examined in-depth the recommendation logics that dating platforms apply. Courtois and Timmermans's (2018) research is perhaps the closest attempt to crack the Tinder code, yet the hypotheses they test are mainly concerned with the users and their interactions with the platform (and less about the logics behind the Tinder algorithm machinery). More specifically, we address the following research question (RQ):

1 Because we are testing the extent to which dating platforms using a matchmaker model when recommending matches consider hypergamy and homogamy principles, our study is limited to heterosexual persons. How the hypergamy principle works for same sex relationships is less known and should be explored by future research.

1. What characterises the construction of heterosexual couples in dating platforms?

To address this RQ, we use the literature on the hypergamy and homogamy principles and assortative mating (AM). AM refers to the tendency of two partners' characteristics to be matched in a systematic manner, usually in the form of similarity (Luo, 2017) To gather data, we conducted a reverse-engineering study of four dating platforms using a matchmaker model operating in the Norwegian dating market. Reverse engineering is a method that understands algorithms inside-out by reversing the engineering process, and shares many aspects with the app walkthrough method (Light et al., 2018). Both are useful methods for empirically understanding how algorithms work (Bucher, 2018). This study is the first to do an in-depth examination of the underlying matching model in dating platforms. By studying algorithmic matchmaking practices using the reverse-engineering method, we contribute to science and technology studies as well as to how the interdisciplinary field of digital anthropology is informed today (Geismar & Knox, 2021).

The paper is organised as follows. In the next section, we present the theoretical framework and literature this study builds on. This is followed by the methodology section in which we present how we collected and analysed the data, and then, we share our findings. The paper closes with a discussion of our findings, a conclusion, our study's limitations, and a call for further research.

Theoretical framework

This paper is positioned in the field of digital anthropology, which is profoundly interdisciplinary and shaped by conversations with science and technology studies, communications, media studies, internet studies and others. In digital anthropology, 'the digital' is defined as new technologies that are reducible to binary code, and the digital is always approached in context (Horst & Miller, 2012; Geismar & Knox, 2021). One of the areas digital anthropology is informed by today is the global, networked and infrastructural qualities of digital technologies (e.g. algorithmic bias, computer code and how people shape and are shaped by infrastructural systems) (Geismar & Knox, 2021). One of the pioneers that paved way for this stream of research in social anthropology was Diana Forsythe (1993, 2001) in the 1990s. Some of her key findings echo much of todays' contemporary research on digital technologies, algorithms and data practices in that computer systems include the system builders' – who are typically male software engineers – own tacit assumptions.

Algorithms and recommendation systems

Online dating has received considerable attention in the past decades from various academic disciplines (see Wu and Trottier (2022) and Degim et al. (2015) for comprehensive literature overviews). Yet, it is not our aim to provide a literature review of this body of research because we are not directing our lens to different aspects concerning how people use or perceive dating sites per se. Rather, we are interested in the underlying model(s) employed by dating sites when constructing and recommending matches. Gaining insight into the inner workings of a platform's algorithms is difficult as they are not disclosed by the companies running them, and even experts only have limited access (Seaver, 2014; Parisi & Comunello, 2020). Courtois and Timmermans (2018) used an experience sampling method to grasp user actions, exposure and effects on Tinder. Although their study reveals interesting findings about the users' interaction patterns with the Tinder platform, their theorising on how the Tinder algorithms work are based on hypotheses with the aim of constructing 'informed assumptions on the mechanics of algorithms by considering the economic and technological logics that pressure platform owners and developers' (p. 5). Moreover, dating platforms claim they use scientific matching methods. However, scientific evidence for the efficacy of online matchmaking methods is lacking (Houran, 2004), and there is no compelling evidence supporting the platforms' claims that their mathematical algorithms work (Finkel et al., 2012). Algorithms are used to calculate matches and recommend potential candidates. An algorithm is a set of defined steps set up to produce particular outputs and is available in various forms, where the algorithms in recommender systems are one of several kinds (Just & Latzer, 2017). As previously mentioned, dating platforms have adopted recommendation systems. Recommendation systems use algorithms that suggest to new and relevant items to the user, such as which movies to watch, products to buy or persons to date, presented in ranked lists (Latzer et al., 2014). Nader (2021) points to important ethical considerations that might arise when the same methods employed to build recommendations for users on online platforms such as Amazon and Google are used on dating apps. Through recommender systems, dating apps are increasingly influencing whose profiles the users can see or match with and thus who they date and potentially marry (Nader, 2021).

As mentioned in the introduction, two types of methods are used in recommendation systems to suggest relevant items or content: (1) collaborative filtering methods, where suggestions and recommendations are based on the users' past interactions with the system (e.g. articles read, pictures liked, films watched, etc.), and (2) Content-based methods, where the platform uses self-reported information about users and/or items (e.g. age, gender and preferences) to model their recommendations. The first method builds recommendations based on the users' behaviour (a "more of the same" logic in order to provide relevant content, as denoted by 'filter bubbles'). The second method concerns how the system decides what would be a relevant suggestion based on the information the system has at hand about the user (e.g. categorical stereotypes such as 'woman, white, 50 years, high education' receiving ads for expensive holidays or anti-aging facial cream).

As stated, several forms of dating platforms exist. Schmitz and Zillmann (2016) distinguish between two kinds of platforms: (1) platforms where the users provide brief or limited personal information in the registration process and who browse potential candidates independently (e.g. Tinder). (2) The matchmaking model where the user follows a registration process similar to that in the first model, yet here the system requires more information about the user and uses this input when suggesting potential partners in a list of best matches as output (e.g. Match). Parisi and Comunello (2020) distinguish between dating apps based on the extent to which they collect data from Facebook to build the user profile and recommendations. On dating platforms using a content-based method and a matchmaker model (e.g. Match and eHarmony), the user is guided through an introductory process when creating a profile that includes providing the platform with information through answers to a series of questions. This information serves as input to the platform, which in turn uses this as a basis when creating recommendations of matches and ranked lists of potential partners. It is this type we examine in our study. This enables us to see the ranked list of recommendations offered by the platform and thus study in detail the characteristics of these recommendations. This, in turn, enables us to see whether these recommendations consider the hypergamy and homogamy principles as well as understand the ideal model and discourse underlying the platforms' matching logic.

Although an algorithm is a set of defined steps to produce particular outputs, considerable expertise, judgement, choice and constraints are exercised in its creation (Gillespie et al., 2014; Kitchin, 2017). Behind the practices of machine learning (i.e. collecting, cleaning and curating data; managing training datasets; choosing or designing algorithms and altering codes based on outputs), cultural values are embedded into systems (Elish & boyd, 2018; Forsythe, 2001). The model that decides which persons would make a good fit on dating sites is thus based on the preferences and values of the platform creators. Although matching algorithms are business secrets, and dating sites are reluctant to share how their algorithms work (Courtois & Timmermans, 2018; Parisi & Comunello, 2020), several studies suggest that they typically match on various measurements of similarity (homogeneity) (Houran et al., 2004; Finkel et al., 2012; Parisi & Comunello, 2020). Houran et al.'s (2004) study of the dating platform eHarmony finds that the platform follows the notion that romantic compatibility equates with greater similarity than dissimilarity between two individuals. However, as stated, to our knowledge, no research has examined in depth the models behind the construction of couples in the matching machinery of dating platforms. It is our aim to provide insight on this knowledge gap.

Partner preferences in practice

Choosing a partner is one of the most important aspects for the individual and the society. How and with whom people marry is a classical issue in anthropology. How marriage, reproduction and cohabitation are arranged varies globally but always involves families. Marriage and reproduction are surrounded by formal and informal legal, secular and religious rules. However, some find that dating apps lack important socioeconomic and institutional aspects (Bandinelli & Gandini, 2022). The concept of hypergamy is especially known through the work of anthropologist Louis Dumont and his studies in the 1950s and 1960s on the caste system in India, where social strata are socially determined and form part of open cultural norms. Hypergamy denotes the tendency that women choose partners of similar or higher social status (education, rank, class, income and occupation) compared to themselves, while males do the opposite (Chudnovskaya, 2017; Mohanadoss, 1995). Hypergamy has been an empirical fact in most societies (Shackelford et al., 2005).

The hypergamy principle can be divided into biological and sociological dimensions. From a biological perspective, men, for example, tend to choose women who are shorter than themselves, while women prefer the opposite. Sociological dimensions concern resources that Bourdieu (1986) labelled as capital. Bourdieu distinguished among three types of capital: economic, cultural, and social. According to Bourdieu, resources can compensate for one another because capital is convertible. In other words, one capital type (e.g. education) can be exchanged or used to acquire other capital types (e.g. income). A short male with high economic and social capital can, thus, still attract a woman, for example Tom Cruise (170 cm) or Martin Scorsese (160 cm). Following the logic of hypergamy, the male should have more capital than/be superior to the female. Homogamy, on the other hand, denote marriages in which the partners share some key characteristics, such as having shared values, religion, and views on life. Homogamy in these factors is important for partner choice and a long-lasting relationship (Kalmijn, 1998; Kalmijn & Flap, 2001), while homogamy in socioeconomic variables produces an increasing number of couples of equal status, which might lead to a larger gap between classes and reinforce their social status (Blossfeld, 2009). The homogamy and hypergamy principles are in many ways complementary: One look for a partner with shared values and religion within the same social group, class or strata (homogamy) (Kalmijn, 1998; Kalmijn & Flap, 2001), yet at the same time a fe/male who has 'lower'/'higher' status within the same group (hypergamy) (Chudnovskaya, 2017; Mohanadoss, 1995).

In psychology, assortative mating (AM) refers to the tendency of two partners' personal characteristics to be matched in a systematic manner, usually in the form of similarity (homogamy) (Luo, 2017). Ranzini et al. (2022) examined whether principles of assortative mating apply to dating apps. Their results pointed to educational assortativity for higher-educated participants (those with higher education seek a partner also with higher education). Despite many studies indicating that individuals are more likely to select partners with similar, as opposed to dissimilar, personality characteristics, comparable findings extend to couples' perceived similarity across the variables of physical and social attractiveness, socioeconomic status, and level of intelligence (Houran et al., 2004). However, a great amount of research increasingly speaks to the importance of complementarity in a relationship (Houran et al., 2004). Matching with partners similar on a range of factors (personal as well as social and societal factors) might have profound implications for social and economic inequality (Schwartz, 2013).

An ongoing debate in the social sciences concerns whether the hypergamy principle is eroding due to the global educational gender gap, in which women today outnumber men in higher education in nearly all Organisation for Economic Co-operation and Development (OECD) countries (Chudnovskaya & Kashyap, 2020). As women are gaining increasing access to higher education, it is becoming difficult or impossible for them to find a partner with a higher or equal education level (Chudnovskaya & Kashyap, 2020). In contrast, research from Sweden indicates that despite the educational gender gap, resources and status continue to play a key role when women choose a partner to create a family union (Chudnovskaya, 2017, 2019; Chudnovskaya & Kashyap, 2020). This indicates that despite structural and societal changes over the past decade, the hypergamy principle is still valid, including for people in the Nordic countries that are perceived to be egalitarian and with high levels of gender equality.

Methodology

Reverse-engineering method

To empirically understand how dating platforms construct matches, the reverse-engineering method was used. Reverse engineering is a

> process of articulating the specifications of a system through a rigorous examination drawing on domain knowledge, observation, and deduction to unearth a model of how that system works. (Diakopoulos, 2013, p. 13)

As all computer systems have two openings that enable lines of enquiry (input and output), we can examine what data are fed into a computer system and what output is produced by the platform (Kitchin, 2017)[2]. This method encourages, amongst others, a walkthrough technique to systematically and forensically move through the various stages of platform registration and entry. By analysing the input and output in-depth, we were able to examine, to a large extent, how the platforms operate between (throughput) these two stages. The reverse-engineering method is an example of how anthropologists can use new ways of collecting data.

Sample

We chose four established platforms that market themselves as dating sites for singles seeking serious heterosexual relationships. Our study is limited to heterosexual persons as we wanted to examine whether the platforms consider the hypergamy and homogamy principles when recommending matches. How the hypergamy principle works for same sex relationships is less known. The platforms were chosen because they are well known in the heterosexual Norwegian dating market and thus are expected to have large pools of candidates in their databases. The platforms were Match, The Meeting Place (no. Møteplassen), Sugar (no. Sukker) and Academic Singles. Our analysis finds that at least three (Match, Academic Singles and Sugar) of these platforms were created and established by white, male IT workers and businessmen.

Sugar was established in 2004 by Norwegians Morten Gulliksen and Morten Berg. The CEOs also run the company Warm System AS, which delivers systems in physics, thermal design, electronics, and 3D construction (Gulbrandsen, 2016). The American company Match.com was founded in 1993 by Gary Kremen and Peng T. Ong. They turned Enter Electric Classifieds Inc. into internet matchmaking as a profitable, full-time enterprise (Krieger, 1995). Academic Singles was founded as a matchmaking service in 2004 by Robert Wuttke (founder) (IDEA, 2008) and Andreas Etten (co-founder) and is operated by be2 S.à.r.l., a Luxembourg company (Academic Singles, 2023) that specialises in information retrieval services. The Meeting Place was created in 2001 by Norden A.B. in Sweden and bought by the Norwegian media conglomerate Schibsted in 2005 (Larsen, 2021) when Kjell Aamodt was CEO. In 2021, The Meeting Place was sold to Hungarian Dating Central Europe (Ibid.).

We intentionally did not include any platforms in our study that base their recommendations on proximity (e.g. Happn) because these do not follow a matchmaker model. Also worth noting is that, since our study has ethical implications, we did not study users' identities or actual people on the platforms but rather the key characteristics (e.g. religion, income, educational level, etc.) of the people the platforms recommended.

Pilot study and ghost profiles (GPs)

Before beginning the experiment, we conducted a pilot study in January 2019 to gather key insights required for designing the GPs we wanted to test in our experiment. A GP is a fake account in online services. Two profiles of each gender were created on the four platforms. The pilot study provided key insights that were implemented in the experiment conducted between April and May 2019. We collected (as screenshots) the full registration process for all four platforms. This enabled us to plan in detail what the GPs should fill in when creating a profile. Note that the six GPs answered all the four platforms' questionnaires identically; thus,

2 See Pettersen (2021) for more technical details about how we used the method of reverse engineering in this study.

the platforms' matching suggestions could not be explained due to different answers in the surveys.

We also interviewed one person who was involved in creating questions for one of the platforms to learn more about the questions asked on the platforms during the registration process and how the platforms modelled matches. Due to privacy issues, we have kept this person and platform anonymised.

Based on our insights achieved during the pilot study, in the experiment we created four GPs, two males (M1 & M2) and two females (F1 & F2) (Table 1) on four Norwegian online dating platforms. In addition, two control GPs (F3 & M3) (Table 1) were created to control for the hypergamy aspects we wanted to test (height, educational level, occupation, and income) as well as the homogamy dimension of religion.

F1 and F2 had identical characteristics in terms of age, height, figure, religion, and location but differed in educational level and occupation as well as income. All the GPs were set as 32 years old as this is the time when most persons in the Nordic countries form a family (Norway Statistics, 2020). The hypergamy principle is most important in the family-formation phase as decisions on with whom to reproduce and grow a family are made. The principle is less important for young persons or people looking for a fling, for example.

M1 and M2 had characteristics identical to those listed for F1 and F2. The control profiles, F3 and M3, differed from the other four GPs on all tested dimensions except age, figure, religion, and location. This enabled us to determine the extent to which the matching algorithms accounted for the differences in height, income, occupation, and educational level as well as gender perspectives.

TABLE 1

	Male 1 (M1)	**Male 2 (M2)**	**Male 3 (M3)** (control person)	**Female 1 (F1)**	**Female 2 (F2)**	**Female 3 (F3)** (control person)
Age:	32 years	32 years	32 years	32 years	32 years	32 years
Height:	1,69 cm	1,69 cm	1,80 cm	1,76 cm	1,76 cm	1,67 cm
Figure:	Normal	Normal	Normal	Normal	Normal	Normal
Educational level:	High school	PhD	Master's degree	High school	Phd	Master's degree
Occupation:	Truck driver	Medical doctor	Consultant	Hairdresser	Medical doctor	Consultant
Income:	400 000NOK	1 000 000NOK	600 000NOK	400 000NOK	1 000 000NOK	600 000NOK
Religion:	Christian	Christian	Christian	Christian	Christian	Christian

Table 1: Characteristics of the GPs used for testing four dating platforms. All six GPs listed Oslo (the capital and biggest city in Norway) as their location.

Hence, six GPs were created and tested on the four dating platforms, and 24 profiles were cross-examined. We created non-paying memberships, except for one that required a paying membership, to collect the required data on the key characteristics of the profiles the platforms suggested as matches.

Data analysis

First, we gathered input data from the registration process as screenshots from all the questions and statements asked on the platforms and the answer categories. The number of inputs varied considerably among the four platforms, from 33 to 190 questions. This was followed by a close text analysis, where we studied what type of questions were asked on the platforms as well as the response alternatives. The questions were then classified and ordered into groups based on the questions' nature and then analysed in detail. This was followed by a close study of how the systems stated why combinations of candidates were a good match. We collected output data from the top five matches that the platforms suggested for the six GPs on the four platforms. We collected details about these matches' match scores and ranks; socioeconomic aspects, such as educational level, occupation/occupational level, income (sociological hypergamy); height (biological hypergamy) and religion (homogamy). We also collected data on how the platforms argued that a couple was a 'good' match.

We coded this data into tables and analysed the details in depth, which involved moving back and forth, including new dimensions along the way. The two authors individually reviewed the screenshots and the tables several times to identify overall themes and findings, coding and analysing them to look for key patterns, similarities, and differences. The main findings were then discussed in depth by the two authors. Finally, we studied the four platforms thoroughly (e.g. information provided on their websites, the platforms' search options, affordances, information architecture, interaction design, and other profiles that were not recommended from the system).

Despite designing the study as an experiment, being two anthropologists, we performed the study using an inductive and holistic approach, where we used qualitative methods to analyse and interpret the collected data.

Due to research ethics, none of the GPs uploaded a profile picture, and in cases where the platform required a profile text for profile creation, these were kept as anonymous as possible. The profiles were deleted shortly after the data were collected. All nicknames used in this article are fabricated.

Findings

Feeding the system

As stated, the four dating platforms studied use a content-based filtering method, not basing their recommendations on user behaviour, because we wanted to uncover what kind of matching model the platforms employed. Our analysis of the platforms' input revealed that the questions or statements answered by the user when creating a profile can be grouped into the following seven categories: (1) expectations about relationships (N = 70); (2) desired characteristics in a partner (N = 40); (3) singles' personality (N = 178); (4) singles' values and attitudes (N = 43); (5) singles' taste, hobbies and interests (N = 28); (6) communication needs (N = 9) and (7) personalia and practical information (e.g. inclusive thirst for knowledge, IQ; N = 63). Thus, the platforms collect most information about the singles' personality (N = 178), followed by their expectations of being in a relationship (N = 70). Hence, the platforms' largest input concerns the singles' personality and other personal characteristics.

We found that all four platforms use larger or smaller parts of personality tests (e.g. the NEO-PI-3 (the Big Five) test, and the ECR test) in their questionaries. This, logically, forms the starting point from which the matching machineries construct matches. However, despite that the platforms are clearly inspired by personality tests, they do collect some hypergamous information. The third largest group of questions is information that, to varying degrees, includes hypergamy aspects (e.g. height, educational level, income, occupation and homogamy dimensions such as religion). This information is mainly located under a personalia page.

Interestingly, we found that the response options to hypergamy questions suffer from well-known fallacies in survey methodology, which Houran et al. (2004) also found in their analysis of eHarmony.com. All hypergamy dimensions (income, educational level and occupation) in our study suffer from unfortunate classifications, response options that are not mutually exclusive, missing response options, and lack of choice of variable types. Taking the category of 'education' as an example, The Meeting Place sorts educational level into three categories of primary school, high school, and college. Therefore, on this platform, college is the alternative that denotes the highest possible education the user can tick off. This means that four of our six GPs are placed in the same educational category on this platform ('college') regardless of whether s/he has a college or a PhD degree. On the Sugar platform, the user's education is measured as a numerical variable – in terms of length (years of studies) and not educational degree. Both Academic Singles and Match lack a category for education lower than high school. Nevertheless, these two platforms capture the educational level appropriately (Table 2).

TABLE 2

<table>
<tr><td rowspan="4">EDUCATIONAL LEVEL</td><td>Academic Singles</td><td>High school</td><td colspan="2">College</td><td>Bachelor's</td><td>Master's</td><td colspan="2">Phd</td></tr>
<tr><td>Match</td><td>High school</td><td>Technical college</td><td>College</td><td>Bachelor's</td><td>Master's</td><td>Phd</td><td>Choose not to answer</td></tr>
<tr><td>The Meeting Place</td><td>Primary school</td><td colspan="3">High school</td><td colspan="3">College</td></tr>
<tr><td>Sugar</td><td>Not high school (1)</td><td colspan="4">2-9 years</td><td colspan="2">Hold or plan to take a university degree (10)</td></tr>
</table>

Table 2: Response categories for educational level on the four dating platforms.

The same methodological flaws revealed for education are also observed for occupation (Table 3).

TABLE 3

OCCUPATION	**Academic Singles**	A list of incomplete and not exclusive job categories				
	Match	A list of incomplete and not exclusive job categories				
	The Meeting Place	Employed	In-between jobs	Retired	Self-employed	Student
	Sugar	Does not include occupation or work in the calculations at all due to 'work' or 'occupation' not being part of the input				

Table 3: Response categories for occupation on the four dating platforms.

Actually, all the variables that represent aspects of the sociological hypergamy principle suffer from methodological flaws in the input data.

When analysing height, three of the four platforms capture accurate values. On The Meeting Place platform, however, height is a non-exclusive and categorical variable categorised in groups of five (e.g. 170–175 cm and 175–180 cm). Measuring height in groups of five centimetres leaves a highly inaccurate value for the dating platform to calculate and match people.

In terms of input for religion, Academic Singles and Match have a categorical variable including the most prominent religions. On The Meeting Place, however, only one among the 190 input questions concerns the category 'religion'. Here, religion is a numeric variable with a value ranging from 1 (disagree) to 7 (agree) for the statement 'I am religious'. Which religious perspective an individual holds is not captured by the platform although the user can choose to fill in the religion themselves after their profile is created. However, we find that this does not affect the platform's matching calculations (see below). The same flaw is observed on the Sugar platform, where the user lists a value from 1 to 10 to denote religious degree.

Constructing matches

A key finding is that three of the platforms are using an assortative mating model when constructing matches. One of the platforms (Sugar) constructs matches based on a similar-in-all-facets practice, where all facets (from frequency of café visits to tidiness) are weighted equally. The platforms construct matches based on similarity in the answers the users gave when creating their profile. For example, if an individual has equal income and/or educational level, this is signalled by Sugar as good, yet if the male has higher or lower income and educational level than the female, this is signalled as worrying.

None of the four platforms accounts for the socioeconomic aspects in the hypergamy principle (educational level, occupation or a person's economic capital or resources) when constructing and recommending matches. For example, on the Match platform, a construction worker whose profile states that he has 'low income' is suggested by Match to be among the top five matches for both F2 and F3. All our female GPs are suggested by the Match platform as the top five matches for all our male GPs – regardless of their differences in educational level, occupation, and income (Table 4).

TABLE 4

P	GP	R	NN	MS	Age	CM	Education	Occupation	Income	Religion
MATCH	F1	**1**	**Freddie (M1)**	**98**	31	**169**	High school	Other	300-500 000	Protestant
		2	Jarvis	78	29	180	High school	Other	500-750 000	Protestant
		3	Lemmy	68	37	180	College	Other	-	Protestant
		4	Tommy	81	31	178	High school	Truckdriver	300-500 000	Agnostic
		5	Iggy	73	31	179	Bachelor	Secretary	300-500 000	**Atheist**
	F2	**1**	**Freddie (M1)**	**98**	31	**169**	**High school**	**Other**	**300-500 000**	Protestant
		2	Jarvis	78	29	180	**High school**	**Other**	500-750 000	Protestant
		3	Lemmy	68	37	180	College	Other	-	Protestant
		4	Tommy	81	31	178	**High school**	**Truckdriver**	300-500 000	Agnostic

P	GP	R	NN	MS	Age	CM	Education	Occupation	Income	Religion
MATCH		5	Miles	74	30	170	**High school**	**Construction worker**	**Low**	**Muslim**
	F3	**1**	**Freddie (M1)**	**98**	31	169	**High school**	**Other**	**300-500 000**	Protestant
		2	Miles	74	30	170	**High school**	**Construction worker**	**Low**	**Muslim**
		3	Cliff	80	37	174	**College**	Other	500-750 000	Atheist
		4	David	76	38	170	**High school**	Self-employed	-	Not telling
		5	Syd	82	33	170	**Bachelor**	Other	500-750 000	Not telling
	M1	**1**	**Madonna (F1)**	**98**	31	**175**	High school	Hairdresser	300-500 000	Protestant
		2	**Janet (F3)**	**98**	**31**	**175**	**Master**	**Consultant**	**500-750 000**	Protestant
		3	**Patti (F2)**	**98**	**31**	**167**	**PhD**	**Doctor**	**+ 1 000 000**	Protestant
		4	Joni	78	29	166	**Master**	Other	-	Protestant, not practicing
		5	Tori	74	28	**178**	College	Student	100-200 000	Agnostic, not practicing
	M2	**1**	**Madonna (F1)**	**98**	31	**175**	High school	Hairdresser	300-500 000	Protestant
		2	**Janet (F3)**	**98**	31	**175**	Master	Consultant	500-750 000	Protestant
		3	**Patti (F2)**	**98**	31	167	PhD	Doctor	+ 1 000 000	Protestant
		4	Joni	78	29	166	Master	Other	-	Protestant, not practicing
		5	Tori	74	28	**178**	College	Student	100-200 000	Agnostic, not practicing
	M3	**1**	**Janet (F3)**	**98**	31	175	Master	Consultant	500-750 000	Protestant
		2	**Madonna (F1)**	**98**	31	175	High school	Hairdresser	300-500 000	Protestant
		3	**Patti (F2)**	**98**	31	167	**PhD**	**Doctor**	**+ 1 000 000**	Protestant
		4	Joni	78	29	166	Master	Other	-	Protestant, not practicing
		5	Olivia	76	32	165	Bachelor	Administrative leader	500-750 000	Atheist, not practicing

Table 4: Top five matches for K1, 2 & 3 and M1, 2 & 3 in the dating platform Match. P=platform, GP=ghost profile, R=ranked order, NN=nickname, MS=match score, CM=height in centimetres.

On Academic Singles, variations in the same sample of women are recommended as the top five matches for all three male GPs. The same pattern is revealed for both The Meeting Place and Sugar platforms. Thus, socioeconomic aspects are ignored by all the platforms.

In terms of the homogenous aspect of religion, none of the platforms account for the users' religion when creating a match. For example, in Match, a Muslim profile is recommended among the top five matches for two of our female profiles of which both are Christian (Table 4), and on the Academic Singles platform, one of the top five females for all three male profiles is (the same) Hindu. Hence, the matching machinery of the four dating sites does not account for the users' religion when recommending matches. Despite a consistent matching pattern following an assortative mating model, similarities in the persons' religion are not taken into account when recommending potential matches.

A person's height is, at least to some extent, included in the matching machinery by two of the four platforms (Academic

Singles and Sugar), both of which only recommend candidates who are taller than the female GPs. On Sugar, female GPs are suggested as good candidates for male GPs only when the man is taller than the woman. Match and The Meeting Place, however, ignore singles' height when they recommend matches. This is shown, for example, when Match suggests the female GPs to be among the top five candidates for the male GPs regardless of these persons' heights. The Meeting Place suggests four candidates who are taller than M1 and M2 in their top five matches.

Including height in the matching algorithm accords well with the biological hypergamy principle. However, it ignores the important fact that height is only one of the several types of capital that – following Bourdieu's (1986) theory of capital forms – can be outperformed by, for example, males' educational level, occupation, income, socioeconomic resources, or social status.

Match score and value

As previously stated, dating sites claim that they use scientific tests as a basis for matching (Houran et al., 2004; Finkel et al., 2012). This is also the case with all four platforms we studied here (see Table 5). Our analysis of the platforms' statements on how they create matches finds that they point to scientific personality tests and psychology experts as well as a 'magical' technology. When analysing the GPs' matches, we find that the degree of a match is presented in line with a psychological-personality discourse. This is illustrated by the default text that the system generates. For example, the Match platform, for a match between one of the GPs and a male with 74 for a match score (maximum = 100), lists the characteristics the two shares as the following:

'Areas you share:

- You both open yourself easily.
- You have both a special ability to listen and understand.
- You can both imagine the future.
- Both of you are easily influenced by stress.

Areas you complement:

- You prefer being optimistic, while he sees things realistically.
- He enjoys more than you to be with other people.
- You prefer to be alone.
- You think it is easy to make a first move. He prefers being contacted by others.
- You think intuitively, he thinks logically and rational'.

TABLE 5

Platform	Scientific matching arguments stated by the platform	Scientific matching arguments stated by the platform	Match value
Academic Singles	Calculates a personality report they state help them to determine the persons' personal profile. The result's from this test is stated to identify personal characteristics, define the user's behaviour in a relationship, and help him or her understand what the platform list as seven dimensions in a harmonic relationship.	The user's input provides her a value along four psychological axes: 1. Rationality versus emotions (concerns how decisions are made) 2. Tradition versus innovation (concerns whether one is open to change) 3. Distance versus closeness (one's attachment to people – concerns emotions) 4. Observations versus intuition (concerns whether one is an emotional or fact-oriented person) According to a person's value along these four axes, the system calculates a match score based on the extent to which two persons are 'psychologically' similar.	Numeric value, 0–max. value not known
Match	Uses what they label an 'attraction test' that is designed by an 'AssessFirst team', which, according to the platform, comprise of an expert group consisting of psychologists and psychometric tests. The test is stated to provide a very reliable foundation for the users' search for a life partner. Because the attraction test is stated to be created by experts, this is claimed to provide a bigger probability of finding someone the user fits with.	The personality report that describes the singles' matches with other users is divided into three main areas: • Your values and what you believe in • Your attitudes about many topics, such as relationships, family, sexuality, education, work, money, and religion • Your personality and the way you behave The test has 71 key areas that, the site argues, determine how two persons will get along in a relationship.	Numeric value, scale 0–100

Platform	Scientific matching arguments stated by the platform	Scientific matching arguments stated by the platform	Match value
The Meeting Place	Calculates match scores based on what they state is a scientifically developed personality test. Using the person's personality profile as a basis, the platform argue that the system will find the members who best fit the candidate based on personality, values, and interests.	Using the persons' personality profile as a basis, the platform state they will find those members who best fit the users' personality, values, and interests. The matching value provided by the platform is based on the same five areas that were captured as input to the system: personality, communication, cohabitation, attitudes, and interests.	Numeric value listed in percentage (0–100)
Sugar	Claim they use what they label "a very powerful algorithm" that is stated to continuously calculate and sort long and unique match-lists to every single user in which, due to their calculations, consider both persons' desires and presents a sorted list of what they label as the persons best candidates in the kingdom.	The platform states their matching-system covers 70 characteristics without reducing them and uses a very powerful algorithm that continuously calculates and sorts long and unique match-lists to every single user.	Numeric value, scale 0–100

Table 5. Overview of our analysis of the platforms' scientific test arguments, what the platforms weight when calculating matches, which model their calculation relies on and how matches are materialised as numeric values.

After creating a profile, the platforms present a list of best matches to the user. However, we find that in all the four platforms, ranked order does not necessarily correspond to a match value. For example, GP F1's number one/best match (on top of the list) is suggested to be 'Elton', for which F1 has a match score of 136. However, number two in the list ('Axel') has the highest match score (142) with F1. 'Elton', though, is taller than 'Axel' (Table 6).

TABLE 6

GP	Rank in list of matches	Nickname	Match score	The person's hight (cm)
F1	1	Elton	136	183
	2	Axel	142	178
	3	Mick	128	180
	4	Bruce	133	180
	5	Simon	127	179

Table 6: Numeric rank of top five matches for F1 as suggested by Academic Singles.

Because the platforms do not account for any hypergamy or homogamy aspects, the differences in rank cannot explain the ranked order of the best matches. If this was the case, 'Bruce' who has 133 in match score and has the same height as 'Mick' should have been ranked 3 and not 4, because 'Mick' has lower match score (128) than 'Bruce'. This suggests that the ranked list of recommendations are persons who pay or that new members trump older members. Following the same logic as in search engines, since people tend to click on the items listed at the top of the results list (Keane et al., 2008), it is likely that the profiles at the top in the recommended list on dating platforms will be more visited than those listed further down.

Discussion and conclusion

This paper has examined the basis on which four dating platforms construct couples (matches) and the extent to which these constructions comply with how heterosexual persons choose partners in practice, which, according to social science, follows the hypergamy and homogamy principles.

We find that three of the four platforms employ an assortative mating model that relies heavily on personality tests, while one (Sugar) uses a strict homophily model in the construction of matches. None of the four platforms considers either the hypergamy or homogamy principle when constructing and recommending matches for single candidates. Because the six GPs entered identical answers (except for the hypergamy dimensions we were testing) in the questionnaire, they were often recommended as good matches for each other by the platforms. Recommending potential partners based on degree of similarity in the answers entered by the user resulted in the platforms recommending mainly the same sample of top five matches for our GPs. Matching with partners similar on a range of factors (personal as well as social and societal factors) might have profound implications for social and economic inequality (Schwartz, 2013). Similarity in these factors produces an increasing number of couples of equal status, which might lead to a larger gap between classes and reinforce their social status (Blossfeld, 2009). Hence, following a strict assortative mating model when creating matches is worrying. It also ignores how, according to the social science literature on hypergamy and homogamy, heterosexual people choose a partner in practice.

We also revealed that all the platforms suffer from severe methodological weaknesses in the questionaries the user fills out when creating a profile, including unfortunate classifications, response options that are not mutually exclusive, missing response options and lack of choice of variable types.

Another key finding is that the match value is a main component in the platforms' matching machinery. A match value is a numeric value presented as an objective and scientific score by the platform regarding how the system interprets the degree to which how well two persons 'fit' together. The logic the platforms follow is that the higher the numeric value, the better two persons fit each other and the better the match. The match value illustrates the platforms' considerable power in terms of constructing matches, in accordance with Nader's (2021) theorising. The match value seems to combine elements from recommendation systems built on a 'more of the same' logic, where 'same' are similar versions of yourself, as we know as the filter bubble logic. The match value can be interpreted as a pendulum in the user's compass of navigating choices—the (im)possibility of evaluating potential opportunities (Bandelli & Gandini, 2022, p. 15). The match value can also be interpreted as a type of rating of relationships provided by the platforms. That said, we have examined neither whether people use the match value as a trust-building symbol nor the degree of correspondence between persons' match value and those ending up pairing off. We can only question whether technology per se can construct relationships that in turn can increase the number of people establishing a relationship. Joel et al. (2017) used machine learning to test how well people's self-reported traits and preferences predict people's overall tendencies to romantically desire other people and to be desired by other people, amongst others. They created an algorithm to match participants based on their self-reported personality tastes. The system, however, could not predict who ended up pairing off.

The underlying model which constructs matches and matches persons on dating sites is based on the preferences and values of the creators of the platforms. In our study, the majority of the platforms were created by white, male IT workers and businessmen, and their cultural values are thus embedded into these systems. The underlying model for the construction of couples embedded by the creators of the platforms is, as stated, based on an assortative mating approach. This model is explicitly used by the platforms as a selling argument for why their platform will help the single user to find someone s/he fits with. As marketing rhetoric, the platforms point to scientific claims and have an optimistic view of technology. Yet, as we have shown, few of the top five matches for all our GPs would be, according to the hypergamy principle, a good fit in practice. According to the hypergamy principle, women tend to look for a partner that is taller than she (and men the opposite) and with similar or higher education or income than she. In this study, none of these factors were taken into sufficient account when recommending and constructing matches. We can only speculate on why the platforms use an assortative mating and similarity model as the basis for recommendations. It could be because the underlying models are inspired by the psychological literature on partner preferences, which mainly points to mate value as a key indicator when choosing a heterosexual partner. Mate value denotes the perceived degree of attractiveness from the opposite sex as a potential mate (Fernandez et al., 2014; Kirsner et al., 2003; Sprecher, 1998). The theorising and construct of mate value builds on Darwin's theory of evolution and selection as well as the social exchange theory of relationships (Fernandez et al., 2014). Mate value concerns both men and women, yet the components in mate value differ between the genders (Ben Hamida et al., 1998). Attractiveness, youthfulness, figure, and body features are, according to this literature, consistent indicators, with certain characteristics predicting an increased mate value for women (Singh, 2002; Fernandez et al., 2014). Men's tendency to select traits such as attractiveness, youth and body shape and size suggests a preference for more uncontrollable qualities. This, however, differs from what the mate value literature finds for females, which are traits that can be controlled or achieved, such as status, ambition, job prospects and physical strength (Ben Hamida et al., 1998). Since most of the platforms were created and established by white, male IT workers and businessmen, the matching logics in the platforms could thus mirror a male's mate value perspective. Another explanation could be that well-known partner preferences and principles from the social sciences are less known and present in the public discourse. It is psychologists that have television shows, columns in newspapers and podcasts, or are authors of books offering their advice and comments to couples. Social anthropologists do not study individuals or interpersonal aspects and are thus also less present in the public discourse on these topics. Moreover, psychologists are concerned with interpersonal aspects that are most important when *being* *in* a relationship, not *prior to it*. Anthropologists and sociologists, however, direct their lenses to aspects that are important for *the creation* of relationships and thus for matching criteria.

Dating platforms, as with other new technologies, are reducible to binary code (Horst & Miller, 2012). Creating matches based on similar or different characteristics in two persons' answers entered into a system is quite simple programming. It is either 0 or 1. Yet, future dating platforms should take into consideration when construction matches that, following Bourdieu (1986), one kind of capital (e.g. income) could outperform another (e.g. education). A good place to start would be to tidy up all the methodological flaws that the systems using a content-based method with a matchmaker recommender logic are fed with.

This study is not without limitations. We do not know if the platforms' suggestions regarding top matches are based on a poor sample of members (few candidates available on the platform), if the time of establishing a membership plays a role (new members are ranked higher) or the extent to which paying members benefit in terms of higher match scores and ranks than non-payers – an aspect that Courtois and Timmermans (2018) also point to as a limitation in their test of Tinder's algorithms. Another ongoing study by the first author on dating apps using collaborative filtering methods where recommendations are based on the users' past interactions with the system suggests that paying members indeed enjoy benefits. Moreover, researchers on partner preferences should explore potential risks with dating platforms using an assortative mating matching model.

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