Media Framing: A Typology and Survey of Computational Approaches Across Disciplines

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Abstract

Framing studies how individuals and societies make sense of the world, by communicating or representing complex issues through schema of interpretation. The framing of information in the mass media influences our interpretation of facts and corresponding decisions, so detecting and analysing it is essential to understand biases in the information we consume. Despite that, framing is still mostly examined manually, on a case-by-case basis, while existing large-scale automatic analyses using NLP methods are not mature enough to solve this task. In this survey we show that despite the growing interest to framing in NLP its current approaches do not capture those aspects which allow to frame, rather than simply convey, the message. To this end, we bring together definitions of frames and framing adopted in different disciplines; examine cognitive, linguistic, and communicative aspects a frame contains beyond its topical content. We survey recent work on computational frame detection, and discuss how framing aspects and frame definitions are (or should) be reflected in NLP approaches.

1 Introduction

Media framing refers to the packaging of information in a way to evoke a specific association in the reader, often with the aim to alter opinions, attitudes or behavior (Entman, 1993; Semetko and Valkenburg, 2000). This process involves three aspects: linguistic choice of how to encode the information (semantics); associations evoked in the reader which depend on individuals' existing cognitive schemata, categories or stereotypes (cognition); and the communicative act of (repeated) emphasis of a particular frame, and its effect on the audience (communication) (Sullivan et al., 2023).

Computational approaches to frame detection have predominantly compared different contexts in which a given issue is discussed, emphasizing the communicative dimension, which has led to a disproportionate emphasis on asking *how a message is conveyed*, rather than *how it is framed*. For framing to occur there needs to be an underlying ambivalence which gives rise to conflicting cognitive associations that may be evoked (Scheufele and Scheufele, 2010).

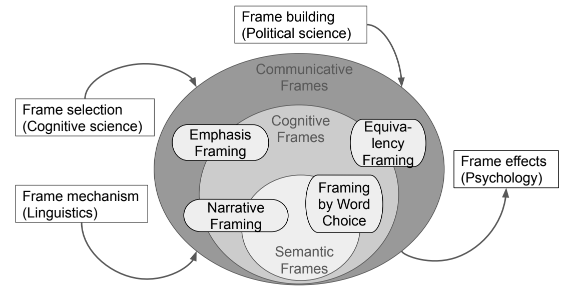

Figure 1: Connections of Framing Levels (circles) with Framing Types (rounded boxes) and Disciplines (boxes).

Here, we lay out the multi-disciplinary origins of framing, and draw connections across disciplines and theories. We present a typology of framing by grounding the most prominent framing types covered in NLP in their cross-disciplinary foundations (Figure 1). We note that semantic, cognitive and communicative framing have all been addressed in NLP separately, and point to opportunities in combining these research directions for a more integrated and ecologically valid research agenda. We contextualize our discussion in a survey of work on automatic frame prediction.

Our work relates recent surveys on framing in media studies (Hamborg et al., 2019), cognitive linguistics (Sullivan, 2023), and social psychology (Borah, 2011) to NLP. Unlike Ali and Hassan (2022), who survey NLP methodologies for frame detection, we focus on the conceptualizations adopted (or, rather, omitted) in the field.

2 Methods

We collected literature on computational and quantitative approaches to media framing, following the methods adopted in systematic reviews (Lacey et al., 2011), as described in Appendix A. The resulting set contains 147 papers, published between 1997 and 2024. 19% of included papers do not mention "frame" or "framing" in their title, while 8% do not have these words in their abstract either. This shows that it is easy to overlook a substantial part of relevant research when relying only on these search keywords, as it was done previously (Ali and Hassan, 2022). The majority of included papers (112) address framing in English, with a small number of studies on German (7), Chinese, Italian, Persian, Russian, Spanish (2 each), and some multi-lingual approaches (18).

52% of the articles (77) were published in computational linguistics and NLP conference proceedings and workshops; 18% (26) at other machine learning and computer science venues; around 8% each in social science (12) and media studies (11) venues, and 6% are in political science journals, and other disciplines (general research methods, psychology, environmental studies, cognitive linguistics, etc.). The overall trend for the number of papers published in NLP vs non-NLP venues over time is shown in Appendix D.

3 Aspects of framing across disciplines and their coverage in NLP approaches

3.1 Three levels of framing

In its broadest sense framing means "packaging" the meaning of concepts and events so as to facilitate their interpretation as a single unit or "schema of interpretation" (Goffman, 1974). Such packaging happens at three levels: semantic, cognitive, and communicative (Sullivan, 2023), which are, however, interrelated and support one another (Figure 1, concentric circles).

Semantic frames describe the semantic types of arguments they afford. For example, the word *imprison* implies the existence of a person being sent to prison (*prisoner*), someone who does the act of imprisoning (*authorities*), a destination (*prison*), and optionally the reason (*offense*)[1]. The event of *imprisonment*, however, is not fully described by the agent-patient relations within this particular semantic frame: it also implies the existence of events which led to the imprisonment, such as *detention* or *court order*, the fact that the offense was severe enough to require incarceration, and other facts that we associate with *imprisonment* based on our world knowledge. Such clusters of concepts that help us to understand and process events are *cognitive frames*. Finally, *communicative frames* happens when we activate one or several cognitive frames by conveying information "in such a way as to promote a particular problem definition, causal interpretation, moral evaluation, and/or treatment recommendation" (Entman, 1993): when we say *The refugees were imprisoned in Park Hotel* rather than *The refugees were detained in Park Hotel*, we imbue the message with our moral judgment against the detention, evoking the negative connotations of imprisonment such as the fact that refugees are treated as prisoners (as follows from the semantic frame) who committed some serious crime (as follows from the cognitive frame).

3.2 Approaches to framing across disciplines

As the example above shows, media framing is grounded in all three levels of framing and arises across disciplines. The internal mechanics of semantic and cognitive frames such as their constituents were examined by cognitive linguists, starting from Fillmore (1982), and were thoroughly captured and studied through such initiatives as FrameNet (Baker et al., 1998; Ruppenhofer et al., 2016). On the other hand, cognitive scientists such as Minsky (1974) explored the dynamics of evoking cognitive frames in a discourse and explored our ability to recognise and conjure complex scenarios without spelling out all their semantic frames and instead relying on more general schemata of interpretation. However, while semantic and cognitive frames form the backbone for understanding and communicating any message, on their own they do not lead to media framing, but must be combined with other communicative devices or external factors to form a communicative frame. Thus, when it comes to media framing, linguistics and cognitive studies, starting from works of Lakoff and Johnson (2008), focus on such phenomena as metaphor and metonymy, which have evocative and emotive functions allowing to transform a message with informative content only into a frame (Burgers et al., 2016).

Semantic and cognitive frames (or "topics", as they are roughly referred to in them) are not enough to convey a particular interpretation of an issue in a way that affects the audience (Entman, 1993; Carragee and Roefs, 2004). Consequently, the ques-

[1] The semantic frame is taken from the *Imprisonment* frame definition in FrameNet (https://framenet.icsi.berkeley.edu/frameIndex)

tion of what turns a message into a frame has been studied by investigating different aspects that activate semantic and cognitive frames. For instance, psychological studies examined cognitive mechanisms that enable framing its impacts on decision making (Kahneman and Tversky, 1984). In the context of media framing, it was asserted that media frames activate a particular constellation of cognitive frames in journalists' or readers' minds, and the framing occurs only when alternative competing activations are possible, i.e. there is some potential ambivalence of interpretation (Scheufele and Scheufele, 2010).[2] The activation of a particular set of cognitive frames draws on relevant beliefs or moral principles already stored in our memory (Nelson et al., 1997; Chong and Druckman, 2007). These then serve as a filter, shaped by cultural knowledge or personal experience, to interpret the information (Schlesinger and Lau, 2000; Lau and Schlesinger, 2005). In our example, a person can feel strongly negative to the frame of *imprisoning* refugees only if they already have a cognitive frame for *freedom* as a basic human value in the set of dimensions against which they evaluate information, and reject an alternative interpretation.

On the other end of the spectrum, political scientists study the role of framing in shaping public opinion, i.e. as a tool to influence the attitudes of citizens (Chong and Druckman, 2007), and a mechanism for citizens to anchor their opinions and take sides in political debates (Sniderman and Theriault, 2004). Accordingly, the main focus of research here is what factors are involved in frame building, and what external variables must be in place for it to be effective. Among the factors that can make (or break) a frame are such as external actors (Gamson and Modigliani, 1989), source credibility (Druckman, 2001), ideological factors (Silcock, 2002), and cultural contexts (Gamson and Modigliani, 1989; Benson and Saguy, 2005).

Most framing research lies between these ends, and examines the interaction of external factors and internal cognitive mechanisms through the medium of text. They explore how communicative frames help individuals to make sense of otherwise meaningless successions of events (Goffman, 1974) and allow journalists to pack the information (Gitlin, 2003; Entman, 1993) and study how linguistic and non-linguistic devices such as metaphors or visual images were used to frame media content.

3.3 Coverage in NLP approaches

In this section, we examine to what extent the perspectives outlined above are reflected in the work covered in our survey.

Linguistic approaches First, we note that semantic and cognitive framing – without connection to media framing – has attracted great interest from the NLP community. A long line of research builds on FrameNet (Baker et al., 1998), including using its semantic and cognitive frames for event extraction (Liu et al., 2016), semantic role labelling (Hartmann et al., 2017), or sentiment analysis (Chatterji et al., 2017). However, in our survey on automatic frame analysis, few studies used FrameNet, mostly for semantic parsing (Sturdza, 2018; Jing and Ahn, 2021; Minnema et al., 2021) or the detection of specific events such as femicide (Minnema et al., 2022). Postma et al. (2020) is the only exception. They expand FrameNet with real-world referents of events to enable comparison of different perspectives (or frames) towards them. The bulk of research neither examines the linguistic mechanisms of framing, nor employs them to improve frame detection and analysis. Moreover, only 7% of papers examine linguistic devices that transform semantic or cognitive frames into media frames, including metaphors, discourse markers, or syntactic structures (Sullivan, 2022; Yu, 2022; Klenner, 2017; Luo and Huang, 2022; Rashkin et al., 2015; Sap et al., 2017; Chen et al., 2022a), or use linguistic features in frame classification (Choi et al., 2012; Yu, 2023; Huguet Cabot et al., 2020).

Cognitive approaches The situation is similar for cognitive scripts and schema, which were introduced 1980s as manually coded structures to represent stereotypical events, derived from knowledge structures that underlie human reasoning (Schank and Abelson, 1975; Bower et al., 1979), and then formalized in a slightly simplified way as narrative schema of event sequences and their participants (Chambers and Jurafsky, 2009), receiving substantial attention in NLP (Mooney and DeJong, 1985; Fremann et al., 2014; Ferraro and Van Durme, 2016; Pichotta and Mooney, 2016; Li et al., 2023). However, leveraging narrative schema (in particular probabilistic models, that account for variation in the order or set of associates) as a proxy for the variation in associations evoked by framing, has

[2] Scheufele and Scheufele (2010) refer to cognitive frames in our minds as cognitive schema, and they define a cognitive frame as a set of activated cognitive schemas. To avoid confusion, we explain this idea using our terminology from Section 3.1.

received no attention in research on media framing to date. This is a major gap considering that the founders of cognitive approaches to framing insisted that frames can be *induced* from text, as they are a product of journalists' cognitive frames (Scheufele and Scheufele, 2010), so given collections of articles from different view points, one could model the variations in activated schema using script induction.

Psychological approaches It might seem that the approaches that study the influence of framing on our emotions and decisions are incompatible with computational methods, but there are works that integrate text analytics with the analysis of framing effects. A typical approach records readers' self-reported reactions to tweets or news items of a given framing (Reardon et al., 2022; van den Berg et al., 2019, 2020; Ding and Pan, 2016), while others approximate reactions through such external data as retweets, election vote share, or mobility data (Aslett et al., 2020; Mendelsohn et al., 2021; Walter and Ophir, 2020; Ophir et al., 2021). These studies demonstrate the possibility – and a need – for more efforts to integrate framing devices with framing effects.[3]

Political approaches Only 5% of surveyed studies adopt a political studies perspective to examine frame building, or external factors that influence framing. At the simplest level, Eisele et al. (2022) include external factors such as location and GDP into regression analysis of framing; Li et al. (2020) find correlations of framing with gender. Others consider framing to be the dependent variable (Scheufele and Scheufele, 2010), and use political opinion as a predictor Mendelsohn et al. (2021); Ziems and Yang (2021), or predict media framing of election candidate campaigns using factors at the candidate, state, and race levels Walter and Ophir (2020). Gilardi et al. (2020) examined how prior adoption of a policy frame in one state predicts the frames used in another state, i.e. the policy diffusion process.

We refer to the approaches outlined above as *theoretically grounded*, since they either use theoretically inspired features to predict framing, or examine the effect of framing on other factors in a theoretically sound way. Across all four approaches (linguistic, cognitive, psychological and political approaches), theoretically grounded studies account for 30% of works included in our survey. The bulk of the papers in the review, however, are *theoretically ungrounded*, i.e. their methods cannot be linked to any theories. Among them, some at least contrast frames used by different agents (such as Republicans vs Democrats), or examine changes in framing along some timeline (28% of all surveyed papers, full list in Appendix E.1). We refer to such papers as *framing analysis* studies. On the other hand, a large number of media framing papers (42%, full list in Appendix E.2) do not do even that; we refer to them as *framing agnostic* since they neither incorporate any theories, nor use framing-specific cues or apply framing analysis to real-world situations.

Next, we examine only the papers which were published at NLP and machine learning venues, to see if the ratio of theoretically grounded vs ungrounded papers improves over time, i.e. if the NLP community tries to incorporate concepts and methods from other disciplines. Figure 2 does reveal a trend of increasing prevalence of theoretically grounded studies (green bars). However, around 70% of total number of studies published in NLP/ML venues are still theoretically ungrounded (doing only framing analysis or completely framing agnostic), which is worse than the ratio for publication in more traditional venues for framing analysis such as political journals (see Figure 4 in the Appendix).

In sum, framing does remain a "fractured paradigm" (Entman, 1993), but not so much in terms of its definition, but in terms of a vast disconnect between the currently used computational approaches, methods used in related areas of NLP, and the motivations and theoretical foundations coming from other disciplines. Moreover, there is still no unified or generally accepted system of media framing types, which we try to address in the next section.

4 Types of media framing and their coverage in NLP approaches

Media framing is a complex phenomenon not only because it can be studied from different perspectives, as we discussed in Section 3.2, but also because it is realized in text using a variety of discourse devices of different levels of abstraction. Moreover, to the best of our knowledge, there is no widely adopted typology that explains how dif-

[3] Note, however, that it would be incorrect to analyse emotions and reactions caused by framing using sentiment analysis (as it is done by Nisch (2023)), as it only can detect the sentiment encoded in the frame rather than incited by it.

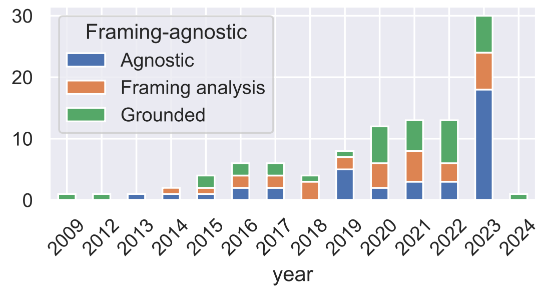

Figure 2: Numbers of theoretically grounded, framing analysis, and agnostic studies published in NLP venues over the years

ferent types of framing operate and interact with each other. Perhaps, for this reason, researchers commonly lump together frames of different types and granularities in their analyses (see, for example, Yu (2022); Card et al. (2022); Mendelsohn et al. (2021); Sheshadri et al. (2021), among others). Here, we propose a typology of the most common high-level types of framing in NLP, grounded in the three levels of framing we discussed in Section 3.1. Then, in Section 4.2 we drill into their subtypes and discuss how well they are detected and analysed using automatic methods.

4.1 Media framing typology

Emphasis framing is perhaps the most well-known type of media framing, in which some aspects of an issue are highlighted by means of explicitly excluding or conceding other aspects. For example, when we talk (or hear) about a hate group holding a rally, we can focus either on their right to express their opinions, or on the potential risk of violence. Accordingly, we can either activate the cognitive frame of *freedom of speech*, or the cognitive frame of *public safety*[4], which would imply a completely different problem definition, causal interpretation, moral evaluation, and "treatment" recommendation (Entman, 1993). Though emphasis framing is grounded in particular aspects of an issue, it is different from bringing up different subtopics of a particular topic, for example, talking about Japanese vs Italian food: as we discussed in Section 3.2, framing is possible only when there is ambivalence, or competition between such aspects (cognitive frames) (Sniderman and Theriault, 2004). It is the competition that makes the selected frame seem more important, emotionally charged, or morally superior than the excluded ones, and allows to emphasise it.

While in emphasis framing the competing cognitive frames are not necessarily mutually exclusive (free speech by itself does not presuppose the absence of public safety), in **equivalency framing** they are. In this type of framing, we are "casting the same information in either a positive or negative light" (Druckman, 2004), e.g. activating a *gain* or *loss* cognitive frame with the corresponding sentiments and associations (Kahneman and Tversky, 1984). For example, a media source can talk about "90% employment" vs "10% unemployment".[5] The respective semantic frames are different ("employment" vs "unemployment"), and thus have different (positively or negatively charged) cognitive frames assigned to them.

Framing by word choice and labelling also activates some associations and sentiments, but they are applied to the same event, object, or entity (Hamborg et al., 2019). For example, the choice of the term "undocumented workers" vs. "illegal aliens" to describe immigrants can elicit different levels of prejudice toward that group (Pearson, 2010). Unlike for equivalency framing, there is a single semantic frame ("immigrants") but we activate different cognitive frames depending on how we refer to it. This can also be done indirectly through labelling the semantic frame rather than choosing a less neutral word to denote it, when we use a modifier or predicate charged with particular associations. For example, we can use a neutral word "immigrant", but imbue it with a negative cognitive frame of "disaster, calamity" if we say that "immigrants flooded the neighbouring city". This particular type of framing by labelling, which focuses on predicate, has been named connotation framing in NLP community, following the seminal work by Rashkin et al. (2016) that organized multiple dimensions of *implied* meaning (sentiment towards entities, values, effects on reader interpretation) in a unified structure. It is important to note, though, that connotation, or underlying level of meaning implied by a particular word beyond its explicit or literal definition (Sonesson, 1998), is not restricted to the labelling of the predicate: it can be expressed through a different word choice for a semantic frame, or a paraphrase using a complementary semantic frame, as we showed above.

Finally, in **narrative framing** we are abstracting away from specific semantic and cognitive frames

[4] Example from Sniderman and Theriault (2004).

[5] The examples are from Chong and Druckman (2007).

used in text, which allows us to derive framing from the most schematic and abstract devices used to shape the discourse (Jones and McBeth, 2010; Fremann et al., 2023). This can be syntactical, rhetorical structures as well as script structures (the expected sequences of events) and thematic structures (the relationships between concepts; (Hallahan, 1999; Pan and Kosicki, 1993)). The Narrative Policy Framework (Jones and McBeth, 2010) operationalized these structures in the context of political communications. It posits that the narrative story consists of four elements: setting, characters, plot, and a moral, and the narrative characters occupy three general categories: Heroes (fixers of a problem), Villains (causing the problem), and Victims (harmed by the problem). Accordingly, the framing of a message can depend on what character role is assigned to a particular entity. Consider the following examples:

[A] Climate activists inspire citizens to take action.

[B] Climate activists frighten citizens into taking action.

Semantically, both sentences are equivalent, and both mean that the actions of climate activists cause citizens to take action. The different cognitive frames (and thus connotations) of the verbs used in A and B, however, lead to assignment of different narrative roles to “climate activists”: in A, they are framed as heroes, while in B they are villains oppressing citizens. This is, of course, also an example of framing by labelling (connotation framing), but here we are more interested in the most prototypical roles that such framing allows to assign to otherwise neutral entities. Thus, when we examine the relation between the semantic roles (agent and patient) determined by the predicate, we speak of connotation framing; when we assign those roles to prototypical slots of Hero, Villain, or Victim, which come with their own strong cognitive frames and thus associations, we focus on the narrative framing of the message.

4.2 Coverage in NLP approaches

In this section we examine which types of framing are covered by the existing methods as covered in our survey. As a single study can focus on several types of framing, the numbers reported below do not sum to the total number of studies in the review.

Emphasis frames are indeed the most often studied type of framing (106, or 72% of included papers; full list in Appendix E.3). 48 studies examined *generic* frames, i.e. cognitive frames that can be applied across a variety of issues, such as “Economic consequences” or “Security”. Most of the work here (31 studies) relies on the Policy Frames Codebook Boydstun et al. (2014), the Media Frames Corpus Card et al. (2015) based on it, or its derivatives such as the datasets proposed by Piskorski et al. (2023a), Ajjour et al. (2019) and Mendelsohn et al. (2021), with 15 generic frames. Some studies use even more high-level classifications such as 5 frames proposed by Semetko and Valkenburg (2000) (del Barrio and Gática-Pérez, 2023; Burscher et al., 2014; Frermann et al., 2023; Reardon et al., 2022) or more targeted sets of frames such as “Loyalty” or “Harm” coming from the Moral Foundations Theory.

On the other hand, issue-specific framing studies (54 in our survey) aim to detect ad hoc frames, which are not linked to theoretical frameworks or codebooks. This issue has been noticed in qualitative media framing studies, and the tendency to create unique frames with no connection to broader theories was previously critisized in sociology (Hertog and McLeod, 2001; Borah, 2011). Despite that issue-specific framing constitute for over a third of studies in our corpus. Moreover, the majority of theory-agnostic studies (Figure 2, blue) are issue-specific ones, which raises a question of their validity and usefulness.

Overall, we agree with Ali and Hassan (2022) who noted that most NLP work on emphasis framing treats frames as (sub)topics, ignoring their special features. Almost universally, emphasis framing studies use topics (through topic modelling or issue classification) as a proxy for frames: some openly claim that frames can be understood as topics (for example, (DiMaggio et al., 2013; Nguyen et al., 2015)), some admit that topics are only an approximation (Sarmiento et al., 2022), while the majority ignores this question whatsoever. Few studies attempt to reevaluate detected topics in terms of their “frame-ness” (Aslett et al., 2020; Nicholls and Culpepper, 2020), both studies coming from political sciences, while others attempt avoid inducing topic-like information e.g., by controlling relevant aspects in the data, or removing topic-like information from induced clusters post-hoc Ophir et al. (2021); Walter and Ophir (2019); Ajjour et al. (2019). While such attempts are a step in the right direction, they still miss the essential aspect of framing – its ambivalence – as we discuss in Section 5.

Equivalence frames, or "loss vs gain" frames, are the rarest: only 4 studies in our review examined them. All of them, however, incorporate linguistic features in addition to lexicons associated with loss and gain: Dalton et al. (2020) use semantic role labelling, Luo and Huang (2022) examine the associated information structures (rheme and theme), Chen et al. (2022a) study metaphors used in equivalence framing, while Postma et al. (2020) add referent annotations to FrameNet which allows to compare equivalence frames referring to the same entity.

Word choice and labelling studies (26 in our review, full list in Appendix E.4) explore connotations and associations of entities, their modifiers and relations. Some notable directions here are detection of metaphorical framing, including dehumanizing metaphors (Mendelsohn et al., 2020; Giorgi et al., 2023; Card et al., 2022)); studies that examine modifiers employed in framing using pairs of antonyms (Kwak et al., 2020b; Jing and Ahn, 2021) or adjectives belonging to different dimensions of interest (Luo et al., 2023; Sheshadri et al., 2021; Dreier et al., 2022); and detection of connotation frames of power and agency (Sap et al., 2017; Mendelsohn et al., 2020; Khanehzar et al., 2023). A large part of research here, however, is still ad hoc and does not follow any frameworks: labeling is derived from the context using such approaches such as collocations or similarity (Sheshadri et al., 2021; Hamborg et al., 2019; Lind and Salo, 2002), among others).

Lastly, **narrative frames** (25 studies in our review) have been explored from two different perspectives. Some studies looked at specific narrative types which are commonly used to structure the story around elections, namely game vs policy frames[6] (De Vreese et al., 2003), or to assign the responsibility for a societal issue, i.e. episodic (individual) vs thematic (systemic) frames (Iyengar, 1994). Each of these narrative schemas comes with a clear-cut set of characters and rhetorical devices that differentiates it from the competing frame: for example, unlike the policy frame, the game frame focuses on winners and losers and involves the language of sports and war; the episodic frame marks the individual as a Villain who is responsible for the society's problems, while in thematic framing the role of Villain is assigned to government and society, while the individual is a Victim. Detecting and analysing such narrative types is important because some of them have been linked to very marked framing effects; for example, episodic frames tend to undermine the trust of the audience in the news (Boukes, 2022). Among the studies included in our review, Walter and Ophir (2020) report similar negative effects of strategic (game) framing on the election success. On the other hand, Ziems and Yang (2021) demonstrate that high-profile shootings lead to increase in systemic framing, i.e. it is perceived as a society's issue rather than individual's fault. However, the other studies addressing these narrative schemas only attempt to detect them (Chebrolu et al., 2023; Avetisyan and Broneske, 2021; Mendelsohn et al., 2021; Pan et al., 2023a) and do not perform any frame setting or frame effects analysis.

Other studies looked at narrative framing in terms of devices that are used for "storytelling". These can be rhetorical devices such as presupposition cues (Yu, 2022), discourse connectives (Yu, 2023), and hedging (Choi et al., 2012); syntactical structures, such as the ones that encode different level of agency or other implied meanings (Greene and Resnik, 2009; Minnema et al., 2022; Baumer et al., 2015); or more high-level narrative structures based on links between entities and their relations (Reiter-Haas, 2023; Reiter-Haas et al., 2024; Ash et al., 2021). Another prominent direction here is narrative character detection. Some studies only detect important entities (characters) (Card et al., 2016; Stammbach et al., 2022), while others also examine which role (Villain, Hero, or Victim) the character is assigned in the narrative (Roy and Goldwasser, 2023; Klenner, 2017; Zhao et al., 2023; Gómez-Zará et al., 2018; Frermann et al., 2023). Overall, this group of studies is the most theoretically-grounded in terms of incorporating linguistic, discourse and narrative features rather than relying on token-level classification and topic modelling. However, it is disconnected from the line of research described above, i.e. the detected framing devices are not linked back to the prototypical narratives (episodic vs thematic, game vs policy framing etc) they support.

Lastly, as we show in Figure 1, the framing types are interconnected, i.e. the same text can have a specific narrative type, contain a particular empha-

[6]We use the term "game frames" as an umbrella term that also includes strategy and horse race frames, which are slightly different variations (Aalberg et al., 2012). Policy frames are often called issue frames; we use the term "policy frames" to avoid confusion with issue-specific frames which we discussed in relation to emphasis framing.

sis or equivalence frame, and employ labelling and word choice framing to support it. Though there are 11 studies which include several types of framing (for example, Mendelsohn et al. (2021), very few, most notably (Frermann et al., 2023; Khanehzar et al., 2021), examine their interaction.

5 Discussion and future directions

To conclude, we highlight two overarching issues which we believe currently block the maturing of the field. First, the landscape is still fractured and disconnected: only a few studies examine the interaction between types of framing (Section 4.2), connect their experiments with a broader context such as political and psychological studies of frame building and framing effects, or explore (or at least integrate) underlying features of semantic and cognitive framing, as well as the existing resources that could support that such as FrameNet or narrative schema (Chambers and Jurafsky, 2010) (Section 3.3). Thus, we still fail to incorporate theoretical frameworks, related linguistics and NLP resources. The bigger issue, however, is that most current research seems to be oblivious of what a "frame" is exactly, despite almost universally quoting definitions of framing in their work. We hope that our paper will improve this issue.

Much has been said (above and in previous works such as Ali and Hassan (2022)) about the problems with treating frames as general or specific topics, but what actually turns a topic-only message into a framed one? Framing is often linked to the presence of sentiment, moral evaluation, or specific devices such as rhetorical structures or metaphors. These are, however, only a part of it, and do not help to differentiate a frame from, say, an emotionally charged stance.We showed that what makes a media frame is its ambivalence, i.e. the presence of alternative cognitive frames that can be activated in someone else's mind regarding the same issue or event. Consider the following example:

> Luis Garavito ruthlessly killed over 190 people.

Most current approaches would predict a frame: the sentence contains a clear indication of Villain and Victim (narrative framing), a power-agency verb "kill" (connotation framing), which also appears in the Moral Foundations Dictionary (Frimer et al., 2019) so the sentence can be classified as "Harm" generic frame, and negative sentiment ("ruthlessly"). The sentence, however, states a historical fact with our emotional interpretation of it. Garavito is a convicted serial killer, so we do not frame him as a villain: he is a villain, and his name itself brings up the "Killer" association. Now, consider another example:

> Donald Trump unnecessarily killed thousands of people because of his COVID-19 policies.

This sentence also presents all the features we listed above, and it is a frame. The difference is that the entity "Trump" does not have the "Killer" meaning in its cognitive frame: we add it temporarily, inheriting it from the "kill" cognitive frame, and we do it by choosing from a constellation of other possible cognitive frames (Scheufele and Scheufele, 2010). This "constellation" is created because of ambivalence of responsibility: nothing in the "Trump" frame marks him as responsible for the deaths, and we might as well frame him as "Hero" or "Victim". In Garavito's case (as well as in more metaphorical sentences such as "Hurricane Maria killed over 3000 people") our common sense prohibits it, so framing is impossible.

As the example shows, this requirement for ambiguity of interpretation applies not only to emphasis framing but to all types (except for equivalency framing, which already encodes ambivalence, as the presence of a "gain" cognitive frame presupposes the existence of a "loss" one, as we explain above in Section 4.1). Thus, we believe that it would be difficult to differentiate frames from topics, stances, and arguments and thus do meaningful framing analysis unless we integrate the detection of such ambivalence into our methods. Again, this can be done only if we employ semantic and cognitive framing resources and connect different layers of framing: for instance, in the example above we would need a way to detect that the verb "kill" activates the cognitive frame of "villain", and check if the cognitive frame of "Trump" contains that meaning already.

Despite progress in both understanding of and computational approaches to framing since the early days when topic models dominated framing research, many conceptual and methodological challenges remain in unifying (Entman, 1993)'s "fractured paradigm". We hope the current work helps to establish solid theoretical and typology foundations for framing research and shines some light on its current gaps and future opportunities.

6 Limitations

The paper retrieval, inclusion and exclusion, as well as annotation were performed by a single reviewer (the first author of the paper), which means that despite our best efforts to ensure thorough coverage of the published papers as explained in Appendix A, some of the related works could have been undiscovered. Moreover, human errors were possible when assigning papers to categories or referring to them in the survey. However, we strove to avoid such errors by collecting studies from multiple sources and annotating the paper categories twice. Thus, despite the fact that minor inconsistencies or omissions might remain, we believe that this survey is still the most thorough review of computational framing methods up to date and it objectively captures the main trends in research and reveals existing issues.

7 Ethics statement

Our work focuses on summarising and analysing main approaches of computational framing research, which we believe is helpful for researchers both in media framing and in related fields such as media bias or misinformation detection. We strove to make this survey as objective as possible and to avoid over- or underestimating some trends. The examples used in this study are artificial, i.e. they do not reflect the opinion of the authors, media sources, or any other people and are only provided to highlight difference in potential framing. We do not anticipate any ethical concerns arising from the research presented in this paper.

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A The process of searching and selecting the studies for the review

To ensure that our review thoroughly covers all published literature on computational approaches to framing, we adopted practices used systematic reviews such as comprehensive search, pre-defined eligibility criteria, double pass of eligibility checking (using only titles and abstracts at the first past and referring to the full text of studies at the second), and annotation of exclusion reasons at the second pass.

First, to ensure inclusion of papers from non-ACL venues such as journals on sociology and political science, we conducted a series of 24 searches in Semantic Scholar [7]. Each search query contained the word "frame", "framing", or a related term which is sometimes used as a near synonym of framing in political and social sciences, such as "discourse", "packaging", or "narrative theme" (the complete list of search queries is in Appendix B). For each of the queries, we used the top 50 returned results (1200 papers overall). We scanned the titles and abstracts of these papers, using the inclusion and exclusion criteria we defined beforehand to judge if the paper is relevant (refer to for the full list of exclusion and inclusion criteria). This resulted in selection of 75 papers for analysis. Next, we scanned the forward and backward citations for previously published surveys related to the automatic detection of media framing in text, including Ali and Hassan (2022), Hamborg et al. (2019), and Vallejo et al. (2023), which resulted in inclusion of 31 additional studies. Because it was unfeasible to track forward and backward citations for all 106 papers collected so far, we first sorted them by the citation count and tracked the citations for the first 30 most cited papers, and then – to ensure we include not only what is prevalent but what is also emerging – we sorted the list by the published year in decreasing order and repeated the process for 30 most recent papers. This allowed us to add 72 papers into the preliminary list. Finally, to make sure we did not miss any papers published at *ACL, we repeated the search in ACL Anthology[8] with the same list of queries as for the Semantic Scholar. Again, we scanned the abstracts and titles of the first 50 results for each query, which led to inclusion of 32 additional studies.

Overall, we retrieved 210 results, which we loaded into a systematic review tool (Rayyan[9]) for further analysis. We automatically detected and removed 4 duplicates, and then the first author of the paper read the full texts of papers and coded them in terms of reasons for inclusion or exclusion, essentially removing studies which upon more thorough review were either not focusing on media bias, not quantitative/computational, or were near duplicates of already included papers (i.e. a proposal and published results, or a method description and a system demonstration based on it). While doing

[7] https://www.semanticscholar.org/
[8] https://aclanthology.org/
[9] https://rayyan.ai/

that, we also tracked the citations mentioned in each of the included papers, which resulted in addition of only 6 papers, demonstrating good coverage of our original search.

B List of search queries

We used the following queries when retrieving results from Semantic Scholar:

- framing detection *NLP
- frame detection *NLP
- frame analysis *NLP
- discovering frames *NLP
- frame identification *NLP
- identifying frames *NLP
- textual frame analysis *NLP
- discourse analysis *NLP
- computational frame analysis *NLP
- narrative analysis *NLP
- packaging *NLP
- narrative themes *NLP

Note that each query has an optional term "NLP"; we ran each query with and without this term to both find the studies from non-NLP venues which often did not mention this term, and to ensure inclusion of studies that specifically mentioned NLP. In a similar way, we use both more broad and more specific terms ("frame analysis" vs "computational frame analusis") to improve coverage.

C Inclusion and exclusion criteria

C.1 Inclusion criteria

Only quantitative studies: the title or abstract should mention "computational", "automatic", "statistical", "machine learning", "model", "supervised", "unsupervised", "NLP", or the paper should have been published at a machine learning, computation linguistics, or NLP venue. Computer-assisted or computer-aided (such as using spreadsheets to analyse manually coded data) are to be excluded.

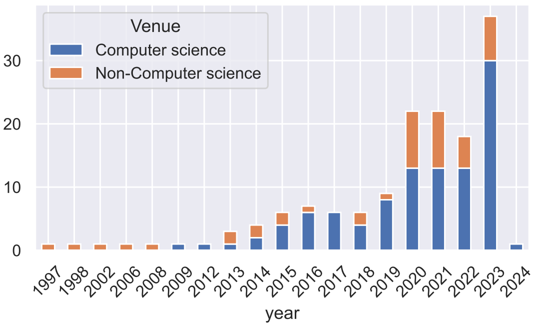

Figure 3: Breakdown by the general venue type across the years

C.2 Exclusion criteria

Other meanings of framing: exclude papers where "frame" has an irrelevant meaning such as in "video frame analysis" or "case frame".

Papers focusing on concepts related to framing: exclude papers focusing on media bias, stance, political orientation, polarization, propaganda and misinformation.

Surveys: exclude surveys and reviews.

Mitigation of framing: exclude papers targeting mitigation of framing effects and re-framing.

D Studies distribution by venue type

Figure 3 below shows the number of studies published in different fields across years. Starting from 2015 the number of computer science publications has overtaken the number of studies from the fields where media framing analysis originated from (such as media, sociology and political studies). Conversely, the amount of quantitative studies in these traditional fields remained low until 2020, when COVID 19 together with political and economic unrest instigated the interest in larger scale studies.

Figure 4 examines how grounded the publications from different venues are in terms of their use of theoretical principles, linguistically motivated features, or practical applications.

E Lists of studies not directly referred to in the text of the review

In this section we provide the references to the studies that could not be mentioned in the main text of the reviews due to the large number of papers in a corresponding category

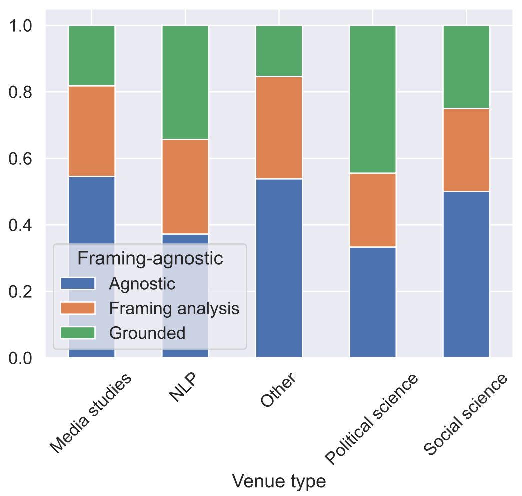

Figure 4: Distribution of theoretically grounded, framing analysis, and agnostic studies across disciplines.

E.1 Papers with framing analysis only (no theoretical grounding

Miller (1997); Sagi et al. (2013); Diakopoulos et al. (2014); Tsur et al. (2015); Shim et al. (2015); Johnson and Goldwasser (2016); Fulgoni et al. (2016); Johnson et al. (2017a,b); Johnson and Goldwasser (2018); Field et al. (2018); Morstatter et al. (2018); Demszky et al. (2019); Hamborg et al. (2019); Shahid et al. (2020); Kwak et al. (2020b); Mokhberian et al. (2020); Akyürek et al. (2020); Roy and Goldwasser (2020); Heinisch and Cimiano (2021); Kang and Yang (2021); Nakov et al. (2021); Sánchez-Junquera et al. (2021); Roy et al. (2021); Hofmann et al. (2021); Supran and Oreskes (2021); Reiter-Haas et al. (2021); Ylä-Anttila et al. (2021); Park et al. (2022); Kim and Johnson (2022); Card et al. (2022); Zhao and Wang (2022); Sarmiento et al. (2022); Dreier et al. (2022); Dore (2023); Zhao et al. (2023); Zou et al. (2023); Chebrolu et al. (2023); Luo et al. (2023); Rao et al. (2023); Pan et al. (2023a)

E.2 Papers with no framing analysis and theoretical grounding (agnostic)

Jasperson et al. (1998); Lind and Salo (2002); Koenig (2006); Sanfilippo et al. (2008); DiMaggio et al. (2013); Boydstun et al. (2013); Fornaciari (2014); Burscher et al. (2014); Boydstun et al. (2014); Nguyen et al. (2015); Touri and Koteyko (2015); Cheeks et al. (2016); Hsu et al. (2016); Burscher et al. (2016); Naderi and Hirst (2017); Johnson et al. (2017c); Bai et al. (2018); Liu et al. (2019); Hartmann et al. (2019); Ajjour et al. (2019); Khanehzar et al. (2019); Walter and Ophir (2019); Zhang et al. (2019); Kwak et al. (2020a); Nicholls and Culpepper (2020); Yang and Kang (2020); Niven and Kao (2020); Sanderink (2020); Chen et al. (2022b); Tourni et al. (2021); Sheshadri et al. (2021); Avetisyan and Broneske (2021); Bhatia et al. (2021); Weinzierl et al. (2021); Mou et al. (2022); Lai et al. (2022); Yu and Fliethmann (2022); Heinisch et al. (2023); Mahmoud and Nakov (2023); Eisele et al. (2023); Guo et al. (2022); Kermani et al. (2023); Syed et al. (2023); Nisch (2023); Stede et al. (2023); del Barrio and Gática-Pérez (2023); Kermani (2023); Baumann and Deisenhofer (2023); Koreeda et al. (2023); Liao et al. (2023); Reiter-Haas et al. (2023a); Khanch et al. (2023); Piskorski et al. (2023b); Hasanain et al. (2023); Sadeghi et al. (2023); Jiang (2023); Afzal and Nakov (2023); Pauli et al. (2023); Pan et al. (2023b); Cuadrado et al. (2023)

E.3 Emphasis framing studies

E.3.1 Generic emphasis framing

(Boydstun et al., 2013; Diakopoulos et al., 2014; Burscher et al., 2014; Boydstun et al., 2014; Johnson and Goldwasser, 2016; Fulgoni et al., 2016; Cheeks et al., 2016; Naderi and Hirst, 2017; Johnson et al., 2017b,c; Johnson and Goldwasser, 2018; Field et al., 2018; Ajjour et al., 2019; Khanehzar et al., 2019; Zhang et al., 2019; Kwak et al., 2020a; Shahid et al., 2020; Mokhberian et al., 2020; Huguet Cabot et al., 2020; Heinisch and Cimiano, 2021; Nakov et al., 2021; Khanehzar et al., 2021; Roy et al., 2021; Mendelsohn et al., 2021; Hofmann et al., 2021; Reiter-Haas et al., 2021; Mou et al., 2022; Reardon et al., 2022; Dore, 2023; Heinisch et al., 2023; Eisele et al., 2023; Frermann et al., 2023; Syed et al., 2023; del Barrio and Gática-Pérez, 2023; Baumann and Deisenhofer, 2023; Koreeda et al., 2023; Liao et al., 2023; Reiter-Haas et al., 2023a; Khanch et al., 2023; Piskorski et al., 2023b; Rao et al., 2023; Hasanain et al., 2023; Sadeghi et al., 2023; Jiang, 2023; Afzal and Nakov, 2023; Pauli et al., 2023; Pan et al., 2023b,a; Cuadrado et al., 2023)

E.3.2 Issue-specific emphasis framing

Miller (1997); Jasperson et al. (1998); Koenig (2006); Sanfilippo et al. (2008); DiMaggio et al. (2013); Fornaciari (2014); Tsur et al. (2015); Shim et al. (2015); Nguyen et al. (2015); Touri and Koteyko (2015); Hsu et al. (2016); Burscher et al. (2016); Ding and Pan (2016); Johnson et al.

(2017a); Sturdza (2018); Morstatter et al. (2018); Bai et al. (2018); Demszky et al. (2019); Liu et al. (2019); Hartmann et al. (2019); Walter and Ophir (2019); Nicholls and Culpepper (2020); Yang and Kang (2020); Niven and Kao (2020); Akyürek et al. (2020); Gilardi et al. (2020); Shurafa et al. (2020); Sanderink (2020); Roy and Goldwasser (2020); Aslett et al. (2020); Kang and Yang (2021); Chen et al. (2022b); Tourni et al. (2021); Sánchez-Junquera et al. (2021); Bhatia et al. (2021); Supran and Oreskes (2021); Weinzierl et al. (2021); Ophir et al. (2021); Ylä-Anttila et al. (2021); Lai et al. (2022); Kim and Johnson (2022); Card et al. (2022); Zhao and Wang (2022); Yu and Fliethmann (2022); Sarmiento et al. (2022); Yang and Men (2022); Mahmoud and Nakov (2023); Kermani et al. (2023); Zou et al. (2023); Reiter-Haas et al. (2023b); Nisch (2023); Stede et al. (2023); Kermani (2023)

E.4 Studies of framing by word choice and labelling

Lind and Salo (2002); Sagi et al. (2013); Rashkin et al. (2015); Sap et al. (2017); van den Berg et al. (2019); Hamborg et al. (2019); Mendelsohn et al. (2020); Acken and Demszky (2020); Postma et al. (2020); van den Berg et al. (2020); Kwak et al. (2020b); Jing and Ahn (2021); Sheshadri et al. (2021); Minnema et al. (2021); Eisele et al. (2022); Sullivan (2022); Park et al. (2022); Card et al. (2022); Chen et al. (2022a); Yang and Men (2022); Dreier et al. (2022); Giorgi et al. (2023); Guo et al. (2022); Luo et al. (2023); Khanehzar et al. (2023)