

Lost in Translation

Multilingual Misinformation & Its Evolution

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ABSTRACT

Misinformation and disinformation are growing threats in the digital age, spreading rapidly across languages and borders. This paper investigates the prevalence and dynamics of multilingual misinformation through an analysis of over 250,000 unique fact-checks spanning 95 languages. First, we find that while the majority of misinformation claims are only fact-checked once, 11.7%, corresponding to more than 21,000 claims, are checked multiple times. Using fact-checks as a proxy for the spread of misinformation, we find 33% of repeated claims cross linguistic boundaries, suggesting that some misinformation permeates language barriers. However, spreading patterns exhibit strong homophily, with misinformation more likely to spread within the same language.

To study the evolution of claims over time and mutations across languages, we represent fact-checks with multilingual sentence embeddings and cluster semantically similar claims. We analyze the connected components and shortest paths connecting different versions of a claim finding that claims gradually drift over time and undergo greater alteration when traversing languages.

Overall, this novel investigation of multilingual misinformation provides key insights. It quantifies redundant fact-checking efforts, establishes that some claims diffuse across languages, measures linguistic homophily, and models the temporal and cross-lingual evolution of claims. The findings advocate for expanded information sharing between fact-checkers globally while underscoring the importance of localized verification.

KEYWORDS misinformation, fact-checking, multilingual NLP, information diffusion, social media

1 INTRODUCTION

Misinformation is a global challenge responded to in myriad local ways. The International Fact-Checking Network (IFCN) currently has 112 verified active member organizations across 75 countries¹. There have been experiments with collaborative fact-checking across countries such as #CoronavirusFacts led by the IFCN and #UkraineFacts led by Spanish fact-checker Malditas as well as collaborations within countries (e.g., #FactsFirstPH,² EKTA³, and Confirma 2022 in Brazil⁴). To date, however, there is no centralized repository of global fact-checks as there is for child abuse imagery (the Internet Watch Foundation) or extremist content (the Global Internet Forum to Counter Terrorism).

On the one hand, greater collaboration between fact-checking organizations could help meet the increasing demand for fact-checks. Increasing use of social media—and soon generative AI—has resulted in the volume of misinformation far exceeding the capacity of human fact-checkers [24, 32]. Furthermore, fact-checking capacity is unequally distributed with more fact-checkers working in English than in other languages. If a large proportion of misinformation is shared across languages, centralization of fact-checks and cross-language claim matching [e.g., 22] could help identify misinformation even in less-resourced languages.

On the other hand, it's not clear how often the same misinformation is spread across languages or countries.

¹<https://ifcncodeofprinciples.poynter.org/signatories>

²<https://factsfirst.ph/>

³<https://ekta-facts.com/>

⁴<https://www.poynter.org/fact-checking/2023/dubawa-cek-fakta-brazil-globalfact-10-awards/>

For example, there are large differences in general content across language editions of Wikipedia [17, 26] and only a small percentage of users author content in multiple languages online [17, 18].

In this article, we investigate the extent to which misinformation claims are fact-checked by multiple fact-checking organizations (RQ1) as well as how often similar misinformation is fact-checked across different languages (RQ2). While answering these questions, we also examine the differences between content fact-checked by one vs. multiple organizations and in one vs. multiple languages. Finally, we analyze how much misinformation claims change over time and explore what is most likely to be fact-checked more than once or across languages (RQ3).

This paper presents an investigation into the prevalence and dynamics of multilingual misinformation through analysis of over 250,000 fact-checks in 95 languages. We find that 11.7% of claims, corresponding to more than 21,000 claims in our dataset, are checked multiple times, highlighting opportunities for greater collaboration between fact-checkers. A third of repeatedly checked claims are found in multiple languages, establishing some diffusion across languages, but there is strong language homophily. Our analysis reveals a gradual drift in claims over time and greater changes between languages.

2 RELATED WORK

2.1 Fact-checking efforts

Misinformation predates the World Wide Web [5], and probably existed throughout human history [8]. Nonetheless, misinformation and disinformation appear in scholarship about the World Wide Web in 1995, only two years after the release of the first graphical web browser: Hernon [20] defines disinformation as a ‘deliberate attempt to deceive or mislead’ and misinformation as ‘an honest mistake’ (p. 134). As intention is difficult to reliably infer, we follow recent scholars in using misinformation as an umbrella term for any false or misleading content regardless of the user’s intention [e.g., 21, 33]

With the spread of user-generated content and social media platforms, there has been a marked increase in scholarship about misinformation online [5]. Over the same period there has been an increase in fact-checking organizations: teams of journalists aiming to fact-check or debunk misinformation [14, 37, e.g.,]. Meta’s third-party fact-checking program pays organizations to write fact-checks about content on its Facebook and Insta-

gram platforms [4] or to host ‘tiplines’ on WhatsApp where users can search fact-checks [21, 23]. Google also pays fact-checkers to provide it copies of fact-checks in ClaimReview markup for use in its news and search tools [2]. Much of the data Google collects is freely available and is one of our data sources for this study.

Many, if not most, fact-checking organizations are signatories to the IFCN Code of Principles⁵. Indeed, being a signatory to the IFCN code of principles is required to participate in Meta’s third-party fact-checking program.

Fact-checking resources are unevenly distributed across the globe. North America, Europe, and Australia have more fact-checking organizations than other regions of the world, although the difference is decreasing [38]. English remains the most-resourced language: 47.51% of fact-checking organizations in the IFCN use English.⁶ This stands in stark contrast to the global distribution of people and Internet users in the world [13].

2.2 (Mis)information across languages

Most research on misinformation diffusion has not explicitly considered cross-language spread but more general research has found geography, language, and culture, as general impediments to the spread of information [e.g., 6, 15, 16, 19, 41]. According to the culture proximity theory, people tend to prefer content that is most proximate to their location, language and culture [40].

Language stands as a salient explanation for the cultural proximity in information consumption, and scholars have identified several major online content consumption clusters [25]. Rather than people consuming content from the entirety of the *World Wide Web*, audiences tend to consume information in their preferred languages [e.g., 25, 9, 39]. However, the development of social media technology and the convergence trend of global events (e.g., pandemic and climate change) may render language barriers, facilitating a higher percentage of cross-language diffusion than before [43].

Nonetheless, there may now be a higher percentage of common misinformation across languages as shared social media platforms and translation technology as well as bilingual users make it possible to consume more diverse content [43, 18]. Global events (e.g., COVID-19,

⁵<https://ifcncodeofprinciples.poynter.org/know-more/the-commitments-of-the-code-of-principles>

⁶We counted all 181 verified fact-checking organizations in IFCN, and 86 of them are using English. The second and third most-used languages are Spanish and French with only 11 and 10 organizations respectively.

climate change, and Russia’s war in Ukraine) also attract attention across languages. As noted, COVID-19 and the Russian invasion of Ukraine have formed the basis of new fact-checker collaborations (#CoronaVirusFacts and #UkraineFacts).

We’re unaware of any study examining the spread of misinformation across languages globally, but Lu et al. [28] found misinformation in their study of Chinese and English messages on social media and Li [27] found COVID-19 misinformation in multiple languages.

3 DATA

The dataset used in this study is a combination of data from Google Fact-Check explorer [3] and data directly crawled from the websites of verified signatories of the International Fact-Checking Network (IFCN) code of principles. We structure crawled pages as ClaimReview, a markup for fact-checkers to standardize their work, and the format of the Google data.⁷ The markup consists of multiple data fields. First, each fact-check has an associated author and date. Additionally, it contains the *Claim*—that is the statement of misinformation—that is being fact-checked, a *Review*, and a *Rating*. The Google Fact-Check Explorer data contains 54,150 unique fact-checks. We noticed, however, that many IFCN-certified fact-checking organizations were not included; so, we directly crawled the websites of IFCN-certified fact-checking organizations creating a dataset of 262,439 unique observations. Deduplication and data cleaning steps are outlined in Section 3.1. We combined these two datasets to generate the final dataset. We limit our analysis to the period of time from March 2020 to March 2022 as there is minimal data before period.

3.1 Data Preparation

Not all fact-checkers adhere completely to the ClaimReview format. Fact-checks on websites are particularly problematic as they might not include ClaimReview or leave some fields empty. When the `claimReviewed` field is missing or empty, we consider the `headline` and `description` fields. We employ a heuristic to determine which part of the fact-check contains the claim: If the fact-checking entry contain any string in the `claimReviewed` field, we return this unaltered. Otherwise, we check whether either the length of the `headline` or the `description` fields is within two standard deviations of the average length of a

⁷<https://developers.google.com/search/docs/appearance/structured-data/factcheck>

`claimReviewed` entry. If this is the case, we return either one (with preference for the former). If both are longer we remove the fact-check.

Similarly, not all fact-checks contain the name of the organization posting the claim. To remedy this, we extract the domain name of the final redirect of each URL associated with a fact-check and use this as our primary entity identifier. Another pre-processing step taken to assure that only the claim is contained in the final data-set, we manually inspect tri- to six-grams within each fact-checking domain that appear suspiciously often. We used the LaBSE tokenizer to split each fact-check, and aggregate token counts by the domain of the fact-checker. Examples of tokens, unrelated to the actual claim are “WHATSAPP - CHECK,” “Verificamos,” “Fact-Check:”. After manually reviewing the most repeated substrings, we found 84 that are not part of the claims being fact-checked and remove these. In addition, we remove exact duplicates of fact-checks (retaining the earlier in time), and fact-checks that did not contain a valid claim, according to the aforementioned heuristics employed, after the pre-processing.

Lastly, the initial data contained a significant number of fact-checks that appear to only be editorial mistakes. These fact-checks only differ based on punctuation, or slight editorial fixes, and were posted extremely close in time. To remove these fact-checks we check for duplicates after removing any punctuation and non-alphanumeric characters and ignoring case. Additionally, we remove any fact-checks that have a cosine similarity exceeding 0.95 measured with LaBSE and are posted by the same domain or author.

3.2 Final Dataset

Our final dataset consists of 251,590 unique fact-checks. Each fact-check has an associated claim, verdict (also know as a rating), date, and author. The language of each claim was determined using the Google Translate API: we found a total of 95 unique languages, showcasing the diversity of fact-checking organizations dedicated to improve the information environment worldwide.

Figure 1, shows the IFCN signatories, contained in our dataset and their respective countries of origin. The top pane highlights all countries based on the number of fact-checking organizations, while the bottom pane shows the number of fact-checks by IFCN signatories contained in our dataset. The map demonstrates that fact-checking is a global activity, with numerous organizations active in countries that primarily speak low-

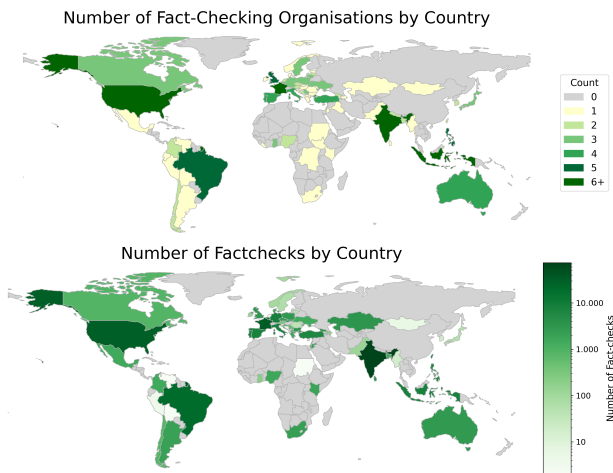


Figure 1: Geographical Distribution of Fact-checking Organizations and Fact-checks

resource languages. The breadth of the linguistic and geographic diversity of fact-checking organizations highlights the need for research into multilingual misinformation, extending beyond a focus on European languages and Western cultural and political contexts.

The dataset spans from 2018 to 2023, and covers a broad array of topics. Figure 2 displays the total number of fact-checks per month in the dataset on the left y-axis in red. We observe that the number of fact-checks per month is relatively consistent between March 2020 and March 2022 at seven thousand fact-checks per month. Before this period, we see around four thousand fact-checks per month and after it around one thousand. This difference stems from the joining of the two datasets which span different time-periods. In blue, we show the percentage of the claims that are “unique.” A thorough discussion of the definition of a unique claim will follow in Section 4. In the periods before and after the observations period (March 2020–March 2022), the percentage of unique fact-checks is significantly distorted due to the lower number of available fact-checks. We therefore restrict ourselves to this time period.

Fact-checks have several notable limitations that constrain their ability to fully capture misinformation dynamics. First, they rely on the subjective judgments of fact-checking organizations in deciding what claims to investigate and assessing their accuracy. There is inherent subjectivity in these choices determined both by varying mission statements of fact-checking organizations, different funding incentives, and that different

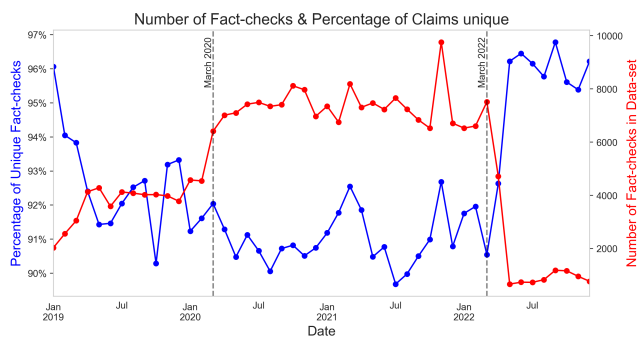


Figure 2: Number of Fact-checks in Dataset & Percentage of unique Claims

types of claims will require different levels of attention and scrutiny [14]. Second, fact-checks tend to focus only on high-profile viral claims that gain widespread traction, meaning they likely overlook more subtle or less visible misinformation spreading. Additionally, the availability of fact-checks varies by region based on where fact-checking initiatives exist. Importantly, fact-checks often lag behind the initial viral spread of misinformation. By the time a claim is investigated, initial spread and damage may have already occurred.

However, despite these limitations, fact-checks remain a useful proxy for studying global misinformation by documenting the details of specific dubious claims. Fact-checks, by their definition, offer insights into the spread, subject matter, and timeline of misinformation. Furthermore, our diverse dataset of 251,590 unique fact-checks in 95 languages underscores the global and multilingual endeavors in fact-checking. This is a testament to the universal scope of the problem of inaccurate information, crossing different geographical, linguistic, and cultural boundaries. Unlike focusing on a single social media site, which may overlook misinformation in countries where that platform is not dominant, the study of fact-checks transcends these boundaries. The number of fact-checks, as depicted in Figure 2 and the word wide distribution of fact-checking organizations shown in Figure 1, further solidifies the case for using fact-checks as a proxy to study the undercurrents of misinformation across various social media platforms.

4 METHODS

To compare misinformation spread across languages, we embedded all fact-checks with Language-agnostic BERT Sentence Embedding (LaBSE) [12]. LaBSE combines Masked Language Modeling (MLM) where

a representation is learned by randomly masking tokens in one language, and letting the model predict the token, and Translation Language Modeling (TLM) where bi- or multilingual sentences are concatenated words are masked in both sentences. The model then predicts the masked words, encouraging it to learn cross-lingual representations. In contrast to other multilingual sentence embedding models, LaBSE supports at least 109 languages, enabling us to include a larger number of fact-checks, even in languages typically considered low-resource. LaBSE is therefore ideal to retrieve similar sentences across languages. Nevertheless, as a robustness check we embedded all covered fact-checks with distiluse-base-multilingual-cased-v2, paraphrase-multilingual-MiniLM-L12-v2, and paraphrase-multilingual-mpnet-base-v2 [35]. The results were qualitatively similar regardless of the embedding model used. We proceed with LaBSE as its 109 languages cover 99.3% of our data.

To cluster the fact-checking claims we utilize the LaBSE embeddings and retrieve other fact-checks with a cosine similarity exceeding a given threshold. To retrieve the approximately nearest neighbors we employed Locality Sensitive Hashing (LSH), specifically Spotify’s ANNOY library [1], to reduce the number of computations. We used 100 hyperplanes to retrieve the nearest neighbors. To gather the approximately nearest neighbors, we started by retrieving 10 nodes, and doubled the number of retrieved claims until the last element of the retrieved neighbors fell below the cosine similarity threshold. We then performed a binary search within the last batch of returned nodes to determine the last element to be included. The resulting data-structure can be modeled as an extremely sparse graph. We then extracted all connected components to yield the final set of clusters. Our methodology to embed fact-checks, retrieving the approximate nearest neighbors with a cosine similarity surpassing a given threshold, and subsequently extracting connected components, has proven particularly potent when grappling with the high-dimensional LaBSE embeddings and the sparse nature of the resulting graph. Contrasting this with other clustering methods, k-Nearest Neighbours (kNN) exhibits difficulties in high-dimensional spaces due to the “curse of dimensionality” [34]. Density-based approaches such as HDBSCAN [30] or DBSCAN [11] offer advantages in terms of identifying clusters of various shapes and densities and have robust noise-handling capabilities. However, they are computationally intensive and struggle to define density in high-dimensional,

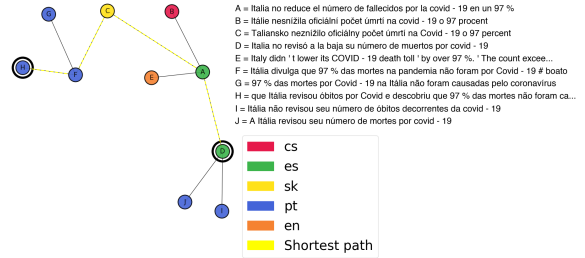


Figure 3: Exemplary Multilingual Cluster with Shortest Path. The two most dissimilar nodes are circled in black, the shortest path between them is highlighted in yellow.

sparse spaces, making them less ideal for sentence embeddings. Centroid-based clustering methods, like k-Means [29], though widely adopted, can be adversely affected by noise and outliers, and assume clusters to be convex-shaped, which may not hold true in our context. By comparison, our proposed strategy balances computational efficiency and robustness to noise. The use of a preset cosine similarity threshold facilitates control over cluster granularity, and the extraction of connected components naturally separates noise and outliers into distinct clusters. This combination of strategies results in an efficient, interpretable, and scalable solution to the problem of clustering multilingual sentence embeddings.

Figure 3 displays an example cluster of ten fact-checks authored in six different languages. The embeddings of the claims are projected on two dimensions with Uniform Manifold Approximation and Projection [31]. The two most dissimilar nodes are circled in black. The shortest path between the two nodes is highlighted in yellow.

4.1 Clustering Evaluation

To evaluate the robustness, accuracy, and consistency of the clustering, we went through four rounds of human validation to test the performance of different clustering thresholds. We randomly sampled 100 clusters each time and asked the expert coders to qualitatively code the most dissimilar pair as indicated by the cosine similarity and evaluated whether they were talking about the same misinformation claim. The coding scheme follows the work of Kazemi et al. [22]. The first three rounds of human evaluation identified the need for better pre-processing to remove strings from claims such as publishers’ names, special characters, and formatted fact-checking claims. We implemented this pre-

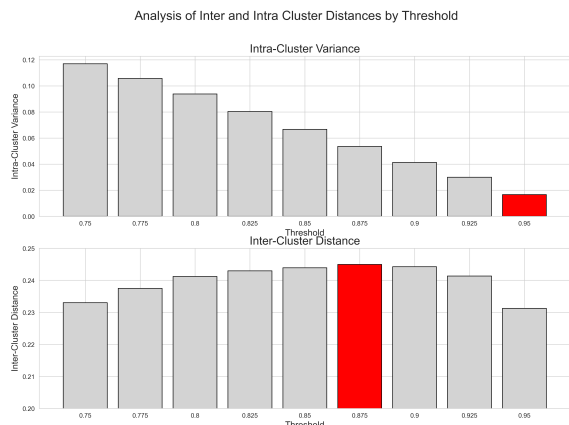


Figure 4: Mean *intra*-cluster cosine variance (top) and mean *inter*-cluster cosine distances (bottom) by threshold. Highlighted bars show the minimised intra-cluster variance and the maximised inter-cluster distance

processing (see Section 3.1) before our final evaluation round.

In addition to the qualitative analysis, we examine three measures of the goodness of fit of the clustering. First, we analyzed the variance of cosine distance within clusters (intra-cluster variance). Better clusters should lead to a reduced variation for higher thresholds. Additionally, we looked at the between-cluster (or inter-cluster) cosine distances. Here we selected the centroid of a cluster and sampled up to 10,000 additional centroids for which we then calculated the average cosine distance. The mean *intra*-cluster variance and *inter*-cluster distance are shown in Figure 4 for different thresholds.

The mean intra-cluster variance consistently falls with higher thresholds (Figure 4 top). This is a positive result because it signifies that our clusters are becoming more cohesive—the elements within each cluster are more alike. This increased cohesiveness is crucial for our clustering methodology as we aim to gather similar fact-checks together to facilitate their analysis. The highlighted bar shows the cosine similarity threshold for which the intra-cluster variance is minimized.

Conversely, the inter-cluster distance is the average distance of two randomly chosen clusters for each threshold. An increasing inter-cluster distance signifies that—as we increase the cosine similarity threshold—the clusters are becoming more distinct and there is better separation *between clusters*. The highlighted bar in the bottom plot of Figure 4 shows inter-cluster dis-

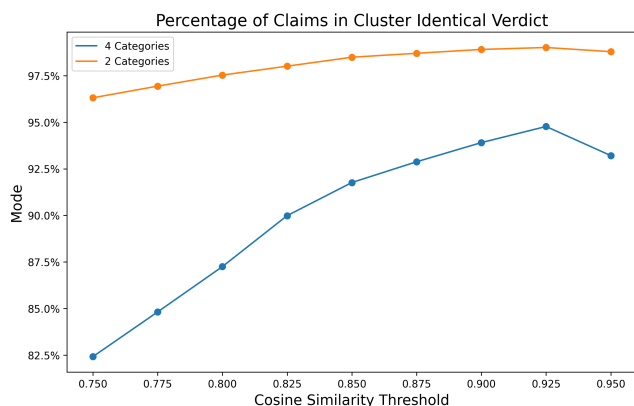


Figure 5: Evaluation of clustering goodness of fit by comparing consistency of the fact-check verdicts/ratings of claims in each cluster. Ratings are mapped into two categories (true and false) or four categories (true, mostly-true, mostly-false, and false).

tance is maximized at 0.875.

While intra-cluster variance is minimized with a cosine similarity threshold of 0.95—the maximum similarity we tested—the inter-cluster distance is maximized with a threshold of 0.875. Increasing the cosine similarity beyond this point leads to clusters that are closely linked, to be split into two components, thereby reducing the inter-cluster distance. We also find larger thresholds yield smaller sized clusters. At a cosine similarity threshold of 0.875, the average non-singleton cluster size is 2.52. This contrasts with average cluster sizes of 6.12 and 2.1 at thresholds of 0.75 and 0.95, respectively.

Lastly, another heuristic measurement available to use is the rating associated with each fact-check (e.g., ‘True,’ ‘False,’ ‘Misleading,’ etc.). As different media organizations employ different rating schemes, we first removed potentially confounding spellings, white-spaces, punctuation, and case from each verdict. We then selected any verdict that appeared at least 50 times in the dataset and mapped these to “false,” “mostly-false,” “mostly-true,” and “true.” For this evaluation of clusters, we ignored the 30% of fact-checks with verdicts not in this mapping.

Figure 5 show two measures of the clustering accuracy. First, top plot displays the weighted average of the percentage of nodes that have the modal (i.e., most common) verdict in each cluster. We can see that for any cosine-similarity higher than 0.825 we find that over 90% of fact-checks in the same cluster have the same as-

sociated rating. This holds both when we map ratings to two labels (true, false) and when we map them to four labels (true, mostly-true, mostly-false, false). This indicates that our clustering methodology effectively groups fact-checks that are not only semantically similar but also share similar ratings of truthfulness. Having fact-checks in the same cluster generally share the same rating is an important signal of the cohesiveness of our clusters. Since most items fact-checked are rated as false or mostly-false, meeting this criteria alone is not proof of a good clustering, but if our clustering did not satisfy this criteria it would suggest the clusters were likely too broad.

We finally settled on a cosine-similarity threshold for edges of 0.875 after analyzing all available measures in conjunction with our qualitative evaluation. This measure is in line with previous research [e.g., 22]. Where possible we perform measures with a range of thresholds, and we find the same general patterns.

With a threshold of 0.875, our qualitative analysis showed 7 of the 100 pairs of most dissimilar nodes we sampled from clusters did not belong to the same cluster. Overall, we have high confidence in the precision of our clustering methods from the qualitative analysis, consistency of ratings, and high intra-cluster similarity. Similarly, the low inter-cluster similarity suggests recall is generally good: nonetheless there could be instances where we fail to identify two claims as similar.

5 RESULTS

5.1 Research Question 1: To what extent are misinformation claims fact-checked by multiple fact-checking organizations?

To answer *RQ1* we extract the connected components of our sparse graph. Any component (or cluster) with two or more nodes contains a claim that has been fact-checked at least twice. The remaining nodes are singletons, and have not been matched with any other fact-check. The proportion of singleton nodes ranges from 67.6% for a cosine similarity threshold of 0.8 to 92.9% for a threshold of 0.9. For our the 0.875 threshold we find that 88.2% of nodes are singletons—or conversely—that 11.7% of fact-checks investigate a claim that has previously been fact-checked. In total, at this threshold we find more than 21,000 claims that have been fact-checked multiple times. This represents a significant proportion of repeated work across fact-checking organizations investigating the same claims.

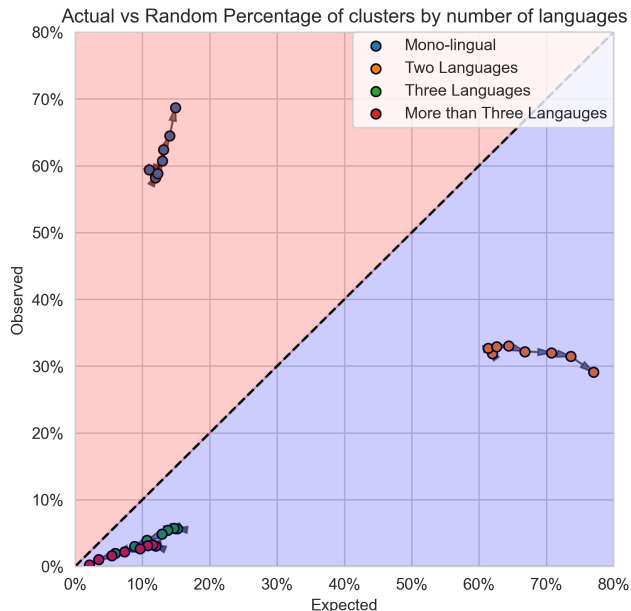


Figure 6: Experimental Evaluation of Language Homophily: Different thresholds are shown for each group, and arrows show the direction with an increasing threshold.

5.2 Research Question 2: What percentage of non-unique fact-checks spreads across languages

To address our second research question, we quantitatively investigate the spread of non-unique fact-checks across languages. From the claims that are fact-checked more than once, we find that approximately 33.79% are fact-checked in multiple languages, suggesting the original misinformation claim was present in multiple languages. This finding helps situate previous studies showing that misinformation does not exist in isolation within language-specific silos, but rather has the potential to traverse language barriers [42, 22].

Despite this, our research also indicates a pronounced inclination for misinformation to disseminate predominantly within the same language. To substantiate this, we compare our observed data against a null model, which assumes no language-based preferences for misinformation spread. In this comparative analysis, the null model’s expectations are calculated by randomly sampling languages from the overall language distribution but keeping all edges of the graph unchanged. To clarify the concept of randomness in our null model, we assume

that the spread of misinformation is not influenced by language barriers, behaving as if language preference does not exist. As the languages associated with misinformation claims are chosen by random sampling from the overall language distribution, we nullify any inherent language-based patterns or preferences. Comparing to this null model as a baseline allows us to understand how language could specifically impact the dissemination of misinformation. We depict this analysis in Figure 6, where we plot the expected frequencies from the null model against the empirically observed frequencies of mono-, bi-, tri-, and four-or-more-lingual clusters. Each point corresponds to a distinct cosine similarity threshold. If there were no language-specific effects in the clustering, we’d expect the points to lie on the 45-degree line $y = x$ as we’d observe the value just as often as is expected. The empirical data deviates significantly ($\alpha = 0.01$) confirming the influence of language on our clustering of misinformation claims. We mapped each language to a language family based on data by Ethnologue, a catalog of languages [10]. Of the 33.79% claims found in multiple languages, 80.7% of these were found within languages belonging to the same language family.

5.3 Research Question 3: Evolution of Misinformation claims

Understanding the temporal evolution of misinformation claims offers valuable insights into their dynamics. This line of inquiry helps us track how claims change over time, revealing whether they become more or less similar as they spread. By analyzing the factors that influence this evolution, we can start to gain a deeper understanding of the mechanisms that drive the spread of misinformation. This serves as a natural extension to our previous analyses, bridging the gap between static properties and temporal behaviors of misinformation claims.

While we intentionally chose not to restrict clustering based on time—due to the multiple peaks in the temporal diffusion pattern of misinformation, as revealed by Shin et al. [36]—we found that the majority of edges within each cluster are still closely linked in time, indicating that the corresponding fact-checks were often created near each other temporally.

Figure 7 shows the propensity of fact-checks to be closely linked in time. It displays the cumulative percentage of time differences lower than or equal to x days for unconnected nodes within one cluster (i.e., fact-checks checking the same claim). For our chosen cosine similarity threshold of 0.875, 56.26% of edges have a

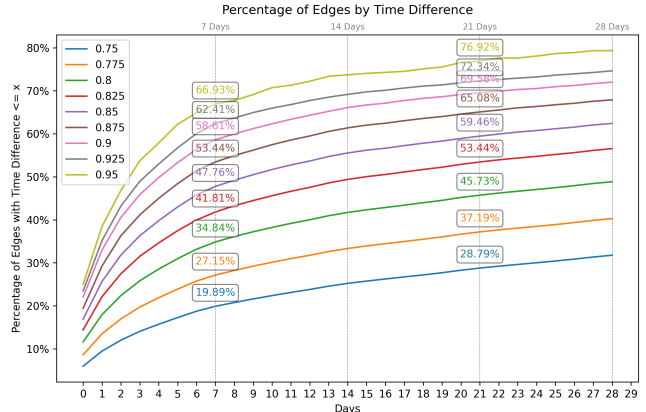


Figure 7: Edges by Times Difference, the difference of the fact-check date of both claims.

time difference less than or equal to a week. 68.18% of edges have a time differences less than or equal to three weeks. Even within each cluster, the time difference of connected nodes is significantly higher than unconnected nodes for all cosine-similarity thresholds ($\alpha = 0.01$).

While directly connected edges always have a cosine-similarity exceeding the pre-set threshold, nodes within the same cluster that are unconnected have lower cosine similarities. We can therefore, inspect how the similarity between unconnected nodes within the same cluster changes over time. A monotonically decreasing cosine similarity would indicate a gradual evolution of the misinformation claim over time.

The top plot of Figure 8 illustrates the average cosine similarity between all unconnected pairs of nodes within clusters, specifically for our selected cosine-similarity threshold of 0.875. This average is taken across all clusters and plotted as a function of the time difference between the nodes. The lower plot encompasses all lower cosine-similarity thresholds. Importantly, we only report the average distance for unconnected nodes, as nodes that are directly connected inherently have a similarity of at least the threshold value. The shading in the figure represents the standard error. The similarity of unconnected nodes continues to decrease for the first month. For all cases, we see a strong indication of a monotonically decreasing cosine-similarity, showing how misinformation claims change over time. The same effect is also observed for longer time periods. The effect is consistent for all clustering levels below or equal to our chosen similarity of 0.875. The average similar-

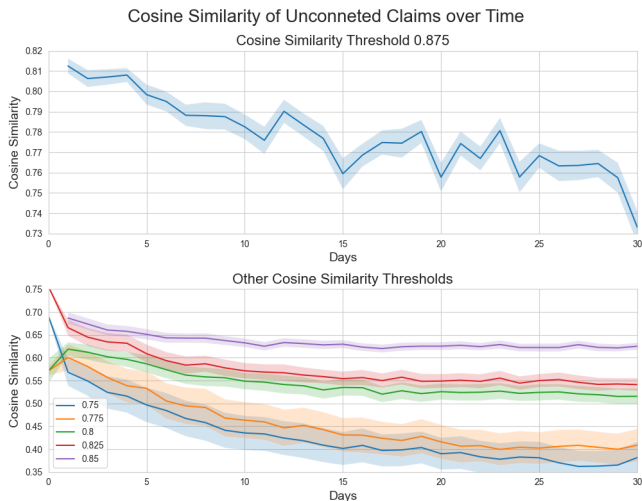


Figure 8: Average cosine similarity of unconnected Claims Over Time in the first 30 days. Shading shows the standard error.

ity between disconnected nodes within the same cluster drops by around 10% within one year from 0.8 to 0.73 ($t = 6.41, p < 0.01$).

Similarly, we can inspect what factors influence the evolution of misinformation claims within clusters. To do that, we determine the two most dissimilar nodes per cluster. Subsequently, we determine the shortest path connecting these dissimilar nodes. Figure 3 shows an example multilingual cluster. The color of each node refers to the language of the fact-check. The two most dissimilar nodes, F & A, are circled in black. The shortest path between these two nodes is highlighted in yellow. This way of looking at each cluster allows us to investigate how misinformation claims within the same cluster evolve. Figure 9 shows the average cosine similarity of the two most dissimilar claims in each cluster plotted against the number of language switches and the length of the shortest path. The shaded area is the 95% confidence interval. We only plot observations with at least 100 valid pairs.

We find that the average cosine similarity of the two most dissimilar nodes varies considerably with the length of the shortest path (i.e., tracing the most probable path of evolution). Both the number of unique languages and the number of language switches are highly significant predictors of change in the cosine similarity.

To test whether the effect remains significant when controlling for the length of the shortest path, we per-

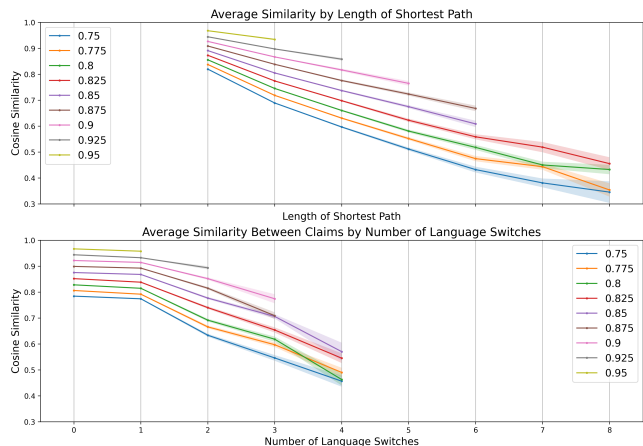


Figure 9: Average Similarity of most dissimilar Fact-Checks per Cluster by Length & Number of Languages

formed a regression analysis (Table 1). The effects of both remain consistently negative and significant, even when controlling for the length of the shortest path between the two most dissimilar nodes.

To investigate which claim topics are most likely to be fact-checked multiple times and spread across languages, we first machine translate all claims to English using Google Translate. We then extract and lemmatize all noun tokens from the claims field. We then calculated the relative frequency of each token under two conditions. First, whether the claim is a singleton (cluster size = 1) or not (cluster size $\neq 1$). Secondly, for non-singleton claims, whether the claim cluster is monolingual or multilingual.⁸ Before calculating the relative frequencies, we filtered both lists to tokens present in both conditions. When calculating the relative frequencies, we only included tokens that appeared at least 50 times.

Table 2 presents tokens that are most and least likely to appear in multilingual clusters (left column) and in clusters containing multiple fact-checks (right column). For instance, the token most indicative of multilingual clusters is “Pfizer”, emphasizing that Covid-19 is a globally discussed topic. Other top multilingual tokens like “viral” potentially relate to the pandemic. Conversely, tokens like “school,” “law,” and “government” are primarily confined to single-language discourse. Similarly, tokens such as “Ivermectin,” “Soros,” and “Greta Thunberg” are often found in claims checked multiple times.

⁸We look at the original dataset before machine translation to determine whether a cluster is mono- or multilingual.

Table 1: Regression Cosine Similarity of two most dissimilar nodes by cluster

	<i>Dependent variable:</i>	
	Cosine Similarity	
No. Unique Languages	-0.002*** (0.0006)	
No. Language Switches		-0.0014** (0.0005)
Length	-0.0625*** (0.0005)	-0.0626*** (0.0005)
Constant	1.0354*** (0.0012)	1.0335*** (0.0012)
Observations	8362	8362
R ²	0.666	0.668
Adjusted R ²	0.666	0.668

*p<0.1; **p<0.05; ***p<0.01

In summary, this analysis identifies words that tend to appear in claims that either spread widely across languages or remain localized.

6 DISCUSSION AND CONCLUSIONS

This paper investigates fact-checking in the online multilingual space. Above all, we find that while most misinformation claims are only fact-checked once, 11.7% of misinformation claims are fact-checked multiple times. This observation highlights the existence of a recurring subset of claims that undergo continual scrutiny. It suggests a persistent pattern where certain claims, due to their nature, importance, or controversy, command repeated attention from fact-checking organizations. Our token analysis further illuminates this phenomenon. We find some words that are more likely to be appear in claims in multiple languages and in claims that are fact-check multiple times. Such words include “Pfizer,” “Ivermectin,” and words related to conspiracy theories. These recurring, high-scrutiny topics present an opportunity for more efficient allocation of fact-checking resources to minimize repeated work.

Next, we find that 33.79% of misinformation claims that are fact-checked more than once are checked in multiple languages. Nevertheless, misinformation still diffuses predominantly within the same language. This highlights the importance of global cooperation on fact-checking, as the majority of misinformation claims stay

Table 2: Tokens Most and Least Associated with Multilingual Clusters or Clusters with Multiple Fact-Checks. Relative frequencies are calculated by dividing the relative frequency in both conditions.

Multilingual		Multiple Fact-Checks	
Multilingual	Rel. Frequency	Singleton	Rel. Frequency
pfizer	2.86	thunberg	9.39
name	2.66	greta	7.65
gandhi	2.41	missionary	4.56
viral	2.30	anil	4.20
daughter	2.25	soros	4.06
rahul	2.15	ivermectin	3.68
japan	2.05	sonia	3.20
delhi	1.98	priyanka	3.08
ram	1.90	dilma	3.06
priyanka	1.89	ceo	3.05
...
use	0.53	school	0.41
law	0.51	plan	0.42
government	0.48	city	0.42
trump	0.48	story	0.43
number	0.45	investigation	0.44
show	0.44	user	0.45
rumor	0.42	mother	0.48
facebook	0.36	facebook	0.48
fact	0.29	teacher	0.48
brazil	0.25	tax	0.49

in their own language. This echoes the culture proximity theory that culture and language are still the most influential factors that decide online users’ information consumption. Though technologies such as machine translation and social media make it easier for cross-language communication, they do not necessarily function that way in everyday use. In other words, our research highlights the importance of local fact-checkers and the cooperation of global fact-checking communities, as most misinformation claims stay local and in single-language communities.

Moreover, we show that misinformation claims do change over time and changes are especially common when a claim is found in multiple languages. Our data, however, only contains the misinformation claims as reported by fact-checkers. There is some degree of editorial voice in how fact-checkers write or phrase the misinformation; so, future work should seek to analyze a global dataset of the original misinformation posts on social media. Such posts are often removed, which makes this a challenge and will require closer collaboration between academics and fact-checkers.

Most misinformation is fact-checked closely in time which mirrors other work on the diffusion of information more generally; however, the time scales are slower than

those observed directly on social media [7]. While our results show claims change over time, the specific mechanisms and consequences remain unclear. Future research should delve more deeply into how claims change and the role of cross-lingual spread in this process, which may help fact-checkers better anticipate what claims will enter their languages from elsewhere.

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