Visual Analysis Methods

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Scholarship has long ignored the intrinsically visual character of (violent) extremists' actions and communications. In recent years, however, a range of visual analysis methods have emerged, building on pioneering work that theorised the visuality of violence. This chapter offers a typology, succinct presentation, and appraisal of these methods, which span from in-depth interpretations of a few images to large-scale AI-powered scans of large visual datasets. Distinguishing between human and computational methods, the chapter highlights the advantages and limitations of each method, lays bare their logics and assumptions, and advocates for a multi-methods research agenda articulating them together in a coherent and productive way.

Extremist and violent political actors have long sought to supplement their texts with images; in 1641 already, for instance, engravings showing Irish mobs attacking helpless women and piercing babies with pitchforks accompanied English colonists' propaganda pamphlets calling to exterminate Irish rebels. Four centuries after these events, visuals have not only become more prominent in extremist communications, they have also arguably become their central component. Even though this centrality reflects the growing importance of the visual in societies more generally, which has been studied for a long time from various perspectives,[1] it has long escaped extremism and terrorism scholars' attention. Indeed, Bolt's (2012) conceptualization of the "violent image", which theorized the striking visual dimension of (post-) 9/11 "propaganda of the deed", was one of the first such contributions to the field. As Baele, Brace and Naserian (2025: 37) explicate, "analysing extremist and terrorist imagery presents a range of difficulties that explain why scholarship has not taken off earlier or been more extensive" (Baele, Brace & Naserian 2025); even before these methodological difficulties arise, researchers face the fact that storing (let alone sharing) images from terrorist organisations is prohibited or severely constrained in most research-intensive countries.

Three main events of the 2010s have ended this neglect. First, visual "turns" taking place with great effects in adjacent fields[2] began to percolate through multidisciplinary initiatives; Conway's (2019) oft-cited call to take such a visual turn in terrorism studies explicitly draws from these developments. Second, the scale and shocking character of the Islamic State's propaganda, which made great use of photo reports, videos, and pictures-heavy magazines, made it untenable to ignore the visual centre of gravity of the organisation's communications (and those of other jihadist organizations beyond). Third, the expansion of sprawling far-right and misogynistic online ecosystems has brought attention to the ways through which extremist worldviews express themselves on visual-centric and multimedia digital platforms such as the "chan" boards, Instagram, or TikTok. The digitally connected nature of contemporary extremism, be it Salafi-jihadist or neo-Nazi, means that visual studies prompted by these three triggers have developed as part of a more general turn towards "online data" (see Macdonald et al. 2023). The mid-2010s and 2020s have consequently seen a multiplication of projects studying visual expressions of extremism and terrorism, in the tail of influential work such as Doerr's analyses of far-right posters and images (e.g., Doerr 2017), Engstrom's (2014) investigations of the British National Patry's ingroup symbols on social media, or Winkler and Dauber's (2014) volume *Visual Propaganda and Extremism in the Online Environment*. Collectively, this endeavour has shown that, to take Milman and Doerr's (2021) words, visual analysis does unlock a "unique and rich angle for analysis"; it has also helped correcting or complementing, through methodological triangulation, findings delivered by other

[1] Consider for instance Benjamin 2008 [1936], Sontag 1997, or Barthes 1981.
[2] Such as IR with e.g., Bleiker 2001, or communication and media studies with e.g., Schill 2012 or Veneti et al. 2019.

methods such as text analysis (Ging et al. 2025), and avoid misinterpretation of the extremist message (read Dauber & Winkler 2014).

Aims and goals of visual analysis within research designs.

Before presenting available methods, it is necessary to first clarify what visual analysis seeks to achieve, and more precisely to highlight that studying extremist or terrorist images can serve a diversity of aims and therefore answer different types of research questions. These aims and questions, in turn, determine the kind of image or visual dimension selected for empirical analysis (and therefore, as we detail in the next section, the specific method).

As always, the main factor should be theory: each theoretical framework highlights certain factors and dynamics claimed to be crucial and subsequently calls attention to specific visual tropes. For instance, an investigation informed by Social Identity Theory, which emphasizes intergroup processes and in-/out-group identifications, will naturally examine the visual displays of in-/out-groups in extremists' photos, cartoons, and the like; studies influenced by semiotics (such as Engstrom's abovementioned study) logically focus on symbols or visual icons; theories of online radicalisation and mainstreaming are more likely to focus on viral memes with extremist subtexts (as in Zanettou et al. 2018). The range of possibly relevant dimensions and aspects of images produced by extremists and terrorists is therefore vast: do they include important symbols? Which groups do they display and how? Are they gruesome/shocking? Do they crystallize particular discourses? Etc.

It is useful to think of these different aspects and dimensions as either being "manifest" content (such as the presence of a flag on an picture) or participating to establish the image's "latent" meaning produced through the interplay of its various manifest elements and its cultural and ideological contexts and subtexts (latent meaning can be the narrative conveyed by the image, the way it constructs an outgroup archetype, its role in constituting what Hokka and Nelimarkka [2020] call visual "affective economies", etc.). For example, AI-generated pictures of "beautiful" white women and children in idyllic landscapes – which proliferate in today's far-right social media –[3] convey the message (inter alia through contrast with other types of images such as beaten white women) that such an ideal world is both under threat and possible. As this example shows, manifest content and latent meaning ought to be understood together, as two ideal-typical heuristic ends of a "continuum between highly manifest and highly latent content" (Bouko 2023: 94).[4]

Crucially, as Milman and Doerr (2021) recall, visual analysis should pay attention not only to what is featured in images, but also to what or who is *not* displayed, that is, made invisible. In that, visual analysis has one of its roots in classic framing and agenda-setting research (which respectively asks how particular issues are presented in the media, and how much coverage they are granted), where what is included is as important as what is excluded. Scholars should also integrate into their research design the fact that images are but one of the four visual "sites" identified by Rose (2016), who warns that researchers should not forget how they are produced ("site of production"), how they circulate ("site of circulation"), and how they are appraised ("site of audiencing") – three "sites" that call for specific methodologies such as data-mining or experiments, which are beyond the scope of this chapter.

Data and Data Collection

Several typologies of visual methods already exist – such as Caiani's (2024) three categories ("critical visual analysis", "visual grammar approach", and "multimodal discourse analysis") or Milman and Doerr's (2021) three "pathways into studying visual forms and formats" ("visual forms of expression", "visual representations", and "visibility"). However, because they do not encompass all options, I offer here a more complete two-level classification that distinguishes between *human* and *computational* approaches, each comprising several distinct methods. Both rely on the preliminary collection of

[3] For examples and a discussion, see Baele & Brace 2024, and Tebaldi 2023.
[4] The chapter in Bouko's book (2023) from which this quote is taken offers a clear and detailed discussion on this and other distinctions.

relevant images from an empirical universe, where several scenarios are possible: the images can gathered from the source either by hand or computationally in automated ways (using, for example, custom web-scrapers developed in Python), and the corpus can be either the entire empirical universe (for example, Baele, Boyd & Coan 2019 analysed every single images contained in ISIS magazines) or a rigorously selected sample taken from it (when the empirical universe is too big; here traditional sampling rules should apply).

a) Human methods

Traditionally, visual analysis has relied on human methods whereby researchers examine a number of images to identify theoretically significant content and/or expose dominant latent meaning. Broadly speaking, two types of human methods exist, which respectively align with the qualitative and quantitative traditions.

Codebook categorization is the quantitative one. Here, the researcher deduces from theory the importance of particular visual elements, and then examines all or a sample of images (from several hundreds to several thousands) from her/his visual corpus to count the presence/absence (in each of them) of these elements. For example, Baele, Boyd and Coan's (2019) ISIS magazines study manually numbered each picture contained in the publications – approximately 1,500 images – and then verified on a yes/no basis, for each, if there were elements like the group's flag or gruesome content. Rigorous scientific standards should be obeyed when conducting such categorization, including full transparency and convincing justifications for corpus size, potential sampling, codebook categories inclusion/exclusion criteria (especially with regards to possible overlaps) and types (nominal, ordinal), and codebook validation (Bouko 2023). At least two coders are needed to avoid findings based on a single person's perceptions, and their "intercoder reliability" must be measured with the right statistic (typically Cohen's κ or Kripendorff's α).[5] To limit the risk of low intercoder alignment, the process is usually iterative, with one or two coding and verification rounds on limited samples before the codebook is finalized and applied throughout. This method not only provides a reliable measurement of key visual elements in a corpus, which together give an overview of a group's "visual style", it also lends itself to a range of dynamic statistical methods such as time-series analysis looking for evolution of this visual style, which can indirectly document dynamics such as ideological or strategic evolutions (Baele et al. 2029).

Interpretive analysis is the qualitative option, and has numerous variants whose specificities cannot be spelled out here. Here, the researcher conducts an in-depth, interpretive analysis of one or a handful of particularly important, iconic image(s) to explain their symbolism, communicative function, embedded narrative, or/and emotional appeal. For example, Doerr's study of the (in)famous Swiss People's Party poster featuring immigrants as black sheep offered rich insights into the transnational dissemination of common far-right visual references and metaphors. Such thorough studies often investigate a particular visual genre, that is, a heuristically-constructed class of images displaying limited variation and performing a common role – Tebaldi (2023) for example discussed pictures of health and nature disseminated by white supremacists.

In sum, human methods can be either quantitative or qualitative, depending on whether they seek to characterize the (theoretically) most relevant features of a coherent visual corpus or reveal the meaning of particularly important or iconic images as well as their position within a larger extremist context. In the first case, the method involves a clear sequence of practical steps to be rigorously implemented; the second case is much less codified, with ample leeway left to the researcher. While codebook categorization is more suited for studying the manifest content of images, the second approach is more

[5] *Intra*-coder reliability is often measured, too.

apt at uncovering latent meaning – attempts to "count" latent meaning conveyed by the images (such as a specific narrative) typically result in low reliability and superficial findings, raising obvious concerns not only about validity but also about replicability.

b) Computational methods

The rise of Artificial Intelligence (AI) in the 2010s and 2020s has transformed computer vision from a slow and impractical technique into a fast and high-performing tool whose two joint advantages are speed and ability to scan very large corpora – useful assets in our times of expanding extremist online ecosystems. At the time of writing this chapter, AI visual models are only starting to enter extremism/terrorism studies' methodological toolkit; given their power and gradual democratization (in terms of skills/financial entry costs), however, their future prominence raises little doubt.

Two main types of computer vision models exist that perform different tasks. First, some models (like YOLO, freely available at https://github.com/ultralytics/ultralytics) operate *object detection*: they screen each image of a corpus to identify all instances of a given object deemed relevant by the researcher ("object" is understood broadly as a *category*, such as "gun", "woman", or "Bin Laden"). These models are, ultimately, a direct alternative to human-run codebook categorization, and lead to the same kind of statistics and insights: both account for the absence or presence of easily identifiable visual objects in all images contained in a dataset. Beyond speed and scale, AI models have another advantage: they shield researchers from repeated exposure to harmful content (such as extreme violence or abusive pornography). Yet even though models pre-trained on relevant objects start to emerge (e.g., Noor & Isa 2021 on weapons), this approach remains dependent on often strenuous training processes if researchers are interested in niche visual tropes not recognized by off-the-shelf models (e.g., neo-Nazi symbols, individuals making a specific gesture).

The second type of computer vision models is *clustering*, where all the images of a corpus are automatically separated into several classes on the basis of their similarity. The number of clusters is either chosen a priori by the researcher, or left entirely for the model to decide on the basis of set parameters, or corresponds to an optimum reached iteratively (typically with expert, qualitative input). For these reasons, visual clustering is comparable to what topic modelling does for a text corpus (see CHAPTER X on TEXT ANALYSIS) and serves the same function in research: it provides a quick representation of the respective saliency of the dominant tropes (visual, instead of linguistic) within a large corpus. As such, the graph renderings of clustering (in the form of histograms or even networks) represent what can be thought of as the "visual landscape" of an extremist visual production. Baele, Brace and Naserian (2025) illustrated this use of clustering by displaying as Sankey diagrams the "landscape" of both the incelosphere and the constellation of US far-right Telegram channels. A range of clustering models exist, each with its strengths and weaknesses that ought to be carefully considered.

Besides these two methods, a newer generation of models such as the latest GPTs also exist that immediately operate in a *multi-modal* way, that is, are built from the outset to analyse – and generate – both visual and text data simultaneously (with, in some cases, integration of sound as well). This means that they are able to run complex tasks beyond pure visual analysis, like recognizing text embedded inside images or convert the visual information into textual information (image-to-text conversion, and conversely). Although these models involve computer vision, they usually reflect a methodological shift towards other approaches, such as text analysis (using a text corpus containing the descriptions of each image in the visual corpus), and are therefore beyond the realm of the current chapter. For example, Lokmanoglou and Walter's (2025) *VisTopic* workflow combines several AI models to generate a text caption for each image of a corpus and run topic modelling on all these captions.

c) Inductive vs. hypothetic-deductive logics

It appears from our description of the four methods (and their variants) that they don't share the same epistemic presuppositions; in other words, they correspond to different social science paradigms. **Figure 1 below** represents this diversity alongside the inductive – hypothetic-deductive continuum spelled out in the Introduction of this book. This shows that computational methods are not necessarily associated with the Popperian conception of science,[6] or human methods with the more interpretive tradition. Indeed the only fully inductive method is computational clustering in its unsupervised version, whose key asset is precisely to question the data without any human input. Interpretive analysis, although seeking to carefully reconstruct the meaning of certain images through a process of learning, inevitably contains a dose of deduction in the sense that this interpretation always relies on theoretical frameworks (be it from social movement sociology, feminist philosophy, etc.) set beforehand to infer which visual images, genres, or elements ought to be considered *a priori* important. The logic guiding both codebook categorization and object detection has to be fully hypothetic-deductive (when these methods are conducted in a rigorous way), with theory dictating what is to be detected and coded/counted (the only inductive dose being the iterative process of codebook refinement).

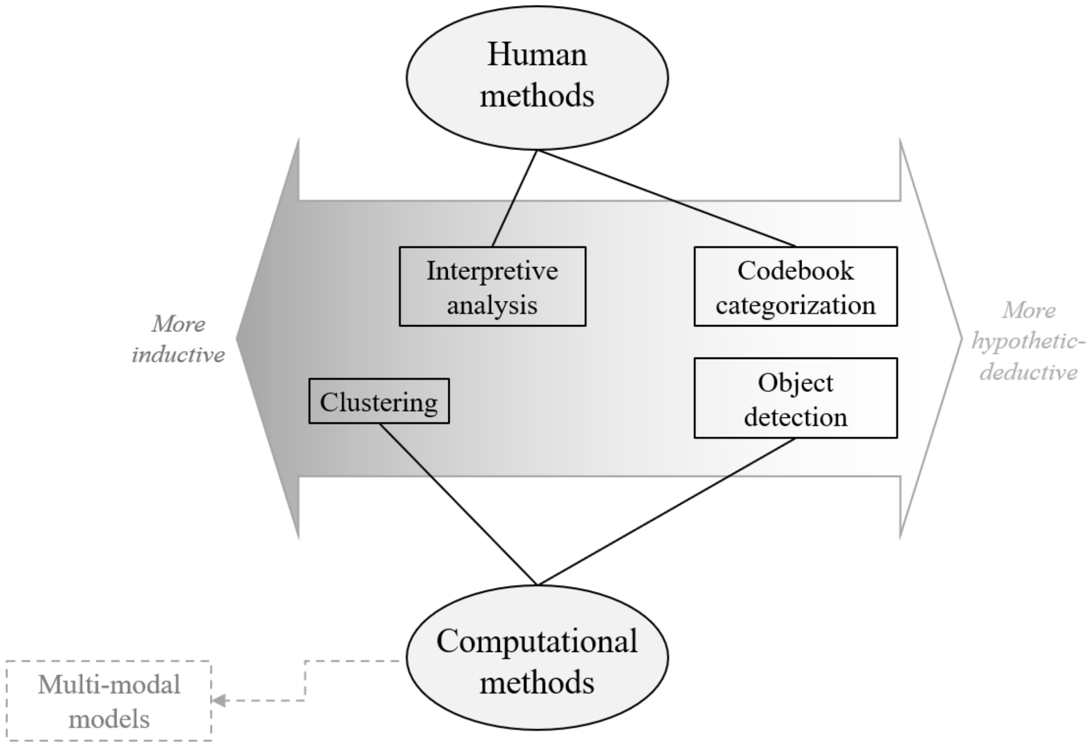

Figure 1. Human and computational visual methods, situated along the induction/deduction axis.

Alt-text: A diagram displaying four methods of visual analysis in extremism/terrorism studies (two human methods and two computational methods). Represented as text-boxes, these methods are positioned from left to right along a two-directional arrow pointing towards induction (left hand-side) and deduction (right hand-side).

Visual analysis: Strengths and limitations

Mixed-methods designs should be encouraged both within visual analysis, and in larger research projects involving other methods such as text analysis or interviews.

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[6] In their seminal presentation of computational *text* analysis, Grimmer and Stewart (2013) already made clear that computational methods combine inductive and deductive logics.

Within visual analysis, the strengths and limitations of computational methods mirror those of human methods, meaning that they are natural complements (Baele, Brace & Naserian 2025). Human methods can only deal with small-n corpora, are slow, produce variable results, and expose researchers to harmful content; however, they are cheap, do not require high technical skills, can successfully deal with images' multi-dimensionality and latent meaning, and are required to generate deep insights. Conversely, computational methods are made to deal with large-N corpora, are fast, produce less variable output, and shield researchers from exposure; however, they can be costly (storage space, high-end computing, AI running costs, etc.), involve more technical skills, struggle with multi-dimensionality and latent meaning, and are ill-suited for in-depth work. For ambitious research projects aiming to conduct the strongest, most convincing and comprehensive analysis of extremist imagery, thus, ought to apply "integrated mixed-methods designs making the most of human and computational visual methods while mitigating each one's shortcomings" (Baele, Brace & Naserian 2025, p. 52).[7] In a way, this is what Caiani (2024, p. 4) already alluded to when stressing the importance of the collection of information and (meta-)data on the studied visuals to "contextualize images both socially and politically" – a task best handled by computational methods. Crawford and colleagues' (2021) study of the dissemination of far-right memes was probably the first example of such a fruitful combination, articulating machine learning computer vision scanning a very large dataset with qualitative interpretation of a limited number of particularly significant visuals.

Visual analysis also holds promise when articulated with other, non-image focused methods as part of genuinely composite research designs. Indeed extremist imagery is always part of a broader form of expression entwining visuals with texts and other hybrid formats, which means that focusing solely on images can only yield limited insights. As Dauber and Winkler highlight, "viewers do not typically see or process visual images in isolation […], they see images presented in combination with captions, audio soundtracks, or other textual material" (Dauber & Winkler 2014, p. 11). As such, and while genuinely multimodal non-AI methods studying images and text *simultaneously* are still in infancy (e.g., Tan et al. 2018), designs that combine visual analysis with text analysis are most pertinent to provide a more comprehensive analysis of extremist content.

But more fundamentally, multi-methods designs are required because visual analysis alone offers little direct inroads towards the causal mechanisms underpinning extremism, radicalization, and terrorism. For example, what do images found on an extremist website or magazine do to their viewers, and why do they have these effects? This crucial question not only calls for a rigorous analysis of the images at hand, but necessitates a joint research design using focus groups or experiments (see CHAPTER Z on EXPERIMENTS/FOCUS GROUPS). On the other end of the image "life", why are these images first produced and then shared? Here, visual analysis would need here to be combined with archival work, producers/users' interviews (see CHAPTER X on INTERVIEWS), or netnography (see CHAPTER Y on NETNOGRAPHY), methods that are geared to reveal the meaning actors give to their actions or the strategies some follow to reach target audiences. For example, Bouko (2023: 99) refers to Rose's "sites" of visuality to suggest using interviews to complement the analysis of imagery "with concrete insights concerning its production, audiencing and circulation".

Conclusion

Given the highly visual nature of today's extremist and terrorist environments, visual analysis is much needed, and robust methodological guidelines are now readily available. Yet three major challenges remain. First, visual methods remain scarce in the field, and are usually carried out with too little rigour (one reason being that, until this piece, dedicated terrorism/extremism handbooks have

[7] Grimmer and Stewart (2013) made exactly the same argument for text analysis.

ignored them). In her *Visual Citizenship* book, Bouko (2023) put forward a scathing diagnosis of this situation, evidencing that methodological standards in visual content analysis remain poor and inconsistently followed. Second, the ubiquity of the *video* format has further complexified the "visual challenge", furthering the need to build novel rigorous methods for both the still and the moving image (see CHAPTER Y on VIDEOS). Third, collecting and analysing images from extremist and terrorist milieus raises a series of ethical issues such as researcher' exposure to gruesome or pornographic content (at times illegal), which are in need of a comprehensive charting and solutions. Only with a renewed rigour, solid ethical best practices, and intelligent attuning to moving images, could visual methods fulfil their potential.

Recommended Readings

A programmatic text in using "images as data" in political science and conflict studies:

- ✓ Joo and Steinert-Threlkeld (2022).

Theoretical frameworks on visual extremism:

- ✓ Baele and colleagues (2019).
- ✓ The first chapters of Winter's book ' *The Terrorist Image* (2022).

Detailed methodological guidelines:

- ✓ Caiani (2024): qualitative approaches.
- ✓ Milman and Doerr (2021): qualitative approaches.
- ✓ Baele, Brace and Naserian (2025): mixed, computational and qualitative workflow.
- ✓ Bouko (2023): detailed instructions on best practices in both quantitative and qualitative approaches.

Key empirical studies:

- ✓ Winkler and colleagues (2019): study the "about to die" pictures in jihadist magazines.
- ✓ Macdonald and Lorenzo-Dus (2021): analyse pictures of "good Muslims" in johadist magazines.
- ✓ Awad and colleagues (2022): examine Danish People's Party's "othering" images on social media.
- ✓ Ging and colleagues (2025) provide a large-scale, quantitative analysis of images circulating in the "incelosphere".
- ✓ Kraidy (2017) theorizes on the "projectilic" image genre.
- ✓ Zannettou and colleagues (2018) use AI models to detect antisemitism online. (
- ✓ Hokka and Nelimarkka (2020) use AI models to identify national-populist imagery on social media.

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