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Representation of Arctic Indigenous Languages in Social Media: Is There a Disinformation Effect?

Exploratory research

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Introduction

After declaring 2019 as the International Year of Indigenous Languages, UNESCO has declared the decade 2022-2032 as the International Decade of Indigenous Languages. Indeed, according to the UN, by 2100, 40% of the indigenous languages spoken today could become extinct (UNESCO, 2022). This Decade aims to protect indigenous languages and prevent their extinction through sustainable change (UNESCO, 2021).

This article presents exploratory research as part of the International Decade of the World's Indigenous Languages. It aims to shed light on the effects of the representation of realities in Arctic indigenous languages in social media. More specifically, our study proposes to verify whether mis/disinformation hurts the representation of these realities and, consequently, on the social acceptability of measures put in place to protect indigenous languages in the Arctic and to explain the elements that promote or hinder the dissemination of disinformation.

To do this, we will define our problem, summarize the main findings from the literature on the subject, and then present the theoretical framework underpinning our analyses and their conclusions.

Problematic

According to UNESCO, the protection and promotion of the use of indigenous languages can only be achieved if States adopt legislative tools to protect, preserve and revitalize indigenous languages (UNESCO, 2021).

However, as the literature on public policy teaches us, the functioning of legislative tools - like all public measures - depends primarily on their acceptability by the population (Lascoumes & Le Galès, 2012). This acceptability, in turn, depends on how the population perceives a public issue (Howlett & Ramesh, 2003), such as protecting native languages. Thus, the public measure will be well accepted if the problem is perceived as significant and deserving state action. On the contrary, if the population poorly perceives the issue, then the public measure will not be accepted, and state action will be contested (John et al., 2011; Knoepfel et al., 2015). Consequently, we propose the postulate that the usefulness of legislative tools to protect, preserve and revitalize indigenous languages depends on the population's perception of this issue.

Since 2022, some states have passed native language laws, but assessing their impact is still too early. In this article, we take a more upstream approach to this issue, looking at the public's perception of native languages since, as we have pointed out, we see this perception as a predictor of the social acceptability of legislative tools to protect native languages.

More specifically, we study the perception of this issue in social media - specifically on Twitter (now X) - focusing on misinformation about the realities of indigenous languages in the Arctic. We argue that misinformation can produce a negative perception of the realities of indigenous languages in the Arctic and undermine the acceptability of legislative tools. In this respect, based on a model of information dissemination in social media developed by Caron (2023), we ask: 1. what elements lead to the production and use of mis/disinformation? 2. what hinders or discourages the production and use of mis/disinformation?

These questions take the following assertions for granted. First, social media presents a significant amount of misinformation about the realities of indigenous languages in the Arctic. Secondly, there is a great deal of negativity surrounding this issue. This implies that the Indigenous Languages Act recently adopted by the Canadian Parliament would have a relatively low social acceptability in the Canadian Arctic region.

Literature Review

Our research into current work on Indigenous languages and social media revealed that two themes stand out: work addressing the case of Indigenous languages and social networks during the COVID-19 pandemic and discussing the preservation and revitalization of Indigenous languages in the context of social media.

Concerning the first theme, research shows how integrating indigenous languages into messages aimed at these populations has led to better protection. For example, Miguel et al. (2022) concluded that videos culturally and linguistically tailored to Guatemala's indigenous populations and disseminated via social media, including Facebook, countered vaccine misinformation and increased vaccination rates among this population. The work of Fapide and Salawu (2022) supports the findings of Miguel et al. (2022), showing that messages published in indigenous African languages ensured better dissemination and understanding of public health authorities' messages concerning social distancing and personal hygiene measures, although misinformation still spread in this respect.

Other works examine the social effects of using native languages in the media during the COVID-19 pandemic. Thus, Corntassel et al (2020) explain how social networks were a crucial element in the resurgence of community practices during the COVID-19 pandemic on Turtle Island, while the work of Chew et al (2022) and Budrikis and Bracknell (2022) explain how in Canada and Australia, efforts to adapt and convey messages in indigenous languages to these communities led to the adoption of strategies to claim, promote and revitalize indigenous languages.

The issue of indigenous language preservation and revitalization is also being researched outside the context of the COVID-19 pandemic. Cassels (2019), for example, looks at how online platforms encourage speakers of indigenous languages to become grassroots activists fighting for recognition of their linguistic rights. He concludes that online platforms encourage this activist empowerment of indigenous language speakers and serve as a site for the spontaneous production of new indigenous literature, eventually leading to a movement of indigenous self-determination. Ligidima and Makananise (2020) conclude their work that supports those of Cassels. Analyzing the effects of the creation of social media platforms for speakers of indigenous African languages in South African universities, these authors' work establishes that although English remains the dominant language in exchanges between students in this community, young speakers of indigenous African languages play an essential role in promoting the use of these languages through social media platforms. The work of Kotut and McCrikard (2022) also supports these conclusions. The authors compare Indigenous people's engagement with their traditional knowledge online and offline. The authors find that in online discussions of indigenous knowledge, the role of elders tends to disappear drastically, which is not the case in offline discussions. However, online platforms have made it possible to bring in the debate (in native languages) members who, although born in the community, have left it. Thus, using indigenous languages in social media changes the dynamics of sharing and protecting indigenous knowledge and serves as a guardian or protector of these languages since it promotes their use.

Finally, the study of using indigenous languages in the media also poses ethical dilemmas that some authors address. Istighfari (2019) questions the biases and limitations that "modern" information can induce when it is the only mode of analysis of indigenous knowledge conveyed in social media. The author, therefore, proposes new alternative methods, such as creating interactive linguistic maps and public use of indigenous knowledge, which depend on community co-construction with indigenous peoples. As Nordström (2019) points out, this methodology has already been adopted by the Arctic University of Norway, which is developing an interactive language map with the support of indigenous institutions and organizations in Canada, Finland, Greenland, Norway and Russia. However, Istighfari points out that there are still significant barriers to the participation of indigenous communities in this kind of project, not least the discordance of indigenous and non-indigenous social structures and the dissonance of worldviews between indigenous and non-indigenous peoples. Despite these dissonance discordances, the author insists on the importance of involving Indigenous communities in a fruitful dialogue regarding Indigenous linguistic research so that this work can highlight Indigenous knowledge and ensure the self-determination of these peoples.

In our research, we are interested in the representation of indigenous languages in social media. However, our literature review reveals that very few works deal specifically with this subject. The texts we have found deal mainly with using indigenous languages in the context of the COVID-19 pandemic or with the various social, political and ethical considerations linked to preserving, revitalizing and promoting indigenous languages. We have yet to find any work dealing with misinformation/disinformation about indigenous languages, whether in social media or any other field. The field in which our research falls remains understudied, and in this respect, our exploratory study will contribute to advancing knowledge in this area.

Theoretical Framework

To understand what promotes or hinders the presence of misinformation in social media, Caron (2023) draws on the *Jobs Demands-Resources Model*, which she adapts to the reality of information production and dissemination in social media. She also draws on a model classic in public policy analysis: the *Advocacy Coalition Framework* (Sabatier & Weible, 2007).

The Jobs Demands-Resources Model aims to explain what causes stress in an employee's job (Bakker & Demerouti, 2017) and affects an organization's results. The model is based on the principle of balance between the demands of a job and the resources (personal and workplace) of an individual. If the balance between needs and resources is maintained, the employee can perform their job without the adverse effects of stress. If, on the other hand, the balance is upset, then the demands become more significant than the employee's resources, and the latter finds himself overwhelmed by stress and the adverse effects this entails (exhaustion, burn-out, depression). Developed in the early 2000s, this model has undergone several iterations over the past twenty years (Tummers & Bakker, 2021). However, regardless of its iteration, the model always presents several demand categories and resources, which are put in parallel to demonstrate how a resource-dominant approach leads mainly to motivation and, consequently, to good results for an organization. On the contrary, a demand-dominant approach leads to stress and, consequently, poor results for the organization.

In the Advocacy coalition framework, the authors attempt to set out the conditions that explain changes in public policy. They defend the postulate that, under normal conditions, the political subsystem is stable and that there is always a coalition of ideas and interests that dominate (a postulate also defended by Muller 2009 in his model of the public policy referential). According to this model, the dominance of ideas and interests can be explained by the strength of beliefs and the resources available to coalitions to maintain these beliefs. This dominance can be broken either by shocks external to the political subsystem or internal, which modify beliefs, affect resources and allow another coalition to become dominant, leading to changes in public policy (Sabatier & Weible, 2007).

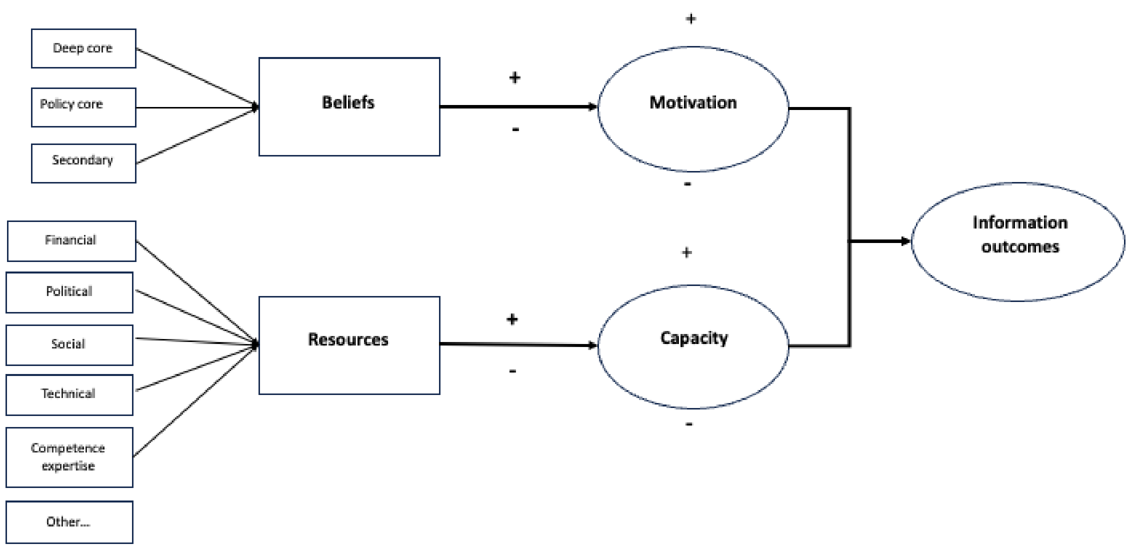
It may seem surprising to combine a conceptual human resource management model with a public policy analysis model to explain information dissemination in social media. However, when you think about it, this dissemination of information is often an expected outcome of various organizations, often for political and public policy reasons. In this sense, Caron's proposal is undoubtedly less esoteric than it may at first appear.

Thus, according to her, information outcomes are influenced by a balance between the beliefs and resources of an individual or an organization to which an individual belongs (Figure 1). Caron takes up Sabatier and Weible's idea that individuals present three categories of beliefs: deep core, policy core and secondary core. Deep core beliefs relate to an individual's core values and are extremely difficult, if not impossible, to change. Policy core beliefs relate to an individual's political and social values (progressive vs. conservative; left vs. right; etc.), and although theoretically, they may be easier to change than policy core, in practice, they rarely evolve in a person's life. Finally, secondary core beliefs are ideas accepted by a person but more easily modified according to the information and opinions with which a person is confronted. As Sabatier and Weible (and Muller) point out, when faced with facts, information and opinions, a person perceives these elements through a cognitive filter that generally leads them to accept those that reinforce these beliefs and reject those that invalidate them. It is in this way that value stability is maintained in a society. This implies that shaking this cognitive filter and modifying beliefs requires many resources.

Figure 1 shows that there are also a series of resource categories that can be personal or linked to an organization, which directly impact an individual's ability to disseminate information in social media. For example, the more technical resources, skills and money you have, the greater your ability to disseminate information on social media. As we have seen, this idea is directly inspired by the Job Demands Resources Model.

Figure 1 illustrates Caron's idea that the balance between motivation and ability influences the outcome of information dissemination in social media. Thus, the more a piece of information corresponds to an individual's beliefs, the more motivated they will be to disseminate it. Conversely, the more this information contradicts their beliefs, the less motivated they will be to transmit it. This is where the idea of deep core, policy core and secondary beliefs plays a vital role because depending on whether the information confirms or contradicts one of these value categories, it will amplify the motivation or demotivation to disseminate it, depending on the type of value the information touches. The positive or negative reaction will be stronger for deep core and policy core beliefs but weaker for secondary beliefs. However, motivation is not everything: the more valuable resources an individual has at his disposal, the more their ability to disseminate information will be amplified, and, once again, on the contrary, the more it will be diminished. So, it is understandable that a highly motivated individual with solid capabilities will achieve better results in disseminating information than a demotivated individual with few resources. Between these two extremes, several scenarios may emerge to explain the outcome of information dissemination (e.g. highly motivated but low capacity or high capacity but low motivation).

Figure 1 - Information Spreading in Social Media Model



It is important to note that Caron is talking about the diffusion of information in social media, which needs to be validated information, misinformation, or disinformation. The model, therefore, makes it possible to explain the diffusion of information, regardless of how it is qualified. Its use in the study of misinformation/disinformation is appropriate, but this is our choice and not a feature of the Information spread in social media (ISSM) model.

Methodology

As mentioned above, our social media data came from a single source: Twitter (now X). This is because it was the only social media platform we could access an API to extract data from Canada. It might have been possible to extract data from other social media using different techniques, but these are either frowned upon or forbidden by the companies operating these social media. Using such techniques would, therefore, have been unethical (Veltri, 2020). Furthermore, for political reasons, companies such as TiTok and Meta were not granting Canadian researchers access to their APIs at the time of our research.

Our research is based on textual data extracted from the Twitter API between January 2020 and May 2023. We could only extract data by May 2023 because, after Elon Musk's takeover of Twitter, he made a series of gradual changes to increase revenues, including closing APIs. Thus, in May 2023, we lost access to the Academic API, which was closed like the others. Still, unlike the other types of API, at the time of conducting our research, X (formerly Twitter) still needed to reopen a specific API for academic research (in this regard, see Savard & Landriault (2023)). From all the tweets we extracted from the Twitter API, we selected and retained, using a sorting algorithm, those that addressed the theme of indigenous languages in the Arctic. We were thus able to keep 833 publications for our analysis.

We subjected these publications to quantitative and qualitative analysis to answer our research questions and test our hypotheses. Regarding our quantitative textual analyses, we began with simple descriptive analyses to paint a picture of the use of these publications. We then carried out an influence analysis to measure the relative impact of tweets published on Twitter. We followed this up with a sentiment analysis to measure the level of negativity observed in the tweets analyzed. We produced all our quantitative analyses using the R language (statistical and data analysis language), more explicitly using the packages dplyr (Wickham et al., 2023), tidytext (Silge & Robinson, 2016) for quantitative textual analyses and wordcloud (Fellows, 2018) and ggplot2 (Wickham, 2016) for graph production.

We opted for a traditional in vivo coding method for quantitative analyses without recourse to specialized software. Instead, we imported the 833 publications into a *Word* document and manually coded and categorized the publications following the method proposed by Saldaña (2021). To do this, we assigned specific colours to the codes we created by reading the corpus texts and highlighted the passages corresponding to these codes with *Word*'s "highlighter" function. We assembled the different codes into categories and, following Saldaña's method, went through them twice more to create families and ensure their relevance.

We followed up our qualitative analysis with content analysis as outlined by Lejeune (2014), and thanks to our code categories and category families, we were able to identify, in our corpus of 833 tweets, specific themes and patterns - which we discuss in the next section - and measure their relative importance. Qualitative analysis also enabled us to verify the results of our quantitative analysis in terms of indications of the presence or absence of misinformation in our corpus (it is worth noting that usually, our quantitative textual analyses are carried out on corpora of over a million tweets, making it impossible to verify the results of the quantitative analysis qualitatively. Given the small size of the corpus (just 833 publications), we qualitatively verified these results because we had the opportunity to do so, and we wanted to make sure that a small number *of tweets did not* bias the quantitative analysis).

Presentation of Results and Discussion

As specified in the previous section, the corpus we analyzed consisted of 833 tweets published by 309 authors. These figures give the impression of a discussion involving several actors. However, this is a case of the forest hiding the tree since when we look closely at the distribution of publication frequency by author, we quickly notice that this discussion is concentrated around a small number of authors. Indeed, of the 309 authors, only eight published more than ten tweets, while 128 published only one tweet and 108 published only two tweets. In other words, 2.6% of authors published a quarter of the tweets in our corpus (24.7%, to be precise). Moreover, the texts published contained an average of 21 words, making them relatively short and more easily disseminated.

Knowing that there was a specific concentration of the publication (and consequently distribution) of tweets in the hands of a few authors, we wanted to determine whether this concentration followed the same trend. In other words, we tried to determine whether certain publications were more widely republished than others. To do this, we analyzed the following measures: the number of retweets, the number of quotes, the number of likes and the number of replies. Some retweeting methods require more effort than others (quotes, replies), so we expected to see a lower frequency of these measures. As a result, we found that 54% (450) of tweets were retweeted, and 73% (611) were liked. On the other hand, unsurprisingly, only 17% (143) were quoted, and 23% (194) were replied to. These figures indicate that retweeting of tweets was reasonably active.

However, we wanted to determine whether the retweeting of tweets was mainly aimed at the publications of our small core of most prolific authors or whether, on the contrary, there was no link between an author's number of publications and their ability to be retweeted. Using the above measures, we created an influence index (the sum of each measure per author) and selected the eight most republished authors to check whether they were the same eight authors who had published the most. To our surprise, only two of the eight authors with the most published tweets were among those with the most reposted tweets. Among the group of most-published authors, they still came second and third. Not surprisingly, they were among the most widely published authors. Nevertheless, their publications ranged from just 1 to 9 for the other six. This means that an author who has published only once is still among the most widely circulated, indicating a strong influence.

After studying these measures of frequency and influence, we conducted a sentiment analysis on our corpus. The analysis revealed that 73% of publications were positive, compared with 14% negative and 13% neutral. Therefore, we must conclude that the corpus is generally positive regarding discussing indigenous languages in the Arctic. It should be pointed out, however, that the algorithm we used to determine the type of sentiment associated with each publication could not qualify a quarter of the corpus. Therefore, the corpus may be less positive than our current results indicate. However, given the low negativity rate, we can still conclude that the discussion that emerges from our corpus is more positive than negative.

To understand the content of this discussion and determine what makes it such a particularly positive dialogue, we turned to our content analysis. After conducting this analysis (as we describe in the methodology section), we were able to identify three dominant themes that emerged from our corpus: event announcements, putting indigenous culture forward, the use and preservation of indigenous languages, asserting rights, references to articles or websites, denouncing indigenous languages, decolonization and digitization. The most important themes are event announcements - which account for 37% of publications in our corpus - and the use and preservation of native languages - which account for 30% of publications in our corpus. The other themes comprise less than a third of the corpus, and their relative importance is as follows: Reference to an article or website - 9%; Putting culture first - 5%; Claiming rights - 2%; Decolonization - 3%; And digitization - 2%.

Interestingly, the only negative theme - denouncing native languages - accounts for only 2% of our corpus. This explains why our sentiment analysis is so powerfully positive and weakly negative. Dominant themes mainly attract reinforcing dialogues (promoting the language, preserving it, announcing events) or simply neutral ones. As negatively dominant discussions are mostly centred around a theme that ultimately has few publications, it is customary to observe a low rate of negativity in our corpus.

As far as misinformation is concerned, we only observed misinformation in tweets denouncing indigenous languages. This was not so much misinformation as disinformation, as the authors misinterpreted language laws and the scope of the 1982 Constitutional Act of the Canadian State. For the rest, the information in our corpus did not disseminate anything that could be recognized as mis/disinformation.

Let us return to our conceptual model to take our analysis further. The content analysis of our corpus reveals that the most prolific authors publish tweets linked to their social and political commitment, with one exception: the author who has published the most significant number of tweets. The latter, an organization, uses its publications to promote specific events. Thus, in the first group of authors, publications are anchored in core policy values; in the second, they are secondary values. This observation contradicts our conceptual model, but we will return to it later. The texts are anchored in policy core values for the other authors who have published at least ten times. An analysis of the content of publications by authors who have yet to publish many times (less than 5) reveals that, except for a few rare occasions, these texts are mainly based on secondary values since they convey mostly neutral factual information, such as event announcements.

So, as our conceptual model predicts, belief type plays a big part in the motivation to publish on social media since the authors who published the most put forward texts anchored them in policy core values. In contrast, those who published the least put-forward texts anchored them mainly in secondary values. This gives us a better understanding of the dissemination results.

Earlier, we pointed out an exception to this conclusion: the author who published the most actually transmitted factual messages that fall within the scope of secondary values. We explain this apparent anomaly with the second part of the ISSM model. We have pointed out that this author is an organization (our commitment to Twitter and our ethical rules do not allow us to identify this organization or to offer information that could enable it to be identified). Here, the availability of resources explains the results of the dissemination of information published by this organization. Indeed, the organization has a good quantity of financial, human and technical resources, which undoubtedly enhances its capacity, particularly in comparison with individual authors. Once again, the ISSM model enables us to understand what influences the outcome of information dissemination. However, our data on authors and their available resources to publish on social media do not allow us to verify the balancing act between belief/motivation and resources/abilities in information dissemination outcomes. This is one of the limitations of our research.

On the other hand, although we can draw some conclusions about the dissemination of information in social media concerning the theme of indigenous languages in social media, we have to admit that, contrary to our ambition, we were unable to observe any misinformation or more precisely, we observed so little that we could not conclude anything in this regard. The ISSM model is still helpful in understanding the spread of misinformation, but this has yet to be demonstrated.

Conclusion

As we stated at the outset, our research was exploratory, and in this sense, while the results are not always conclusive, they remain essential because they pave the way for future research. Thus, this research looked at the representation of indigenous language realities in social media from the angle of misinformation/disinformation. We hypothesized that this misinformation could produce a negative perception of the realities of indigenous languages in the Arctic and consequently undermine the acceptability of legislative tools aimed at preserving and promoting the use of indigenous languages. This hypothesis was supported by two postulates: 1. Social media present a significant amount of misinformation about the realities of indigenous languages in the Arctic; 2. we find intense negativity towards this issue.

However, our research results invalidate these assumptions. Indeed, our statistical and content analyses reveal that we observed very little misinformation/disinformation about the realities of indigenous languages in our Twitter corpus (barely 2%). Secondly, although we observed little negativity, the corpus of tweets we studied remained largely positive. Moreover, this observed negativity does not necessarily mean they are discriminatory towards native languages. On the contrary, our content analysis showed that only 2% of published tweets propagated misinformation about native languages in social media. Negativity is, therefore, linked to some publications addressing negative social issues, such as the difficulty of preserving an indigenous language.

Our research results, therefore, assume that legislative tools to protect indigenous languages should enjoy good social acceptability in the Arctic region. However, as the Canadian parliament has only just adopted the law and tools, it is still too early to assess this acceptability directly.

Our research also sought to answer two more specific questions using the ISSM model: 1. what elements lead to the production and use of mis/disinformation? 2. what elements hinder or discourage the production and use of mis/disinformation? Our research clearly shows the role of beliefs in motivating people to post messages on social media. The more a topic touches on deep core or policy core values, the more motivated authors are to publish texts on social media. Regarding the resources that encourage authors to publish on social media, our data indicates that financial resources, technical resources and expertise play an essential role in authors' ability to publish extensively. However, we needed more information to answer our first question, and more in-depth studies will be required to answer it fully. Furthermore, we needed help to obtain data that would allow us to answer our second research question. This is unsurprising since misinformation/disinformation was essentially absent from the corpus.

Does this mean that our research has failed? We do not think so for two reasons. Firstly, we must bear in mind the limitations of our research. Firstly, for the reasons outlined in the presentation of our methodology, our analyses were carried out only on data extracted from Twitter and at a time when Twitter exercised tight control over the quality of information disseminated on its network to avoid spreading misinformation. However, since Twitter has become X, this control has loosened considerably, and misinformation seems much more prevalent. Also, conspiracy theorists and other disseminators of misinformation are much more present on different social media platforms we have yet to study.

Secondly, our sentiment analysis could not qualify a quarter of the corpus. A different algorithm would enable us to determine the sentiments of the entire corpus and could modify our observations on the degree of negativity in the corpus. However, we should also remember that our content analysis (which considers the entire corpus) revealed that only 2% of publications constituted misinformation. So, even with a better algorithm, the results may vary very little.

Finally, as the data available was limited to what our Twitter agreement allowed us to extract and use, we could not correctly verify how the balancing act between belief/motivation and resources/abilities influenced information dissemination outcomes. However, we were still able to draw some conclusions.

Secondly, it should be borne in mind that our research was exploratory, so mixed results were to be expected, but they pointed the way to research further. Thus, despite its limitations, this exploratory research contributes to the (relatively scant) knowledge of the representation of indigenous language realities in social media, indicating the need to extend research to other social media. We observed a 2% misinformation/disinformation rate on Twitter, but checking whether these results are the same in X and other social media is essential. It is also important to refine the research design to gather more information about users to test the ISSM model better and see if it can explain what encourages and hinders the dissemination of misinformation. In addition, further quantitative textual analyses may enable us to obtain more nuanced results. Finally, with regard more specifically to the effect of representation or the perception of the realities of native languages in social media on legislative tools for the preservation and promotion of these languages, we will also have to wait a little longer to be able to measure the social acceptability of these tools correctly and to observe or not the impact of representations in social media, to determine whether or not misinformation plays an essential role in this field.

Our exploratory research leads to more questions than answers. However, it has the merit of shedding light on a little-studied phoneme and paving the way for important research work for the International Decade of the World's Indigenous Languages.

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