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Stereotypes, disproportions, and power asymmetries in the visual portrayal of migrants in ten countries: an interdisciplinary AI-based approach

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The visual portrayal of social groups in media reinforces stereotypes and narratives, potentially leading to discriminatory actions and policies. That is particularly true for under-represented or stigmatized groups such as migrants and is a phenomenon that varies per country. Therefore, studying the representation of migrants requires analyzing considerable amounts of visual data from different locations. This work addresses that challenge with an interdisciplinary approach characterizing the visual portrayal of migrants using Deep Learning techniques and analyzing results through the lenses of migration and gender studies. Images associated with migrants found on the internet through a search engine and from ten countries are processed to quantify and analyze the demographic and emotional information of the people portrayed. An intersectional approach is employed regarding gender, age, physical features, and emotions. The general group “migrants” is compared with the specific groups “refugees” and “expats”. Results suggest that portrayals predominantly focus on asylum seekers and associate them with poverty and risks for host societies. Moreover, the demographics in the portrayals do not match the official statistics. For *expats*, an over-representation of “white” and an under-representation of “asian” faces were found, while for *migrants* and *refugees*, depictions align with the demographics of low-skilled migrants. Furthermore, results evidence the power struggle underlying the “expat vs. migrant” dichotomy and its inherent colonial nature. The emotions displayed are predominantly negative and align with emotional and gender stereotypes literature. Positive emotions are more associated with women than men, and with *expats* than *refugees* and *migrants*. Previous results regarding the under-representation of migrant women in media are confirmed. Also, women are portrayed as younger than men, and *expat women* are the youngest. Children appear more in pictures associated with *refugees* and *migrants* than with *expats*. Likewise, *migrants* are often depicted as crowds, but when that is not the case, *migrant* and *refugee* women appear in larger groups than men. A higher proportion of images associated with *expats* do not contain people. All these effects, however, differ per location. Finally, we suggest future directions and analyze possible limitations of automatic visual content analysis using existing Deep Learning models.

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Introduction

Images represent a critical element of media content, and as such, they shape our realities and play a central role in producing and reproducing meaning, knowledge, and power (Rossi, 2007). Media images, as representations, are fundamentally political, and their construction is an act of power (Johnson, 2011). Furthermore, unlike textual communication, which is based on argumentation, visuals are based on association and trigger different cognitive processes that make them appear closer to reality than text. In this respect, their ability to convey un verbalized meanings can lead to more insidious stereotyping than explicit verbal stereotyping (Özcan, 2013). Furthermore, as opposed to text, which tends to influence opinions but not actions, visual communication shapes the perception of realities that the viewer cannot directly experience and drives more powerful emotional reactions than text, which translates into more powerful behavioral responses and attitudes (Powell et al., 2015).

Several studies show how media images reflect societal biases and reinforce implicit associations or stereotypes towards specific groups that can lead to discriminatory behaviors and actions (Bodenhausen et al., 2016; Heilman, 2012; Kim et al., 2018; Plous, 2003; Reny and Manzano, 2016; Verkuyten et al., 2019). Mastro (2019) found that both single and long-term exposure to media content can shape views, emotional responses to, social judgments regarding, and, consequently, behaviors toward the so-called ethnic and minority groups. Moreover, images influence what can and cannot reach the political agenda of different stakeholders at the local, regional, national, and international levels. However, such an impact on political agendas is contingent, as media are more influential regarding sensational and emotional issues related to law and order than other matters (Johnson, 2011; Walgrave et al., 2008; Walgrave and Van Aelst, 2016). Furthermore, media portrayal is a product of framing: selection and salience. For instance, images are taken from a particular perspective in ways that make audiences look at the events from a specific position (Horsti, 2016). That is also the case with the media display of migrants.

Literature on media representation of migrants is not new. Several studies have looked at how different media outlets portray migrants, especially in television shows and in the news (Croucher, 2010; Eberl et al., 2018; Gullestad, 2002; Lawlor and Tolley, 2017; Leinonen, 2012; Suro et al., 2008; White, 2002). Many authors explored how media representation of migrants relates to discriminatory actions towards them (Reny and Manzano, 2016; Suro et al., 2008; Wenzel and Żerkowska-Balas, 2019). Wenzel and Żerkowska-Balas (2019) argue that frequent exposure to migration-related media messages can consolidate attitudes toward migrants, create stereotypes, and even influence vote choices. For instance, different forms of media can increase or decrease agreement with both positive and negative stereotypes about migrants (Wenzel and Żerkowska-Balas, 2019). Moreover, it has been highlighted that though there is variation in migrants' representation in western media, their visualization can be informed by symbolic strategies of dehumanization such as aestification, vilification, infantilization, marginalization, or aestheticization (Chouliaraki and Stolic, 2017).

Martinez Lirola and Zammit (2017) found that migrants who reached Spain and Australia by boat are portrayed in the online press as being illegal, a threat, in need of assistance, unhealthy, and culturally different from the local population. Further, they found a general under-representation of African and Arabic migrant women among migrants. Eberl et al. (2018) argue that migrants are generally under-represented and shown as delinquents in European media discourse. Other studies show that although immigration coverage tends to be negative and conflict-

centered (Eberl et al., 2018), conflict and violence are not always the center of the discourse. For example, in the news narratives around migration in the UK, France, and Italy, security is as preeminent as the economic implications of migration for the host society, such as labor market issues or fiscal costs.

Lawlor and Tolley (2017) show a hierarchy of preference for immigrants over refugees in the Canadian media, where immigrants tend to be framed in economic terms. In contrast, refugees are depicted as a possible threat. The hierarchical representation of different migrant groups has been researched for several years. For instance, Leinonen (2012) argues that the concepts "immigrant", "refugee", and "asylum seeker" are constantly conflated in public discussions in Europe. Moreover, though the groups of refugees and asylum seekers are statistically small in Europe, they are disproportionately visible in the media. Consequently, migrants are associated with oppressed victims, public threats, or opportunistic asylum seekers looking for social benefits from welfare states (Allen and Blinder, 2013; Leinonen, 2012; Martinez Lirola and Zammit, 2017; White, 2002).

Several studies have found that in Europe and the USA, the general assumption is that all migrants are asylum seekers (Croucher, 2010; Gullestad, 2002; Leinonen, 2012; White, 2002). In that framework, migrants are frequently depicted as crowds where facial features are not recognizable, which leads to their dehumanization and associates them with threats to sovereignty and security issues (Bleiker et al., 2013). In her work, Johnson (2011), discusses the UNHCR's ideological humanitarian construction of the "normal refugee" over the last decades. She argues that the image of the refugee has been re-framed from the heroic, political individual who fled the soviet union to reach the "West" to a nameless flood of poverty-stricken, voiceless women and children without political agency. She also argues that this representation shift has been strategic, operating to mobilize public support for the plight of refugees within a humanitarian discourse while managing the threat of instability and difference presented by the refugees' condition (Johnson, 2011, p. 1016). As pointed out by Smets et al., (2019), the refugee-victim trope is also very problematic, as it prevents people in a refugee-like situation from being seen as full-fledged citizens and individuals with their ambitions, lives, and agency.

Furthermore, studies have also examined the differences in the discourses around the so-called refugee crisis between mainstream and social media. For instance, Nerghes and Lee (2019) explored the construction of the so-called refugee crisis as a social problem in news outlets and on Twitter after a highly emotional event (namely, the finding of Alan Kurdi's body). Their results show that while similar themes are presented on Twitter and in the news, Twitter users introduced new ones contributing to an alternative narrative on refugee stories, aiding civic agency and social change to the discussion. Other studies have shown that social media can become a medium to spread hate discourses around migrants and migration (Altamirano and Torres-Toukourmidis, 2021; Ekman, 2018; Olmos Alcaraz, 2018). Siapera et al. (2018) found that, overall, the dominant frames on refugees on Twitter remain the same as those in mainstream media, revolving around security and safety on the one hand and humanitarianism on the other; however, on Twitter, there are explicitly racist hashtags linked to security and safety frames and evidence that political interests subsumed and instrumentalized the refugee issue.

Studies have also found that the representation of migrants strongly differs depending on the political orientation of the media portraying them. For instance, left-wing media outlets tend to show them as victims with a humanitarian vision, as opposed to right-wing media outlets, which show them as a public threat

(Valente et al., 2021; Wirz et al., 2018). In addition, the media also tends to ethnicize migrants. For example, Ash et al. (2021) show that two major US-based media outlets, the New York Times and Fox News, tend to ethnicize migrants by associating them mainly with Latin American migrants. Further, migrants are often represented as undocumented and targeted by immigration enforcement agencies. However, when represented as legal migrants, they are associated with low-skilled jobs.

White (2002) discusses what she calls the “racialization” of the term “immigrant,” which is associated with “blackness” originating from poorer and “non-white areas” of the world moving to the “wealthy and white Western world”. In opposition, “western migrants” moving within the so-called western countries are seen as unproblematic by most of the population due to their high social status and “acceptable” reasons for immigration (Leinonen, 2012). Moreover, several studies have shown that not only do highly skilled migrants tend not to be associated with the term migrant by societies, but they do not refer to themselves as migrants either. They instead prefer to use the “words internationals,” “global citizens,” or “expats,” as, according to them, the word migrant has a negative connotation (Kunz, 2016; Leinonen, 2012). That reflects once more the hierarchies among different migrant groups.

Contextual events in different countries also influence the migrants’ portrayal in media and academic interests. For example, recent literature on migrants’ portrayal in Hungarian media mainly focuses on the government’s representation of migrants. For instance, Kiss (2016) looks at the anti-immigration campaign launched by the Hungarian government in 2015 and its mainstream media representation and found how that campaign remarkably influenced the perception of migration issues by the population and fuelled tension in the society.

In the case of Colombia, another selected country for our study, literature on migrants’ portrayal in the media is still scant. Castellanos-Díaz and Prada-Penagos (2020) focus on the media representations that are built on Venezuelan migrants in two Colombian regional newspapers, *La Opinión* and *La Guajira*, from the departments where many Venezuelan have entered Colombia since 2017. They show that Venezuelan migrants were depicted as incapable of following Colombian values and rules and as unwanted subjects triggering territorial and social conflicts.

Besides and beyond academia, several bottom-up projects devoted to sharing migrants’ stories and showing their lives beyond the victim-threat paradigm have been developed globally. This is, for instance, the case of “Migrant Voice” in the UK and “Moving Voices” in Switzerland. In addition, international organizations are somehow providing a platform for migrants to share their stories through, for instance, social campaigns such as “I am a migrant” by IOM. Organizations, such as, for instance, UNESCO, have worked on recommendations for journalists on how to portray migration in their media outlets (Fengler and Lengauer, 2021).

To conclude, several studies have been done to understand how the media portray immigrants in specific countries. Nevertheless, those studies mainly focus on one or two specific media outlets and usually on newspapers, online press, and television shows. More studies focus on the textual representation of migrants. To the best of our knowledge, no studies have analyzed the visual representation of different groups of migrants, using machine learning techniques through various media outlets in several countries and with an intersectional lens of analysis.

Against this background, we analyze the visual portrayal of migrants in media as context-dependent and related to the perception of migrants in ten countries. Specifically, we respond to the call by Eberl et al. (2018) to investigate the portrayal of

migrants across several countries with diverse political and media systems and migration figures. We do this by carrying out interdisciplinary research where machine learning is used to estimate relevant information from a large number of images while keeping a social sciences perspective to interpret the results and analyze possible limitations. Specifically, we focus on differences in the portrayal of three groups: migrants, refugees, and expats, chosen as they have a strong political connotation that can be context-related. We analyze primary sources of variations in media portrayals concerning demographics and emotional content by focusing on the characteristics of migrants being depicted, such as age, gender, and emotions displayed. With this, we aim to explore new tools for the analysis of visual media content on migration, which is currently much needed, as highlighted by Lecheler et al. (2019).

The rest of the article is composed as follows. In the section “Related work” relevant literature at the core of the studied topics is presented. Section “Methods” presents the approach used for collecting and analyzing the data. The study’s main findings are presented and discussed in the section “Results”. Finally, in the section “Concluding remarks” we conclude and highlight possible future directions and limitations.

Related work

Migrants, refugees, and expats. Before analyzing how migrants, refugees, and expats are visually portrayed and what biases exist, we look at and discuss some international definitions of the terms.

A unique definition of migrants at the international level does not exist. Instead, several actors define migrants in different ways. For instance, governments and international organizations may define migrants differently. In this work, we use the broader definition of migrants provided by the International Organization for Migration (IOM)¹. The IOM defines a migrant as “a person who moves away from his or her usual residence, whether within a country or across an international border, temporarily or permanently, and for various reasons”. This broad definition allows the inclusion of, for instance, seasonal workers and include both internal and international migrants.

Differently from the term migrant, the term refugee has a legally internationally accepted definition, provided in the 1951 Geneva Convention on the status of Refugees (entered into force on 22 April 1954). The Convention define refugee “a person who, owing to a well-founded fear of persecution for reasons of race, religion, nationality, membership of a particular social group or political opinion, is outside the country of his nationality and is unable or, owing to such fear, is unwilling to avail himself of the protection of that country; or who, not having a nationality and being outside the country of his former habitual residence as a result of such events, is unable or, owing to such fear, is unwilling to return to it.” Over the years, other instruments adopted at regional level added to the definition other circumstances that may compel a person to leave their country. For instance, the “owing to external aggression, occupation, foreign domination or events seriously disturbing public order in either part or the whole of his country or origin or nationality” (1969), or “because their lives, security or freedom have been threatened by generalised violence, foreign aggression, internal conflicts, massive violations of human rights or other circumstances which have seriously disturbed public order” (1984).

An “expatriate”, or “expat” for short, according to the Cambridge Dictionary, is someone who does not live in their native country²; this term comes from the Latin words *ex* (“out”) and *Patria* (“native land”). In the classical term, an expatriate is identified as an international migrant who has been relocated by

the company where they work for a certain period. Nevertheless, over the years, the term *expat* has been used to indicate professional or skilled migrants in general, regardless of whether a company has relocated them internationally or not. Furthermore, several scholars argue that the term “expats” became axiomatically applied to so-called “western”, “good” migrants living abroad (Cranston, 2017; Leinonen, 2012). Similarly, the term “migrants” has been used predominantly to refer to people leaving poorer regions for more affluent ones. However, when the people moving are privileged in terms of citizenship, education, or class, they are not referred to as migrants; instead, terms as “expatriates” or “expats” are preferred. These privileged migrants, or “expats”, are often studied as drivers of knowledge and skills transfers, which is assumed to be unproblematic to host societies and migrants themselves (Knowles and Harper, 2009; Leinonen, 2012; Weinar and Klekowski von Koppenfels, 2020). Such a perspective can reproduce a biased and colonial image of migrants as predominantly “non-Western, non-white, non-elite subjects” (Kunz, 2016). Furthermore, the discourse on “expatriates” or “expats” reflects that “western” migrants profit from power relations inherited from colonial pasts, and they entertain attitudes regarding free mobility as their unquestioned right (Leonard, 2010). In many cases, people who understand themselves as “expatriates” do not necessarily identify as migrants and often categorically reject the term. That exemplifies how the categorization of migrant sub-groups (e.g., “*expat*” vs. “*migrant*”) is part of a broader political exercise and not a merely semantic one (Cranston, 2017; Kunz, 2020).

Notably, terms such as “*expatriate*” and “*migrant*” can be unstable or even inconsistent categories (Kunz, 2016, 2020), yet, they are political ones. So, it can be expected that these terms adapt contextually and in a way that, for example, can grant privilege to certain populations in specific contexts. As such, the term “*expat*” and its differentiation from “*migrant*” is an emergent discourse conceivably reflected in how they are portrayed in media. Moreover, as stated by Kunz (2020), through their polysemy and malleability, these categories and their relationships often serve to naturalize or rationalize power relations linked to social inequities or political struggles. Then, the differences between the visual portrayal of the groups associated with those terms can reinforce inequalities and global power asymmetries or be part of their production.

Statistics show that worldwide, about 1 in 7 persons is a migrant and that internal migrants represent 70% of total migrant population. Further, international migrants represent 3.6% of the global population (IOM, 2020)³, and that of the 281 million international migrants, 164 million are migrant workers, 27.1 million are refugees, and 4.6 million are asylum seekers (UNCHR, 2022)⁴. The statistics do not include figures on other migrant groups, for instance, family migrants. While statistics help us understand migration proportions globally, it is crucial to note that migrant categories are socially and politically constructed. When we approach them, we need to avoid falling into an essentialist trap of identifying people as a category. People migrate for several (voluntary or forced) reasons at a specific time of their lives and towards a specific (national or international) geographic location (Elder Jr, 1994; Koser and Salt, 1997; Kōu and Bailey, 2014; Pred, 1981; Spadavecchia, 2017). So, a portrayal of migrants, for example, as people fleeing their home countries in despair and through a stressful or traumatic process is disproportionate and neglects most of the migrant population, which undergoes many different migration processes.

Given the tensions between the terms “*expat*” and “*migrant*”, as well as the disproportional representation of migrants as refugees in media, we want to investigate the visual portrayal of these three groups (“*Migrants*”, “*Expats*”, and “*Refugees*”) to

analyze their differences and similarities further and to unveil existing biases in different national contexts.

Gender. The portrayal of migrants in media can have gender-specific effects. When migration intersects with gender, relevant issues arise. Studies have shown that the representation of migrant women in the news is scant (Collins, 2011; Lind and Meltzer, 2021; Silva and Mendes, 2009). According to Liu (2020), media mainly makes men the default migrant, while turning women invisible.

Silva and Mendes (2009) argue that few studies have researched the journalistic representation of migrant women. Nevertheless, existing studies have shown that women are almost invisible in the news and only appear in limited and stereotyped roles that reflect a view of migrant women belonging to specific and ethnicized migrant groups. For instance, Turkish and Arab migrant women in Germany are portrayed as veiled and oppressed within traditional family structures, while migrant women from Eastern Europe and Africa are contextualized as prostitutes (Silva & Mendes, 2009, p. 252). Liu (2021) found that migrant men are more often associated with economic issues, while migrant women are with cultural issues. Furthermore, women tend to be shown as most actively participating in the community or showing a more traditional culture. Further, literature shows that migrant women are often portrayed as dependent and subordinate to men, frequently in pictures of pregnant women or women arriving with a baby (Liu, 2020, 2021).

Intersection of gender and age. While several studies focus on the role of gender in the construction of narratives around migrants, age is rarely considered. However, it has a significant impact on the shaping of those narratives (Pruitt et al., 2018).

Some studies have looked at the age of migrants and refugees during the so-called European migration crisis of 2015. For instance, Amores et al. (2019) focused on visual framing in a few selected newspapers in France, Germany, Italy, Spain, and the UK. Their results show that most pictures portray males and females (51%) and diverse ages (54.6%), although images stand out that depict only men (39%) and young people (17.4%), usually males. Pruitt et al. (2018) look at the intersection of gender and age concerning recent discourses around conflict-related migration. They have found that young men, representing most asylum-seeking applicants, have repeatedly been characterized as inherently dangerous and persons to be feared. In their article about the representation of gender of migrants in refugee-like situations, Amores et al. (2020) found that in terms of age, there were more female children (30%) than males (23.1%), more young males (37.4%) than females (12%), and only a small portion (4%) of elders were female.

Nevertheless, studies focusing on the age of migrants in visual portrayals seem to look at migrants only, and again, as refugees, especially during the so-called European migration crisis. That is problematic because, somehow, it supports the narrative that all migrants are refugees, denying the existence of several groups of people who migrated for other reasons.

There is a relevant gap in the literature regarding age representation, especially on the intersection of age and gender of migrants. Further, no literature was found regarding age in the representation of *expats* or highly skilled migrants.

Emotions. Emotions are a central factor in the portrayal of migrants and can be used as tools to frame the news in specific ways to cause emotional effects on viewers. For example, the expression of certain emotions can be connected to perceived

levels of dominance and affiliation, status conferral, or socio-economic status (Brescoll, 2008; Hess et al., 2005; Zhang et al., 2021). Further, the literature suggests differences between genders in terms of emotional stereotypes, such as that male faces are associated with anger and female faces with happy expressions (Stephen et al., 2018), or that women experience and express most emotions more often than men (Plant et al., 2000). However, such stereotypes are context-dependent, and their presence in media imagery might inform how such stereotypes are associated with migrants. Notably, there is a relevant gap in studies analyzing the emotions in the visual portrayal of migrants. When studies are found, they mainly focus on newspapers during the so-called refugee crisis (e.g., Amores et al., 2019; Zhang and Hellmueller, 2017). No studies on other groups of migrants have been found.

Zhang and Hellmueller (2017) analyzed and compared the visual framing in the portrayal of “refugees” in a global newspaper, CNN international, and a German national newspaper, De Spiegel, during the so-called refugee crisis. They found a difference between the two media’s visual portrayals of refugees’ emotions. They looked at positive emotions (happy and grateful), negative emotions (fearful, angry, or desperate), and mixed emotions (positive and negative expressions in the same picture). Their results suggest that many pictures did not clearly show facial expressions (25% in CNN and 40% in De Spiegel). While the appearance of positive emotions was low (7.6% and 21%), negative emotions were more predominant (58.5% and 31%). Mixed emotions appeared in <9% in both outlets. Similarly, Amores et al. (2019) found that European media displays of suffering during the so-called European migrant crisis were most common (76.6%) than photographs reflecting positive expressions (32.2%). Existing literature indicates that negative emotions such as fear, suspicion, or suffering tend to be present more often in the news portraying migrants (Chouliaraki and Stolić, 2019; Valente et al., 2021).

Geographical context. The production of media content depicting migrants and their effects also varies with contextual factors, inasmuch as media images are visual practices that emerge in a specific spatial and relational context (Wintzer, 2019). Moreover, average biases toward a specific group are context-dependent as the way social categories are used to describe groups can depend on perspective, time, and geography (Gillespie et al., 2012).

In general, context can be understood as the larger group an individual belongs to and determines how biases affect behavior (Payne et al., 2017). In that sense, geography is the primary variable for defining the context where a phenomenon emerges, which deems necessary cross-country comparisons at a larger scale. In that regard, Eberl et al. (2018) suggest focusing on comparative studies analyzing the portrayals of migrants and migration issues in diverse news outlets and different countries differing in their political and media systems, net migration figures, and even migration policies. All these factors impact media coverage in one way or another. Moreover, analyzing different locations together is also relevant, considering that social categories are more relevant to the formation of implicit biases when they present central features with a role in stereotyping comparable groups across different contexts (Del Pinal and Spaulding, 2018).

Methods

Automatic visual content analysis. Visual analysis is frequently used to examine images in media as it allows insights into how visual constructions of reality are created. Lately, visual content analysis has been applied to study how migrants are portrayed

and how such portrayal shapes perceptions, political views, and agendas, as well as policy-making (Amores and Arcila, 2019; Giubilaro, 2019; Tirosh and Klein-Avraham, 2019; Wintzer, 2019). Nonetheless, manually analyzing images is labor-intensive, which limits studies to a few images. Therefore, we explore the usage of Deep Learning advances to analyze visual media data in migration and gender research.

Previous works have used machine learning to analyze gender biases in films (Jang et al., 2019; Mazières et al., 2021), or estimate demographic information to infer biases towards different groups in news outlets (Ash et al., 2021), but no works focus specifically on migration. Here we use Deep Learning models to numerically quantify the occurrence of specific characteristics of people depicted in images associated with migrants and found in unconstrained online searches. We compare migrant groups, locations, and attributes in the portrayals focusing on: gender, age, facial features, and emotions. That allows exploring the visibility of certain groups; for example, how often migrants are depicted as women, how likely a picture contains children, or how positive or negative the emotions usually displayed are.

Image data collection. Images associated with migrants were retrieved using Google Cloud Platform⁵. The search terms are defined in English, and the Translate API is used to get the corresponding search terms in the target language for each location (see the section “Context”). The images are sought using the Custom search API.

Groups of interest. For this study, we have decided to use the general term *migrants*, and the two specific groups *expats* and *refugees*. The general term “migrant” is often wrongly looked at as a synonym for “refugee”. So, we have selected the term “refugee” to see to what extent the pictures of migrants and refugees relate. Similarly, we chose the term “expat” as it refers to a group that is often seen as privileged among migrants, referred to as the “good and highly wanted migrants” (Cranston, 2017), and represents a highly political distinction (Kunz, 2020) embedding biases and power asymmetries (Kunz, 2016).

We are also interested in the intersection between migrant status and gender; hence, we have included gender, limited to *Male* and *Female*, given the technical challenges and limitations of existing methods to handle other definitions. As a result, three groups per category were defined (e.g., *migrants*, *migrant man*, and *migrant woman*).

Images retrieved by a search engine are relevant until a certain number, then we caped the search to 200 images per group and location. The total number of images retrieved was 17898 as some were corrupted or not downloadable. Moreover, we only use images containing faces to estimate the demographics and emotional information, as explained below.

Face and people detection. Faces are extracted using a freely available implementation⁶ of the Multi-task Cascaded Convolutional Networks framework (Zhang et al., 2016). Before any process, pictures are resized to have 1024 pixels in the largest dimension (height or width). Faces are kept if the detection confidence is above 95%, and the resolution is above 40 × 40 pixels; we use these conditions to define usable faces. If face images are smaller than 64 × 64 pixels we use the face super-resolution technique introduced by Zhou et al. (2020)⁷ to get a reconstructed image of size 224 × 224.

Since faces are not always detectable, we have also detected people separately (either a person’s full body or a visible part of it). Persons have been detected using the model introduced in Carion et al. (2020)⁸.

Table 1 The number of images used per group of interest and other relevant statistics.

| Group | Images | Faces | w/ face (%) | F/I | P/ I | P_{Crowd} (%) |
|---------------|--------|-------|----------------|------|---------|------------------------|
| expat | 1929 | 1087 | 26 | 2.11 | 3.2 | 5.8 |
| expat man | 1948 | 1920 | 64 | 1.53 | 2.4 | 3.0 |
| expat woman | 1970 | 2137 | 64 | 1.67 | 2.5 | 2.7 |
| migrants | 2019 | 1739 | 37 | 1.68 | 3.1 | 43.2 |
| migrant man | 2009 | 2368 | 51 | 1.92 | 3.4 | 7.0 |
| migrant woman | 2001 | 3072 | 61 | 4.06 | 7.4 | 7.1 |
| refugees | 2042 | 1909 | 63 | 1.54 | 2.4 | 23.8 |
| refugee man | 1957 | 2558 | 71 | 1.77 | 2.9 | 4.6 |
| refugee woman | 2023 | 4286 | 54 | 3.82 | 7.0 | 2.5 |

The total number of images for the search terms used was 17,898. The total number of faces found in the whole set is 21,076. Images with face (w/ face) refer to the proportion of images with at least one usable face, as described in the main text. F/I refers to the average number of usable faces per image. P/I refers to the average number of persons per image. The total number of persons found is 59,777 in 15,241 images, thus 3.92 persons per image on average. P_{Crowd} refers to the probability of a picture containing a crowd given the group it comes from.

Analysis of newspaper front pages has shown that asylum seekers are primarily represented as medium or large crowds in a dehumanizing framing that associates them with security threats rather than a humanitarian challenge (Bleiker et al., 2013). Moreover, pictures of large groups can influence how viewers react to news content, and their attitude toward immigration (Madrigal and Soroka, 2021). Therefore, we have compared migrants' images with crowd images to measure similarities. Around 50 images per location were downloaded (528 in total) using the search term "Crowd", and the same automatic process and APIs were used to download the images of migrants. We estimate the probability of finding images of crowds (C) in a given group of interest g : $P_{\text{Crowd}}(C|Group = g)$. To achieve this, we extract feature vectors from the last layer of a pre-trained neural network⁹ and compare the vectors from images in each group to the crowd images using the normalized squared euclidean distance. For each crowd image in a set, the distance between its corresponding vector and those from images in the migrant group of interest is calculated. The 50 lowest distances per crowd image are used to create a normalized histogram over groups, and then a total average is calculated and normalized to define a probability distribution.

Table 1 presents the nine categories defined, the number of images retrieved per group, the percentage of images containing at least one face, the total number of faces analyzed, the number of persons detected, and the probability of images from a given group to contain crowds.

Context. We include context by constraining image searches to specific geographies (countries) and official languages and perform a twofold analysis. First, we analyze the characteristics in pictures by aggregating all locations to look for specific features present across contexts. And then, we study images from different locations separately to determine contextual differences (understanding context as dependent on geography).

We consider ten countries ranked on the high, middle, and low scale of the new Gallup Migration Acceptance Index¹⁰ (Fleming et al., 2018). For instance, we have selected Australia, Sweden, The Netherlands, Spain, and the USA, among the top 20 countries in terms of migrant acceptance. Hungary is the second most negative country towards migrants. Colombia is in the middle range, and its relevance for this study is also given because the index detected a significant negative turn in attitudes towards migrants in 2019 (after the increased migration from Venezuela). Similarly, from the Eurobarometer¹¹, we found discrepancies in

some selected countries; for example, most citizens in the UK and Spain believe that migrants can strongly contribute to the country's economy, while only 34% of Italians think the same.

Finally, the selected countries vary significantly regarding the proportion of migrants in their population, varying between 3% and 30%. According to the International Organization for Migration, in the 2022¹² in Canada 21.3% are migrants, in the USA 15.3%, Australia 30.1%, UK 13.8%, the Netherlands 13.8%, Hungary 6.1%, Italy 10.6%, Colombia 3.7%, Spain 14.6%, and Sweden 19.8%.

The locations analyzed are Australia (au), Canada (ca), Colombia (co), Hungary (hu), Italy (it), Spain (sp), Sweden (se), The Netherlands (nl), The United Kingdom (uk), and The United States of America (us).

Estimation of demographics and emotional information. To estimate gender, age, and facial features we use the model presented in Karkkainen and Joo (2021)¹³, and for emotions the model from Toisoul et al. (2021)¹⁴. Those models have been published with open-source implementations, so their performance is assumed to be as reported in the corresponding articles.

Demographics. We use the model from Karkkainen and Joo (2021), which presents a dataset based on images taken from the internet¹⁵ to address known problems in face analytic models like accuracy disparities for different genders and skin colors (Buolamwini and Gebru, 2018). The pictures contain significant variability of faces and are taken in settings where no control exists over variables such as angle or illumination. Moreover, Karkkainen and Joo (2021) have reported the performance of the model on datasets that can be expected to share many attributes with the images used in the present work.

The model estimates: Gender (Male or Female) with a reported accuracy of 94%, facial features (White, Black, Latino Hispanic, East Asian, South-East Asian, Indian, and Middle Eastern) with a reported accuracy of 73%, and Age (in the ranges 0–2, 3–9, 10–19, 20–29, 30–39, 40–49, 50–59, 60–69, 70+) with a reported accuracy of 51.5%.

The model classifies faces into possible classes per demographic characteristic by assigning an output probability for every possible value given a face. We use that distribution for each face, so we do not get the class with the highest probability as the true value. Instead, an average distribution over all faces is calculated per image (a formal description of this can be found in the supplementary material).

We do this for categorical variables (including emotional expressions) per group, and location.

Validation with demographic statistics: To validate the results, the official statistics of some countries regarding immigration are used. The data for European countries is retrieved from¹⁶ for the countries: Hungary, Italy, The Netherlands, Spain, and Sweden (EU). These statistics include the number of immigrants by gender, age range, and country of birth. We also use statistics of first-time applications from asylum seekers¹⁷. Statistics from the United States of America are retrieved from the Census Bureau¹⁸. For Canada, data is retrieved from Statistics Canada¹⁹, including sex and age information. For UK and Colombia, no aggregated data comparable has been found.

Moreover, to analyze the split "migrants"/"expats" we divide data from the statistics into Highly Skilled Migrants (HSMs), defined as immigrants with a bachelor's degree or higher (Spadavecchia and Yu, 2021), and Low Skilled Migrants (LSMs) as those that do not classify as HSMs. We assume that HSMs are associated with expats, given that the latter are generally defined

Table 2 Estimated distribution of gender in detected faces per group of interest for all locations. “M” stands for male, “F” for female, and “All” for the general group.

| Group | expats (%) | | | migrants (%) | | | refugees (%) | | | Mean (%) |
|--------|------------|------|------|--------------|------|------|--------------|------|------|----------|
| | All | M | F | All | M | F | All | M | F | |
| Male | 60.5 | 80.3 | 23.7 | 76.5 | 81.6 | 31.7 | 66.4 | 84.4 | 25.9 | 58.6 |
| Female | 39.5 | 19.7 | 76.3 | 23.5 | 18.4 | 68.3 | 33.6 | 15.6 | 74.1 | 41.4 |

in terms of their jobs, usually highly skilled positions (see the section “Migrants, refugees, and expats”). This is only done for the USA.

We also compare results on facial features to official data from the USA as they have statistics that can be related to facial traits, though they refer to them as “race”. To make the data comparable, we grouped our facial features categories to align with the four categories in the taxonomy from the Census Bureau website²⁰. We created the following groups by merging the categories: White (*White and Middle Eastern*), Black, Asian (*East Asian, South-East Asian, and Indian*), and Others (*Latino-Hispanic*).

Finally, it is important to note that we want to determine differences in the visual characteristics of people portrayed as part of specific groups. So, we interpret the classification by the model from Karkkainen and Joo (2021) as a proxy for facial features, and we report their frequencies of appearance under the provided taxonomy (e.g., “White”, “Black”, “East Asian”, etc.). This is not to classify people from a racial perspective, but it allows us to explore phenomena in the media associated with such kinds of categorizations. As argued by Haslanger (2012), a concept like “race” refers to social kinds that track positions of social status due to which certain groups, categorized by some physical features, are systematically treated differently. In that sense, we use a model that processes faces in terms of physical or visual features to determine differences between portrayals across groups, as those differences can lead to discriminatory behaviors (Mastro, 2019). No other analysis is feasible from this data, as, from a computational point of view, models only respond to the statistical appearance of specific visual features, not to social kinds.

Emotions. For emotional information, we use the model introduced by Toisoul et al. (2021), which estimates valence (how positive or negative the emotional display is) and arousal (how calming or exciting the emotional display looks). This division is envisioned from a bipolar model of the experience of affect (Barrett and Russell, 1999), where arousal ranges from feeling calm to excited, and valence ranges from pleasure to displeasure.

The model in Toisoul et al. (2021) is also trained to perform emotional expressions classification, which means mapping a face’s picture to a specific emotional category (Happy, Sad, Surprise, Fear, Disgust, Anger, Contempt, or Neutral). This approach in the field of computer vision distills from the arguments on the universality of emotional expression (Ekman et al., 1987).

Furthermore, Toisoul et al. (2021) trained the model with naturalistic images taken in uncontrolled settings, increasing the data’s variability and thus the model’s robustness as it has been presented with a wider variety of images taken in challenging settings. Finally, Toisoul et al. (2021) report obtained the best performance when conducting the present study in the evaluated tasks and on different datasets.

The emotions of faces in pictures are estimated as a distribution over possible emotions (Neutral, Happy, Sad, Surprise, Fear, Disgust, Anger, Contempt), and a point value

for valence and arousal (real values). As with demographic information, the distributions over emotions are calculated using the probability given by the output layer of the classifier.

Interactions and differences between locations and groups. The intersection between different demographic characteristics and emotion categories across groups of interest and locations is also analyzed. For example, the interaction between gender and age. The difference between groups or locations is studied by estimating the difference between distributions using the Kullback–Leibler divergence (KL divergence) as a metric. We calculate the KL divergence between any pair of distributions to compare groups and locations. With this approach, we can determine which countries are the ones that relate more to each other and which are diverging the most from the rest.

Results

Here we analyze the results found and the main biases or stereotypes that could be inferred from them and that connect to societal views on migrants that can drive behaviors or attitudes towards these populations (Mastro, 2019).

Gender. We have found a majority of male faces in all groups. Nevertheless, the official statistics show that the actual migrant populations tend to be balanced in gender. That is in line with previous studies that found an under-representation of migrant women in journalistic photographs, news, or in other media (Amores et al., 2020; Collins, 2011; Jang et al., 2019; Lind and Meltzer, 2020; Mazières et al., 2021; Silva and Mendes, 2009). Table 2 presents the estimated gender distributions per group. Male faces are more likely to appear in general (58.6%). For the gender-specific groups (e.g., *migrant man*), the distributions behave accordingly, with a majority of faces from the specified gender; though for *migrant woman* and *refugee woman*, there is a high proportion of male faces (around 32% and 26%, respectively). For the general terms *expats*, *migrants* and *refugees*, there is always a majority of men (60%, 76.5%, and 66.4%, respectively).

This representation is problematic in several ways. For instance, the low representation of women in the category of expats shows persisting gender stereotypes in migration, as it still shows the invisibility of skilled female migrants, perpetuating the constant stereotype of men in their productive and women in their reproductive roles (Aman et al., 2022; Aure, 2013; Cerna and Czaika, 2016; Docquier et al., 2009; Elo et al., 2020; Iredale, 2005; Kaushik and Walsh, 2018; Kofman, 2000; Ramos and Martín-Palomino, 2015; Riaño, 2011; Rodriguez and Scurrey, 2019; Spadavecchia and Yu, 2021). The misrepresentation also persists for the other groups. For instance, migrant women are often associated with family migrants. Even though several women tend to enter the country through a family migration visa, that does not mean that they are not, for instance, working women (Aure, 2013; Chimukuche, 2019; Fossland, 2013; Iredale, 2005; Spadavecchia and Yu, 2021; Webb, 2015). Not recognizing the complexity of the migration process and reducing groups to stereotypical and monolithic categories, often based on state-created categories (designed for visa purposes), have substantial

Table 3 Comparison between estimated distributions per location and statistics about migration and gender for selected countries.

| Group | | Location | | | | | | | | | | | |
|------------|--------|----------|----|----|----|----|----|----|----|----|----|----|------|
| | | co | au | hu | it | nl | sp | se | us | ca | uk | EU | EU-A |
| Images | Male | 67 | 58 | 68 | 67 | 60 | 52 | 48 | 60 | 59 | 64 | 62 | - |
| | Female | 33 | 42 | 32 | 33 | 40 | 48 | 52 | 40 | 41 | 36 | 38 | - |
| Statistics | Male | - | 49 | 57 | 51 | 52 | 49 | 54 | 49 | 49 | - | 51 | 68 |
| | Female | - | 51 | 43 | 49 | 48 | 51 | 46 | 51 | 51 | - | 49 | 32 |

EU stands for the average of all the selected European countries. EU-A stands for first-time asylum applications in the European Union. All numbers are percentages.

implications for migrants. When media portray migrant women as solely dependent women, this has a strong implication on how they are seen by the public of the media outlets, on the policies created for them, and, therefore, on their chances and lives in the destination communities (Johnson, 2011; Reny and Manzano, 2016; Roggeband and Verloo, 2007; Walgrave et al., 2008; Walgrave and Van Aelst, 2016; Wenzel and Żerkowska-Balas, 2019).

In addition, a relation has been found between these results and gender equality indices. Those countries with higher gender equality, as reported in Forum (2021), are as well those with a more balanced gender distribution in the images, at least for the locations included in Table 3.

We have also found that the gender distributions in images do not match that of official statistics on migration in general but are similar to those of asylum seekers in the European Union, where the proportion of migrants registered as asylum seekers is only around 5% of the total migrant population²¹. Moreover, those statistics align well with the estimations from images of refugees in Table 2, further suggesting that portrayals and public discourse on migration mainly focus on asylum seekers, not migrants in general.

Table 3 presents a comparison between the proportions estimated from images and official statistics of selected countries. Generally, the estimated proportion of male faces is higher than official statistics for all the locations except for Sweden (48% of male faces). On the other hand, official statistics show higher proportions of female migrants in Spain and the USA (52% and 60%), which does not match the estimations from images either (49% for both). The locations with higher discrepancies between portrayal and statistics in terms of gender are Italy and Hungary (11% and 16% difference), and those with the lowest discrepancies are Spain and Sweden (3% and 6% difference). However, the average results from images from European countries are in line with the statistics of first-time applications from asylum seekers.

Facial features. *Expats* are predominantly “white” (56% for expat, 61% for expat man, and 64% for expat woman). In the other two groups, male faces are more often estimated as “white” than female groups (49% vs. 37% for migrants, and 42% vs. 33% for refugees). The category “Black” is at least three times higher for *migrants* and *refugees* than for *expats* (22%, 16%, and 5% respectively). Proportions for the category *Middle Eastern* are higher for all the refugee groups, and for the general groups, the proportions are 27% for *refugees*, 20% for *migrants*, and 19% for *expats*.

Table 4 compares data estimated from images and the official statistics from the USA. The statistics of HSMs do not match the estimated data for *expats*. HSMs are depicted as predominantly “White”, which is not the case in official statistics; the percentage of people registered as “white” is around 30% lower than the proportion estimated from images. Moreover, all groups regarded as “Asian” seem to be underrepresented in the *expats* images:

statistics are 26% higher than the estimations from images. Such disproportions seem to hold not only in the USA but in other countries studied, taking as a source the data about HSMs in the G20 countries (OECD, 2019). That indicates that the discourse in media disproportionately associates HSMs with “white” people.

The term “expats” or “expatriates” is broadly associated with privileges and privileged and “good” migrants assumed to be unproblematic to host societies and seen as drivers of knowledge and skills transfers, or HSMs (Knowles and Harper, 2009). This might pose a conflict between the fact that such privileges are mainly associated with “westerners” on the one side and that many of the HSMs come from “non-western” countries on the other. The results we found confirm a predominant view that sees migrants, and not “expats”, as “non-western, non-white, non-elite subjects” (Cranston, 2017; Guo, 2015; Kunz, 2016; Weinar and Klekowski von Koppenfels, 2020). As such, the high proportions of “Asians” in the statistics are not reflected in the media portrayals. Another plausible explanation for the disproportions could connect to the fact that expats are being associated with emigrants from the USA and not with immigrants, which in turn is a misrepresentation, as highly skilled immigrants are being ignored in the media discourse. These results can showcase the colonial perspective in which those who have the right to move freely and be highly skilled are the “westerners” coming from affluent societies, while the rest are mere “migrants,” not “expats”, and can be threat or source of concern.

Moreover, results indicate that the general population depicted as *migrants* in media imagery aligns with the demographics of LSMs, which can be connected to narratives on issues with economic implications, such as the labor market or fiscal costs, as highlighted in Caviedes (2015). That means that the portrayal focuses on risks or adverse effects of specific kinds of migration but neglects a significant part of the phenomena.

Age. Figure 1 depicts estimated age distributions and distributions from official statistics. The estimated data shows relevant gender-related differences that are not apparent in the official statistics. The estimated distributions for males are skewed toward higher ages, while the one for the female groups has a maximum likelihood in the age interval 20–29. The average age estimated from the plotted data for male groups is 40.9 for *expats*, 40.1 for *migrants*, and 39.6 for *refugees*; while for the female groups, they are 34.8, 34.6, and 32.8, respectively. These results align with findings in previous studies on media (Edström, 2018; Ford et al., 1998; Furnham and Paltzer, 2010; Matthes et al., 2016). When combined with results on gender, this suggests that migrants tend to be depicted as men and older than the actual population. Similarly, when women are present, they tend to be younger than men, and their average age is lower than in the official statistics. Again, that is similar to biases in media where age ranges in, for example, films do not match those of the actual populations being represented (Neville and Anastasio, 2019).

Table 4 Comparison of proportions for facial features estimated from images and statistics from the USA.

| Group | Images | | | | USA statistics | | |
|-------|----------------|--------------|--------------|------------|----------------|----------|----------|
| | All images (%) | Refugees (%) | Migrants (%) | Expats (%) | All (%) | HSMs (%) | LSMs (%) |
| White | 62.7 | 56.6 | 52.2 | 75.8 | 51.0 | 48.9 | 56.0 |
| Black | 15.0 | 18.5 | 17.7 | 3.9 | 14.5 | 5.5 | 15.8 |
| Asian | 14.4 | 15.8 | 20.3 | 16.0 | 29.8 | 42.0 | 21.3 |
| Other | 8.0 | 9.1 | 9.8 | 4.3 | 4.7 | 3.6 | 6.9 |

There are four groups for the estimated data, All images, refugees, migrants, and expats. For the official statistics, three groups are presented: All, which include all immigrants reported, and HSMs and LSMs, which divide immigrants by their education level.
 HSMs: Highly skilled migrants defined as possessing a Bachelor’s degree or higher.
 LSMs: Low-skilled migrants are defined as not possessing a Bachelor’s degree or higher.

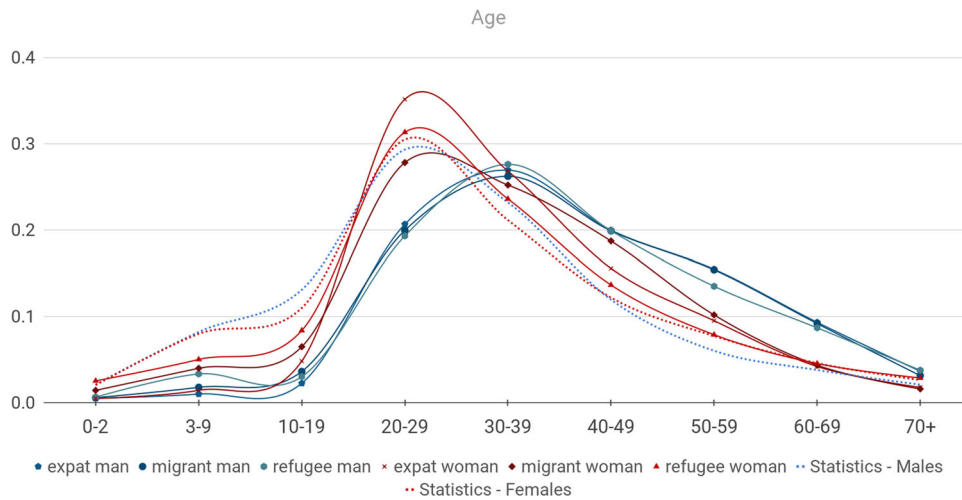


Fig. 1 Estimated age distributions. Plots for all the gender-specific groups (solid lines) and distributions from statistics (dotted lines). Statistics used are from the selected countries Hungary, Italy, The Netherlands, Spain, and Sweden.

Also, in Fig. 1 the number of kids, or faces with estimated ages <10, is higher for the female groups, except for *expat woman*. In contrast, for the male groups, that proportion is higher for *refugee man*. All in all, there is an under-representation of children compared to the statistics; children are present more often in the images of *refugees* and *migrants* than those of *expats*. In particular, there are significant differences for *expat woman*, which has the lowest proportion of children among the female groups. Also, on average, the faces in that group are estimated to be younger than other female groups. That is, *expat women* are portrayed as young and without children, or put differently, focused on careers. That last feature also seems to apply to *expat man*.

These findings can imply that the portrayal of *expats* is not focused on families. This might be because *expats* are associated mainly with male professional migrants (as also discussed in the section “Gender”) and therefore depicted only in their “professional lives”, not including their families. That is problematic because it reinforces the idea that they are only brains in movement and not full-fledged individuals, that in several cases, have families moving with them (Kōu and Bailey, 2014; Rodriguez and Scurry, 2019; Spadavecchia, 2017; Spadavecchia and Yu, 2021; Vergés Bosch and González Ramos, 2013).

Emotions. For both male and female groups, the average emotion of *migrants* and *refugees* tends to be negative, while for *expats* they tend to be positive or neutral. Moreover, the frequency of the expressions *Happy* and *Anger* correlate with gender. As elaborated below, these results align with the literature on emotional

stereotypes and suggest that many stereotypes hold when it comes to migrants.

In Fig. 2, the estimated average valence and arousal per group and location are plotted. We have found that, on average, images of *migrants* and *refugees* display a negative emotional valence, while for *expats* the portrayed emotions tend to be positive or neutral. In particular, for *expat woman*, the valence is higher than for any other group and is the only positive mean value. On the other hand, *migrants* and *refugees* are the two groups with the lowest average valence. Similarly, the arousal follows the opposite trend, though the value difference is not as significant.

The average valence values for the female groups are higher than their male counterparts. The distributions have been compared for the gender-specific groups using a Z-test to evaluate significant gender differences. The null hypothesis being $\mu_{male} = \mu_{female}$, and the alternative hypothesis being that $\mu_{male} < \mu_{female}$. The results confirm significant differences with $p < 0.001$ for all groups.

The frequency of the expressions *Happy* and *Anger* also varies by gender. In Fig. 3a it can be seen that *Happy* appears more often on female faces (above 60%), particularly for *migrants*; while for *Anger*, male groups get higher frequencies, particularly for *expats*. These two emotional expressions are also the most observed ones aside from *Neutral*. Similarly, the distribution of emotions varies per group, but the main emotional categories across groups are as well *Happy* and *Anger*, followed by *Fear*.

A common stereotype is that women experience and express most emotions more often than men, except for anger and pride, which are more often associated with men (Plant et al., 2000). Such stereotypes can lead women to suppress the expression of

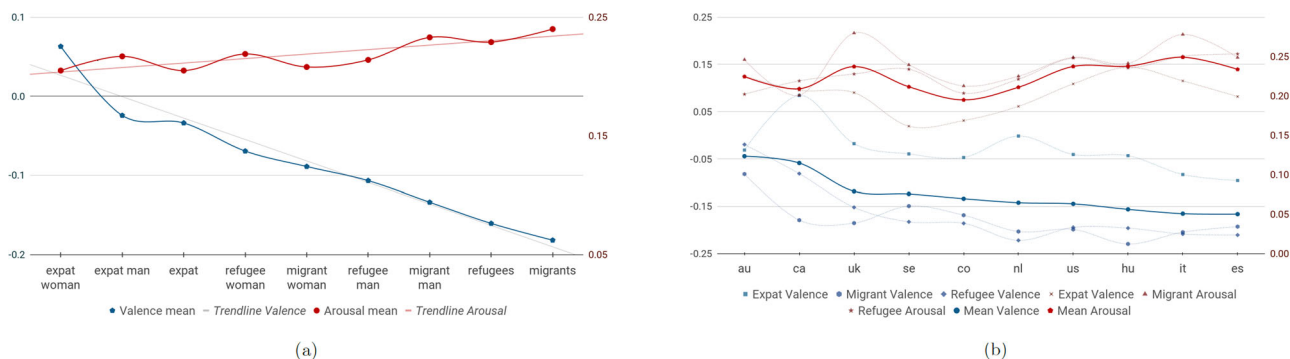


Fig. 2 Average estimated emotional valence and arousal. Results are presented per **a** group and **b** location. The right axis corresponds to valence and the left axis to arousal.

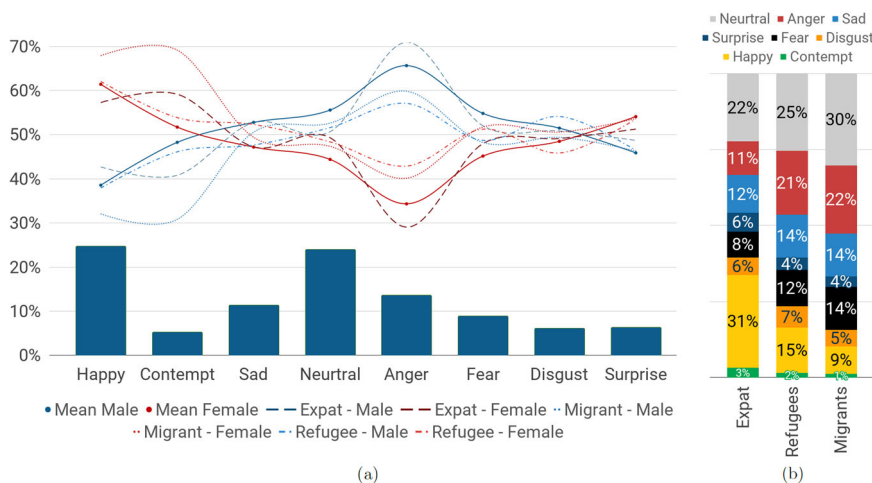


Fig. 3 The distribution of emotions across genders and groups. **a** On the top, a visualization of the conditional probability of gender given an emotion; on the bottom, the probability distribution of emotions over all faces in the dataset in a bar plot. **b** The distribution of estimated emotions per group.

negative emotions as doing so can supposedly contradict stereotypical prescriptions about women being kind and caring or confirm stereotypes about women being overly emotional (van Breen and Barreto, 2022). In our results, male groups display more neutral expressions than their female counterpart, indicating that the portrayal aligns with the stereotypes (or its consequences) that women are more emotional or express more emotions than men. Other stereotypes link emotional expressions by gender to social norms related to levels of perceived dominance and affiliation, and status conferral (Brescoll, 2008; Hess et al., 2005). Additionally, there is evidence that the perception of smiling is not equal across cultures. In particular, higher corruption indicators in society undermine the pro-social perception of smiling and affect trust toward smiling individuals (Krys et al., 2016). Further, facial expression stereotypes also relate to socioeconomic status as rich adults and children are associated with positive emotions, while poor adults and children with negative emotions (Zhang et al., 2021).

Taking into account these stereotypes, our results indicate that *migrants* and *refugees* are associated with a situation of poverty and *expats* to wealth. What is more, the portrayal of the general group *migrants* associates the overall social group with poverty, which can create a bias in society that equates immigration to socioeconomic problems and lead to discrimination and reduce opportunities for migrants. On the other hand, the gender differences within the group of *expats* can be linked to predominant views of masculinity, particularly to dominance or power traits more associated with men than women (Brescoll,

2008, Hess et al., 2005). That is reflected in the emotions displayed (e.g., anger vs. happiness). Anger in *expat man* was the highest amongst all groups.

Finally, we found differences in valence values per location; Australia and Canada have higher average valence values, while Spain and Italy have the lowest values for all groups. Moreover, Canada and the Netherlands present the highest differences between groups, implying substantially different representations of *expats* and other migrants within those countries in terms of the valence of emotions displayed. These differences could be associated with the arrival of refugees to the borders of countries with lower valence. In contrast, those with higher valence are not exposed to similar influxes, so the issue is not part of the dominant discourse in media.

Persons per picture and crowds. The results in Table 1 show that most images with people in them depict around two faces per image, except for *migrant woman* and *refugee woman* which present 4.06 and 3.82 faces per image on average. When considering detected people, the difference is maintained, as in general, the averages range from 2.4 to 3.4, except for *migrant woman* and *refugee woman* with 7.4 and 7.0, respectively. That indicates that these two female groups are generally depicted in larger groups, while the pictures in the other groups show individuals or smaller groups. However, that does not cover the cases when images depict crowds. In those cases, the group's *migrants* and *refugees* are much more likely portrayed as crowds (43.2% and 23.8%, respectively) than the other groups (between 2.5% and

7.1%). These results show a clear differentiation between groups and genders. Moreover, the results on crowds align with the arguments of Bleiker et al. (2013) stating that migrants are depicted in a way in which facial features are not recognizable, which leads to their dehumanization.

Finally, the proportion of images containing faces is the lowest for *expats* with only 26%. Thus, the images associated with *expats* are not mainly focused on people. On the other hand, for *migrants*, the portion is 37%, which is higher than for *expats*, but still low compared to the other groups. However, that lower proportion of faces in images of *migrants* can be explained by the high proportion of images containing crowds, where individual faces are not detected. In contrast, the images of *refugees* containing crowds are lower than for *migrants*, which indicates less focus on groups and more on individuals.

Differences between locations and groups. For the demographic and emotional factors, we calculate the divergence between distributions for all possible pairs of either groups or locations using the KL divergence as a metric. In Fig. 4 the normalized average divergences are presented. When it comes to location, two emerging groups can be observed; on the one hand, the *UK, Canada, the USA, the Netherlands, Italy, and Australia* are more

similar among them. On the other hand, *Colombia, Spain, Sweden, and Hungary* tend to diverge among themselves and when compared to the other countries. That implies that the representations are not always different between geographies but that some countries have representations highly aligned among themselves. The highest differences are found between *Sweden and Hungary*. Regarding groups, there is a clear division between *migrants and refugees* on the one side and *expats* on the other. Moreover, the differences are accentuated for the gender-specific groups, especially for *expat woman* when compared to *migrants* and *refugees*. When it comes to emotions, the differences between *expat woman, migrants, and refugees* get accentuated. Regarding facial features, there is a clear division between *expats* and the other groups. Further details on the definition of the most divergent groups or locations can be found in the Supplementary material.

Since groups might differ for specific properties, the locations and demographic characteristics that presented the highest divergences were studied further. In particular, it was found that ages of *expat man* and *refugee man* diverge significantly between *Sweden, Hungary, and Spain*. These differences might relate to the kind of political views dominant in countries at the time the study was carried out, which is mainly exemplified here by the differences between *Sweden and Hungary*.

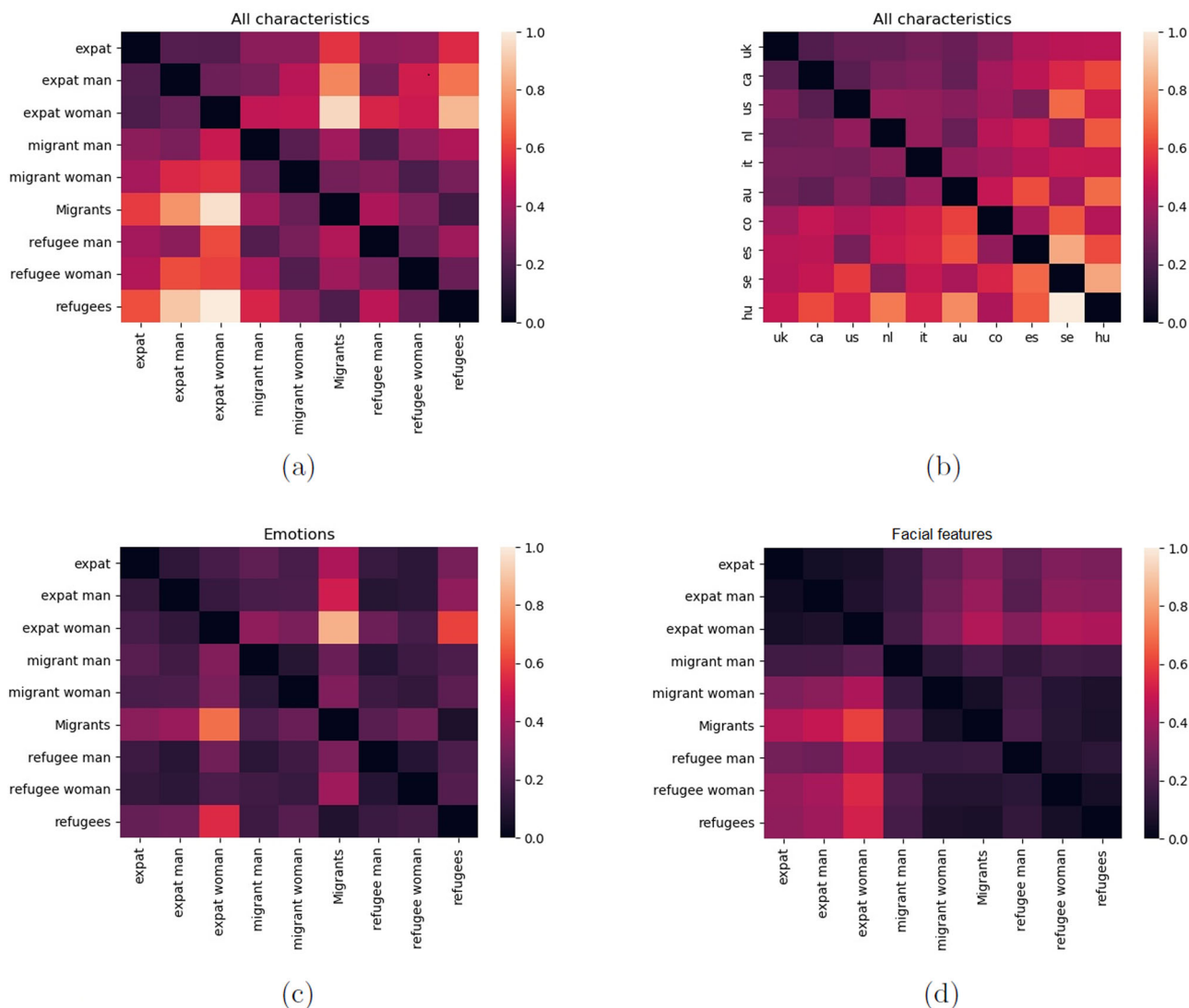


Fig. 4 Average KL divergences across demographic characteristics and emotions. On the top: divergences across demographic characteristics between **a** groups and **b** locations. On the bottom: divergences across groups for **c** emotions and **d** facial features. Lighter colors mean higher divergence.

For *expat man* the estimated ages in *Spain* are more concentrated in the range between 20 and 40, which contrasts with *Hungary*, where the majority of the estimated ages are above 30, and with the maximum in the range 60–69. In contrast, in the distributions for *refugee man*, *Spain*, and *Hungary* behave very similarly and close to the overall average. However, *Sweden* diverges with a peak in the range 60–69, while for ages below 20 there is practically no mass. Contrary to that behavior, there is a higher probability of finding children in pictures for *refugee man* for the overall average. These differences in age distributions per location suggest that the portrayals focus on specific portions of the population in different countries. That indicates variations in the discourse across locations; for example, the high age range of *expat man* in *Hungary* might be showing that this group is not part of the discourse or it is treated as something different.

We also found that regarding emotions the groups with higher divergences are *migrant man*, *migrant woman*, *expat man* and *expat woman*, and the most diverging locations are *Sweden*, *Australia*, *Colombia*, *Spain*, and *Hungary*. In Fig. 5 the distributions over emotional categories for these groups and locations are presented. The main difference lies in the category *Happy*, which is consistently higher for *Sweden* and *Australia*, while for the rest, it is always lower than the overall mean. For *migrant man*, *Anger* also marks a difference as in *Colombia*, *Spain*, and *Hungary* this category is higher, especially when compared to *Sweden*. For *migrant woman* the same occurs, but for *Sad* and *Anger*. Also, *Sweden* presents a significantly higher proportion of *Contempt* than the other locations, while *Spain* presents a higher proportion of *Fear*.

Moreover, when it comes to emotions there are two sets of countries that behave very differently: *Sweden*, *Australia*, *The Netherlands*, and *the UK* on one side, and *Colombia*, *Spain*, and *Hungary* on the other. These results could relate to the relative number of migrants in the countries or the policies and attitudes of specific countries towards migration; for example, efforts to attract migrants (most probably HSMs) or push political agendas by highlighting the impact on jobs or fiscal costs of migration.

For the *expats* groups, the main differences arise from the high proportion of *Neutral* in *Hungary*, especially for *expat women*, and the higher proportions of *Sad* and *Fear* for *Colombia* and *Spain* respectively when focusing on *expat men*.

Concluding remarks

This study analyzed the visual portrayal of three migration-related groups (*migrants*, *refugees*, and *expats*) in ten different countries located in Europe, America, and Oceania. It aimed to explore how those groups are represented and to what extent their portrayal differs in terms of gender, age, facial features, and emotions. Further, it looked at their visual representation in terms of age and gender (in)consistencies with the national statistics. An approach based on the use of Deep Learning models to study the portrayal of migrants on a large scale was presented, focusing on media imagery sought without restriction in a search engine. We have shown that this approach allows us to conclude about such portrayals based on the assumption that average positions or prejudices towards the studied groups are reproduced or reflected in the images found online, given that media images tend to reflect societal biases (Bodenhausen et al., 2016; Heilman, 2012; Kim et al., 2018; Plous, 2003; Reny and Manzano, 2016; Verkuyten et al., 2019). We have found relevant differences between the representation of different migrant groups and between countries through this approach. Moreover, previous results have been confirmed and extended, showing that the method produces a relevant source of quantitative information in the study of the visual representation of migrants. Finally, our method allows for comparing different locations and societies and drawing new conclusions beyond existing literature.

The study clearly shows a series of biases in the visual portrayal of all migrant groups, analyzed countries, and studied characteristics. For instance, we have noticed a mismatch between the visual portrayal and actual statistics in terms of gender and age. Further, in terms of emotions, unsurprisingly, negative emotions are mainly encountered among *migrants* and *refugees* and not

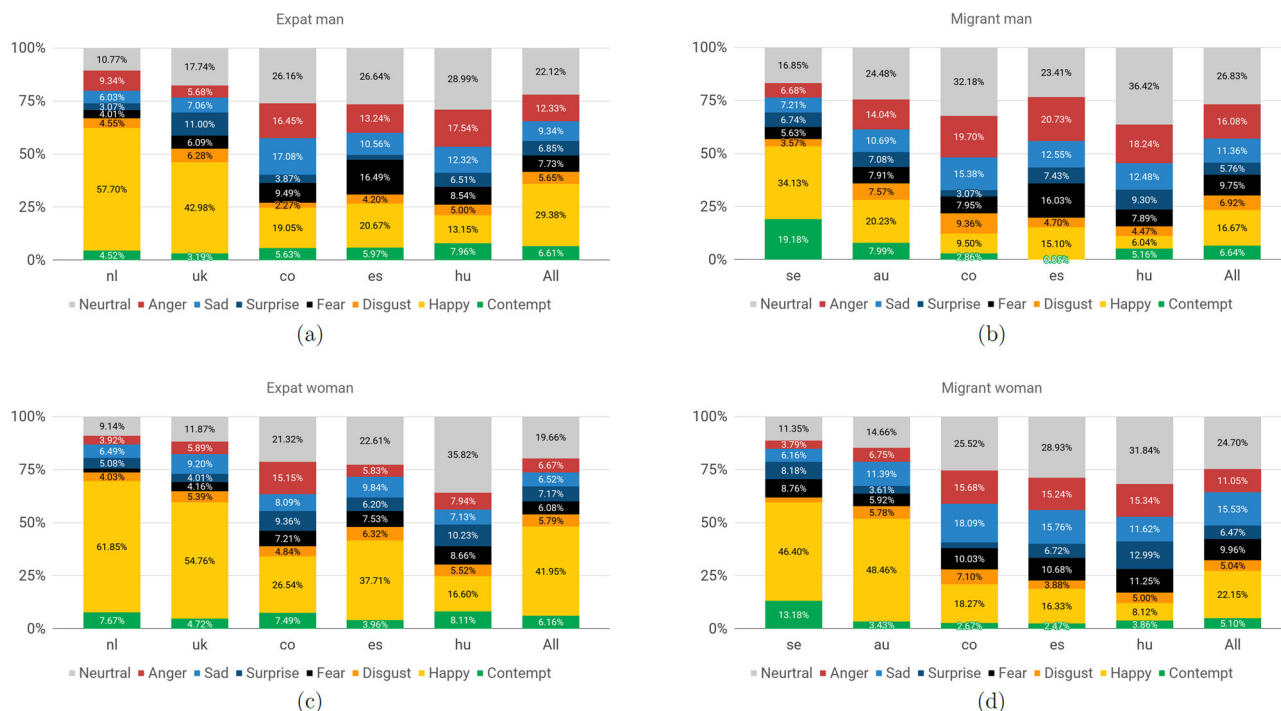


Fig. 5 The distribution of emotions for selected locations. The plots are for the locations Sweden, Australia, Colombia, Spain, and Hungary, and the groups **a** migrant man, **b** migrant woman, **c** expat man, and **d** expat woman.

among *expats*. Women tend to be portrayed as younger, while there is an under-representation of children for all the groups, especially for *expat man*. Refugees and migrants tend to be portrayed in crowded groups, while *expats* tend to be portrayed in smaller groups, alone, or are associated with pictures not portraying people. On the other hand, women, especially refugee and migrant women, are mainly depicted in pictures containing more people. Moreover, our results confirm that the word “*expat*” is mainly associated with “white people” and that Asian people tend to be underrepresented in that group.

These results link to relevant biases or characteristics in society. For example, countries with more equal distribution of males and females in the images, are those ranking higher in the Gender Equality Index as reported in Forum (2021). Similarly, gender distributions of *migrants* are related more to the population of asylum seekers than the overall migrant population. We also evidenced the tension between *expats* being depicted as “westerns” and the fact that many skilled migrants come from “non-western” countries; which in turn exemplifies a predominant colonial view of migrants as “non-western, non-white, non-elite.”

In general, representations of *migrants* and *refugees* align with the demographics of low-skilled migrants which neglects a significant part of the international migration phenomena. Also, the portrayal of the general group *migrants* associates the overall social group with poverty, which can create a societal bias. On the other hand, stronger gender stereotypes and predominant views of masculinity are particularly evident for *expats*. We also show that migrants are often depicted as crowds in a way that facial features are not recognizable. This confirms what was found in previous studies and connects to the concept of dehumanization of migrants.

Finally, our study contributes in four ways: It adds to the literature on visual framing in migration studies by providing a relevant analysis of ten countries with relevant differences in the percentage of migrants population among the overall population and attitudes towards migrants. It uses an intersectional approach, looking at gender, emotions, and age in the representation of the three groups of migrants analyzed. It identifies stereotypes and disproportions in the portrayal of migrants and evidences narratives associated with power asymmetries or colonial perspectives, especially for the term “*expat*”. It shows how machine learning techniques can substantially enlarge the amount of data that can be analyzed for visual content analysis in migration studies.

Future work. We found a gap in the literature in analyzing the characteristics of people depicted as migrants, for example, age distributions and differences between genders. This work has shed light in this direction and has shown discrepancies between the representations and actual data from migrants. Further investigation of these differences and possible causes would be required to explain the reasons for this phenomenon.

The results on emotions show interesting differences based on location, where countries like *Sweden, Australia, Canada, The Netherlands, and the UK* show more positive emotions relative to other countries like *Colombia, Spain, Italy, and Hungary*. That can relate to complex relations worth exploring. For example, that division matches the statistics on GDP per capita and the Protestant/Catholic dichotomy. Interestingly enough, we have also found that, to a certain extent, there might be a relation between depicted emotions (as presented in Figs. 2 and 5) and the attractiveness of the countries for highly-skilled migrants as reported in (OECD, 2019).

Finally, given that the methodology presented here can easily be replicated to study other countries, this work can be a starting point for more comparative studies.

Possible limitations of estimation methods

Age. Our results confirm previous studies on the visual portrayal of women in media, indicating that women tend to be depicted as younger than men (Edström, 2018; Ford et al., 1998; Furnham and Paltzer, 2010; Matthes et al., 2016). However, we have examined the data employed to train and evaluate the model to determine possible biases. We found discrepancies in the age distributions in both the train and validation sets of the FairFace dataset (Karkkainen and Joo, 2021) (see Supplementary material), where female faces tend to be younger than male ones.

The question is whether the characteristics of the data used to train the model are reproducing biases typically seen in media. More so, considering that they come from unconstrained web-based sources. That suggests that biases in the model and the images analyzed here might potentiate each other since both might correspond to the same underlying phenomena. So, this can be a limitation of the models applied, though, at the same time, the results align with the expectations from media imagery. Further research in this direction is required.

Emotions. We inquired whether the observed gender-dependent effects in estimated emotions can be attributed to biases in the model. We found that in the AffectNet dataset, Mollahosseini et al. (2017) used in Toisoul et al. (2021), positive valence values are more likely to appear in female faces and negative ones in male faces. Similarly, the expression *Happy* is more likely to occur in female faces. In contrast, *Anger* is more likely in male ones, confirming results in findings in Chen and Joo (2021) (see Supplementary material for results). That could cause biases in the model; However, gender-related facial appearance and facial expression of emotions often share a physical resemblance, which makes stereotypical and phenotypic information conveyed by the face intertwined or confoundable (Adams Jr, Hess & Kleck, 2015). To a certain extent, that would explain why a model would associate phenotypic characteristics of faces from a given gender with emotions that share the same features. That could lead to results similar to those observed here and would not be dependent on the data distribution or other biases behind it. However, it is also the case that the portrayal of different groups in media is biased and that gender stereotypes related to emotions align with our results. Thus, the model can be biased because the usual representations respond to societal stereotypes. Disentangling these effects would require further research.

Data availability

The datasets generated and analyzed during the current study are not publicly available since many images displayed in image search results are subject to copyright restrictions. However, data sources and the results from the analysis can be obtained from the corresponding author upon reasonable request.

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Notes

- 1 IOM key migration terms <https://www.iom.int/key-migration-terms>
- 2 Cambridge dictionary <https://dictionary.cambridge.org/dictionary/english/expatriate>
- 3 Migration data portal https://www.migrationdataportal.org/international-data?i=stock_abs_&t=2020
- 4 UNHCR, the UN Refugee Agency <https://www.unhcr.org/figures-at-a-glance.html>
- 5 <https://cloud.google.com>
- 6 For extracting faces, we used the implementation in <https://github.com/timesler/facenet-pytorch>

- 7 For face super-resolution we use the implementation in: <https://github.com/ewrfcas/Face-Super-Resolution>
- 8 For person detection, we used the implementation in: <https://github.com/facebookresearch/detr>
- 9 To extract features from images, we used the ViT-S/16 model in <https://github.com/facebookresearch/dino>
- 10 Report on the Gallup's second administration of its Migrant Acceptance Index: <https://news.gallup.com/poll/320678/world-grows-less-accepting-migrants.aspx>
- 11 Eurobarometer <https://europa.eu/eurobarometer/screen/home>
- 12 IOM world migration report: <https://worldmigrationreport.iom.int/wmr-2022-interactive/>
- 13 To get demographic information we use the implementation in: <https://github.com/joojs/fairface>
- 14 To extract emotional information from faces we use the implementation in: <https://github.com/face-analysis/emonet>
- 15 Yahoo Flickr Creative Commons 100 Million (YFCC100m) dataset—<http://projects.dfk.uni-kl.de/yfcc100m/>
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Competing interests

The authors declare no competing interests.

Ethical approval

This research did not require any ethical approval.

Informed consent

This article does not contain any studies with human participants performed by any of the authors.

Additional information

Supplementary information The online version contains supplementary material available at <https://doi.org/10.1057/s41599-022-01430-y>.

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