Declarative Variables in Online Dating: A Mixed-Method Analysis of a Mimetic-Distinctive Mechanism

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Declarative variables of self-description have a long-standing tradition in matchmaking media. With the advent of online dating platforms and their brand positioning, the volume and semantics of variables vary greatly across apps. However, a variable landscape across multiple platforms, providing an in-depth understanding of the dating structure offered to users, has hitherto been absent in the literature. In this study, more than 300 declarative variables from 22 Anglophone and Francophone dating apps are examined. A mixed-method research design is used, combining hierarchical classification with an interview analysis of nine founders and developers in the industry. We present a new typology of variables in nine categories and a classification of dating apps, which highlights a double mimetic-distinctive mechanism in the variable definition and reflects the dating market. From the interviews, we extract three main factors concerning the economic and sociotechnical framework of coding practices, the actors' personal experience, and the development methodologies including user traces that influence this mechanism. This work, which to our knowledge is the most extensive thus far on dating app declarative variables, provides a new perspective on the analysis of the intersection between developers and users of online dating, which is mediated through variables, among other components.

CCS Concepts: • **Human-centered computing~Human computer interaction (HCI)~Empirical studies in HCI;** • Human-centered computing~Human computer interaction (HCI)~HCI design and evaluation methods~User models; • Human-centered computing~Human computer interaction (HCI)~Interaction paradigms~Graphical user interfaces; • **Human-centered computing~Collaborative and social computing~Collaborative and social computing theory, concepts and paradigms~Social engineering (social sciences)**

KEYWORDS: Declarative variables, user representation, matching systems, online dating, mixed-method

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1 INTRODUCTION

Benjamin Franklin suggested applying *Moral Algebra* to his nephew's decision to choose a wife in 1779. This consists in creating a balanced list of two columns (pros and cons) on a sheet of paper with attributed motives and weights [34]. The method was adapted half a century later by Charles Darwin for his cousin [49], where one can observe a sequence of items and short sentences, organized horizontally in lines, thus introducing the "table, as a graphical reduction structuring and ordering knowledge" [35]. Variables such as age, profession, education and traits of character, in more or less structured lists [1], have long served matchmaking purposes. From personal ads in the press to machine-readable paper questionnaires in matrimonial bureaus, these media can be traced back to their 18th-century usage by private individuals and intermediary experts such as marriage brokers [23]. Thereinafter, Minitel France in the 1980s (with its "pink" messaging service) and Bulletin Board Systems in the USA [8] influenced computer-mediated dating through new practices of "technical writing" via graphical interfaces [11]. Today, datafication of dating from mobile apps and websites involves large sets of variables stored in databases, which are interoperable across platforms, for matching, profiling and targeting advertisements [4]. Roughly speaking, these variables can be classified into two categories: (i) the "invisible" variables allowing the collection of data without the user's knowledge, and (ii) the "declarative" variables directly accessible from the GUI, which are presented to users through dedicated profile sections and questionnaires for self-description and defining the target profiles. Both types allow for the collection of user behaviour from both the dating platforms and from exogenous sources, such as social media. Together they feed the input variable set of the algorithms, but only the latter type is directly available to academic scientists (due to intellectual property rights) and can be collected without affecting user privacy. The declarative variables, which are completed during the often-mandatory registration step [81], are the prime mediation between users and the system, and they play an active role in various interactions from online dating to face-to-face meetings. The human-computer interaction and social computing literature, completed by works disseminated in different research communities, reflects a large variety of uses: filtering user research preferences on the interface [38], self-description [80,81] and representation according to an ideal audience [17], safe self-disclosure [30], attractiveness assessment [32], increasing trust [33,71], and as benchmarks for finding new strategies to overcome the constraints of self-presentation and evaluation within the platform [29]. Variables are defined according to the economic logic of dating [2] and are a valuable means for improving user preference learning in computing matching proposals. In addition, the role of declarative variables is extended to in-person meetings in order to start a conversation [48] and to validate the other person's offline identity by comparing it with the profile [47]. Consequently, variables contribute to shaping both user experiences and algorithm search spaces. These are a key component of the collective knowledge that is created by both the users that feed platform databases via input values and by the developers that define them. However, in the computing literature, variables are often considered as abstract components, and the rationale for their inclusion in a profile are most often unknown to users (e.g., [77,78]). In the human-computer interaction and social computing literature, the variable role for users has been studied extensively but, to our knowledge, their implications for the mediation process between the dating app developers and the users have rarely been explored [8,22]. Our paper thus investigates the declarative variables used in these platforms to shed light on user profiles crafted in the dating industry, as an entry point, albeit partial, to proprietary algorithms influencing mate choice preferences. In addition, it elucidates a few mechanisms associated with the practices of the dating app founders and developers that guide the variable construction. Specifically, using a combination of exploratory data analysis and a qualitative approach based on interviews, we address the two following research questions:

RQ1: Given the declarative variables collected from a set of dating apps, which main variable arrangements structure the dating profiles in direct mediation with users?

RQ2: Following dating app founders' and developers' personal and professional experiences, which factors influence the definition of declarative variables shaping user modeling and matching?

To address these questions, we follow a mixed-method research design, which goes beyond the previous analyses based on either qualitative or quantitative data. We manually extracted and built a dataset of 317 declarative variables from 22 online dating Anglophone and Francophone platforms, subsequent to registration and profile creation in each platform as a user. Moreover, we interviewed nine developers and founders involved in the conceptual design of ten dating apps. Our paper includes the following contributions:

(1) To address RQ1, we computed two classifications: one of the variable set and one of the dating app set, based on the presence/absence of shared variables. A preliminary observation of the distribution of the variables on the dating app set shows that it is non-uniform: 34% of the variables are common to two or more apps, and the others appear in only one app. An in-depth analysis of the variable landscape led us to propose a new typology of the declarative variables in nine categories, supported by the literature, that reflect the perimeter they cover, from "individual capital" to "relational dynamics". Additionally, the dating apps' classification reveals four classes reflecting particular dating structures ("communitarian sex-driven", "quick dating", "full commitment", "diversity"), which do not necessarily regroup apps with the same language or common brand agglomerations. To our knowledge, this double classification of declarative variables and dating apps is the first quantitative description of the dating market, and it considers a significantly wider set of variables and a more diverse sample of apps than the most recent quantitative research highlighting the relevance of studying dating profiles as documents [54]. Our study provides insight into the variables profiling the user according to platforms' interests, which serve the mechanisms of filtering tools and recommendation systems.

(2) To address RQ2, we identified recurring themes concerning coding practices captured from the analysis of the founders' and developers' interviews. Results show that the definition of variables is structured by a combination of two mechanisms (mimetism and distinction), which are intertwined at different levels. A mimetic mechanism is shaped by general software development standards to build mobile apps, and by a quest for efficiency through reusing existing techniques. It is exacerbated by the agglomeration of brands and app forerunners that mark trends. Simultaneously, a distinctive mechanism is imposed by the app store release conditions, the advertisement and the app's business model, as well as the founders' personal experiences, which contribute to the creation of what we call "myself-variables". This double mechanism contributes to a stabilization of the similarities and differences between app and variable classes. In addition, we show that the reviewing process of the dating service is fed by the dynamicity of the Agile methodology driving software updates, the analysis of automated user traces and direct feedback. The continuous adaptation environment in which developers find themselves, leads to a reduction in user diversity in favor of standardization for technical, financial and branding reasons. Our in-depth analysis goes a long way towards completing pioneering studies [8,22] that have mentioned the relevance of developers' work in dating apps. We show how these actors influence the

definition of variables, and, consequently, user modeling and computed outputs from their initial conceptual choices.

This paper is organized as follows: Section 2 discusses related work; Section 3 presents the data sets and their respective collection processes; Section 4 presents a typology of the declarative variables and a dating app classification resulting from a comparison based on a presence/absence of common variables; Section 5 analyses important mechanisms involved in variable construction that influence the establishment of structural similarities and differences in the dating industry; Section 6 discusses the findings and limitations of our work; Section 7 concludes the paper and open perspectives in social computing.

2 RELATED WORK

The analysis of self-description variables, the practices of developers, and the socioeconomic and technological factors that shape the construction of declarative variables is related to a body of literature in human-computer interaction and social sciences concerning intimate relationships in dating apps, particularly in CHI and CSCW as highlighted in a proposed research agenda [9] and sociology. While most online dating research has contributed to user experience understanding, this study focuses closely on dating app design and app developers.

2.1 Self-description variables for matching

Algorithmic system design influences users' decision-making processes. It attracts the users' attention via the information that is displayed [72]. Dating apps are conceived as "reciprocal recommendation systems" [57] that measure mutual interest based on messaging interactions, behavioral traces, and user profile characteristics [73,77]. A principal feature of these so-called "social matching systems" is the profile creation, where users are required to create a personal portrait of themselves, specifying their interests, age, gender, and to provide a photo [38]. The volume [27] and content of profile pages can vary from system to system [79]. Various lists of characteristics can be extracted from the literature: 73 traits, preferences, lifestyles and future plans [76]; 9 variables (such as race, education, smoking, drinking, and quick match rating) are taken into account to create "community profiles" between old and new users, which go towards solving the cold-start machine learning problem [78]. A coarse-grained classification of self-description variables was compiled from a review of attraction literature, which contains five general trait categories influencing a person's attractiveness [81]: "*physical attractiveness:* physical or visual appearance; *demographic traits:* height, weight, race, ethnicity, age, religious affiliation, income, education, marital status; *lifestyle traits:* attitudes, values, interests including lifestyle choices associated with demographic traits (e.g., how often one goes to church), attitudes about life (e.g., should women stay at home while men work), and other interests and activities (e.g., smoking habits, going kayaking); *personality traits:* the psychological five-factor model of personality, intelligence, and sense of humor; *relationship goal:* perception of the person's preference for a long-term relationship or short-term casual encounter."

Some of these variables are not new to online dating and are etched in long-standing practices from traditional matchmakers to computer-readable questionnaires [37]. These artifacts dispose and coerce precise ways of organizing knowledge and expertise about matchmaking. In sociological studies, user profile variables are roughly categorized into "sociodemographic", "geographic" and "psychological" [47], often undescribed [40] or aggregated to construct "cultural and economic capitals" [63]. The latter being inherited from Bourdieu's sociology of tastes [16] affirming that tastes concerning arts and food, and even potential mates, are practices defined by an individual's structured socio-spatial position. In these structural analyses, individual tastes regarding mate preferences depend on "socioeconomic" (e.g., education) and "sociodemographic" (e.g., age) characteristics that define a certain lifestyle [64]. Bourdieu's capitals have also been classified in online dating as "social" (i.e., variables describing resources and benefits of social ties) and "cultural" (i.e., variables describing symbolic and incorporated resources) [38]. Additionally, upon culmination of the present study, a comparative analysis of ten popular American dating apps was published [54] wherein 18 variable fields were common, and 65 were unique. Authors contribute with the introduction of Document theory, to show that variables reflect market and power structures that rule intimate platforms. They highlight the fact that users have limited freedom when creating a profile, since they can mainly only choose from predefined options, as the majority of these are fixed by the system. In this sense, variables serve for "self-representation and profit extraction" [54]. While the study is one of the first quantitative studies of variables, it is restricted to describing only the most commonly required fields.

Our paper extends the state of the art by the analysis of self-description variables, which also contribute to the definition of user preferences: this is the most extensive quantitative and comparative study of dating app variables, extracted from an extended set of Anglophone and Francophone platforms. It complements online dating research by providing insight into "what" constitutes user representation and the dating experience.

2.2 The dating industry's mimetic-distinctive strategies

The dating industry consists of an agglomeration of brands that gathers the most popular apps in different markets, and small independent companies targeting uncovered niches [4,8,31]. The development of online dating as a business can be associated with the precursor website Match.com, launched in 1996, because of its brand positioning that translated into quality-type variables describing a person [5]. Currently, Match makes up part of the major brand agglomeration, The Match Group, with around 30 worldwide applications and 9.6M paying users (Q3 2019). Generally speaking, online dating is a widespread practice as various surveys in several countries show: 30% of adults in the United States have used a dating app or website (2019)[1] and 18% of French have too (2014) [8], except that the percentage resulting in adults forming couples is lower. In the U.S, 12% of adults committed to a relationship, whereas in Switzerland that result was only 1,1% (2018)[2]. Its spread is reinforced by the common adoption of components of advertising strategies, associated with the business model of the most popular platforms [13,14]. Moreover, spearhead dating apps, like Grindr with its real-time mobile geolocation and Tinder with its the swipe gesture [68], are used as references that foster mimetic design practices. These different elements have led to the current situation, where the most popular apps serve to mark trends, and the small independent companies follow them, but both have to guarantee a certain distinctive element that will potentially define the innovation and the community they are addressing [9]. In our work, we investigate this dual influence of mimetism and distinction in variable construction and, more generally, how the economic logic of the dating industry guides the developers' work.

[1] Pew Research Center (Feb 2020): The Virtues and Downsides of Online Dating. Retrieved from https://www.pewresearch.org/internet/2020/02/06/the-virtues-and-downsides-of-online-dating/
[2] Federal Statistical Office (Nov 2019): Families and Generations Survey. Retrieved from https://www.bfs.admin.ch/bfs/fr/home/statistiques/population/enquetes/efg.assetdetail.10467789.html

2.3 The mobile app technical framework

Dating apps, as with other mobile apps in the software industry, follow the standards of American tech companies, which foster mimetic programming practices. Apps are coded and released under the landmarks of Google and Apple, via their respective operating systems. The companies offer APIs (Application Programming Interfaces) and SDKs (Software Development Kits) to facilitate coding tasks. Indeed, Android provides developers with a rich software stack and environments, of which they may choose to exploit aspects such as virtual machines, emulators, testing tools, documentation and code. Similarly, iOS structures the mobile market with some distinctive features and programming languages [42]. For instance, the most common SDK is Facebook Connect or Login, which is used as a "third-party identity provider". This Single Sign-On (SSO) system allows users to log in to a new app with their existing Facebook account, and developers can "request access to read parts of the user's Facebook profile or write data back to their profile" [58]. In dating apps, cross-platform connectivity has been identified [4,38], and is made possible via the APIs and SDKs delivered by the aforementioned companies. Therefore, the dating industry relies on this particular technological availability whereby software developers at dating companies are "API consumers" who write code to call an API (e.g., from Facebook), and software developers at Facebook, Google and Apple are "API producers" [66] who write and deliver the implementation. In our work, we identify the impact of this IT development environment, shared by all stakeholders, on the definition of variables.

2.4 Practices of dating app developers

To our knowledge, there are no comprehensive studies dealing with the practices of dating app developers, and few authors have pointed out the relevance of studying the makers of these platforms. One of the first studies, carried out in partnership with Yahoo! Research and Personals for identifying strategic directions for growth, conducted interviews with four designers, developers, and managers [22]. More recently, a sociological study [8] showed that the "dating technicians" convey their definition of intimate experiences via the platform, anticipating the users' desires in their absence, and the image of their profession. Interviews with founders and webmasters indicate that their technical choices arise from the focus on developing an online service under the influence of marketing, and not under that of dating expertise. The results of the study disclose three design principles: mimicry of other competitors, segmentation of the target audience, and stereotyping love and sex in heterosexual normative relations. The functioning of dating apps seems to reflect the strategies of its producers more than the uses of its consumers [7,8]. The observations from these two studies are consistent, showing that there are business processes of customer targeting and market segmentation entangled with a "sensitive branding strategy" [22]. The oldest study relates to user practices and their understanding of interfaces and algorithms via profile construction, search, and offline interactions, without explaining the coders' work. In particular, some users have confidence in the accuracy of the compatibility score between matches visible in the interface, while others feel excluded from the profile categories offered.

As explained, interfaces are developed so as to produce algorithm-appropriate inputs [22]. The entanglements of different stakeholders within a sociotechnical dating system were schematized in a public presentation [26]. User profiles, along with their variables, are the entry point of potential communication between users, coders and other elements of the dating business. Focusing on another type of expert, authors in [81] show that online dating coaches develop their techniques partly from the variables available in the interfaces, in order to provide users with advice.

Beyond the dating industry, various in-depth studies have been conducted in the CSCW community, highlighting the relevance of studying the development and engineering processes to improve design accuracy and user interaction [28,36,70]. Ethnographies are suggested as a methodology to follow actants in the making [75], but dating app companies seem impervious to this kind of field study. Online dating remains a "Pandora's box", with several methodological issues relating to the users' "recruitment, deception, institutional review and intersectionality" [82], but also when relating to companies and developers.

To our knowledge, our work is the first to integrate an understanding of dating app developers' practices. Herein, we refer to "software developers" as actors who are related to coding a dating app in some way, who may come from different educational backgrounds (e.g., engineering or computer sciences), and who may have different responsibilities. Often, "their working practices differ from the fields of specialization that engineers follow" and "with the increase of private companies, engineers also become managers" [60]. As pointed out by Boudreau [10], it is necessary to see dating apps as "multi-sided platforms" that support interactions across multiple sets of actors, and that can facilitate technical development. One could conceive of these developers as "a figure that articulates the technical issues and constraints to the social, economical, practical, and political reality in which a project takes place" [62]. Consequently, developers contribute to the design of "an artifact which, beyond its technical materiality, is part of a system of uses and beliefs that must be taken into account to allow the usability and intelligibility of the programs" [62]. We, therefore, study these actors within a sociotechnical system, to understand why the declarative variable design space is what it is.

3 DATA COLLECTION

Our work is based on a mixed-method approach, in order to benefit from the complementarity of quantitative and qualitative research [66]. First, we present the set of variables extracted from the dating apps for an exploratory data analysis. We then describe the interview methodology we followed so as to study the economic and sociotechnical factors influencing the definition of variables. The study adhered to ethical procedures, and a data management plan concerning personal data that was approved by the EPFL Human Research Ethics Committee (HREC), No. 007-2018 / 22.02.2018.

3.1 Dating app variables

A set X of p = 317 variables were manually gathered from a set D of n = 22 online dating platforms, composed of 9 websites and 13 mobile dating apps (14 Francophone and 8 Anglophone) accessed and downloaded from the first author's smartphones in a Western European country. It should be noted that the app language depends on the IP address, mobile phone language configuration and app version. The language chosen was either the option by default on the first author's device, or the only one available. Therefore, we verified — from their privacy policies and other references (see e.g., [38,54]) — that the majority of these apps are accessible and well-known worldwide, as they belong to American or other international investors. Data were collected between February and November 2019, and the platform versions are described in Table 1. Three factors guided the selection of the dating apps: (1) the diversity of the population targeted according to the sex options available when registering to describe oneself and to find another user. The sex options and their combination constrains, for example women seeking women (homo) AND men (bi) OR women seeking men (hetero), are presented in Table 1, see "Population (sex or status options)"; (2) a distinctive element of innovation advertised in the app's website or in media coverage; and (3) the accessibility to a finite number of declarative variables. The first two factors are relevant as dating apps are created under a marketing logic throughout population segmentation strategies [8] and more broadly, technological innovations are created by advertising a new improved component from another app or a distinctive one for market penetration [3]. To find the apps online, the first author used the Digital Methods tool "Search Engine Scraper"[3] to query the browser without the influence of personal history and cookies, with the following keywords: "dating apps", "online dating", "sites de rencontres", "mobile hook-up apps", "apps de rencontres" and "rencontre en ligne". After consulting every link and clearing the list of unrelated websites, the most recurrent app names were retained, as well as those containing a distinctive component or message. Some examples being: Adopteunmec where heterosexual women can "shop" men by adding their profiles in a shopping cart.

Table 1. List of 22 dating apps and websites analyzed.

No.	Name	Platform	Population (sex/status options)	Version/ Access date	Language
1	**AdopteunMec**	website	hetero	feb 2019	FR
2	**AdultFriendFinder-Aff**	website	hetero/bi/homo/ single/couple	oct 2019	FR
3	**Badoo**	android	hetero/bi/homo	v5.137.1	EN
4	**Bumble**	android	hetero/bi/homo	v5.139.1	EN
5	**CasualLounge**	website	hetero	nov 2019	FR
6	**Feeld**	android	hetero/bi/homo/ single/couple	v5.5.7 Build 364	FR
7	**Grindr**	iOS	homo (men only)	v5.20.0	FR
8	**happn**	android	hetero/bi/homo	v24.17.3 #633	FR
9	**Her**	iOS	homo (women only)	v6.5.14	EN
10	**Hinge**	android	hetero/bi/homo	v7.1.0	EN
11	**Lovoo**	website	hetero/bi/homo	nov 2019	EN
12	**Meetic**	website	hetero	jul 2019	FR
13	**MeeticAffiny**	website	hetero	jul 2019	FR
14	**Once**	iOS	hetero/bi/homo	v2.8.10	FR
15	**Parship**	website	hetero	nov 2019	FR
16	**Passions - Meet over 50**	iOS	hetero/bi/homo	v2.1.1	FR
17	**PlanetRomeo**	website	homo (men only)	oct 2019	EN
18	**Pure**	android	hetero/homo	v2.19.33	FR
19	**Scruff**	android	homo (men only)	v6.0019	EN
20	**Tinder**	iOS	hetero/bi/homo	v11.2.1	FR
21	**Tomorrow**	android	hetero/bi/homo	v1.0.8	FR
22	**UnitedMen**	website	homo (men only)	nov 2019	EN

[3] Digital Methods' tools from the University of Amsterdam (Dec 2020). Retrieved from https://tools.digitalmethods.net/beta/searchEngineScraper/

The app also blocks direct messages from men to women; AdultFriendFinder fosters sexual libertinism for singles and couples with video streaming; Badoo promotes a social profile including the possibility of obtaining a popularity score and gaining money in exchange. The latter selection condition (a finite number of declarative variables) led us to exclude OkCupid as the profile page is organized on sliders, where a few variables are visible, but not all are previewed by default. Instead, a user can keep adding new variables interminably, that each lead to the appearance of a new profile section. These sections are organized according to different topics, and each topic has between 5 and 8 predefined variables that can be chosen from a list. For instance, in the section "About me", one can choose: My self-summary, favorite thing about the place I live, Me- a Haiku, etc. Moreover, OkCupid crowdsources the match questions, leading to the creation of more than 460,000 questions, which were intractable for our analytical framework. Including such websites, while limiting them to only a few pages like "Basics" where sexual orientation is presented, would lead to an unbalanced proportion of number of pages for some apps. The p variables were extracted from GUIs, where they were then organized into four families of pages: registration, profile-editing, profile-view, and research criteria or preferences. Together, these pages form the declarative user identity and the ideal date — often a compulsory process for accessing the online dating service, which acts as the first mediation between the system and the user.

The diversity of programming languages, design formats, and dynamic contents did not allow for the efficient use of automated scrapping methods. Therefore, we resorted to a manual extraction, with a preliminary registration and profile creation in each platform as a user. The various pages of the apps were browsed so as to understand the whole system, and for every page where an online form with questions was found, all variables were collected. No personal data was collected, and no contact was made with the users. All the profiles created specifically mentioned that it was a "researcher" profile, and that it was possible to contact us for further information about the research. For dating apps targeting heterosexuals exclusively, and for generalized apps for heterosexuals, homosexuals, and bisexuals[4], as well as for apps for women seeking women, a female profile was created when collecting data. In dating apps for men seeking men, a male profile was created.

Variables were collected using their original name and later translated into English for Francophone apps. The diversity of the naming conventions was standardized for the sake of comparison in the following way: long sentences were shortened and were coded into a more general description, and variables that had an ambiguous name (mainly because they were using jargon) were labeled by a specific variable that reflected their meaning, after browsing their usages on the platform. This data pre-processing avoids doubling up on variables referring to a similar question. Let us note that one major difficulty we faced was labeling variables from the extensive questionnaires, — about sexual preferences, social life and psychology — which are integrated into the following four apps: AdultFriendFinder, Hinge, Parship, and MeeticAffiny. These are very specific, often building scenarios to capture the users' behavior in precise situations.

[4] We use these three categories because in a general manner dating apps target users via binary sex combinations (M-M, F-M, M-F, F-F or both F-M-F, M-F-M). It is a mandatory field on the registration page, despite the fact that some apps offer myriad sexual identities at later stages.

3.2 Founder and developer interviews

3.2.1 Sample construction. Seven interviews were conducted with nine founders and developers from ten dating apps, between March 2018 and January 2020. Participant recruitment was a difficult task. Twenty dating companies in France, Switzerland, Germany, United States, and India were contacted by e-mail, contact forms, and LinkedIn. Most of them did not reply, and only one company accepted to do an interview. Engineers and developers were also contacted personally through LinkedIn, but did not answer. Participants were finally recruited by word of mouth: two were met during an annual technology conference, and others were introduced by acquaintances that knew about the research. The issues encountered regarding reaching such companies and developers, reflects the opacity of the dating industry: algorithms are fiercely protected and developing practices are not reported externally. Although the sample is thus limited, it allows for access to additional knowledge about dating apps. This study being exploratory, there was no expectation of being representative, but we aimed to preserve diversity for two dimensions: job position and type of dating app market. In addition to educational background, job position helps to identify the type of knowledge engineers acquire due to experimental practices [74] in relation to their company responsibilities. Participants had to be either the founder or the developer of a dating app, and either currently employed in or having worked in that industry previously. It was also important to have participants from different dating apps, following the assumption that marketing segmentation strategies have an influence on the design that app technicians conceive [7,8]. Consequently, the sample is composed of nine participants: six individual interviews, and one group interview with three participants that are partners and had created five dating apps using the same code. Despite the apparent homogeneity due to recruitment barriers, we were able to meet our diversity objective, at least partially, and ten dating apps are represented in this sample (see Table 2 for details). However, all the participants in the sample are men. The lack of gender representation, reflects the demographic characteristics of the IT environment [24]. Few apps are founded by women, and the two we located were contacted without success. One woman was interviewed, but she was excluded from the study because she was working in the customer service department, without any direct involvement in programming practices.

3.2.2 Interview methodology. Semi-structured interviews were conducted and audio was recorded via phone calls or Skype by the first author, who also transcribed them. Recordings ranged in length from 54 minutes (min.) to 75 minutes (max.). Discussions continued with three interviewees via e-mail and chats. Participants gave their written consent, their names are pseudonymized, and the names of the apps are anonymized to protect their identity and avoid possible links between the interviewees and the companies included in the quantitative study. The author who conducted the interviews is a female researcher who has previous professional experience in development, which facilitated the communication and comprehension of the technical vocabulary. Moreover, by recruiting developers directly, the interviews were experienced as a space for free expression, enabling interviewees to value their work and express themselves outside of commercial constraints.

Table 2. List of participants and dating app characteristics.

No.	Qty. Participants	ID	Profession / Position in the company	Qty. apps / Main markets / Popularity acc. to interviewees	Creation year / working period
1	1 developer	I1	Software engineer / Quality assurance engineer	1 / Portugal, France, Russia / medium popularity	2016-today
2	1 developer	I2	Computer scientist / Server developer	1 / Switzerland / app sold to an advertising company	2015
3	1 founder-developer	I3	Computer scientist / Founder and server developer	1 / France, Belgium / low popularity	2017-2020
4	3 associates, of which one is a developer	I4	Sociologist / Product owner and Founder	5 / France and Spain / medium popularity	2004-today
		I5 I6	Engineer / Full stack developer and Founder Lawyer / Associated partner		
5	1 developer	I7	Computer scientist / Android lead developer[5]	Portugal, France, Russia / medium popularity	2016-today
6	1 founder with technical skills	I8	Architect / Founder	1 / United states / low popularity	1990-2000
7	1 developer	I9	Applied mathematics / Data engineer	1 / United States, Worldwide / high popularity	2004-today

The interview protocol focused on the participants' educational and professional profile, a description of the app's functionalities, its design, most important variables, business model, match definition, daily work, tools, releases, and problem-solving. Demographics, not being of particular interest for this study, were excluded to protect participant identity. Open discussions were allowed when new questions arose or when the interviewees wanted to talk about other topics. This approach favored a two-step reflexive analysis, since interviewees instinctively opened with their standard speech taken from marketing and business strategies, and then later, when they went into detail about daily practices, they encountered moments of doubt, hesitation, and various issues that had to be disentangled before we were able to see action and cooperative work emerge [67]. A grounded theory methodology was employed in this analysis, using NVivo software for qualitative coding. The first author coded the emergent terms in the interview transcripts, in an inductive manner. The first In Vivo [53] coding cycle was based on participants'

[5] Working on the same dating app as I1

own language, as identified in the data when referring to development practices or components such as server deployment, testing, tracking and databases. Terms were discussed with the second author before performing a second coding cycle with descriptive short phrases, in order to select those that were evoked by more than one subject and that were related to the definition of variables.

4 VARIABLE LANDSCAPE AND DATING APP CLASSIFICATION (RQ1)

The distribution of the number of declarative variables over the dating app, set D, is very heterogeneous (Fig. 1), with a maximum for Aff equal to 123 and a minimum for Pure equal to 5. It is worth noting that the nine apps containing less than 20 variables are geared towards a practice of immediate matching, through the minimization of variables presented to users. The main variables common to these minimalistic apps are demographic (binary sex, age), socioeconomic capital (occupation, university name) and online sociocultural capital (cross-platform connectivity), which are also present in the other apps. More precisely, the variable set X can be partitioned into two subsets: subset $X_{1,}$ which contains the p_1 =109 variables common to two or more apps of D, and subset X_2 which contains the p_2 =208 variables appearing in only one app. In the following subsections, we first create a typology of the declarative variables, and then we analyze the dating app similarities and identify their differences. As shown in subsection 2.1, the lack of ontologies upon which to base our analysis made it difficult to draw *a priori* assumptions. Consequently, we followed an exploratory data analysis approach.

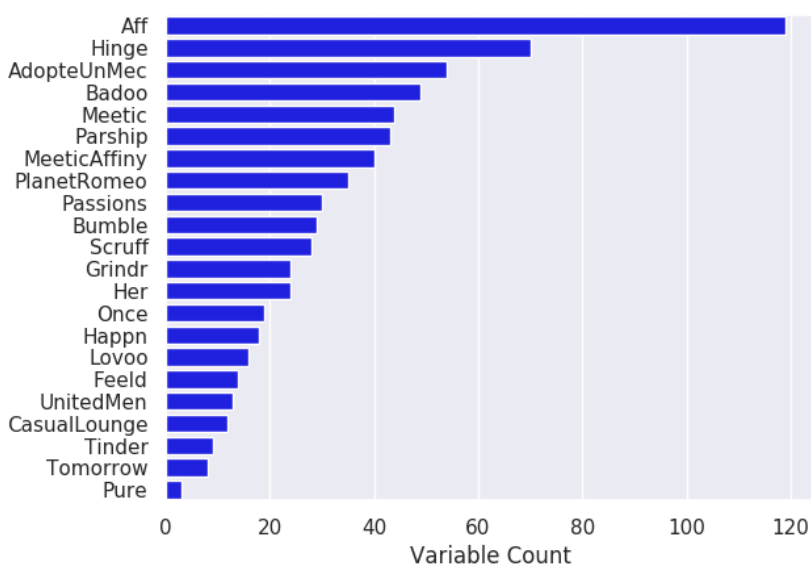

Fig. 1: Distribution of 317 declarative variables over 22 dating apps.

4.1 Declarative variable typology

The new typology of the variable set X in nine categories is deduced from an inductive approach based on three criteria: (i) who is the variable referring to (user, ideal partner, couple, interaction itself), (ii) which tense is used (past, present, future), and (iii) does the app already present a category (myself description, personality, lifestyle, etc.). The observations of the empirical data were compared to previous sub-classifications published in the psychological and sociological literature. As reflected in Section 2, part of this literature mainly focuses on attractiveness evaluation concerning the user's demographic, physical, psychological and social characteristics [31,32,81]. Another complementary part focuses on what constitutes a person's capital in a social context, drawing on Bourdieu's theory [38,64]. In a process of self-description, these variables mainly address one initial stage of the encounter, which includes both the description of oneself (to be chosen) and the description of another person (to choose). A first subset of our empirical data covers this initial choice stage. A second one, however, concerns the description of the online and offline encounters between two users (e.g., relational goals, daily organization as a couple, importance of sexuality). The dynamics of relationships was studied in the in-depth literature review on couple formation by Kellerhals et al. [46]. Overall, they identify certain dimensions distinguishing that which refers to the individual from that which refers to the couple. More precisely, they establish four dimensions: (1) psychological characteristics, (2) socio-cultural heritage, (3) relational dynamics, and (4) problem solving or "coping". From these indicators, in combination with previous literature on online dating, we draw a new typology T(X) of X in nine categories, described in Table 3 (variable details are sent via email upon request). Let us note that concepts are defined and measured differently across disciplines. Therefore, the new categories are defined according to three dichotomous criteria: (i) individual/couple, (ii) personal patrimony/behavioral dynamics, and (iii) offline/online environment.

The three most representative categories on the variable corpus are individual capital (32%), relational dynamics (27%) and sociocultural capital (13%). Online dating is in general, formed by personal history, the users' representation of their own capital and behavior, and what can be built *in situ* on dating apps, as a socializing space on its own. Jointly, these dimensions characterize the user, or "casting mold" of intimate platforms [54]. The heat map in Fig. 2 displays a variety of category combinations for each given platform. The dating apps on the x axis are organized by a decreasing number of variables. For instance, in first position, Aff (AdultFriendFinder) possesses numerous variables relating to individual capital (30%) and relational dynamics (26%). In last position, Pure mainly has demographic variables (60%). In the middle, Her focuses on demographic (29%) and sociocultural capital (25%). Overall, the least exploited variables are those that concern coping and online relational dynamics. The statistical distribution of the different categories of the typology T(X) is given in Fig. 2: for each category of T(X), the value presented in the heat map corresponds to a rounded percentage of variables per category, divided by the total number of variables per app.

4.1 Dating app similarities and differences

In this subsection, we focus on dating app similarities and differences by successively considering their description with the two previous-established variable sets, namely X_1 and X_2. First, we built a hierarchical classification of the dating app set D from X_1, where the previous typology T(X) helped us to explain the obtained classes. Then, we manually analyzed the role played by the unique variables of X_2 in the 14 apps which contain at least one of them.

Table 3. Category definitions and references.

	Category	Definition	References
1.	Demographic:	Individual characteristics within the population, e.g. nationality, civil status, sex.	Kessous [47], Zytko et al. [81], Macleod and McArthur [50], Sumter and Vandenbosch [68], Fernandez and Biltholtz [30]
2.	Individual capital:	Individual's psychological, morphological and health factors, e.g. dreams, skills, body parts of sexual excitation, sexually transmitted diseases.	DeSingly [25], Fiore et al. [31], Zytko et al. [81], Hutson et al. [39], Kessous [47], Zytko et al. [81], Schwartz [65]
3.	Sociocultural capital:	Individual's material and symbolic possessions, e.g. tastes in music, arts, transportation means.	Bourdieu [16], Schmitz et al. [63,64], Hsiao et al. [38]
4.	Socioeconomic capital:	Individual's professional and financial position or projection, e.g. income, level of education, company name.	Bourdieu [16]
5.	Relational dynamics:	Behavior referring to boundary setting between the couple and the outside world (family, friends), including goals, sharing and work organization, e.g. common dreams, family exchanges, dirty talk preferences.	Kellerhals et al. [46] (page 49). Sumter and Vandenbosch [68], Zytko et al. [81]
6.	Coping:	Behavior in problem solving, alone or with a partner, e.g. heartbreak reactions, behavior when disliking physical appearance.	Kellerhals et al. [46] (page 143)
7.	Online individual capital:	User's descriptors within online platforms, e.g. login status (last connection time).	Derived from Individual capital
8.	Online sociocultural capital:	User's possessions in relation to others within online platforms, e.g. PlayStation Network, Instagram login.	Derived from Sociocultural capital and Albury et al. [4]
9.	Online relational dynamics:	User interactions with others within online platforms, e.g. cybersex experience.	Derived from Relational dynamics

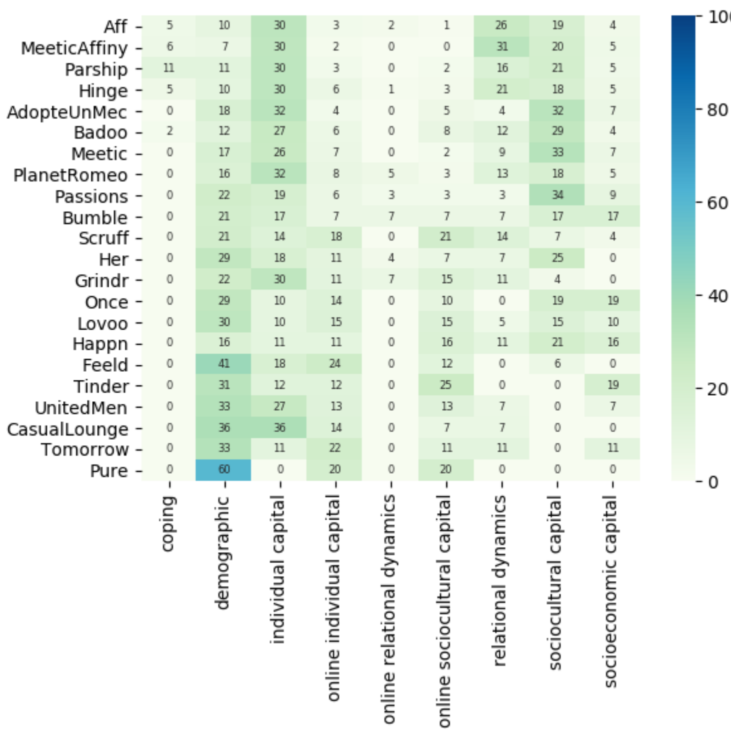

Fig. 2: Heat map of variable distribution percentages by category for each app.

4.2.1 Similarities. The presence/absence of each variable of X_1 in each dating app can be described by a binary matrix A_{nxp1}, where each element a_{ik}= 1 (one), if the variable a_k is present in the ith app, if not then a_{ik}= 0 (zero). We denote that a_i = (a_{i1}, …, a_{ij}, … a_{ip}) the binary vector associated to a row of A_{nxp1}, which describes the app a_k. The classification of the app set D depends on the choice of the function that measures the resemblance between each pair (a_i, a_j) of apps. Numerous functions have been proposed in the literature and we retained one of them, the classic Jaccard index [43], to measure the proximity between two apps a_i and a_j:

$$s(a_i,a_j)=1-\left(\frac{n(a_i\&\overline{a_j})+n(\overline{a_i}\&a_j)}{n(a_i\&a_j)+n(a_i\&\overline{a_j})+n(\overline{a_i}\&a_j)}\right)$$

where $n(a_i,a_j)$ denotes the number of variables present in both apps, and where $n(a_i\&\overline{a_j})$ denotes the number of variables present in the app a_i and absent in the app a_j, and $n(\overline{a_i}\&a_j)$ the number of variables absent in a_i and present in a_j.

A preliminary comparison of the observed distribution of the s values on A_{nxp1} with the distribution of the Jaccard index for randomized data revealed substantial differences, and highlighted that the set D is structurally heterogeneous, with some apps being similar and some being different. More precisely, four classes of dating apps can be extracted from a hierarchical classification H(D) of the dating app set D with the Jaccard index and the standard Ward aggregation (Fig. 3). The classification H(D) is robust with respect to potential minor coding errors in the construction of the matrix A_{nxp1}: we randomly selected 5% of the X_1 variables to remove them from A_{nxp1}, then re-computed the classification, and the result stays stable for 50 trials. The four main classes of H(D) are the following:

1. Class 1 (green) “communitarian sex-driven” contains five Anglophone and Francophone apps, which mostly share the following categories: relational dynamics (e.g., sex position, sex protection, sexual activities), individual capital (e.g., male hairiness), demographic (e.g., birthdate), and online sociocultural or online individual capital (e.g., twitter, login status). The app class is characterized by the granularity required for describing sexuality and physicality, and it contains all apps exclusive to male users, as well as CasualLounge for heterosexual ones, conveying mainly sexual encounters.
2. Class 2 (red) “quick dating” contains four Francophone apps, which mostly share the following categories: online sociocultural capital (e.g., Spotify songs, link partner’s profile), and socioeconomic (e.g., university and company name). The class conveys a minimalistic portrait of the user so as to speed up interactions, leaving more room for uncertainty about the encounter and the other person’s identity.
3. Class 3 (blue) “full commitment” contains six apps (only one being Anglophone), which mostly share the following categories: socioeconomic capital (e.g., revenues), demographic (e.g., nationality) sociocultural capital (e.g., smoking, diet, instruments, underwear), individual capital (e.g., hair length, look satisfaction, ambitions), and relational dynamics (e.g., ease of communication). This class is characterized by a large amount and variety of detailed variables in comparison to other classes. It conveys committed relationships, for which a holistic view of the user is required.
4. Class 4 (purple) “diversity” contains seven Anglophone and Francophone apps which mostly share the following categories: sociocultural capital (e.g., gendered pronouns), demographic (e.g., gender identity), online sociocultural or online individual capital (e.g., Instagram, Google connect, login status), relational dynamics (e.g., looking for), socioeconomic (e.g., university and company name), and individual capital (e.g., political leanings, mysticism). This class presents an experience balancing quick dating with full commitment. It adds social segregation but with more inclusiveness.

It is worth noting that the distribution of Anglophone and Francophone apps per category, shows that the contribution of the language to the app similarity is low: some Anglophone apps like Badoo and PlanetRomeo closely resemble Francophone apps like Adopteunmec and CasualLounge, respectively. Only the “quick dating” class exclusively contains Francophone apps, but, apart from Tomorrow, these apps are also available in English and other languages. The categories reveal a homogenization of online dating profile structures despite their language, which suggests that apps reuse variables from companies outside their origin country. For instance, Tomorrow, Meetic, Adopteunmec, happn and Once, were founded in France and closely resemble Tinder (United States), Parship (Germany), Badoo (UK), Lovoo (Germany) and Bumble (United States), respectively.

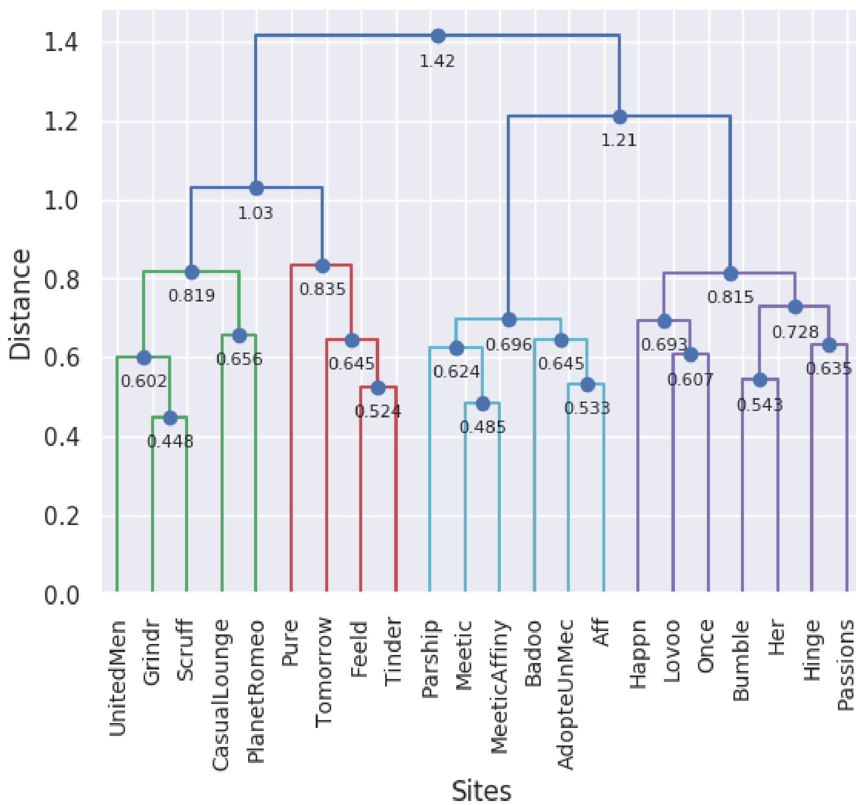

Fig. 3: Four classes of dating app extracted from a hierarchical classification using the Ward index.

4.2.2 Differences. Eight apps do not have unique variables for the set X_2, but 14 apps contain at least one unique variable (see Fig. 4), which contributes to the distinction of the apps among themselves. By manually analyzing the unique variables present in these 14 apps, we deduced the following rough classification into three classes:

1. Class 1 contains four apps (Aff, MeeticAffiny, Hinge, and Parship) with extensive psychological questionnaires, and more variables in the form of taking a personality or compatibility test. In particular, there are questions about individual capital (e.g., "Describe the most important things in your life" on Aff). These require a significant amount of, mainly introspective, work on the part of the user.
2. Class 2 contains apps (e.g., Grindr, Badoo, and Scruff) including online relational dynamics (e.g., "accept NSFW -Not safe for work- images" on Grindr) or online sociocultural capital variables (e.g., "PlayStation network" on Scruff). They reflect the users' sociability and identity online.
3. Class 3 contains apps (e.g., Adopteunmec and PlanetRomeo) that provide details about individual capital (e.g., woman's hairstyle on AdopteunMec). This thoroughly describes the users' external perspective.

It is worth noting that each class contains both Anglophone and Francophone apps, which suggests an imitation mechanism similar to the one observed in the previous sub-section.

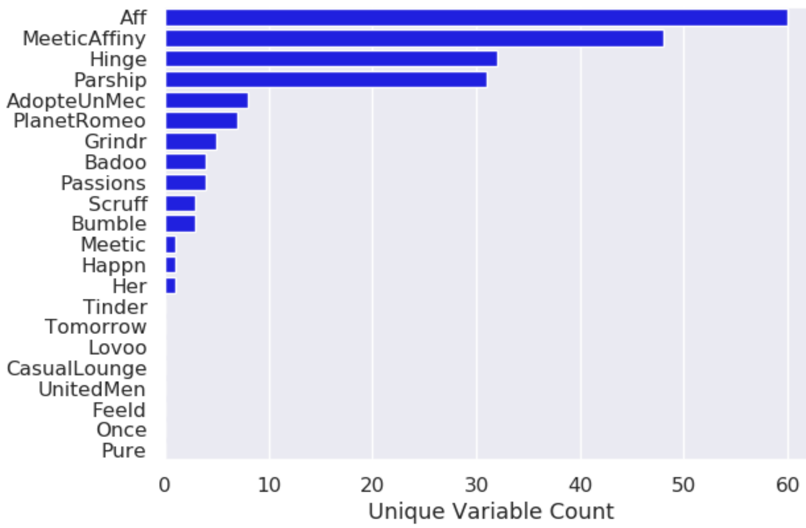

Fig. 4: Distribution of 208 unique variables in 14 apps.

Our dual analysis shows that the variables can be separated into two sets: one-third of the variables are common to more than one app, while the rest are used once only. The first set plays a part in creating a degree of similarity between dating apps, and our classification reveals a structuring of the dating app's landscape depending on this similarity distribution. The second set serves to differentiate the apps from one another, and, as mentioned, different strategies are carried out in order to compile the specifics for each app. The main factors involved in the construction of these two classifications are described in Section 5.

5 VARIABLE CODING MECHANISMS: BETWEEN MIMETISM AND DISTINCTION (RQ2)

The previous analysis reveals both strong similarities and differences between apps. The similarities and differences result from a design and coding process which combines mimetism and distinction mechanisms that regulate the creation of dating apps and stabilize the dating industry. Our interviews contribute to confirming the influence of factors previously identified in the literature, and to clarify them according to actual coding practices in online dating companies. In the following subsections, we first analyse four intertwined economic and sociotechnical factors triggering mimetism and leading to app similarities. Secondly, we identify three distinction mechanisms creating app differences. Lastly, we draw the attention to the need to integrate an additional component into the analysis: the dynamic nature of app development, influenced by both software methodologies and by user traces and feedback, places developers in a position of mediation between business and the user satisfaction that frames their creativity. Such settings put founders and developers into a position requiring continuous adaptation, driving user modeling from a self-referential process towards standardization.

5.1 Mimetic mechanisms

Dating app mimetism is favored by four factors: (i) the facility of coding mobile apps via available solutions such as SDKs and APIs, (ii) the efficiency of reusing code and copying functionalities, which is exacerbated by the agglomeration of brands, (iii) the rapid trends imposed by longstanding apps that implement the newest technologies, and (iv) for apps targeting heterosexual customers, the retention of women in order to attract men that are more financially profitable in the current model.

First, available technologies influence variable choice, and the quantity and volume of data that can be collected. A pioneer (I6), who created a dating service in 1990, recalled the difficulties of early programming and the transformation of the data collection process, where paper questionnaires were transformed into a digital database. At first, he and his associate were distributing questionnaires to clients by hand in public spaces. Once they were filled in, they initially used a scanning program to collect the data, but eventually abandoned this method in favor of adopting the Microsoft database, Access, and created a website so that the entire data collection process became an online one. The founder stated that: *"Problems were primarily keeping updated technologically and developing the web interface to stay fresh and appealing, and technologically to be able to do complicated searches on a variety of factors — it was very challenging."* Similarly, other founders who were also developers mentioned merging from website to mobile dating services. This transition obliged them acquire specific skills in line with the dominant operating systems, namely iOS and Android. Google and Apple make standardized development kits available that cover the whole chain of app production, including data structure and storage. One founder (I3) illustrates this well: "*The matching algorithm is on the server I developed in Java. It was deployed on Google servers. We use Google technologies, what they call the Google Cloud Platform, with the deployment of the server they call the App Engine. Everything, the databases, etc., are on those servers and on Google technologies. For example, the Google Data Store."* The choice of using Google server to store data was linked to costs, he stated: *"There are trial versions with a budget they allocate in advance. So in the beginning you don't pay the first couple of hundred euros, they pay them. And in fact for it to become expensive you have to reach a number of users that is very high. At the moment, to be transparent, we pay zero for the servers because we have to get to tens of thousands of users, quite large numbers, so that it becomes expensive to start having costs."* The storage is not only dependent on the number of users but also on the dimensions that describe them. In this app, the profile page comprises nine variables, and the conversations are deleted after 24 hours, so as to reduce the amount that has to be stored. The main variables in this app were extracted from the users' Facebook profiles. In the same vein as Google and Apple, Facebook offers a Login adopted by the majority of dating apps in our sample. This SDK allows one to call upon an API that is intended to provide user authentication and data access according to the variables defined by Facebook, although, as CSCW researchers have pointed out in other implementations, "more permissions can be granted without the developers knowing how much data is extracted" [58]. The same founder (I3) said: *"It's true that it's rather simple to integrate, it's used a lot now [...] and it allows us to reach 90% of users".* The implementation convenience promotes (and even implicitly steers) platforms to define part of the users' identity according to the same variables defined by Facebook: name; age; sex; photo; education; high school/university.

Secondly, the agglomeration of brands affords communication among companies, which favors the reproduction of functionalities across apps. A data engineer (I7) recalled his experience: "*We were talking to our sister companies, hey what are you doing? Can we borrow your stuff? Take some* *of that. It depended on the company how open they were. Tinder was particularly open, and Match occasionally played along, so it really depended."* In particular, apps replicate variables, when companies merge, under the same code. The practice of reusing code and assembling components is common among programmers, as "rewriting available code without a good reason is perceived as redundant" [20]. This makes it possible to save on developing time and costs, which companies capitalize on. Three founders (I4, I5, I6), who own five apps, decided to team up, as explained by one of them (I6): *"Each [of us] has our own company, he has his own company, we have our own company, and we have created a joint venture […], we are 50-50 owners of the platform, so everyone develops their sites from the platform."* The developer-owner (I5) added: *"not the brands but the technical platform, the code in fact, the program is there anyway."* The five apps contain the same variables despite targeting different markets (countries and communities with specific origins and sexual orientation) according to their brands. From the app classes in Fig. 3, one notices the presence of at least one of the apps of the well-known agglomerations or one of the oldest apps in the market. For instance, Meetic -Match Group- and independent European companies (e.g., Parship, AdopteunMec) are in the same class, suggesting that smaller and newer companies copy them and are merely positioned in different countries.

Thirdly, actors can also imitate apps implementing the newest technologies, which play the role of a model to follow. For instance, Grindr has seen exponential growth, mainly by its pioneering introduction of mobile geolocation, which has rapidly spread to other apps due to smartphone expansion [68]. One founder (I5) explained: "*when Grindr arrived [...] it forced us to go mobile very quickly, [...] [Our application] arrived very, very late [...] it wasn't great because we weren't specialized in it, it was still very new to us [...]. Technically, we still integrated the same Grindr technologies. Very quickly, we realized that it was quite important, things that we couldn't do before the smartphone era, […] now all our services are like that because it's the most logical and it's true that it's Grindr who imposed the standard."* Geolocation is now enabled by default in every mobile app in our sample, and some websites too, unless it is disabled by the user. Websites without geolocation require entering the city, zip code, region or country manually. This reflects a convention in online dating, along with the profile picture and the Facebook login.

Finally, one variable plays a specific role in heterosexual dating apps that display extensive market penetration: the sex variable is present in all the heterosexual apps of our corpus, and it is either obligatory to fill it in, or it is extracted by third-party implementations. Dating apps are a "class of technologies […] built for specific users, e.g., women as customers […] which in effect codify gender difference and reinforce the traditional gender hierarchy" [6]. Specifically, the variable "sex" provides the subscription plan setting (e.g., Pure and Adopteunmec, where only men pay) and defines profile result options that are sometimes set by default according to the app, as previously observed in CSCW research [38]. Our interviews confirm that attracting women is a business goal that developers' practices must be aligned with. As explained by an engineer (I7): *"women are the principal draw of dating apps, otherwise its full of dudes. We were completely ignoring non-straight people, you can safely ignore them and nothing will change, maybe like 5/10% unless you are targeting those demographics. […] You know 90:10% is considered the gender split, though it's more like 95:5 or 99:1, but in general getting young women onto the platform was considered crucial to its continuous growth and health. So you can still see a lot of marketing effort in the west, pushing to try to [attract] 18 to 30ish women, trying to campaign to that demographic."* In dating apps "the exemption from payment granted to women makes them the service to be offered by removing their status as clients on the same level as men" [8]. This configuration is coded into functionalities as one developer (I1) expressed: "*We introduce features, and they are mainly for* *women (e.g., initiate video calls) to give [them] more advantage. [...] As a male user, if you want to get noticed by all the women in your area you can pay a bit more to get that feature."* A study has confirmed the importance of the sex variable for targeting men, and it is used in the definition of an objective function for recommendation systems like Tinder [44].

Reusing available technology reduces costs, allowing time savings for some tasks, and reproducing successful cases is considered a strategy for preventing apps from being left behind, but this limits what can be created following on from this pattern of imitation. In addition, replicating a heterosexual business model based on the sex variable, preconfigures the dating experience.

5.2 Distinctive mechanisms

As a pendulum effect to mimetism, differentiation from competitors is a compulsory strategy, as is acquiring broader markets, which is common to the more general production of innovation [3]. The distinction strategy can be observed in the variable landscape. Tinder, Meetic, and Hinge, belonging to the same agglomeration, namely the Match Group, appear in different classes (red, blue and purple, respectively) in Fig. 3. Another agglomeration, the Meet Group (purple class) that owns Lovoo, is closer to Hinge from the other corporate group. Bumble shares its infrastructure with Badoo, both from the agglomeration MagicLab, but the two companies are regrouped into two different classes. A distinction is consequently applied as a business strategy, within or outside the same business associations. Such economic decisions impact the apps' conception and developers' work, as explained by a lead developer (I7): *"I've implemented new features and fixed bugs but the company wasn't engineering driven, so I was always involved in endless discussions regarding product and business models."* To attract users, niche dating apps are created as a differentiation strategy based on market segmentation [8]. More precisely, what we found in our study is that distinctive variables are defined through three mechanisms: (i) the app store release conditions, (ii) advertising and the app's business model, and (iii) the "I-methodology" [3] expressed by app founders, which introduces their own lifestyles and meeting expectations in the development phase.

First, one identifies a distinction mechanism imposed by the operating system markets when publishing an app. *"In Android, you can release [immediately], you just put it in PlayStore, and it will be in PlayStore,"* explained one developer (I1). His colleague (I5) added: *"In AppStore [...] they demand you have different features from your competitors [...] I'm not sure what effective ways [there are to do this], but I think it passes by changing metadata and pictures of the app and paying for reviews"*. This could partially explain why, in our quantitative analysis, multiple apps have several unique variables.

Secondly, specific variables play an important role in advertising, which is a significant component of the dating business models. This integration is facilitated through SDKs that allow the creation of a coded bridge between dating apps and third-party advertising implementations. According to a recent Norwegian Consumer Council report[6], four dating apps share the data provided by their respective users for the following variables: birthday, age segment, sex, sexual orientation, relationship type desired, country, ethnicity, religion, education level, and GPS

[6] Mnemonic: Technical report "Out of control" (Jan 2020). Retrieved from https://fil.forbrukerradet.no/wp-content/uploads/2020/01/mnemonic-security-test-report-v1.0.pdf

location. Declarative variables are also used to market the platform by contributing to identifying users and shaping algorithm outputs. The owners of five apps target specific populations and communities (e.g., Arabic-French gay men or French-speaking countries) using the variables "origins" as one developer (I5) highlighted: *"We're lucky again [because Grindr is losing popularity], so it's actually the secondary platform that's going to stand out with other features, or by offering a more specific niche, or by offering something that Grindr doesn't necessarily have or can't offer, simply because of its concept."* The variable "sex" has a particular dual status, in addition to the already identified status in the mimetic mechanism. Apps can define two distinctive business models by either ignoring the sex variable, as in Parship where both men and women pay a subscription, or by not requiring it, as in homosexual-oriented apps like Grindr and Her. The latter, together with more generalized apps like Bumble and Tinder, do not define a subscription according to sex. Users have limited free access to the service and can then either choose to pay subscriptions, or unblock functionalities via one-time purchases. All our interviewees adopted one of these three business models according to their segmentation strategy.

Finally, the entrepreneurship, empowered by the founders' coding skills or engineering profile, permitted the integration of their personal experiences into the profile construction. As indicated in [56] and [3] "when there is no other available means of bringing in the end-user, or when organized tests seem too complicated or too expensive, designers become the layman and rely on personal experiences". Our study shows that what we called "myself-variables" emerge from the founder's private perspective as an implicit user representation technique for product design. In particular, from the reproduction of their lifestyle and relationships, and their own self-image in the community to which they belong, this could be considered as personal market research. The four founders interviewed, drew on their own dating frustrations offline and when using existing services, to transform these experiences into a new product. One founder (I3) claimed to be a user of several dating apps for a long time, and explained that he was tired of not meeting women in real life, although he had been chatting frequently with them online. In his app, the main variable captures dates for a meeting, and is coded to shorten the time spent online: *"The idea was to say, from the moment you say 'I'm available on Thursday night,' how can I minimize the time spent on the app? So we decided to only show the profiles available the day before, which says you only have 24 hours to chat — because I think now in 24 hours people get to chat and see if there's a feeling, and it's a little less like before that people needed to chat for 3 weeks. I think that's less the norm, so 24 hours was enough, and then the last idea to continue minimizing time is that everything is deleted the day after the appointment."* At the same time, translating the owner's profile into variables contributes to brand construction as made apparent by the founder of Attractive World [51]; the website's service was defined for *"qualitative, serious, original and selective top-end singles".* He was attending a business school, was single, and had an active finance network. Users were then expected to match a specific civil status, location (Paris area), and occupation, i.e. "*superior socio-professional categories such as communication, advertising, arts, and finances".* This brand definition, using self-reference for developing a new app, is an attitude shared in innovation, far beyond the online dating app industry. However, in this industry, one specific factor plays an important role: the founders' communities of affiliation. When defining declarative variables, all founders in our sample, regardless of their sexual orientation, did not recall standard user modeling methods — instead, they followed an informal process. In particular, two founders made the explicit point of considering their practices as a generalized culture in gay male apps, thereby distinguishing it from heterosexual communities. Founder (I5) claimed: *"[There is] almost no need to do market research. You just have to look around you to see how people, your friends around you, use all these* *apps and you immediately understand very quickly how the market works, between our experience, those of our friends and those of our interlocutors, through these apps we have a perfect view."* Another founder (I4) said, *"stats, numbers [...], all those things are not particularly useful. What is useful is to understand the needs of gays that are quite specific, because the guy needs to know: is the person on the screen nearby, is he available, is that the real picture, [...] what does he like to do, is he active, is he passive, etc., that's the real need of gays. If the app helps them, actually it can't help them, [the app] identifies them, it has to at least meet those needs, and that's what we're trying to do by adding features or by adapting those features to meet those particular criteria that are related to the gay world, to the gay dating world".* Our quantitative study confirms that the variables referred to above (e.g., “location”, “login status,” and “sex position”) are present in apps for men, where the first two play a particular role: the variables are used as filters to manage the number of profiles to browse in a grid by providing immediate access to users who are nearby and available online. The “login status” by default shows results in a chronological order, such as Grindr and Scruff, for example, which differentiates the user experience from apps like Bumble.

Although “dating app technicians are rarely trained on love or sexual encounters” [8], this industry retains artisanal know-how, which is built on the initial choices made by founders based on their personal dating experiences, as well as the technical skills they develop throughout the mimetic and distinctive mechanisms of general standards, between the collaborative practices within agglomerations and the specific requirements of their platforms. The developers’ expertise is constrained to market segmentation, business models and technological availability, expressed by variables that frame their work and ultimately influence matching outputs and user experiences.

5.3 Continuous adaptation — Traces and feedback

Software engineers work in an environment of continuous experimentation [61]. Consequently, variables initially defined by founders are transformed over time from internal practices (those of developers) and external practices (those of users). Similarities and differences between apps are lost in daily activities and are stabilized via platform versioning and user modeling standardization. Dynamicity is induced by three factors: (i) Agile methodology that affects the daily development work, (ii) user traces, and (iii) user feedback, which cannot be captured from automatic tracking, yet contributes the most to engendering modifications, as previously identified [3].

First, all the programmers and founders, except the pioneer (I6), specified using “Agile Software Development” methods [52] for work organization. Let us reiterate that, for the precursors’ manifesto[7], agility means closer contact with users, collaborative work with colleagues and customers, testing, permanent deliveries, and corrections within shorter periods. However, defining technical specifications, prioritizing functionalities, and A/B testing (e.g., running two or more variants of an application in parallel) is a large part of the daily work of developers according to the company leaders, product managers and clients (in the case of a contracted developer working at a creative agency), which leads to bypassing or putting aside the variable definition task. Besides the development model, Agility helps app versioning following each operating system update, which is contingent on the materiality and diversity of the mobile

[7] Manifesto for Agile Software Development (2001). Retrieved from: https://agilemanifesto.org/

devices manufactured. Two interviewees involved in testing tasks insisted on their efforts to continually adapt.

Secondly, dynamicity is stimulated by the automatic analysis of online user traces as expressed in four interviews. Traces are integrated into business metrics to evaluate platform performances and are examined by developers [61], while also contributing to the revision of the founder's initial idea. One founder (I3) explained he was using Google Analytics Firebase SDK to analyse user engagement. The tool also provides an understanding of the app's main concept. The app was based on the functionality "calendar" containing the variables "dates" and "times" where the users indicate when they are available so that the matching system suggests results with similar availabilities. However, when analysing the traces, it is mainly the interface design that captures the founder's attention. He said: "*I was looking at everything that is analytics in particular to see the people who came once but who did not come back, the people who opened the pop-up but did not create an appointment, was the pop-up too complicated? I was trying to understand things a little bit.*" Indeed, human interpretation is necessary to complement automated tracking tools, where uncertainty remains high about the quality of the information provided by the traces, along with the fact that user behavior is hardly controllable and only partially captured through traces. Herein lies one main conflict, i.e. between the founder's myself-variables and what users think about his user model. Thus, software updates are required, as a trial-error dynamic, in order to attain a certain level of general satisfaction.

Finally, due to the incompleteness of automated traces and the difficulties with respect to adequately adapting software to each user, direct user feedback emerged in different forms as being a useful resource for updating the user model. Since, when reporting—bugs and improvements, this activity "engages users and developers in active and participative communication" as CSCW researchers have observed in other collaborative spaces [18]. One founder (I6) said: "*[Friends and customers were] telling us how they would like to find somebody. It started with age range, yeah, we would allow people to search by age range, so ridiculous thinking of it now; some people say, 'oh no I don't want 20 to 30, I want 20 to 24, or 30 to 32', or something like that, so we would basically end up making it more flexible, and you could save your own search, some sort of like looking for real estate where you could create a search and save it, well we did it for people.*" Big companies have dedicated customer service teams to filter users asking for modifications that are to be handled by the development team. Generally, the presence of dating apps in social media provides another form of contact. For companies, trade-offs need to be made between the user's requests and what can be implemented within a budget, and the overall impact on system designed. As one developer (I2) pointed out, *"you cannot make everybody happy"*. There is a continuous struggle between offering a personalized versus a one-size-fits-all service, and it is the latter that contributes to having more users in the pool and enough profit to respond, in particular, to Apple and Google app stores conditions claiming a 30% share of mobile app transactions[8].

The increase of user adoption, necessary for business growth, transforms the myself-variables from the founders' personal experiences into a standardized user profile and definition of the dating experience, resulting from an aggregation of accepted user requests and internal updates in Agile development, where the variable definition is lost in the app production chain. While variables gain attention during the initial steps of dating app creation, mainly for business

[8] See Match Group's financial report (2019). Retrieved from: https://s22.q4cdn.com/279430125/files/doc_financials/2019/ar/Match-Group-2019-Annual-Report.pdf

positioning reasons, these entities have an impact throughout the whole process through different components (design affordances, user profiles, matching systems, SDKs, trace analytics, feedback), wherein developers play a major role. These actors are in a position of mediation between technical and business user components, where similarities and differences can be re-examined.

6 DISCUSSION

In the present study we have shown that the mimetic and distinctive design of apps, previously observed through general marketing strategies [7] and innovation principles [9], is reflected in specific declarative variables. A double classification of 22 dating apps and 317 declarative variables collected on these platforms enabled the identification of similarities and differences associated with the variable definition process and, more generally, with the actual coding practices clarified by founder and developer interviews. This first extensive comparative mixed study provides CSCW and CHI researchers with more insight into both the potential and limitations of online dating profile and system design. In particular, we show that despite the platform transition from website to mobile, apps continue to define declarative variables (14 apps have more than 20), and that having a large amount of them is also a positioning strategy. For instance, Parship advertises an extensive questionnaire for testing matching compatibility. Let us note that since our first data collection, the seemingly minimalistic app, Tinder, has increased its number of declarative variables to 14 in the profile editing section. More broadly, our study confirms that dating apps are an extension of traditional matchmaking practices [8] that contribute to objectifying mate choice selection, as exemplified by Franklin and Darwin in earlier times. Dating apps datafy dating [4] on a different scale. No matter the era, as digital platforms rely on the same mechanism, the construction of these variables is contingent on the actors that define them. Although the number of existing studies analyzing the role of developers in dating apps is relatively small [8,22], thanks to the present in-depth qualitative analysis conducted with founders and developers, we are able to identify their agency in the creation of online dating experiences. Our results will contribute to future CSCW research pertaining to online dating developer practices. With the rise of the dating industry, and increasing user engagement, this is definitely a fertile field of study with an operational impact. Notably, however, while app proliferation prevails, the success rate of certain apps remains moderate. One of the founders interviewed, for example, had already removed his app from the market due to a lack of users and resources. A deeper understanding of the design mechanisms involved could thus assist in identifying the vulnerabilities of these apps. In the following section, we discuss the limits of user complexity coding for filtering and matching, and then identify the methodological limitations of our work and open up new avenues for future complementary research.

6.1 Coding user complexity for filtering and matching

Previous studies in user representation have described the tendency for some developers to become the user model [56], and here we show how founder preferences and experiences are translated into and explicitly expressed in some variables of the dating app profile pages. More generally, when designing technology, “user representations are often simplifications of the complexity of and differences among people in the real world” [55]. These observations are also dealt with in our study: the subjects’ diversity and the richness of their personal traits and life trajectories are massively diminished throughout the tasks that the actors are engaged in during the process of research, design, and tests. User feedback aim at completing the available information. As previously explained, current software development conducted in the Agile framework combined with the ongoing information gathering from users, promote continuous improvements. However, digital traces are far from being sufficient for capturing the diversity of individual behavior [61], particularly when trying to grasp the complexities of couples underlined in sociological studies [46]. As observed in our study, in an attempt to overcome this limitation, users provide direct feedback through other means (e.g., direct mail, social media, founders speaking to them), but their requests are not all implemented due to technical, financial or branding reasons. Consequently, users feel limited with respect to describing themselves and their preferences, which define the matching outputs, and tend to ignore variables when assessing profiles [32]. This attitude is counterproductive to bonding [79] and to algorithmic prediction, which leads researchers to capturing other invisible traces [2]. However, increasing the number of variables could engender cognitive overload and memory confusion due to being confronted with too many options [72]. Variable definition therefore involves a subtle balance between the abundance of information, which is potentially easy to collect, and its quality and effective added value, which is based on user involvement. As graphical and textual landmarks, variables act as "grasps" and establish two mechanisms described by Boullier [12], namely "procedural" and "declarative", where subjects are required to engage as both a reader and a user on the platform; they *say, do, interpret, exchange, negotiate* the reality built upon the system by designers and the users themselves. Collaborative dynamics between these actors, as well as the development of data structures have been studied in the CSCW literature in other areas (e.g., [59,75]). Their transcription into the online dating context could contribute towards evaluating *how* variables are defined for profile pages and matching, as influenced by the dating industry and larger mobile app development practices. It would then be possible to re-establish closer ties between developers and users, as claimed in the original Agile manifesto, and to rethink dating services beyond user adoption standardization.

6.2 Limitations

The main limitations of this study concern two aspects: (i) the construction of the sample, and (ii) the data collection process, for both qualitative and quantitative analysis.

First, as regards qualitative analysis, a larger sample of developer interviews, including female participants and those working on different apps, would be necessary in order to assess the significance of our findings. As seen in our exploratory analysis, personal and professional experience, as well as the resources available at the company, have an impact on the definition of variables that are transformed during programming practices. Therefore, one would need to check whether or not other categories of actors and settings have a similar impact on the role of variables. Actor diversity is also linked to the type of position they occupy in a company. We sampled only a few job positions (e.g., lead developer, QA engineer, data engineer, product owner) associated with our recruitment process. Those holding other positions could also be interviewed to evaluate their degree of influence according to their responsibilities, and their interactions with other teams. Concerning the data collection process, ethnographies would prove useful for observing in-situ developer work, as have been carried out by CSCW researchers in other domains [45], especially if they allow for comparison and are not limited to single-case thick descriptions [15]. However, these proposals remain conditional to dating companies welcoming research of this type. Moreover, for quantitative analysis, dating apps for specific communities (e.g., Catholic, vegan, transgender) could be sampled, and there are various less popular apps that might present relevant new variables, potentially excluded in our results.

Secondly, during data collection, the fact that the variables displayed are sometimes dependent on the sex chosen when registering in a heterosexual dating app, must be taken into account. In addition, platforms requiring paid subscriptions can also extend the options available. Let us note that the app's specificity might increase according to the pre-defined attributes attached to each variable, which were not accounted for in this study. If collected, they could provide better insight into the extent of user representations available in the interface and the outputs of the matching systems. Nevertheless, capturing such diversity in future work is labor-intensive. As recently confirmed [54], methods for data collection in dating apps remain a challenge for research considering the plurality of modern apps' designs and programming languages, in addition to the fast versioning they experiment with. One illustrative example is OkCupid where it was not possible in this study to collect data due to the platform design complexity as discussed in Section 3.1. Moreover, we noticed that several dating apps deleted or added a small set of variables between the first data collection and the writing of this paper. Automatic scripts could be developed, depending on the patterns identified between platforms, and this information could be indexed in a collaborative wiki, such as the project personaldata.io has done for other types of apps. Another possibility is to recruit users, from different apps, who consent to sharing their profile information. We are willing to provide the variable set via email upon request.

7 CONCLUSION

Through a mixed-method approach, we analyzed a set of 317 declarative variables, collected on 22 Anglophone and Francophone dating apps, that shape user representations and contribute to construct algorithm search spaces for matching systems. Our classification analysis was established through elucidation of the main conceptual choices made by founders and developers at dating companies, who contribute to defining variables through software development practices. To conclude, we revisit the initial research questions:

RQ1: Given the declarative variables collected from a set of dating apps, which main variable arrangements structure the dating profiles in direct mediation with users? By analyzing the presence/absence of variables in dating apps, we propose a new typology with nine categories that covers the entire set of collected variables. Its labeling is supported by previous works in social science literature dealing with couple formation and online dating. Results show that categories vary across apps and that they are not limited to attractiveness evaluation for mate choice. The predominant variables in each category translate complementary dimensions of users, what forms their capital and behavior, both offline and online. This variable typology has been used to analyze a second classification of the dating apps based on the Jaccard's measure. This app classification contains four main classes that reflect a double mimetic and distinctive mechanism within and outside dating apps classes for representing dating experiences.

RQ2: Following dating app founders' and developers' personal and professional experiences, which factors influence the definition of declarative variables shaping user modeling and matching? Based on the interviews, we first show that these actors establish a mimetic coding mechanism that emerges from technical and conceptual choices inherent to the app development process and the business model definition. Reusing existing techniques is a common practice, particularly when there are collaborative settings facilitated by brand agglomerations or when apps mark trends. Secondly, a distinctive mechanism takes place, in parallel, via the app store release conditions, as variables serve the advertising economy, and founders mirror themselves and their community in order to define variables. Finally, we show that this initial personal market research, performed by founders, can be updated through continuous adaptation through Agile software development and by capturing user traces and feedback, requiring interpretation and trade-offs. More broadly, we discuss to what extent user choices are limited in the online dating environment compared to daily life settings, and provide new insight into the information available to researchers analyzing mate choice [64]. Our analysis elucidates some aspects of the quantification of online courtship and its different categories, which adds to the current discussions on the rationalization of romanticism [41], as well as the part played by serendipity, as expressed in users' experiences [21].

Our results highlight two areas for future work. First, the study of variables in conjunction with GUI affordances is lacking, as they have often been studied separately in the CSCW and CHI communities, as well as in media studies. This combination could provide a deeper understanding of how users interpret signs for action and why they are discarded in specific settings. Secondly, an extended study of dating app developers' practices could contribute to the understanding of their hitherto undetectable role in the dating experience. Our study represents a step towards discerning the intersection between developers and users, requiring a type of online dating collaboration, which is mediated through variables, among other components.

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