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The Role of Algorithmic Literacy in Countering Misinformation in Developing Countries

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Abbreviations

AI – Artificial Intelligence

TPE – Third-Person Effect

ICT – Information and Communication Technologies

Symbols

M= average

N= number of observations

1 Curated Realities: Algorithmic Literacy and Misinformation in the Digital South

Algorithms are presumed to have been created to facilitate the connection between individuals and their interests, bridging cultural, political, social, and cognitive gaps imposed by traditional media. In this context, Mark Zuckerberg, CEO of Facebook, discussed the platform's ability to bring together people who may not otherwise meet, emphasizing the importance of the internet in sharing ideas and information. However, these algorithms have actually widened existing gaps, especially in knowledge (Abdalkader and Djeffal 2024).

Misinformation, disinformation, and fake news have become gradually more common in the digital era and highlighted and amplified by the use of AI-driven algorithms on digital platforms. Efforts to counter misinformation include both automated measures, such as misinformation detection, tracking, and stance classification, and human- driven approaches like fact-checking, content moderation, and media literacy campaigns (Shawky El Mokadem 2023). Among these, media literacy stands out as a strategy for equipping individuals with critical thinking skills to assess credibility and detect false information (Washington 2023).

Building on media literacy, algorithmic literacy has emerged as a vital tool to address misinformation in the context of algorithm-driven content. By understanding how systems generate and amplify information, individuals can enhance critical behaviors such as fact-checking, content flagging, and source validation. However, recent research suggests that many social media users fail to engage critically with content beyond its headline thus reducing the likelihood of sharing “real” news (Sundar et al. 2024). This behavior highlights the challenge of fostering algorithmic literacy when users engage with content in a passive and superficial manner.

In addition, spread of misinformation is also exacerbated by platform policies that don’t focus on fact-checking. Meta’s recent decision to remove fact-checkers from Facebook and Instagram, raises concerns about the increasing difficulty of curbing misinformation at a systemic level (McHanon et al. 2025). The model, which began in 2016, is set to be replaced by a system of “Community Notes,” wherein users themselves reach consensus on the accuracy of potential misinformation or hate speech, this approach has been modeled after X (formerly Twitter).

The case of Honduras offers a compelling case for studying the dynamics of misinformation in digitally mediated environments. According to data from ILifeBelt (2016), 92.6% of Honduran users accessed the internet via smartphones, and the dominant platforms across Central America were WhatsApp (79.7%) and Facebook (77.6%). More recent statistics from We Are Social and Hootsuite (2020) show that in January 2020, Honduras had approximately 4.1 million internet users, a figure that matched the number of social media users, underscoring the widespread reach and influence of these platforms in everyday life.

The decision has been met with widespread criticism, particularly from stakeholders in the UK and Europe, where governments and regulators have called for increased platform accountability on issues such as fake news and hate speech. In Latin America, reactions have been equally skeptical. Several independent fact-checking organizations (previously partnered with Meta) have expressed concern that the policy change will not be confined to the U.S. but will eventually affect countries in the region. These concerns are heightened in contexts where media polarization is high, and the institutional safeguards against misinformation are relatively weak. In the case of Honduras, where journalism is often politically divided and digital news consumption increasingly reliant on social platforms, such shifts in policy may have disproportionate consequences for the integrity of information ecosystems.

1.1 Problematization and Research Gap

Against this backdrop of shifting platform policies and heightened regional vulnerabilities, it becomes increasingly important to examine not only how misinformation spreads, but also how users respond to it within algorithmically curated environments. As social media platforms delegate greater responsibility to users for identifying and evaluating misleading content, the ability to critically engage with algorithmic processes becomes more than a technical skill. In regions like Honduras, where digital access is increasing but formal digital education is limited, understanding the extent to which users are equipped to navigate these systems is critical. This context underscores the urgency of investigating algorithmic literacy not only as a cognitive or technical capacity, but also as a behavioral and socially motivated response to the challenges posed by misinformation.

This gap is especially relevant in regions like Latin America, where digital inequalities and media polarization intensify the risks posed by algorithmically amplified misinformation. Furthermore, individual action may not always stem from deep technical understanding. Psychological mechanisms—such as the Third-Person Effect (TPE)—may also play a role by motivating users to act out of concern for others' vulnerability to misinformation, even when their own algorithmic literacy is limited or inaccurate. Without better insight into how these factors interact, interventions aimed at improving user agency and accountability online remain incomplete.

1.2 Research Goal and Research Questions

This study seeks to contribute to the ongoing conversation around misinformation by investigating how algorithmic literacy influences user behaviors such as fact-checking and content flagging. Despite growing efforts to combat online misinformation, much of the existing research has centered on either technological solutions or general media literacy, leaving the behavioral impacts of algorithmic literacy underexplored. In particular, while algorithmic literacy has been identified as a promising framework for understanding how users engage with content curation systems, there is limited empirical evidence on whether it actually translates into proactive behaviors such as fact-checking or flagging misleading content. As such, the research asks, how does algorithmic literacy influence users' behavior to counter misinformation?

The first chapter reviews literature on misinformation, tracing its conceptual evolution and distinguishing it from related terms such as disinformation, malinformation, and fake news. It further examines the mechanisms by which misinformation spreads online, emphasizing the role of recommendation algorithms and user cognitive biases. Chapter Two builds upon this by outlining the key theoretical frameworks that underpin the study: the multidimensional model of algorithmic literacy by Oeldorf-Hirsch and Neubaum, the Third-Person Effect (TPE), and digital inequality theory. These frameworks are instrumental in situating the research within broader academic discussions on media literacy, user agency, and structural access to information. Chapter Three details the methodological approach, explaining the rationale for selecting university students in Honduras as a focal group and describing the mixed-methods design used to assess behavioral expressions of algorithmic literacy. Together, these sections scaffold a nuanced investigation into whether algorithmic literacy translates into meaningful engagement, such as fact-checking or flagging misinformation, and how psychological and socio-technical variables influence such behaviors.

2 Research Background

This chapter presents the conceptual basis and relevant literature that inform the present study. It defines key terms, examines mechanisms behind misinformation dissemination, and reviews existing responses to algorithmic misinformation. The chapter also introduces the theoretical models that support the study's analytical framework.

2.1 Literature Review

This literature review explores key research on misinformation and algorithmic literacy. It examines how misinformation spreads online, the technological and educational measures used to counter it, and the role of algorithmic literacy in shaping user behavior. The review also identifies gaps in existing studies, particularly the lack of research focused on the Global South, including Latin America.

2.1.1 Understanding Misinformation: Definitions and Distinctions

Misinformation, such as false rumors, is a universal feature of human societies, not a modern phenomenon (Altay et al. 2023). One should not assume that misinformation is more common today simply because it is more available and measured. Indeed, it has been around for many decades through different means of diffusion, from oral retelling to print and audiovisual content, to AI and algorithmic driven content curation in digital platforms. Because of the latter and its ability to enhance the speed of it, widen its reach, and even recommend it based on user behavior and beliefs, it has caught the attention of researchers and policy makers. Its definition, however, continues to be debated.

Misinformation, the antonym of information (Adams et al. 2023), as it relates to information theory brings about the philosophical conundrum on whether misinformation, given its lack of "informativeness" is or should be classified as information at all (Zeng and Brennen 2023). As some researchers have contended, misinformation, i.e. false information, falls under more appropriate term of pseudo-information (Floridi 2002).

Other authors have advanced its definition from the point of view of the accuracy of the content, descriptions such as misinformation being a "claim that contradicts or distorts common understandings of verifiable facts". Misinformation is "unintentionally promulgated, inaccurate information"

The definitions agree that misinformation thus far has two specific characteristics to it, the first, is the lack of accuracy to it, and the second, it is spread or shared without the intent of deceiving. Misinformation can in addition be uncertain, as presenting most likely more than one choice; or, can also be ambiguous in that it can be exposed to various explanations (Yesmin 2024). A key issue that stands out from these descriptions is that, the person spreading the misinformation believes it true, and can thus misinform and misguide people, often due to an honest mistake, negligence or unconscious bias. This distinction leads to the landscape of terms used in social media and research to talk about the issue. Various terms exist, misinformation, disinformation, malinformation, and fake news among others.

As detailed earlier, misinformation generally refers to inaccurate or false information. Disinformation on the other hand, is meant to describe information that is intentionally false information (Scheufele & Krause, 2019). The European Commission's report, "A Multi-Dimensional Approach to Disinformation", defines disinformation as "includes all forms of false, inaccurate, or misleading information designed, presented and promoted to intentionally cause public harm or for profit". The intent behind the claim and its spread is what distinguishes misinformation from disinformation. As Lim, 2023 states, disinformation is false information shared by the sender despite knowing its truth (e.g., fabricated or manipulated content).

Conversely to the first two terms discussed, malinformation is recognized generally as true information. Walker 2019, describes it as genuine information that is shared to cause harm. The most widely accepted definition is that of Wardle and Derakhshan 2018, information, that is based on reality, but used to inflict harm on a person, organization or country. Truth and accuracy is found then in malinformation, as well as an intention to harm another.

Lastly, the term "fake-news" was originally used to sum up mis- and dis- information in news reporting (Hussain and Soomro 2023). As Ha et al., 2021 describes it, it is any type of misinformation presented as news with the purpose of misleading audiences. It has since evolved into a political arena where fake news is described as a political maneuver by its actors in an attempt to discredit news reporting and reported facts they dislike.

Understanding the distinctions between misinformation and its counterparts is essential, but so too is exploring the mechanisms that facilitate its spread. Because misinformation is often shared without intent to deceive, it highlights the importance of algorithmic literacy: people may unknowingly spread false or misleading content simply by trusting what they see online, without questioning how it got there or why it's being shown to them.

To sum up the most important terms Figure 1 illustrates them for further clarity. It shows the differences between mis-/dis-/mal- information based on the most consistent criteria identified, falseness and intent to harm. Misinformation is presented as being completely false, but with no intent to harm, disinformation on the other hand possesses both characteristics. Finally, malinformation, is true information, that also intends to harm.

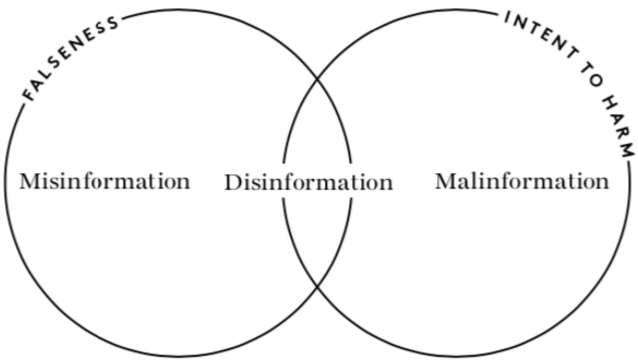


Figure 1: Information Disorder, adapted from Wardle, C., & Derakhshan, H. (2017)

While all three concepts described above pose distinct challenges, this thesis focuses specifically on misinformation due to its ambiguous nature and cognitive implications. Malinformation, though harmful, is based on factual content; its danger lies not in the user's inability to differentiate truth but in how that truth is weaponized. As such, it seen as an issue more aligned with ethical concerns than informational accuracy. Disinformation, by contrast, is intentionally false and often shared with full awareness of its inaccuracy. In this case intent is pivotal, not the users' ability to discern the truthfulness of the information encountered. Misinformation however stands out as uniquely problematic because it thrives on uncertainty and lack of clarity. Users may unknowingly share false content, not because they wish to deceive, but because they lack the tools or literacy to distinguish truth from falsehood.

This makes misinformation difficult to manage in algorithmically curated environments. As such, understanding the distinctions between misinformation and its counterparts is essential, but so too is exploring the mechanisms that facilitate its spread. Because misinformation is often shared without intent to deceive, it highlights the importance of algorithmic literacy: people may unknowingly spread false or misleading content simply by trusting what they see online, without questioning how it got there or why it's being shown to them.

2.1.2 How does misinformation spread online?

Early research in the field of communication and media studies suggested five major categories of actors involved in the curation of information digested by users: strategic communicators (e.g., public relations), individual media users themselves, social contacts (e.g., friends), and algorithmic filters. As the information landscape has increasingly moved to cyberspace, these perceptions have changed, encompassing a deeper perspective in the technical systems behind information sharing.

Misinformation can thus be analyzed as a social-technical problem with various influencing factors; among them are: i. the way information is constructed and presented, ii. Users personal values and beliefs, iii. the presence of bots and malicious accounts, iv. the architectural characteristics of the digital platforms where information is shared, and v. the algorithms that recommend information (Fernandez et al. 2024).

Literature about recommender systems is prolific. It addresses not only novel algorithms that enable the recommendation of products and services to a broad range of users in various domains but also considers the consequences of interactions between the users and the recommender systems themselves. In social media, they form users' habits of sharing information that draws other people's attention. Once habits are established, information-sharing becomes automatically activated by machine learning on the platforms without users considering critical response consequences. Thus, without considering its long-term effects, twitting, sharing, exaggerating, and posting on social media have become habitual practices. Worth noting, this behavior can be seen most particularly among university students. They are among the most active digital users, relying extensively on social media for news consumption and communication (Hargittai et al., 2020). Research shows that their engagement occurs in environments where algorithmic ranking systems prioritize sensationalist and emotionally charged content, which often includes misleading or false information.

Despite researchers recognizing that RAs can have some responsibilities for misinformation diffusion in social networks, there is not any available framework considering both user and RA behavior, to study and quantify the impact of RAs in spreading misinformation (Pathak et al. 2023).

2.1.2.1 Recommendation Algorithms (RAs)

Algorithms have for decades played a pivotal role in computer science. They are in essence sets of instructions designed to solve a specific problem or perform a specific task. With this starting point, social media algorithms have emerged as programming means to curate and filter content for individual users based on behaviors, interactions, and preferences; in this way creating what has become to be known as "filter bubbles"; comfort zones for individual users that amplify the tendency to favor information that supports preexisting beliefs while dismissing contradictory facts. As such, the implications of algorithms go beyond personalization (Albekri et al, 2024). They can change and shape public opinion, behavior and knowledge dissemination.

Writer Amani Albedah, in her study Humanities in the Age of Digital Exchange, criticizes the dominance of algorithms in shaping intellectual discourse. She also argues that algorithms prioritize content based on financial profitability rather than factual truth, and in the process rejecting the method, principles and rigor of academia and scientific research. It is also certain, that because algorithms are shaped by users past behavior, the environment of created by filter bubbles and RAs prevent unexpected encounters that could fuel creativity, innovation and a democratic exchange of ideas (Fernandez et al. 2024). Other critics point to the lack of consideration of negative consequences in RAs, as well as a lack of ethical considerations to their existence and use. Researchers have supported this conclusion noting that RAs prioritize engagement over accuracy, reinforcing cognitive biases and filter bubbles (Zarouali et al. 2021).

It has also been noted that the virality of misinformation is often driven by its novelty and emotional intensity, which are favored by RAs . Arda and Başarır (2024) describe this as a "post-truth" condition where emotional resonance replaces factual accuracy as the metric of truth. This has been supported by observational and experimental work that has demonstrated that social media posts and news containing moral and emotional language spread quickly online. The latter, thus pointing to another relevant facet in misinformation online studies, which is the role of human behavior.

A 2015 study conducted with 40 Facebook users indicated that 62% of those users were entirely unaware of any curation, believing instead that every single story from their friends and followed pages appeared in their news feed (Fernandez et al. 2024).

While the role of recommendation algorithms in shaping users' information flow is undeniable, the spread of misinformation cannot be fully understood without considering the human behaviors that interact with these systems. User cognition, emotion, and sharing practices are deeply entangled with how content gains visibility and credibility online. As such, the next section discusses the human dimension of misinformation spread, focusing on individual-level factors such as cognitive biases, motivations, and the psychological appeal of misleading content.

2.1.2.2 User behavior, exploring the human dimension of misinformation spread online

Algorithms can facilitate or constrain the flow of information by displaying a small set of available information and further recommending more information that users might be interested in (Shin and Valente 2020). In these recommendations, information can be truthful or not, therefore understanding what drives users in sharing misinformation remains crucial to improve online platforms. The way social media disseminates information plays an important role in how users interact with it.

According to Sundar et al, 2024 , users have become more spontaneous and less deliberate when sharing social media content, a byproduct of the rushed nature of online interactions. This has lead to the phenomenon of "shares without clicks", where users consider superficial cues such as the headline and/or number of likes without perusing the actual contents of a news story. For example, research by Camarero Calandria et al. (2022) about university students in Honduras shows that young people face significant challenges when dealing with online information. 89% of students that were surveyed reported confidence in their skills navigating information online on social media platforms, yet 2% actually demonstrated the ability to effectively select or identify reliable online content. The data also reveals that 80% of youth click on the first search result, 70% trust content based on who shares it, and 50% struggle to distinguish between information and advertising.

Many studies have also critiqued different aspects of how information is presented in online contexts, for example, studies carried out on social media platforms like Facebook or Twitter pose that information flows from multiple sources with different levels of trustworthiness. Social media's streamlined design obfuscates and confuses users concerning the actual information source (Kang et al., 2011; Tandoc et al., 2018). Users can then believe be inclined to believe satirical posts or misinformation if it appears alongside legitimate news content.

In addition to how information is presented, users can have difficulties verifying the veracity of the information online because they are cognitively reluctant to conduct critical analysis of information and news, especially if its of no relevance to them (Bordia et al., 2005; Rapp, 2016). This has lead to the belief that users fall into believing misinformation usually for a lack of reasoning.

What is also relevant to the discussion of why users could share misinformation online that had been mentioned earlier is the presence of filter bubbles. Social media allows individuals to choose what type of content to view a lot more than traditional media sources, leading to RAs promoting content that would reinforce users' views and opinions (Lazer et al., 2018; Sunstein, 2018). In an environment or country where news outlets and information tend to be politically polarized, studies have shown that filter bubbles not only reinforce existing political viewpoints but also tend to propagate misinformation (Tornberg, 2018 and Del Vicario et al. 2016). Despite the relevance of these issues, the development of a specific framework to understand how these interactions impact the spread of misinformation online is yet to be established. Ideally, it would also study what factors or incentives exist to share misinformation, or content that is not completely reliable.

As such, although without a concrete framework, the latter has been studied, and some cognitive factors have been found to help explain the sharing of misinformation. For example, social biases have proven to be relevant to the study of misinformation spread, i.e. information that comes from friends or accounts users know or follow, tend to have a bigger impact on users. The same can be said for cognitive biases, specifically confirmation bias where users tend to be believe information that aligns with their already held beliefs (Fernandez et al 2024), regardless of their accuracy.

Scholars have also identified several message-based and social factors that drive sharing behavior, including emotional appeal (Berger & Milkman, 2012; Valenzuela et al., 2019), the perceived ability of content to spark discussion (X. Chen et al., 2015), and its thematic relevance to the user (Berger & Milkman, 2012). Additionally, users may share content to entertain, express themselves, help others, or signal affiliation with a group (Chadwick et al., 2018; Osmundsen et al., 2021). These motivations highlight that engagement with misinformation often occur not because of value of truth attributed to the information, but for reasons having to do with social and emotional interactions.

Pennycook et al. (2021) argue that accuracy frequently becomes secondary to social and emotional factors, leading users to share content without critically evaluating it. This further reinforces the conceptual boundary between misinformation and disinformation: the former is rooted in unintentional spread driven by everyday social interaction, while the latter involves calculated deception. Understanding these distinctions is essential for developing effective interventions, particularly in environments where trust in media is already eroding.

2.1.3 Counter measures to mitigate misinformation

Due to the complexity outlined regarding the misinformation landscape, it stands today that countering misinformation, and its spread remains equally complex. Researchers have studied various forms of debunking, counter checking and literacy mechanisms to counter misinformation, all with varying degree of effectiveness, complexity and adoption.

2.1.3.1 Leveraging tech to counter misinformation

Currently literature highlights technical systems to counter misinformation, specifically AI based solutions. These focus on automated solutions for detection, tracking and prevention of misinformation. These measures however can create an “arms race” whereby as detection systems evolve, so can “malicious actors”.

An example of this type of approach involves algorithm-based strategies, where systems are developed to detect problematic content prior to its publication. A notable example is the use of Curb algorithms, which are designed to identify potentially misleading or harmful information before it is uploaded onto social media platforms (Luthfia et al., 2025). Another method that is being explored is the use of blockchain technology to ensure the veracity of online content. Blockchain provides a decentralized and tamperproof log to authenticate sources by recording original information on secure ledgers. In doing so, it creates a system that verifies the legitimacy of information at its origin, thus making it harder to manipulate or distort primary sources of information (Luthfia et al., 2025). It does not however prevent, misinformation being created or spread, rather it focuses on the traceability of it.

Artificial Intelligence (AI) has been increasingly proposed as a measure to detect and mitigate the spread of misinformation on social media. AI systems offer a promising avenue to tackle a problem that evolves faster than traditional fact-checking or human moderation systems can keep up with (Niazi et al., 2024). Because of its computational capabilities it allows for the identification of patterns commonly associated with misleading content. For this reason, researchers have suggested that artificial intelligence, being detached from the emotional and cognitive limitations of human decision-making, could provide an objective and consistent mechanism to detect misinformation, thereby reducing the risk of personal bias (As pointed out by Mark Zuckerberg).

Despite its potential, AI solutions are not without limitations. One of the primary concerns relates to algorithmic bias, AI systems are only as neutral as the data on which they are trained, furthermore, AI models can struggle to accurately interpret satire, irony, or context-specific language, leading to potential misclassifications of legitimate content Moreover, although AI is designed to scale, the sheer volume of data produced on social media daily often outpaces the system's ability to provide real-time interventions, reducing its overall effectiveness. These challenges suggest that while AI presents a compelling technological solution, its implementation must be paired with ongoing evaluation, human oversight, and ethical safeguards to ensure it serves as a reliable tool in the broader fight against misinformation (Saeidnia et al, 2024).

2.1.3.2 Fact-Checking Approaches: Debunking and Prebunking

A number of studies have documented that correction is one of the most effective strategies for addressing misinformation (Walter and Murphy,2018). The most common method to date, is debunking misinformation after it has been spread. A method of course that doesn't prevent misinformation from existing or being spread, rather mitigates its effects and counters it by providing truth after the fact. Recently though, prebunking has garnered attention as a more effective way to counter misinformation.

Many studies such as those by Pennycook & Rand, 2022, have confirmed that prebunking can curb misinformation spread on topics like healthcare, climate change and other political issues. It works by alerting individuals and users of why a source of information may not be completely informed and in this way impacting its spread before it occurs (Shin, 2024). Pre-bunking is further supported by Kim et al, 2019 who argues that users tend to evaluate online news more critically when they suspect that its quality might be low. In this regard, encouraging users to more carefully examine news or information sources already nudges them towards a more critical inspection about information online and with it diminishes the possibility of sharing misinformation (Nekmat 2020).

Another concept in the literature that helps understand user fact checking or flagging content online is the third-person effect. This theory proposes a dual mechanism: first, individuals tend to perceive information as having a greater influence on others than on themselves, this is referred as the perceptual component and this perception, in turn, motivates behavioral responses aimed at mitigating perceived negative consequences of media exposure. The gap between perceived effects on the self and others becomes particularly relevant when the content in question is viewed as socially undesirable, such as aggressive online discourse or cyberbullying (Chen & Ng, 2017; Ho et al., 2019). Given that misinformation is often framed as a form of harmful content (Mitchell et al., 2021), several recent studies have examined the third-person effect specifically in relation to misinformation and its spread (Chung & Kim, 2021; Jang & Kim, 2018). Within this framework, user concerns about misinformation are understood not only as cognitive assessments of media credibility, but also as affective responses shaped by perceived threats to others. In this way the third person effect is seen as complementary process to understand what motivates users to fact check or support government regulation over digital platforms.

Correction warns individuals of the negative influence of misinformation (van der Meer and Jin, 2020), prevents people from being exposed to misinformation (Tan et al., 2015) and helps individuals change their inaccuracies and accept correct information (Nyhan et al., 2020). Consequently, Talwar et al. (2020) suggested that online users should engage in corrective actions to avoid the spread of online misinformation. While extant research has indicated that ordinary people should engage in corrective actions to debunk misinformation (Margolin et al., 2018), most studies have only focused on utilizing expert sources to address misinformation (Bode and Vraga, 2018; Vraga et al., 2020). Recently, some scholars have utilized the TPE to examine ordinary people's misinformation debunking behaviors; however, they only focused on how the perceptual gap of misinformation influences between others and self affects support for media censorship (e.g. Jang and Kim, 2018). In this light the effect that TPE might have in everyday interactions remains understudied.

These however, are not the only mechanisms in place to counter misinformation. Increasingly, it has been shown that the large amounts of information users are exposed to does not necessarily translate to an increase in knowledge or critical thinking (Islam et.al, 2020). In fact, studies have shown digital literacy competencies can increase discernment between general information flows and misinformation (Anthonysamy, L., & Sivakumar, P. (2024).

2.1.3.3 Literacy to counter misinformation

Several studies have highlighted the importance of digital literacy to increase the detection of fake news and misinformation among social media users. Guess et al. 2020, in an experimental treatment supports the conclusion that higher digital literacy skills improve judgement fake and real news. Similarly Vraga and Tully (2021), determined that digital literacy increases users' skepticism about information found online.

Initial results on such studies indicate that while general algorithmic awareness (an understanding of the existence of algorithms) is increasing (Klawitter & Hargittai, 2018), individuals lacking this awareness may be disadvantaged, as due to missing out on important information deprioritized by algorithms (Rainie & Anderson, 2017). Furthermore, individuals with higher levels of algorithmic literacy may benefit more, creating a new digital divide (Gran et al., 2021). This divide aligns with established digital divide and inequality frameworks (Reisdorf & Blank, 2021), underscoring the disparities in how individuals engage with and understand algorithm- driven systems.

Correction warns individuals of the negative influence of misinformation (van der Meer and Jin, 2020), prevents people from being exposed to misinformation (Tan et al., 2015) and helps individuals change their inaccuracies and accept correct information (Nyhan et al., 2020). Consequently, Talwar et al. (2020) suggested that online users should engage in corrective actions to avoid the spread of online misinformation. While extant research has indicated that ordinary people should engage in corrective actions to debunk misinformation (Margolin et al., 2018), most studies have only focused on utilizing expert sources to address misinformation (Bode and Vraga, 2018; Vraga et al., 2020). Recently, some scholars have utilized the TPE to examine ordinary people's misinformation debunking behaviors; however, they only focused on how the perceptual gap of misinformation influence between others and self affects support for media censorship (e.g. Jang and Kim, 2018).

With the rise of social media, online users are empowered to actively engage in correcting online misinformation (e.g. reporting misleading information to warn others of potential hazards). Therefore, the current study utilizes the TPE theory in order to bridge the abovementioned research gaps and to examine whether TPP of COVID-19 misinformation exists, as well as how TPP affects people in terms of engaging in corrective actions.

2.1.3.4 Addressing non-epistemic motivations

In addition to cognitive and educational interventions, recent research has emphasized that some individuals refrain from sharing misinformation not because they identify it as false, but because of non-epistemic motivations tied to self-image and social consequences. Altay et al. (2020) found that concerns about personal reputation often discourage individuals from spreading false content, with participants stating they would only share misinformation if there were tangible incentives such as payment. This aligns with Duffy et al. (2019), who observed that many users expressed regret after realizing they had unknowingly shared inaccurate information. These findings suggest that reputational concerns and self-image play a non-trivial role in regulating misinformation spread. In contrast to disinformation, which is typically shared with full awareness of its falsehood, misinformation is often disseminated through routine, socially motivated behaviors, not necessarily intended to mislead.

2.1.4 Algorithmic Literacy

To navigate the increasingly algorithm-driven social media landscape, users must thus understand how content is curated, ranked, and disseminated across digital platforms. Social media users should understand, at least in broad terms, how the content in their feeds is curated and how it might influence them. Through the years, skills related to finding, consuming, evaluating, and creating media content have been studied under the umbrella of media literacy. Building on this foundation, concepts like computer literacy, digital competence, information literacy, new media literacy, and social media literacy (Festl, 2021) have emerged, highlighting the cognitive, technical, and emotional skills needed to navigate modern information and communication technologies effectively.

2.1.4.1 Definitions

In the information landscape research has shown 4 key dimensions to literacy in this domain, those being news, media, digital and information. How these are explained varies depending on literacy, being a concept of ability or of cognitive awareness in some cases. News literacy mostly refers to critical thinking skills to determine how reliable news and information are. Media literacy refers to people’s ability to analyze and more importantly create information for specific outcomes. Digital literacy on the other hand can be understood as the skills and competences needed to navigate an increasingly complex information ecosystem. While information literacy has been generalized as the ability to obtain, understand, and use information in all its forms (Apuke et al, 2023).

Building on these concepts, a newer area of research has begun to focus on algorithmic literacy, specifically, how people understand the algorithms that filter and prioritize information, for example a Scopus search on algorithm* PRE/1 litera* yields 1050 results as of 2025. Driven by the newness of the field, as well as the varied landscape information has, some researcher has classified it as part of artificial intelligence literacy (Archambault, 2023), in some other cases it overlaps with terms like media literacy or digital literacy (Cohen, 2019; Dogruel, 2021).

Various definitions can be found, in addition to similar terms (i.e. media literacy, digital literacy, information literacy), algorithmic literacy can be roughly understood as the awareness or ability to critically evaluate algorithmic decision- making, as well as an understanding the social and ethical implications from its use (Head et al, 2018). Despite its novelty, frameworks exist to analyze algorithmic literacy, such as the Oeldorf-Hirsch and Neubaum framework which discusses three dimensions of algorithmic literacy. It is conceptually built from previous literature and captures a more inclusive definition of algorithmic literacy by defining it through the lense of a cognitive dimension, an affective and a behavioral one (Oeldorf-Hirsch and Neubaum, 2023).

Research has also suggested that students' algorithmic literacy skills were too low (Brodsky et al., 2020; Head et al., 2020; Koenig, 2020; Powers, 2017). Other studies have suggested that students' research habits made them vulnerable to algorithmic ranking and filtering. For instance, when students looked for outside sources, they favored the top search results from search engines and clicked on higher-ranked results, even if those results were less credible or relevant (Bhatt & Mackenzie, 2019; Wineburg & McGrew, 2017). Also, students lacked confidence in their ability to distinguish fake news from real news (Head et al., 2018).

Algorithmic literacy has emerged as a crucial component of digital literacy, particularly in societies where misinformation poses a significant challenge. While some studies have examined algorithmic literacy in high-income nations, research remains scarce in Latin America, where structural inequalities shape access to digital education and media literacy programs (Gran, Booth, & Bucher, 2021).

Studies on digital divides indicate that lower-income countries face considerable challenges in fostering algorithmic literacy due to disparities in education, internet access, and exposure to critical digital literacy programs (Reisdorf & Blank, 2021). In countries such as Brazil and Mexico, research has shown that limited digital literacy contributes to higher susceptibility to misinformation, particularly among young social media users (Aruguete & Calvo, 2020). Similar concerns arise in Honduras, where formal algorithmic literacy education programs are virtually nonexistent, leaving citizens particularly exposed to algorithmically curated misinformation without the tools to critically evaluate it (Rodríguez-Pérez et al., 2023).

This necessity highlights the growing importance of algorithmic literacy, which extends beyond traditional media literacy by focusing on how algorithmic processes influence the visibility and credibility of online information.

2.2 Theoretical Framework

To examine how individuals respond to misinformation in algorithmically curated environments, particularly in contexts marked by digital inequality, this study draws on three complementary theoretical frameworks: algorithmic literacy, the third-person effect (TPE), and digital inequality theory. Together, these models provide a multidimensional lens through which user behaviors—such as flagging content or supporting content regulation—can be understood. Algorithmic literacy explains the internal capacities users possess to recognize and respond to platform dynamics; TPE introduces the motivational drivers that may prompt action even in the absence of full technical understanding; and digital inequality theory offers the structural backdrop that shapes access, skills, and trust in information systems. This integrated framework allows for a more nuanced understanding of both the individual and systemic factors that influence corrective engagement with misinformation in the digital age.

2.2.1 The Oeldorf-Hirsch and Neubaum framework

In recent years, a growing body of literature has contributed to the understanding of algorithmic literacy as a multidimensional concept, emerging from various strands of media studies, communication research, and human-computer interaction. One of the more integrative approaches to date is proposed by Oeldorf-Hirsch and Neubaum (2023), who offer a 3 tiered categorization of algorithmic literacy comprised of cognitive, affective, and behavioral components. Their framework stems from an extensive review of the empirical and theoretical research developed in response to the increased presence of algorithmic systems in everyday digital environments.

Oeldorf-Hirsch and Neubaum (2023) conceptualize algorithmic literacy as comprising three interrelated dimensions: cognitive, affective, and behavioral. The cognitive dimension pertains to *knowing*, it includes users' understanding, awareness, and factual knowledge about how algorithms function and influence digital environments. The affective dimension involves *feeling*, it thus captures individuals' emotional responses to algorithmic systems, such as their ability to sense, develop aversion to, or appreciate algorithmic processes and their implications, in this way it belies the earlier dimension by necessitaing users to know algorithms are there and what they do. The behavioral dimension focuses on *doing*, it includes the skills and actions users take to engage with or influence algorithmic systems, such as adjusting settings, flagging content, or managing their data footprint.

Crucially, the authors emphasize that algorithmic literacy is not a fixed or universal competency, but rather one that is inherently context-dependent and platform-specific. It develops through users' situated experiences within particular technological environments and is shaped by socio-cultural, infrastructural, and institutional factors. As such, the framework advocates for a more nuanced and reflexive approach to studying algorithmic literacy, one that moves beyond simplistic measures of right or wrong knowledge and instead recognizes the complexity of users' interactions with opaque algorithmic systems.

Their framework, draws on earlier categorizations, such as Swart's (2021) model of "knowing, feeling, and doing," and Lomborg and Kapsch's (2020) adaptation of encoding/decoding theory, the authors seek to provide a more holistic account of how individuals interact with algorithmically curated media. Rather than limiting algorithmic literacy to awareness alone, the model emphasizes that emotional responses and observable behaviors must also be accounted for to fully grasp how people understand and navigate the environments shaped by algorithms.

Dimensions of algorithmic literacy.

Figure 2: Oeldorf-Hirsch and Neubaum (2023)

This visual illustrates the three dimensions of algorithmic literacy, cognitive, affective, and behavioral. Each of them progresses through subcomponents: knowing (e.g., awareness, understanding), feeling (e.g., sensing, appreciation), and doing (e.g., engaging, skills). It emphasizes that algorithmic literacy involves not just awareness and knowledge, but also emotional responses and practical interactions with algorithms.

While early studies primarily focused on whether users understood that algorithms curated their content, meaning the cognitive dimension of the framework, recent research has begun to explore how individuals behave in response to that knowledge. As such, algorithmic literacy is increasingly seen not only as a cognitive capacity but also as a practical competence. This includes the ability to modify one's digital behavior in response to algorithmic feedback, to exploit or resist platform logics, and to actively engage with or bypass algorithmic filtering mechanisms (Swart, 2021a; Lomborg & Kapsch, 2020). These patterns of engagement reflect an evolving relationship between user agency and algorithmic governance, where users do not passively receive content, but rather interact with systems in ways that shape the content they encounter.

The behavioral dimension of algorithmic literacy therefore encompasses the various practices through which individuals engage with and influence algorithmic systems. This includes both unconscious feedback mechanisms, such as liking, sharing, or clicking on content, as well as more deliberate strategies aimed at shaping recommendations or circumventing certain types of content exposure (Cotter, 2022).

Users, for instance, may attempt to "train" the algorithm by engaging with specific content types, or in the case of content creators, adapt their publication schedules and formats to align with perceived algorithmic preferences (Siles & Meléndez-Moran, 2021; Ma & Kou, 2021). These behaviors are often guided by what researchers call algorithmic folk theories, or informal, experience-based assumptions that users develop to interpret and predict how algorithmic systems function. While not always accurate, such theories influence meaningful decision-making, such as assuming that liking or commenting on certain posts will increase their appearance in future feeds (DeVito et al., 2017; Eslami et al., 2016).

These behavioral expressions of literacy are also deeply linked to questions of control and platform affordances. Studies suggest that users are more likely to act strategically within algorithmic systems when they believe they can influence over the visibility and type of content they receive (Dietvorst et al., 2018; Simpson et al., 2022). Conversely, when users lack this sense of control, they may disengage from the platform or experience what some have called "algorithm aversion." In this regard, behavioral algorithmic literacy is not only a reflection of user competence and skills, but also of platform transparency, trust, and the perceived legitimacy of algorithmic systems.

Importantly, behavioral responses to algorithmic systems are not universal but shaped by individual goals, identities, and contexts. While some users may engage in evasive practices to preserve their privacy, others, like influencers or activists may experiment with algorithmic features to optimize visibility or engagement. This highlights that behavioral literacy is normative, rather than prescriptive. It acknowledges the diversity of user strategies, each rooted in personal values, social conditions, and media goals (Dienlin & Metzger, 2016; DeVito, 2021).

A particularly relevant aspect of behavioral algorithmic literacy relates to user responses to misinformation. While algorithmically literate users may possess the technical and cognitive skills to assess content credibility, this does not always result in active engagement through platform tools such as flagging, reporting, or content verification. Research shows that users frequently express concern about misinformation, but rarely translate that concern into action, especially when it involves effortful practices like verifying sources or flagging content as misleading (Oeldorf-Hirsch & Neubaum, 2023; (Swart 2023). When such actions do occur, they are often inconsistent and dependent on personal motivation, perceived responsibility, and the broader sociotechnical context. The gap between cognitive understanding and behavioral response thus underscores the importance of viewing algorithmic literacy not merely as an awareness of systems, but as a disposition toward meaningful, critical action in algorithmically governed spaces.

In sum, the behavioral dimension reveals that algorithmic literacy is not a static skillset but a dynamic practice that is shaped by user and platform interactions. It encompasses both intentional and habitual forms of engagement, reflecting the ways users learn to navigate, manipulate, or resist algorithmic systems over time. As such, accounting for algorithmic literacy, in its behavioral dimension is essential to understanding how individuals operate within digital environments, particularly in contexts where formal algorithmic education is lacking and critical media competencies are unevenly distributed.

It is also relevant to point out that Oeldorf-Hirsch and Neubaum's is not the only frameworks that exist about algorithmic literacy, though still a growing field, some efforts have been to distinguish and analyze this emerging literacy field.

Aspect	**Oeldorf-Hirsch & Neubaum (2023)**	**Zarouali et al. (2021)**	**Dogruel, Masur & Joeckel (2021)**
Structure	Three dimensions: cognitive, affective, behavioral	Four dimensions: 1) awareness of content filtering, 2) awareness of automated decision-making, 3) awareness of human-algorithm interplay, and 4) awareness of ethical considerations.	Two dimensions: awareness and knowledge. Acknowledgement of other dimensions given, but not explored thoroughly: critical evaluation, coping strategies, and creation and design skills.
Focus	Understanding how users perceive, feel, and act in response to algorithmic systems	Assessing multidimensional algorithmic literacy for critical platform engagement	Measuring algorithmic awareness and interaction outcomes

Origin/Intent	Descriptive and user-centered; grounded in observed user behaviors and media interaction theory	Normative; aims to define competencies necessary for informed interaction with algorithms	Analytical and measurement-focused; aims to operationalize awareness
Use of Emotion	Explicit affective dimension; includes trust, anxiety, comfort with algorithms	Includes ethical perceptions such as fairness and transparency concerns	Includes perception of consequences but not focused on emotional reactions
Behavioral Emphasis	Strong focus on everyday platform practices and feedback loops (e.g., clicking, liking, shaping feeds)	Emphasizes ethical and responsible usage rather than micro-behaviors	Includes interaction behaviors but not as expansive or detailed
Awareness	Awareness is one component (cognitive); not sufficient alone for literacy	Awareness treated as the foundational dimension, leading to more complex competencies	Combines subjective awareness and objective knowledge
Goal	Explain real-world algorithmic navigation; promote critical and reflective use	Develop comprehensive scale for measuring algorithmic literacy across populations	Enable cross-population comparisons and capture awareness gaps

Table 1: Differences in Algorithmic Frameworks

Sources: Author's own creation, using the works of (Oeldorf-Hirsch and Neubaum 2023), (Dogruel et al. 2022), and (Zarouali et al. 2021).

The table above compares the frameworks found that help explain the current approaches to study algorithmic literacy. While they all attempt to explain how users engage with algorithmic systems and RA's, there are some key differences worth highlighting. Oeldorf-Hirsch and Neubaum (2023) find a user centered model that emphasized how users perceive, emotionally respond to and act within algorithmically curated environments. This is presented in contrast to Zarouali et al 2021 whom offer a framework identifying four dimensions necessary to critically engage with social media platforms. They furthermore also include ethical considerations, and the need for understanding of the structure of algorithmic curated environments. The most streamlined model comes from Dogruel 2021, that is heavily focused in awareness and knowledge. Although they acknowledge additional literacy components such as evaluation and coping strategies, these are not systematically incorporated into their framework.

Given the goals of this study the Oeldorf-Hirsch and Neubaum (2023) framework is particularly well suited. Its descriptive, practice-oriented design enables an examination of not only what users know about algorithms, but also how they behave in relation to them. Unlike the other two models presented, this framework is grounded in how users actually perceive, and act in algorithmically mediated environments, making it ideal for analyzing real-time decisions like flagging, sharing, or ignoring misinformation**.**

While the Oeldorf-Hirsch and Neubaum (2023) framework offers a robust account of how individuals understand, emotionally relate to, and behave within algorithmically curated environments, it remains primarily focused on users' intrinsic capacities, meaning it relates to what they know, how they feel, and what they do in response to algorithmic systems. However, these internal characteristics alone may not fully explain why users choose to take specific actions, such as flagging misinformation or ignoring questionable content. To capture the motivational dimension behind such behaviors, the Third-Person Effect (TPE) provides a relevant complement. TPE introduces an external social-psychological driver: the belief that others are more susceptible to harmful media effects than oneself. This perception can prompt individuals to take corrective actions not necessarily out of technical competence or personal concern, but from a protective impulse toward others. In this way, while algorithmic literacy explains how and why individuals are capable of acting within algorithmically curated environments, the Third-Person Effect (TPE) offers an external motivational lens. It helps explain why individuals may engage in corrective actions like flagging misinformation even without fully understanding how algorithms work.

2.2.2 Third-Person Effect

The third-person effect (TPE) theory suggests that individuals perceive information as more influential on others than on themselves, which in turn, influences their behavior and decision-making. This effect consists of two components: perceptual (underestimating media influence on self and overestimating it on others) and behavioral (taking actions to counteract perceived negative impacts). For instance, people may advocate for media censorship or regulations to protect those they see as more susceptible to harmful influences (Perloff, 1999).

Research has applied TPE to various online domains, including internet content, social media platforms, and user comments. In the realm of fake news, stronger third-person perceptions have been linked to decreased support for media regulation (Jang & Kim, 2018). Studies have also shown that individuals perceive others as more affected by cyberbullying and by Facebook content, although such studies often blend content and platform effects (Riedl et al. 2022).
TPE predicts two types of actions in response to perceived media influence:

- Corrective Actions: These individual-level actions involve countering potentially harmful media effects, such as leaving comments warning about bias, sharing counter-information, or exposing problems in media content (Chung, 2023)

- Restrictive Actions: These societal-level actions focus on solutions like censorship or regulatory interventions. For example, in the context of misinformation, concerns about algorithm-driven content amplification, misuse of user data, and lack of platform transparency have driven calls for social media regulation (Chung, 2023).

This study will attempt to apply TPE theory to examine whether people perceive algorithms as influencing themselves and others differently and to explore whether these perceptions drive support for corrective actions, government regulation, or content moderation. Rather than diminishing the explanatory dynamic of algorithmic literacy, the inclusion of the Third-Person Effect (TPE) provides a psychological complement that helps describe the motivations behind user behavior in algorithmically curated environments. Algorithmic literacy, specifically its behavioral dimension, captures the user's capacity to understand and navigate recommendation systems. However, capacity and/or skills alone do not necessarily translate into action as described earlier.

TPE introduces a motivational mechanism: individuals who perceive misinformation as a greater threat to others than to themselves may be more likely to take corrective steps such as flagging, reporting, or verifying content. In this way, TPE does not replace algorithmic literacy but may intensify its behavioral expression, particularly in cases where users recognize the influence of algorithms but are moved to act by a perceived need to protect more vulnerable audiences. This layered interaction is especially useful in explaining why users may engage in corrective behaviors even when their understanding of algorithmic systems is partial, intuitive, or based on folk theories rather than technical accuracy.

In addition, the use of TPE is enhanced when applied to contexts where algorithmic literacy is low or unevenly distributed, such as in many developing countries. In these settings, digital divides often result in individuals perceiving others, especially those with limited formal education or rural backgrounds, as more susceptible to misinformation. This perception activates the core mechanism of the TPE: users may see themselves as less vulnerable, yet still feel a social or moral obligation to mitigate harms that might befall their communities. As such, flagging and fact-checking behaviors can emerge not from knowledge, but from protective instincts rooted in collectivist norms and community responsibility. In environments where institutional trust is fragile and formal mechanisms for regulating information are weak, this bottom-up policing of content becomes especially significant. Here, the TPE offers a valuable lens for understanding why and how users with limited algorithmic knowledge may still engage in practices typically associated with digital competence. By integrating both algorithmic literacy and TPE, this study seeks to provide a more comprehensive account of user agency in the mitigation of misinformation online.

2.2.3 Digital Inequality Theory

Digital inequality theory (van Dijk, 2020) underscores disparities in access, skills, and outcomes related to digital tools. It provides a valuable framework for examining the algorithmic divide, emphasizing how socio-economic and demographic factors shape individuals' access to algorithm-driven technologies and their understanding of these systems, which can influence their vulnerability to misinformation.

Traditionally, studies on digital divides have focused on inequalities in internet access, computer availability, and practical digital skills, such as browsing, navigating, and content creation, as well as usage patterns like email, social media, and entertainment. These studies have primarily examined practical digital skills and concrete usage benefits in daily life but have yet to measure algorithm awareness as a distinct component of the digital divide on a national scale or, considered the digital divide as a wider issue of study.

However, in the context of the Global South this framework is insufficient. The divide must be reframed to incorporate not only infrastructural disparities but also sociopolitical, cultural, and epistemic inequalities that shape how individuals interact with digital environments.

By contrast, the literature in the Global South remains limited, despite the pervasiveness and severity of misinformation there.2 This evidence gap is especially important because interventions that effectively reduce misinformation in the Global North may perform differently in the Global South due to differences in factors such as news consumption, media literacy, state capacity, etc.

Recent literature, such as the report "Researching and Countering Misinformation in the Global South," expands our understanding of the digital divide by emphasizing that digital literacy is not a universally transferable skillset but a specific practice. In developing countries, users often engage with digital content through social heuristics and trust networks rather than formal media verification methods. This is shaped by limited access to data, reliance on mobile connectivity, and an ecosystem dominated by algorithmically curated platforms like Facebook and WhatsApp.

Moreover, the structural design of global platforms often marginalizes users in developing countries. Misinformation moderation strategies are typically not localized thus lacking context-sensitive algorithms, language support, and region-specific content moderation.

Trust also emerges as a crucial variable. In low-trust environments like Honduras, fact-checking initiatives may be viewed as partisan or unreliable. As such, even when users are exposed to correct information, they may disregard it if the source lacks perceived credibility. This necessitates a reconceptualization of digital literacy to include not just technical skill, but also sociocultural awareness, critical thinking, and institutional trust-building.

Lastly, the digital divide in Honduras is compounded by intersectional inequalities. Gender, geography, and socioeconomic status continue to shape access to both digital infrastructure and critical digital skills. For example, rural users and women may face disproportionate challenges in developing algorithmic literacy, making them more vulnerable to misinformation or digital exclusion.

These structural inequalities underscore the importance of examining not just access to technology, but also the capacity to navigate and critically engage with it—what scholars have termed critical or behavioral algorithmic literacy. In contexts like Honduras, where infrastructural and educational gaps limit exposure to formal digital literacy training, understanding how individuals learn to interact with algorithmic environments becomes vital. It is not merely the presence of digital tools that matters, but how users interpret, respond to, and act within these environments. Therefore, the present study not only situates itself within the broader literature on algorithmic systems and misinformation but also seeks to extend it by focusing on the behavioral responses that arise within unequal digital landscapes. This approach foregrounds the importance of individual agency, while acknowledging the systemic conditions that shape, and often constrainit.

Although existing research has explored the role of algorithmic systems in shaping users' exposure to information, and although various studies have emphasized the protective role of algorithmic literacy against misinformation, the relationship between algorithmic literacy and specific corrective behaviors, such as fact-checking or flagging misleading content still remains underexamined. Specifically, the behavioral dimension of algorithmic literacy, which concerns how individuals interact with and respond to algorithmically curated environments, has received limited empirical attention. While models such as the framework proposed by Oeldorf-Hirsch and Neubaum (2023) identify behavioral engagement as a core component of algorithmic literacy, few studies have examined whether such engagement translates into meaningful action in response to misinformation. This is especially relevant in settings where digital inequalities persist and algorithmic systems are poorly understood, such as in Latin America. The present study addresses this gap by investigating whether individuals with higher levels of behavioral algorithmic literacy are more likely to verify information or flag problematic content. In addition, it considers the role of the Third-Person Effect (TPE) as a moderating mechanism that may intensify this relationship by motivating users to act not only out of personal concern, but in response to the perceived threat that misinformation poses to others; in addition to providing a reasoning to why users with limited or inaccurate understanding of algorithms may still act to counter misinformation when they perceive it as harmful to others.

3 Methodology/Research Design

3.1 Methods literature review

A well conducted literature review is a crucial component of any academic work. It lays a solid groundwork for building new knowledge, supports the development of theoretical frameworks, identifies saturated areas of study, and highlights gaps where further research is necessary. This section will outline the methodological approach to conduct the literature review, as well as the inclusion of the theoretical concepts in this study. This followed a structured concept focused approach to carrying out the literature review according to Webster and Waston (2002).

The literature review for this study was conducted in a sequential and exploratory manner, shaped by the evolving focus of the research. The process began by identifying and defining misinformation, distinguishing it from related terms such as disinformation, malinformation, and fake news (Altay et al., 2023; Adams et al., 2023; Guess & Lyons, 2020). In doing so literature about information studies, journalism and mass communication were used to identify these distinctions and develop a sound foundation to specify the analysis. Concepts most relevant to the study's focus on unintentional inaccuracies were retained (Wardle & Derakhshan, 2017; Lim, 2023); in this way, misinformation stands out as counterpoint to other definitions that include a specific intent in their description. This initial step involved examining philosophical, epistemological, and communication-oriented definitions to establish conceptual clarity.

Next, attention shifted to the mechanisms through which misinformation spreads, particularly in digital environments. Here, literature found dated back to the early 2000s when social media platforms, especially Facebook started being used more widely. As the sophistication of these platforms evolved so to did the literature around it, thus showing a high level of attention to recommendation algorithms (RAs), in addition to other topics such as platform design and structure, which for this research were not considered. Another trend found when focusing on misinformation spread was user behavior, key factors that shape it, together they highlight the socio-technical complexity of the problem (Fernandez et al., 2024; Vosoughi et al., 2018; Sundar et al., 2024).

After defining misinformation, and understanding how it became prevalent in social media, the next logical step was to investigate countermeasures, or ways to halt or mitigate the spread of misinformation. Here, most recent literature referenced technological means, highlighting the advent of emerging technologies and their possibility and research to detect and track misinformation. Furthermore, to two other key literatures surfaced: (1) interventions such as debunking, prebunking, and fact-checking, and (2) psychological theories explaining user motivation that include confirmation biases, the effect of echo chambers in user behavior, in addition the Third-Person Effect (TPE) Perloff (1999), Jang and Kim (2018), and Chung (2023) were identified as particularly relevant.

The most significant part of the review revealed the existence of algorithmic literacy and how it could counter misinformation. The term came through the analysis of literacy interventions, which are vast and varied, terms such as, information, AI, news, media, new media, communication, data, social media, technology and digital literacy were all concepts found in literature. To focus the scope of what was chosen in the research a special emphasis was placed on definitions and conceptualization that were general enough to encompass a broad definition of literacy in relation to information. Thus, providing a baseline to build upon in describing and understanding algorithmic literacy.

Most studies addressing this topic were based in high-income or Global North contexts, prompting a targeted search for research conducted in developing regions, particularly Latin America (Gran et al., 2021; Rodríguez-Pérez et al., 2023). This highlighted a significant gap in understanding how algorithmic literacy manifests in settings affected by digital inequality.

Lastly, to frame the relationship between algorithmic literacy and misinformation behaviorally, a review of existing frameworks for algorithmic literacy was undertaken. This resulted in the review of framework that analyze structurally what algorithmic literacy is, and what dimensions should be considered when referencing it. Eventually selecting the Oeldorf-Hirsch and Neubaum (2023) model for its strong behavioral emphasis and user-centered orientation. In doing so, the theoretical concepts used in this study were able to be built, where Oeldorf-Hirsch and Neubaum (2023) provides the behavioral link between literacy and countermeasures to misinformation, namely flagging, fact-checking and support for government intervention. The Third Person Effect provides a motivational amplifier relevant to explain external incentives for countermeasure, and an alternative explanation of users behavior even if literacy levels are not high. Lastly, the inclusion of the Digital Divide and Inequality theories provide a context or backdrop for this study and addresses the gap in research found.

The literature search was conducted using academic databases including Google Scholar, Scopus, and LIMO (the KU Leuven Library search engine). Key search terms included combinations of “misinformation”, “algorithmic literacy”, “recommendation algorithms”, “third-person effect”, “digital inequality”, “fact-checking”, “prebunking”, “debunking”, and region-specific terms such as “Latin America”, “Central America”, and “Honduras”. Despite the extensive scope, the search revealed a scarcity of research focused on Honduras or Central America more broadly, particularly in relation to algorithmic literacy. Studies that addressed algorithmic understanding in low- and middle-income countries were especially limited, indicating a pressing need to expand the literature in these contexts.

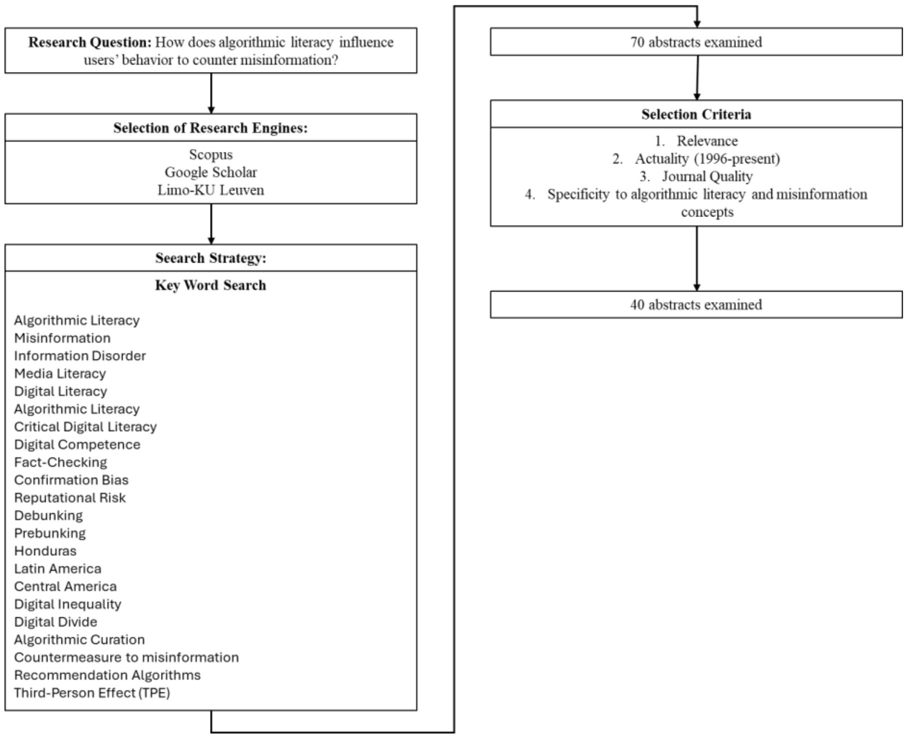


Figure 3: Prisma Chart

This iterative and layered review strategy enabled the integration of diverse literatures, supporting the construction of a robust, multidimensional theoretical framework grounded in behavioral, psychological, and socio-structural perspectives.

3.2 Research Design

This study employs a mixed-methods approach, integrating experimental design, qualitative analysis, and comparative assessment to carry out an exploratory research design to investigate the behavioral dimensions of algorithmic literacy and its implications for misinformation among university students in Honduras. The selection of university students in Honduras as a case study is due to their significant digital engagement, high exposure to misinformation, and the broader implications of algorithmic literacy for misinformation resilience in developing countries. Algorithmically curated content plays a crucial role in shaping digital consumption behaviors, often amplifying misinformation (Pennycook & Rand, 2019). However, algorithmic literacy remains an understudied factor in Latin America. This research, therefore, seeks to fill this gap by examining how algorithmic literacy influences fact-checking behaviors and support for regulation among university students in Honduras, with implications for algorithmic literacy education, digital policy, and social media governance.

3.2.1 The Case for Honduras

Several studies have highlighted the unique vulnerabilities of Latin American digital users in this regard. Research indicates that misinformation spreads widely on social media platforms such as Facebook, Instagram, TikTok, and Twitter (X), where content is promoted based on engagement rather than accuracy (Resende et al., 2019). In Latin America, young adults are particularly susceptible to misinformation due to high rates of mobile internet usage and reliance on social media as a primary news source (Rodríguez-Pérez et al., 2023). Furthermore, studies suggest that many users consume news passively—often reading only headlines without verifying sources—which exacerbates the impact of algorithmically amplified misinformation (Graves, Nyhan, & Reifler, 2016).

Central America is a region characterized by digital inequalities that influence how citizens engage with online platforms and information. More importantly, research has showed that the region lacks critical digital engagement, literacy campaigns and programs are inconsistently implemented, and tend to focus on the technical skills needed to use online platforms and information. Similarly, research addressing these issues is also sparse (Carballo 2024).

The choice to focus this study on Honduras responds to a growing body of evidence positioning the country as a hotspot for digital misinformation and lack of literacy programs addressing algorithmic curated environments, despite the use of these in the genral society. The reach of TikTok, which has recently overtaken other platforms with 4.5 million active accounts in a country of just over 10 million people (Honduras Verifica, 2024a). Despite its popularity, the platform remains largely unregulated in the region and is algorithmically driven in ways that remain opaque to most users.

Public perception studies reinforce these concerns. According to a national study reported by HCH (2023), a significant portion of the Honduran public struggles to distinguish between false and legitimate news, often attributing misinformation to political motives or media sensationalism. The public's skepticism toward both government and traditional media is further validated by findings from SwissInfo (2023), which highlight that the government and political elites are perceived as the primary sources of misinformation in the country.

Further compounding this issue is the concentration of misinformation production among political and institutional actors. A comprehensive investigation published by the Association for a More Just Society (ASJ) found that government institutions and political parties are perceived as the main sources of misinformation, responsible for 48.4% and 39% of false content, respectively(SwissInfo, 2023). This manipulation of public opinion is particularly acute during election cycles and public health crises, where misinformation not only distorts public understanding but undermines democratic processes. As ASJ emphasizes, the lack of effective regulatory frameworks and transparency mechanisms renders the country especially vulnerable to the weaponization of information (ASJ, 2024).

Recent research has also identified Honduras as the nation in Latin America with the highest investment in political propaganda on Facebook, a platform that continues to be widely used in the national information and social media ecosystem (Honduras Verifica, 2022). Moreover, 60% of all recorded misinformation in 2023 originated on social media platforms, underscoring the central role of algorithmically curated environments in shaping public discourse (Honduras Verifica, 2023a).

This challenge is heightened by weak media verification practices: a 2023 investigation revealed that only 3% of Honduran journalists regularly use fact-checking techniques, leaving audiences more vulnerable to the spread of unchecked or manipulated content (Honduras Verifica, 2023b). While civil society initiatives, such as Honduras Verifica's fact-checking workshops, which have trained over 85 journalists and human rights defenders, represent important steps forward (Honduras Verifica, 2023c), yet structural problems persist in the broader information landscape, and it is important to not these type sof literacy campaign are fairly recent.

In this context, Honduras offers a compelling and underexplored setting for examining how users interpret, engage with, and potentially counter misinformation in algorithmically mediated spaces. The prevalence of digital platforms, the intensity of political information warfare, and the relatively low level of institutional media literacy support make it an ideal case for investigating how algorithmic literacy, and perceived susceptibility to misinformation, shape user behavior in environments of high informational uncertainty.

3.2.2 Sample Selection

University students represent a particularly relevant demographic for studying algorithmic literacy and misinformation spread. They are among the most active digital users, relying extensively on social media for news consumption and communication (Hargittai et al., 2020). However, their engagement occurs in environments where algorithmic ranking systems prioritize sensationalist and emotionally charged content, which often includes misleading or false information (Guess, Nyhan, & Reifler, 2020).

In the Honduran context, media consumption patterns further reinforce these risks. Research on gender-based misinformation in Honduras highlights how students often struggle to critically evaluate digital content, particularly when it reinforces existing biases or sensational narratives (Camarero Calandria et al. 2022). Furthermore, research available notes that findings of literacy interventions the Global South are mixed, with some evidence that literacy works but only among populations with high baseline literacy and education levels (Camarero Calandria et al. 2022). This underscores the urgent need to assess whether algorithmic literacy influences fact-checking behaviors in this population, as misinformation consumption without critical engagement can reinforce cognitive biases and misinformation susceptibility. Given these vulnerabilities, Honduran university students represent a critical demographic for analyzing how algorithmic literacy impacts fact-checking behaviors within a developing country context.

3.2.2.1 Sampling Method

A purposive sampling strategy was utilized, with a focus of selecting participants that engage in social media, with a basic unserstanding how social media content works. This non probabilistic method was chosen because its suitability for exploratory research, where the goal is to gain in-depth understanding rather than statistical generalizability. This method is appropriate for capturing a broad spectrum of viewpoints relevant to the study's objectives. Furthermore, the exploratory character of the research necessitates the deliberate selection of individuals capable of offering substantive insights into the topic (Jain, 2021).

3.2.2.2 Sample Size

The sample comprised 21 participants, aligning with qualitative research standards that emphasize the importance of depth over breadth in exploratory studies (Sathyanarayana S, 2024). Guest et al. (2006) demonstrated that data saturation, where no new themes emerge, often occurs within the first 12 interviews in relatively homogeneous populations. Similarly, Boddy (2016) argues that even small samples, including those with fewer than 30 participants, are acceptable in qualitative research, especially when the focus is on depth and conceptual insight rather than statistical generalization. Hertzog (2008) further supports the use of small sample sizes in pilot and exploratory research, noting their value in refining instruments and identifying patterns. Furthermore, adding to the semi-experimental layer of the research, the sample chosen allows for a rich, context-sensitive understanding of algorithmic literacy and misinformation engagement without compromising methodological soundness.

3.2.3 Data Collection Procedure

This section will describe the data collection process used, both instruments that were developed and what basic underlying theories or literature helped in their development. It is important to note that since this study focuses on students from Honduras, both instruments created were translated to local language, i.e. Spanish by the author. This helps broaden and ease the selection criteria for students willing to participate, and also provides a more familiar and real context, that will contribute to findings particularly in regard to the second instrument which is the mock content feed.

3.2.3.1 Pre-Session Survey (Baseline Assessment)

The study begins with a short pre-task questionnaire designed to establish a baseline understanding of participants' algorithmic literacy, beliefs about misinformation, and self-reported behaviors on social media. Pre-task surveys are widely used in misinformation research to control for pre-existing biases and individual differences in information processing (Pennycook & Rand, 2019). It was structured in four sections: demographics, algorithmic literacy and perceived influence, fact-checking behavior, and support for regulation.

The development of this survey insturment aligns with the theoretical frameworks and literature presented earlier. The survey includes:

Demographics
This section collects essential background information such as age, education level, field of study, and frequency of social media use. These variables help contextualize participants' responses and the inclusion of technology engagement frequency is particularly relevant given the study's focus on algorithmic environments.

Algorithmic Literacy and Perceived Influence
This section draws on the Oeldorf-Hirsch and Neubaum (2023) framework to measure cognitive and perceived aspects of algorithmic literacy, including understanding of recommendation systems, platform mechanisms, and critical evaluation. Notably they do not provide a specific way to measure algorithmic literacy, rather a lens to understand it through. Therefore, other interventions aimed at measuring algorithmic literacy, specifically its cognitive dimension which revolves around awareness and knowledge (Zarouali et al. 2021), (Dogruel et al. 2022), (Brodsky et al. 2020), (Koenig 2020) (Fouquaert and Mechant 2022).

To gauge this, question types developed were: My social media feed is only influenced by my interactions (e.g., likes, shares, clicks), (1) I know how to adjust my algorithmic recommendations on social media, (2) Social media platforms use algorithms to decide what content appears on my feed, (3) I understand how social media companies profit from algorithm-driven content. Participants were asked to respond how much they agreed to these questions on a Likert -scale, 1 = Strongly Disagree, 2 = Disagree, 3 = Nor agree nor disagree, 4 = Agree, and 5 = Strongly Agree. Questions also gauge how participants perceive the algorithmic literacy of others, capturing both self-assessed knowledge and third-person perception. This dual focus helps assess both awareness and relative confidence in interpreting algorithmic influence.

Fact-Checking Behavior and Perceived Influence
This section assesses behavioral responses to misinformation, such as verifying news credibility before sharing, and the heuristics used to evaluate content. It also explores perceptions of peer behavior, which ties into the Third-Person Effect (TPE) by comparing self and other judgments. The variety of factors listed enables analysis of how participants navigate credibility in practice. Some of the questions included are: (1) Have you ever verified the credibility of news before sharing it? (2) Do you think your peers verify the credibility of news before sharing it?, (3) When deciding whether to trust online news, which of the following do you consider?

Support for Regulation and Perceived Influence
This section evaluates participants' attitudes toward institutional and platform-based interventions, including regulation, transparency, and user education, building up on previous research such as Chung 2023. It also includes perceived societal support for these measures, reflecting the behavioral and perceptual dimensions of the TPE. These items provide insight into how algorithmic literacy and perceived misinformation risks translate into policy preferences. These were also analyzed with a Likert-scale 1 = Strongly Disagree, 2 = Disagree, 3 = Nor agree nor disagree, 4 = Agree, and 5 = Strongly Agree. Some of the questions included were: (1) The current measures taken by platforms to combat disinformation are sufficient, (2) New measures are needed to curb online disinformation, (3) Social media platforms should be responsible for moderating false or misleading content and (4) The state should require platforms to cooperate with authorities on disinformation issues.

This survey was developed in Google forms, and was shared with the participants during the online session in Google Meets, through which all the data collection would be carried out. Participants were thanked for their time followed by a brief explanation of the session proceeding, first the survey, later a think out loud protocol about content online presented to them, followed by a reflective time afterward. Participants were given the link and asked to share any questions about the content or assesments. Following this step, we moved to the second part of the data collection which involved the mock content feed.

3.2.3.2 Mock Content Feed

A central component of this research design is an interactive, mock content feed used to simulate an everyday digital environment. This method builds upon prior studies that utilize controlled simulations to study user behavior in relation to misinformation (Roozenbeek & Van der Linden, 2019; Guess, Nyhan, & Reifler, 2020). However, this study adapts the methodology to the Honduran context, both in terms of interface design, language, and thematic relevance, ensuring validity and cultural resonance.

To validate the mock content feed used in the semi-experimental portion of the study, a preliminary test was conducted with three university students that also fit the criteria for actual participants in the study. This pretest served to assess both the realism and usability of the simulated environment. Based on their feedback, several adjustments were made to enhance authenticity and user engagement. For example, participants suggested adding visible comment sections to each post, and have language be reflective of how people expressed themselves in online platforms. Since actual commenting was not enabled, a placeholder feature stating “Register to comment” was introduced to mimic typical platform behavior. Additionally, although the simulated nature of the environment was initially disclosed, participants reported that the inclusion of interactive elements such as timestamps, likes, verification badges, and visual profiles contributed to a realistic experience. Other informal feedback included suggestions to vary post content to enhance ambiguity, and to delay disclosure that the environment was simulated, as this could influence participant behavior. This mirrors research by Abilov et al. (2021), which highlights how interface familiarity can shape trust and interaction behaviors.

Their feedback confirmed that the environment was immersive enough to elicit authentic user responses, which strengthened its suitability for studying behavioral dimensions of algorithmic literacy and misinformation engagement.

Participants are presented with eight posts, each designed to mimic the appearance of typical social media content encountered on platforms like Facebook. The posts span two types of informational quality:

- Real news from credible local sources (e.g., Honduran law enforcement or international agencies). Here two types of posts were made, one that reflected a real news, that was taken from a local news source and placed in the mock content feed, these were two posts. And another type of post, that reflected potentially trending topics, that would present in a users feed because of RAs, these were two posts.

- Misinformation, often lacking sourcing or attribution, 4 posts.

The result of this process was a mock content feed that replicates common features of social media platforms. This feed included typical interaction elements such as reaction buttons (e.g., likes, emojis), timestamps, and share counts, along with user profile pictures that were created providing prompts to ChatGPT, and names to mimic authentic engagement. Posts were also accompanied by comments from fictitious users, including varied reactions and tones to reflect a range of plausible public responses. Some accounts displayed verification badges to enhance the perceived credibility of the source, and the visual design incorporated standard layout structures, such as branded headers, post formatting, and call-to-action prompts (e.g., "Comentar", comment, "Compartir", share and, "Reportar" report/flag). These elements were intentionally included to ensure validity, encouraging participants to engage with the feed in a naturalistic manner and assess how algorithmic literacy influences behaviors such as content flagging, trust evaluation, or sharing.

To facilitate the observation of corrective behaviors, particularly content flagging, the "Reportar" (flagging**)** option was made prominently visible in the mock feed interface. Unlike real-world platforms where reporting features are often hidden behind dropdown menus or three-dot icons in less accessible corners of the post, this version deliberately placed the flagging button directly beneath each post. This design choice aimed to reduce the friction involved in identifying and using the reporting function, ensuring that participants were aware of the option and could engage with it. Making the flagging function more prominent allowed the study to better capture intentional corrective behaviors and assess the influence of algorithmic literacy in enabling such actions.

To exemplify this process, below provides actual misinformation feed participants interacted with and had to assess. We provide a detailed description:

Header/Source: The post is made by an unofficial and unverified page named "Noticias Viral HN" with a red-and-white logo, suggesting a viral news outlet from Honduras. It is labeled as posted "Hace 6 h" (6 hours ago) and is "Público" (Public) — mimicking real Facebook post visibility.

Headline: The post claims, "Toda Honduras se quedará sin energía este lunes por apagón nacional" *(Translation: "All of Honduras will be left without power this Monday due to a national blackout")*. This dramatic and misleading claim sets up the scenario for assessing user reactions to misinformation, as typically while Honduras does suffer from power cuts they are announced by the National Electric Power Company, and accompanied by scheduled times when the power cuts will happen, as well as the specific residential areas where these will occur.

Image: A professional-looking photo shows a candle next to a fallen lightbulb, symbolizing a blackout. The overlaid text reads: "Cortes de energía eléctrica en Honduras" *(Translation: Electric Energy cuts in Honduras)* with the source "tu nota" — a fictional or ambiguous source, adding to the realism and ambiguity of the post's legitimacy.

Reactions: Shows 32 people reacted, with emoji icons that resemble Facebook's reaction buttons. This gives a sense of social proof and engagement.
Shares: 55 veces compartido (*55 times shared*), implying high levels of engagement, an important cue in misinformation studies.

User Comments: Oscar V. Puente: Says *"Otra vez apagones, a preparar las velas." ("Blackouts again, time to get the candles ready.")* This comment implies belief in the post and passive resignation. Joel B.: Says *"Acabo de comprar helado… justo ahora pasa esto 😂." ("I just bought ice cream… and now this happens 😂.")* This reaction is more humorous but also suggests acceptance of the claim.

Figure 4: Sample of Mock content feed

As such, and following with the example provided above, each post addresses themes informed by prior research on misinformation and media consumption in Honduras:

Post #	**Post Title**	**Type**	**Justification**
1	DNVT confiscates 3,500 licenses; 155 accidents during Holy Week	Real News	Traffic safety and Holy Week incidents are recurrent public concerns, often featured in national media due to their relevance to safety in the country.
2	Pope Francis called all women neurotic	Misinformation	Reflects religious authority misrepresentation, a recurrent form of disinformation in Latin America, leveraging Catholic figures for virality considering its the predominant religion in Honduras (Siles et al. 2023).
3	Honduras will lose power this Monday	Misinformation	Exploits public frustration over electricity shortages, a persistent problem tied to national

			infrastructure and often used to generate panic (Mejía 2025).
4	Illuminati captured in Honduras	Real news: Algorithmic Bias (possible sponsored content)	Taps into conspiracy theories popularized by entertainment culture, serving as clickbait.
5	Only the rich: the first Cybertruck arrives in Honduras	Real news: Algorithmic Bias (possible sponsored content)	Targets class resentment and aspirational consumerism; appeals to emotion and identity signaling.
6	Yani Rosenthal and Nasralla secretly negotiate power deals	Misinformation	Mirrors known political disinformation trends in Honduras, especially during election seasons (Amado Suárez 2022).
7	WHO: Honduras will have 531 million obese people by 2030	Misinformation	Mimics scientific or health data but with implausible figures, reflecting a common strategy to fabricate credibility (Herrera and Orellana 2024).
8	Traffic monitors social media to detect violations	Real News	Factual reports about surveillance practices, an emerging issue in digital rights discourse in Honduras.

Table 2: Descripion for topic selection in Mock Content Feed

This mock feed not only tests the participants' ability to discern informational integrity but also replicates the algorithmically mediated environments in which such content circulates. Posts vary in engagement metrics (likes, comments) and visual layout, which serves to test the role of interface cues in trust and judgment, phenomena repeatedly observed in the Honduran digital landscape, where users often rely on heuristic shortcuts such as branding or popularity to evaluate credibility.

Participants were shared a link to the mock content feed and given the follwoing instruction through this script that ws followed with all participants:

"Thank you for completing the survey. For the next step, I will ask you to follow the link shared in the chatbox and review the content presented. Please reflect on how you would typically respond to this type of post. Would you share it, react to it, fact-check it, comment, report/flag it, or simply ignore it? After making your choice, I kindly ask that you explain your reasoning on what aspects informed your decisions."

As participants scroll through the feed, they are asked to choose different courses of actions for each post. These responses allow the study to capture the spectrum of user behavior, from passive consumption to proactive counteraction. Moreover, they reflect the diverse ways in which misinformation may be reinforced or mitigated based on individual choices, digital confidence, and contextual understanding.

In addition to recording these actions, participants are asked to verbalize their thoughts in real time using a think-aloud protocol (Ericsson & Simon, 1993). This method is critical for unpacking the reasoning, heuristics, and emotional cues behind user behavior, especially in a country where internet penetration has increased and trust in institutions still plays a pivotal role in shaping users' engagement to information.

Originally, after the participants had gone through all the content presented to the, the protocol was to follow a semi-structured interview with some probing question to gain more depth and richness into their decision making. However, it was found, and will be discussed further in the Results section of this study, several participants were unable to identify misinformation, and thus prior to carrying out the interview an additional protocol was followed. Where participants were prompted in the following way: *Thank you for your valuable input. This exercise has been very insightful. I should now let you know that some of the posts you just reviewed contained misinformation, meaning, false or inaccurate information shared without the intent to mislead. Could you go back through the posts and try to identify which ones you believe are true and which are not?*

Following this second review of the content, it is worth noting that all participants were debriefed about which posts contained misinformation and which did not. This ensured that ethical standards were upheld, particularly those relating to transparency and the mitigation of any potential harm caused by exposure to false content. Following the simulation, a semi-structured debrief interview is conducted with each participant. Sample questions include:

- How did you find the experience of going through this feed?
- Are you familiar with tools to report or flag misinformation?
- Were there any posts you thought were clearly false? Why?
- What do you usually do when something seems questionable online?

These post-task reflections serve to validate and deepen the interpretation of user responses by exploring self-perceived digital competence, moral reasoning, and critical awareness of algorithms. They are particularly important in the Honduran context, where the digital divide intersects with broader socio-political dynamics, such as media polarization, religious influence, and low levels of institutional trust.

In sum, the simulated feed offers a controlled yet realistic environment for studying misinformation-related behavior in a country where algorithmic curation, structural inequality, and polarized discourse converge to complicate users' ability to distinguish fact from fiction.

3.2.4 Data Analysis Approach

To analyze the qualitative data from interviews and think-aloud protocols, a thematic analysis approach (Nowell et al. 2017) was employed using a combination of deductive and inductive coding. Initial codes were informed by the study's theoretical framework, including concepts such as cognitive heuristics, third-person perception, and algorithmic transparency. This guided the development of a codebook, which was then iteratively refined based on close readings of the transcripts.

The deductive codes included the following categories:

- Privacy Concerns and the Social Costs of Interaction

- Perceptions of Sensationalism in Journalism
- Sharing as a Form of Social Responsibility
- Platform and Source Skepticism
- Heuristics and Interface Cues
- Differentiation Between Public and Private Sharing
- Generational Contrast and Third-Person Perception
- Avoidance and Fatigue
- Contextualization of Misinformation

Coding was conducted using NVivo, enabling the clustering of excerpts, comparison across demographic groups, and co-occurrence analysis to explore interrelationships between themes.

In addition, a comparative analysis will be conducted by examining the relationship between participants' self-reported algorithmic literacy and attitudes from the pre-survey, and their observed behaviors during the mock news feed simulation and follow-up interviews. This will explore differences in fact-checking behavior, variations in engagement with misinformation, different levels of trust in digital platforms (Rodríguez-Pérez et al., 2023).

Descriptive Statistics (Supporting Analysis)

- Although the study is primarily qualitative, basic quantitative measures will be used to support the analysis, including:
- Frequency of fact-checking, sharing, and ignoring behavior.
- Time spent on different post types.

This mixed-methods approach allows for a more comprehensive understanding of misinformation-related behaviors by integrating self-perceptions from survey data with observed actions and contextual reflections captured through the simulation and interviews (Creswell & Plano Clark, 2017).

3.2.5 Limitations

Self-Reported Measures of Literacy

The categorization of algorithmic literacy was based on participants' self-assessment through Likert-scale responses. While useful for capturing perceived literacy, this approach may not accurately reflect actual knowledge or practical skills. Indeed, discrepancies observed between reported competence and observed behavior suggest that self-perception may be inflated or imprecise, particularly among moderate-literacy participants. Future studies should consider integrating objective knowledge tests or behavioral performance tasks for more accurate classification.

Artificiality of the Mock Newsfeed Exercise

Although the experimental simulation of a newsfeed allowed for controlled observation of user behavior, it cannot fully replicate the complexity of real-world digital environments. In actual social media platforms, variables such as emotional involvement, algorithmic personalization, social endorsements, and cumulative exposure may exert stronger influence. The brief and decontextualized exposure in the study may have underestimated or misrepresented participants' typical responses to misinformation.

Temporal Constraints and Prebunking Effects

Participants' awareness that they were part of a study, combined with the structured questioning after initial exposure, may have induced a "prebunking effect," in which critical awareness was temporarily heightened. While this supports the idea that anticipatory reflection can influence user behavior, it also raises concerns about ecological validity: would similar cognitive shifts occur without researcher prompts or outside experimental settings?

4 Results

This chapter presents the findings of the study based on the two primary data collection instruments: the structured survey and the semi-experimental mock content exercise. Results are organized by instrument to highlight distinct insights derived from participants' self-reported algorithmic literacy and observed behavior in response to curated content. Quantitative results from the survey capture participants' beliefs, confidence, and prior engagement with algorithmically mediated content, while the mock content feed task provides behavioral data on their ability to identify, interpret, and interact with real and false information. Comparative analysis across both instruments is used to identify patterns, inconsistencies, and relationships between self-reported literacy and actual engagement with misinformation.

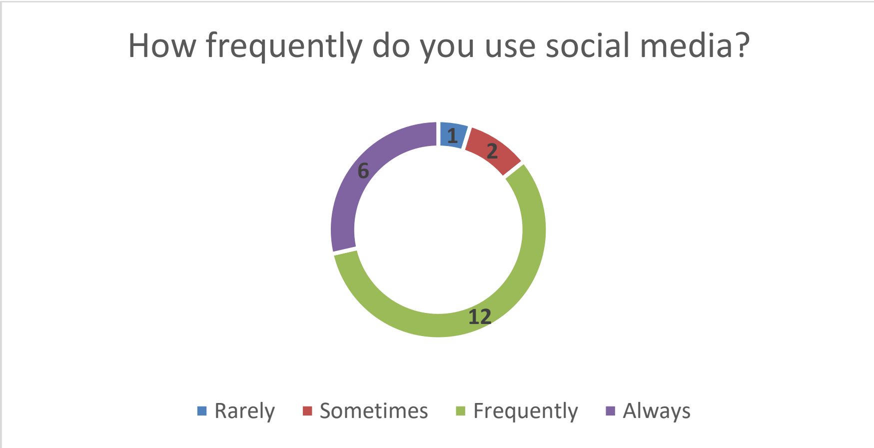
4.1 Descriptive Analysis of Survey Results

An important component of this research relates to a survey administered to a sample of 21 participants, composed primarily of undergraduate students pursuing degrees in economics, mathematics, and related disciplines. The objective of the survey was to gather insights into participants' perceptions of algorithmic literacy, their attitudes toward misinformation and its regulation, and their beliefs regarding individual versus institutional responsibility in the digital information ecosystem. All participants responded it, and the average time of completion was 7 minutes.

4.1.1 Sociodemographic Profile of the Sample

The respondents were young adults, ranging in age from 20 to 26, with the average among participants being 22 years old. The gender distribution was skewed toward women (N=12), and all participants reported having completed or currently pursuing a bachelor's degree. Their academic specializations were concentrated in economics and mathematics, fields that arguably promote analytical thinking and familiarity with data systems and thus should influence their competence related to the subject matter.

4.1.2 Usage of Socia Media and common news sources



Firgure 5: Frequency of Use of social media

An analysis of participants' reported frequency of social media usage reveals a predominantly high level of engagement with these platforms. As illustrated in the chart, a majority of respondents (N=12) indicated that they use social media "frequently," followed by six participants who selected "always." Together, these categories account for approximately 86% of the sample, suggesting that social media is deeply integrated into the everyday routines of most individuals surveyed. In contrast, a small minority reported more limited interaction: two participants selected "sometimes," and only one indicated using social media "rarely."

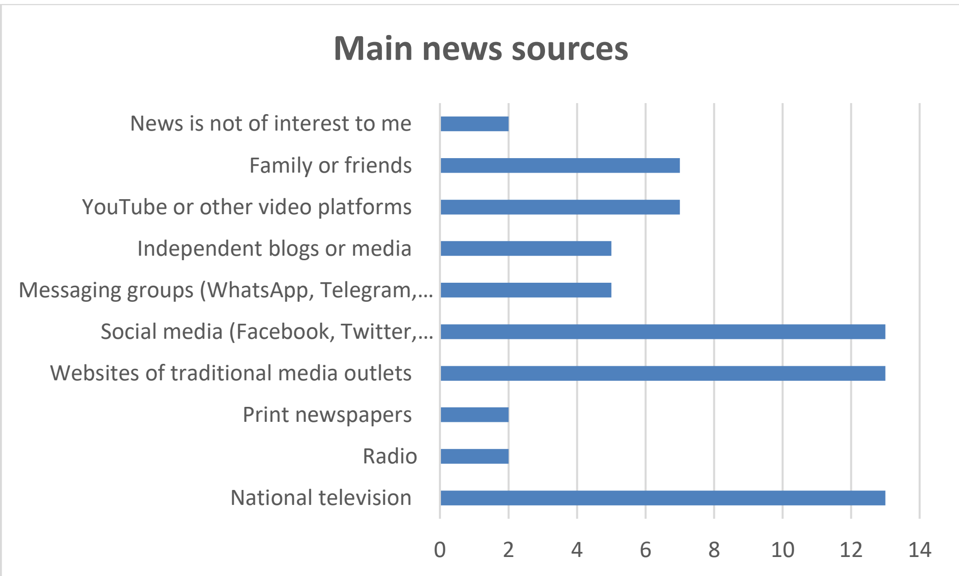


Figure 6: Main News Sources

Participants were also asked to indicate the sources from which they most commonly access news content. The responses reveal a diverse but clearly stratified media landscape, with a preference for digital and audiovisual sources over traditional print or interpersonal channels. National television emerged as the most frequently cited news source, selected by 13 participants. This was tied with sources from websites of traditional media outlets and social media platforms (e.g., Facebook, Twitter, Instagram), both also cited by 13 respondents.

YouTube and other video platforms were mentioned by seven participants, equaled by those who rely on family or friends for news. Messaging applications such as WhatsApp and Telegram, as well as independent blogs or media outlets, were reported by five respondents each. While less dominant than mainstream channels, these sources nevertheless represent alternative avenues for content exposure, particularly in the context of decentralized or user-generated information flows.

Conversely, traditional print newspapers and radio were identified by only two participants each, suggesting that these mediums hold diminished relevance for the surveyed population. Similarly, the category "news is not of interest to me" was selected by only one respondent, affirming that news consumption remains a regular practice for the overwhelming majority.

4.1.3 Reported Algorithmic Literacy

In terms of the cognitive dimension of algorithmic literacy, which relates to users' awareness of platform mechanisms, the vast majority of participants demonstrated a basic understanding of algorithmic curation. Specifically, 19 out of 21 participants agreed or strongly agreed with the statement: *"Social media platforms use algorithms to decide what content appears on my feed."* In contrast, responses to the statement *"My social media feed is only influenced by my interactions (e.g., likes, shares, clicks)"* showed more varied opinions: only 2 participants strongly agreed, 6 agreed, 8 were neutral, while 4 disagreed or strongly disagreed. This suggests that while most participants acknowledge the presence of algorithmic influence, a significant number still hold misconceptions or incomplete views about how content is curated.

More technically oriented dimensions of algorithmic literacy were also explored. In response to the item *"I know how to adjust algorithmic recommendations on my social* *media,"* 14 participants provided a positive response, indicating that over half the sample perceives themselves as having some level of control over algorithmic outputs. Similarly, 14 participants agreed that they could critically evaluate whether content was promoted by an algorithm. Notably, 18 participants—representing approximately 85% of the sample—claimed they could identify whether a piece of content was part of a misinformation campaign. These findings reflect a relatively high level of self-reported algorithmic literacy.

Finally, given the focus of TPE in this study, participants were asked if they believe others also understand how RAs work. The responses provided initial evidence of TPE as 10 participants disagreed with the statement which is almost half of the sample, while 5 agreed. Notably this question received the most nor agree nor disagree responses, with a total of 6.

4.1.4 Fact checking and perceived influence

Participants' views on misinformation and content regulation revealed a tension between institutional accountability and individual responsibility. When evaluating the role of social media companies, users and governments in combating misinformation, participants overwhelmingly supported users‘ onw responsbilities to verify information prior to sharing over govenrment regulation and media companies‘ accountability. All participants either agreed or totally agreed that users‘ have a rsponbility to verify information prior to sharing, for social media companies, 19 agreed or totally agreed that they should be accountable for misinformation being shared by RAs online. While for governments, 12 participants agred and totally agreed about heir resposniblity, while 7 are unsure. Complementary to this, respondents agreed that platforms should be legally obligated to increase transparency regarding their content curation practices and should cooperate with governmental authorities in addressing disinformation.

A strong majority expressed the belief that fact-checking mechanisms are effective in curbing the circulation of false information, and that algorithmic literacy should be prioritized within educational curricula. Interestingly, in response to whether they have ever verified the credibility of content before sharing, the overwhelming 85% (N=18), said they had, though only half these do it routinely. Once again, worth noting the level in which they believe others fact check or verify sources is not mirroring their own reported behavior, only 9 respondents believe that others check the truthfulness of content before sharing.

When probed about what factors do they consider to trust online news. Most verifiy and rely on the source of the information, and few on interactions online and verification badges.

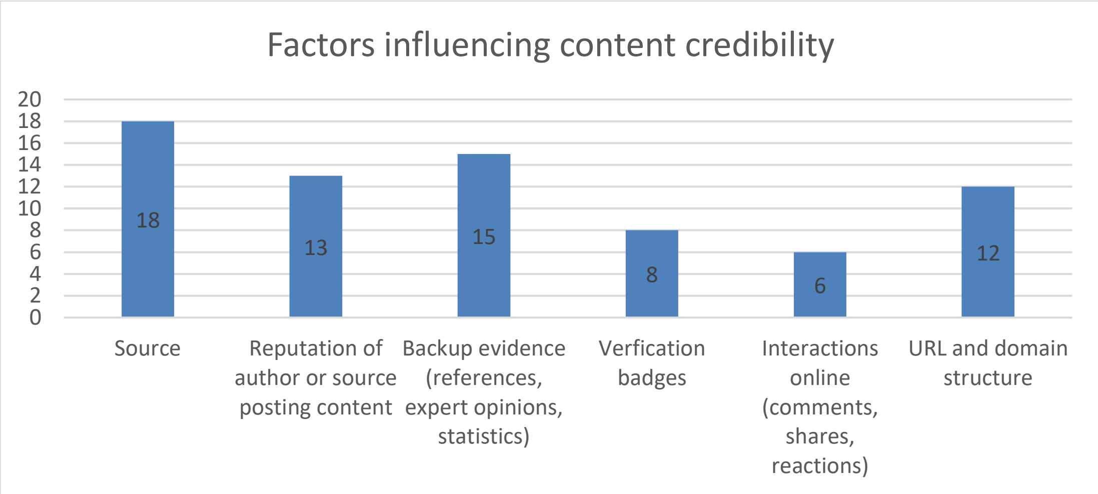


Figure 7: Factors influencing content credibility

4.2 Analysis of mock content simulation think out loud protocol and interview results

A consistent behavior observed throughout the mock content feed exercise was the use of informal verification strategies by participants to assess the credibility of posts. Many reported checking the source link, seeking visual markers of legitimacy such as logos of familiar outlets, or conducting quick online searches to cross-reference claims. For example, one respondent stated that they would "*Google it to see if any real news sites were reporting the same thing,*" indicating a proactive, albeit surface-level, attempt to evaluate truthfulness. Importantly, and most relevant to the research out of 21 participants, though any showeved various degrees of skepticism, and questioned the validity of content presented, only the participants flagged content.

Privacy Concerns and the Social Costs of Interaction

Privacy emerged as a salient concern, particularly in relation to content of a political or religious nature. Multiple participants voiced a reluctance to engage with such posts, not due to disbelief, but because of perceived social risks. One participant explained that liking or commenting on a religious post “ *This one is controversial. Nowadays everything is sensitive. You have to be really careful before sharing things like this. Some people could definitely be offended.*” with friends or relatives, while another feared that interacting with political content might result in being “profiled” or labeled.

Perceptions of Sensationalism in Journalism

Another recurrent theme was participants’ critical view of journalism as increasingly sensationalist. Several users described posts as “exaggerated,” “too dramatic,” or “made to stir emotions,” even when the underlying events were real. This perception signals a growing cynicism toward the informational quality of news encountered online, particularly when algorithmic recommendation systems privilege emotional engagement over factual accuracy. Such views were especially directed at headlines or visuals deemed overly provocative, suggesting that users are aware—at least intuitively—of the attention economy dynamics driving content visibility. However, this recognition did not always lead to disengagement; some participants expressed a simultaneous skepticism and curiosity, underscoring the complex relationship between emotional appeal and critical reflection. These findings align with existing research suggesting that sensationalism, while often criticized, remains effective at capturing attention and driving interaction, especially in algorithmically curated feeds.

Sharing as a Form of Social Responsibility

Despite widespread skepticism and caution, many participants expressed a clear sense of civic or communal obligation in their sharing behavior. Posts containing information about public health, safety warnings, or educational content were often shared “to help others,” regardless of whether the participants personally found them compelling. One respondent noted, “*I’d share it so others can be aware*,” highlighting an altruistic motivation rooted in perceived utility rather than emotional reaction or ideological alignment.

Platform and Source Skepticism

Across multiple interviews, participants demonstrated a clear tendency to judge the reliability of a post based on the platform or media outlet presenting it. For instance, when presented with a post from *Tunota*, a participant promptly noted, “*Tunota doesn’t inspire confidence,”* using platform familiarity (or lack thereof) as a primary indicator of trustworthiness. Another participant dismissed a post simply by stating, "*I don't know the site,*" without referring to the content itself. This behavior underscores the role of platform reputation as a cognitive shortcut in evaluating credibility.

Heuristics and Interface Cues

Several participants mentioned factors such as reaction counts and visual presentation as part of their decision-making process. One participant remarked that a post "only had 15 reactions," suggesting this low engagement was a reason not to trust or interact with it. Others associated design quality or the presence of specific icons with credibility.

Differentiation Between Public and Private Sharing

Participants frequently expressed a clear distinction between content they would engage with publicly versus privately. Posts with political or religious undertones elicited particularly cautious responses. One interviewee explained that while they might believe a post, they would not interact with it publicly for fear of being "profiled" or triggering conflict among friends and family. Another stated that they might "share it on WhatsApp," but would avoid commenting or liking it on open platforms. This selective behavior reflects a strategic navigation of social and algorithmic visibility: users appear acutely aware that public interaction may carry reputational risks, particularly in polarized or sensitive topics. It also highlights a dynamic where truth or usefulness is secondary to social safety, suggesting that engagement is not merely a matter of belief but of calculated visibility management.

Generational Contrast and Third-Person Perception

An overarching theme in many responses was the idea that misinformation is primarily a problem for "others," especially older generations. For example, one participant noted, "*I feel like people in my family, especially older folks, might believe and even share the Pope one right away.*" This statement exemplifies the third-person effect, wherein individuals see themselves as less vulnerable to influence than those around them. Participants often positioned themselves as more discerning, while describing family members as naïve or easily misled. This self-other dichotomy serves both as a defense mechanism and as a narrative of digital superiority, which may inhibit deeper introspection about one's own biases. Importantly, this perception could undermine the effectiveness of media literacy interventions if users do not recognize their own potential susceptibility.

Avoidance and Fatigue

Some participants exhibited a form of disengagement with the newsfeed, particularly with repetitive or emotionally charged content. One participant dismissed a post outright by stating, “I wouldn’t even look at it,” referring to content about local transportation. Others mentioned that political posts were “just the same thing over and over,” signaling a fatigue with both content repetition and the emotional labor of engagement. This selective disengagement can function as a coping mechanism in environments of information overload, where the constant presence of sensationalism breeds apathy.

Contextualization of misinformation

Another insight that emerged from the interviews was the ambiguity participants experienced in defining what constitutes misinformation. This was particularly evident in responses to a news post claiming that the transportation police were using social media to monitor citizens’ behavior, in addition to a similar post about transportation police taking away drivers license during Holy Week. Several participants dismissed the post as false, even though it linked to an official source and appeared to be factually grounded.

Sharing of “novelty” content

While it is mentioned earlier that for privacy reasons participants do not engage, i.e. like or comment, some content online. And, it is also observed that some users identified sensationalist claims and exaggerated headlines used for click baiting. A behavior somewhat in between of these also emerged wherein some sensationalists claims, in some cases, misinformation though not believed are shared as “novelty” news. Moreover, they are not shared in the platform found, but moved to others like Whatsapp, or simply treated in day to day talks with friends and family.

4.3 Results of Comparative Analysis

When considering the level of algorithmic literacy from participants and mixing them with their behavior during the interview, findings suggest that:

High Literacy, confidence anchored in competence: Participants with high reported algorithmic literacy demonstrated not only greater accuracy in identifying misinformation but also greater behavioral discipline, meaning they avoided both the sharing of false content and the misclassification of accurate posts. These individuals appear to possess not just awareness of algorithmic mechanisms but also the ability to apply that awareness in practice. The relatively low rate of false positives (M = 0.57) suggests a measured skepticism, one that avoids both over trust and overcorrection.

Furthermore, when cross checking their flagging tendencies, it is in this group where the only participants flagged fake content. In their survey responses, 2/3 indicated that they don't believe others understand how social media feeds and RAs work, nor do they believe people have the practice to fact check. Interestingly when analyzing their responses to why they assessed content to containing misinformation, not all the cases reflected a cognitive assessment; rather some other affective reactions such as: "I would report this. It doesn't align with Catholic beliefs, and it seems like they've taken it completely out of context. " or, "This one seems off… I don't really believe it. I'd probably report it. It feels like it's just trying to cause a stir."

This group likely benefits from a combination of actual knowledge, digital experience, and cognitive skill a profile consistent with findings algorithmic literacy literature, where self-efficacy rooted in genuine competence leads to more discerning content engagement.

Moderate Literacy, the overconfidence trap: The moderate group exhibited the most contradictory behavioral pattern. Although they performed reasonably in misinformation identification, they shared significantly more misinformation and showed greater difficulty distinguishing true content from false. Their elevated false positive rate (M = 0.75) and high misinformation sharing rate (M = 1.10) point to a critical misalignment between confidence and competence.

This group may be particularly susceptible over estimating their ability and knowledge. Believing they understand how algorithms function and how to critically assess content, they may act decisively but in some cases mistakenly. This finding highlights the risks of partial literacy, where awareness without depth may lead to both false confidence and increased misinformation engagement.

Low Literacy, cautious but inaccurate: Participants with low reported algorithmic literacy identified the fewest misinformation posts (M = 1.25) and had the highest rate of misclassifying true content (M = 1.75). However, they shared no misinformation, suggesting a form of informational hesitancy or digital caution. Rather than engaging with content they do not understand, these individuals may choose to refrain altogether.

This disengagement may reflect a lack of trust in their own judgment or in the platform's content, a finding that resonates with research on digital exclusion and algorithmic opacity. However, their high rate of false positives raises concern: without clear understanding, skepticism becomes blanket doubt, where even credible information is treated with suspicion.

It is important to note that all groups shared a similar behavior, in which when encountered with content that was not 100% reliable, or suggested sensational claims, most participants would simply ignore and not interact. While this was mentioned before, it is has presented itself as characteristic among all groups.

5 Discussion

This discussion interprets the findings of the study through the lens of algorithmic literacy and misinformation engagement among university students in Honduras. Drawing on data from surveys, a simulated social media task, and follow-up interviews, the results reveal complex patterns in how individuals assess, engage with, and respond to online content. While participants demonstrated varying levels of algorithmic awareness, their behaviors were shaped as much by social and emotional factors as by cognitive understanding. This section explores these dynamics in relation to the existing literature, highlighting key themes such as trust, privacy, perceived sensationalism, and selective engagement. The findings also raise important implications for algorthmic literacy initiatives and platform accountability in digitally marginalized contexts.

5.1 Survey

The survey results provide a nuanced view of how university students in Honduras engage with algorithmically curated content and misinformation. These findings are discussed through the lens of algorithmic literacy theory (Oeldorf-Hirsch & Neubaum, 2023), third-person perception, highlighting how incomplete mental models, platform skepticism, and structural constraints shape user engagement in algorithmic curated environments.

5.1.1 Reported Algorithmic Literacy

The survey results reveal that participants generally acknowledge that algorithms influence their social media feeds, suggesting some level of factual awareness, meaning that some personalization occurs. The sociodemographic profile of the sample suggests a population that is, in theory, well-positioned to critically engage with algorithmic systems. However, this knowledge often lacks specificity or is incomplete, many participants either overestimated the degree of personal control ("only influenced by my interactions") or failed to recognize the role of RAs in shaping their experience in social media platforms. This aligns directly with the procedural dimension of algorithmic literacy described by Oeldorf-Hirsch and Neubaum: users may "know that" algorithms exist but not "know how" they function or what factors shape algorithmic outcomes.

This gap is exactly what the authors identify as the central challenge in algorithmic literacy: users possess fragmented and often inaccurate mental models of algorithmic systems, which are influenced more by anecdotal experience than formal education or transparency mechanisms.

Furthermore, the findings lend support to Oeldorf-Hirsch and Neubaum's (2023) assertion that algorithmic literacy is inherently context-dependent and platform-specific, rather than a uniform or universally applicable skill set. Participants in this study demonstrated a reliance on experiential heuristics, such as source familiarity or interface cues, as strategies for evaluating credibility and making sense of personalized content. This behavior reflects a form of practical adaptation within a media environment characterized by limited transparency, infrastructural constraints, and uneven access to digital literacy education, which in turn matches the constraints found by exploring the bhevaior of univeristy students in Honduras and analyzing this against the back drop of digital divide and inquality studies. Instead of stemming from formal knowledge, these evaluations appear shaped by accumulated experience and local media habits, underscoring the situated nature of algorithmic understanding. In this regard, the survey results align with the framework's emphasis on literacy as a situated socio-technical competency, shaped not only by individual cognitive ability but also by broader socio-cultural and technological conditions.

The survey findings also demonstrate deep integration of social media into the daily routines and information habits of participants. Nearly all respondents reported frequent or constant social media use, and the most commonly cited news sources were algorithmically curated platforms or hybrid digital outlets. This high level of engagement, particularly in spaces where recommender systems prioritize content for emotional resonance or engagement metrics, aligns with concerns about exposure to misinformation, both through deliberate amplification and incidental consumption. Moreover, the broad range of cited sources, from traditional television to private messaging apps, suggests that individuals operate within fragmented and overlapping information ecologies, making consistent verification practices and trust calibration more challenging.

In terms of attitudes toward misinformation, the findings reveal a dual nature to it: participants strongly supported the idea that both institutional actors (platforms and governments) and individual users should bear responsibility for combating the spread of false information. This duality reflects a digital ecosystem or platform whereby, agency is both distributed and reciprocal. Users do not see themselves as passive consumers but as moral agents with a role to play, yet they simultaneously acknowledge the asymmetrical power of platforms and the necessity for structural oversight. Such perspectives are promising in that they support calls for both bottom-up algorothmic literacy initiatives and top-down regulatory reform. However, they also suggest that individuals may feel caught in an ambivalent position: aware of the problem, inclined to act, yet doubtful of the efficacy or transparency of the systems they rely on. The latter is further backed by some participants hinting at that during the interviews.

Importantly, skepticism toward current moderation efforts signals a declining trust in platform-led interventions. Participants' ambivalence or disagreement with the sufficiency of these measures may reflect broader disillusionment with the self-regulatory approach adopted by technology companies. In this sense, the survey results echo ongoing scholarly and regulatory debates about the need for enforceable transparency mandates, third-party auditing of algorithms, and co-regulation models that balance public oversight with private-sector innovation.

Taken together, these findings reaffirm the urgency of advancing algorithmic literacy, particularly among populations frequently immersed in digital environments yet insufficiently equipped to evaluate the systems that shape their informational realities. They also point to the necessity of framing misinformation not merely as a cognitive challenge, one of distinguishing truth from falsehood, but as a structural and behavioral problem that involves emotional labor, interface design, platform governance, and sociopolitical context. It further confirms the need for literacy interventions that focus on critical thinking, not just technical skills needed to navigate social media platforms and algorithmic curated environments.

5.1.2 Fact-Checking Behavior and Perceived Influence

The survey results reveal a complex relationship between participants' sense of personal responsibility, their beliefs about others' behavior, and their perceptions of institutional accountability in the digital information landscape. Most participants strongly endorsed the notion that individuals bear the primary responsibility for verifying information before sharing it. This aligns with the literature highlighting the growing emphasis on user-centered misinformation mitigation, where individuals are framed as frontline agents in curbing falsehoods.

However, this belief in individual responsibility coexists with considerable support for platform accountability and transparency. The majority of participants agreed that social media companies should be held accountable for the misinformation disseminated via their algorithms and should be legally required to enhance transparency and collaborate with government entities. This dual position reflects what Tandoc et al. (2018) describe as distributed accountability, where users recognize both personal and institutional roles in mitigating misinformation.

Participants also largely agreed on the effectiveness of fact-checking mechanisms and supported the inclusion of algorithmic literacy in educational curricula. Yet, when asked about their own practices, a more ambivalent picture emerged. While 85% reported having verified content before sharing, only half claimed to do so routinely. This gap between professed values and actual behavior reflects the broader knowledge–action that this research studies. The 85% that reported having verified content before sharing, might be a reflection of their awareness, of RAs or the presence of misinformation online. However, even when self-reported it is noted that little action is taken towards actively countering misinformation in the shape of fact checking.

Furthermore, the significant discrepancy between self-reported fact-checking and perceptions of others' practices, where less than half believed others verify content, suggests the presence of third-person effects. Participants appear to see themselves as more discerning than the average user, a tendency that may reduce their perceived vulnerability to misinformation while reinforcing a normative bias toward self-efficacy, which in turn could also be a reason why fact checking is not so common.

Finally, the criteria participants use to assess content credibility, primarily the source of the information rather than social signals like likes or verification badges, indicates a source-based heuristic model of trust. This is consistent with prior findings that users tend to rely on brand familiarity or perceived source expertise when judging credibility. However, such heuristics, while efficient, may limit deeper content analysis, especially when misinformation is cloaked in seemingly trustworthy formats.

5.2 Mock content simulation think out loud protocol and interview results

The simulated feed and interview data shed light on the nuanced and often contradictory ways in which individuals engage with algorithmically curated content, particularly in contexts marked by distrust, emotional saturation, and limited structural transparency. When analyzed through the lens of the theoretical frameworks reviewed in this thesis, particularly the algorithmic literacy and TPE, the findings point to several key insights.

5.2.1 Implications for Algorithmic Literacy, Informal Heuristics and Selective Engagement

Participants' behavior in the simulation also a partial and pragmatic form of algorithmic literacy, as conceptualized by Oeldorf-Hirsch and Neubaum (2023). Many relied on informal heuristics, checking sources, cross-referencing content, looking for logos or reaction counts to assess credibility. These actions represent a blend of cognitive awareness (knowing that feeds are personalized) and behavioral competence (engaging with verification cues). While such strategies are adaptive, they also reveal the limitations of users' mental models. Most participants operated with surface-level understanding and lacked deeper procedural or systemic knowledge of how content is algorithmically selected or ranked.

Similarly to the survey, this aspect of the research also supports Oeldorf-Hirsch and Neubaum's argument that algorithmic literacy is not a static skill set, but a situated, platform-specific practice shaped by habit, infrastructure, and social context. It is important to note however, that it also supports other algorithmic literacy frameworks that show users tend to form folk theories of algorithmic logic based on trial, error, and anecdotal experience. Although some participants displayed skepticism about low-engagement posts or unknown sources, indicating a degree of algorithmic literacy, this was often guided more by interface cues than by reflective critique of algorithmic governance or commercial motives, confirmation bias also had a role to play when assessing why participants believed certain contents.

5.2.2 Third-Person Perception and Externalized Risk

A consistent pattern across interviews was participants' tendency to perceive misinformation as a problem that affects others more than themselves, a hallmark of the

Third-Person Effect. This self–other asymmetry was most clearly expressed in generational contrasts, where participants framed older relatives as particularly susceptible to fake news, especially in relation to religious or politically charged posts. Importantly, this brings about the question of how third person effects might interact with literacy. If users do not perceive themselves as vulnerable, will they be less likely to reflect critically on their own behaviors, or seek to develop deeper verification mechanisms. This bias what Oeldorf-Hirsch and Neubaum (2023) describe as a failure to engage in critical algorithmic reflection—can reinforce complacency, especially in contexts where misinformation is emotionally resonant or socially divisive. In this way, TPE though originally construed as an amplifier in motivation to engage with correcting actions for misinformation, that includes but is not limited to fact checking, might be in fact doing the opposite in this specific case. Though it is important to note, as highlighted in this study earlier, lack of literacy programs and results showing participants being unaware of flagging, how it works and how to use it, might also be moderating variable to this last construct.

5.2.3 Navigating Misinformation through Emotion, Ambiguity, and Social Cues

The findings also highlight the affective and social constraints that mediate users' engagement with misinformation. Reluctance to publicly engage with political or religious content was less about disbelief and more about reputational risk or safety. Participants managed their visibility selectively, often choosing to engage privately (e.g., via WhatsApp or in some cases in private conversations) rather than publicly (e.g., via likes or comments), particularly on sensitive topics. This calculated form of interaction suggests that misinformation engagement is not merely cognitive, but deeply social and emotional, shaped by concerns over audience perception, relational tensions, and algorithmic amplification.

These behaviors reinforce the claim that addressing misinformation requires more than cognitive corrections, it also demands an understanding of the emotional labor and social negotiation embedded in digital engagement (Oeldorf-Hirsch & Neubaum, 2021). It also brings to light a relevant question about the context of developing countries, and the role this affective dimension has. Is it more relevant in developing countries than developed countries? Is it a direct results of the journalism and information landscape in Latin

America where politicized infromation outlets shape information and digital ecosystems, and thus reveals or emphasizes this other layer.

Similarly, many participants still expressed a sense of communal responsibility in their sharing practices, particularly when content related to public health or safety. This supports prior research (Pennycook et al., 2019; Tandoc et al., 2018) suggesting that altruistic motives can drive the dissemination of even unverified content if users believe it serves a useful purpose. However, such motivations do not necessarily translate into rigorous fact-checking or media critique, especially when emotional urgency or social utility override epistemic caution. This gap between perceived utility and factual accuracy complicates the idea that raising awareness alone will lead to more discerning engagement.

Some participants had in identifying misinformation, despite factual clues or official sources, illustrates the ambiguity of today's information environment. Posts that were misleading but technically true (e.g., the one about transportation police monitoring behavior online) generated confusion, highlighting the gray zones of misinformation where truth, plausibility, and manipulation converge. This underscores what Wardle and Derakhshan (2017) define as information disorder, where users struggle not only to verify content but to define what counts as misinformation in the first place. In such cases, neither algorithmic literacy nor source familiarity was sufficient to guide accurate evaluation, revealing the limits of individual discernment in complex media ecologies.

Finally, it is important to highlight that sharing misinformation or real out of the box news, can have implications within a social network, especially if it extends to those with low comtencies in online environments. What are the effects of such apparent innocent discussions, when they continue to spread among various individuals?

5.3 Discussion from comparative analysis

The comparative analysis of participants' algorithmic literacy levels and their corresponding behavior during the simulated content feed exercise reveals distinct patterns of engagement that deepen our understanding of how algorithmic literacy, or the lack thereof shapes misinformation dynamics. The minimal use of content flagging, despite widespread recognition of misinformation, further sharpens the distinctions between the high, moderate, and low algorithmic literacy groups, reinforcing how knowledge depth, confidence, and behavioral intention interact in complex ways.

High Literacy: Critical Awareness Without Procedural Action

While the high literacy group demonstrated strong discernment and avoided both misinformation sharing and misclassification, they did not consistently report or flag misleading content. This suggests a potential gap between recognition and civic engagement, reflected in earlier literature that differentiates between individual discipline and moderation, and collective action. Thus their behavior does not necessarily reflect a proactive role in platform moderation, although survey results would suggest otherwise for the majority of this group. Such a tendency may stem from skepticism toward platform efficacy, a preference for passive resistance, or simply a lack of habit in using available reporting tools.

Moderate Literacy: Confidence Without Accountability

The absence of flagging in the moderate literacy group further validates the concerns raised in the comparative analysis. Despite their higher rate of misinformation sharing, they did not attempt to correct or report problematic content, reflecting a disconnect between perceived competence and actual civic responsibility. This reinforces the overconfidence trap: individuals believe they are acting appropriately but do not question or revisit their actions, nor do they see themselves as responsible for mitigating harm. Their behavior may also suggest a lack of procedural familiarity with platform tools, highlighting how partial literacy can obscure both accountability and correction mechanisms.

Low Literacy: Cautious Engagement Without Corrective Action

Although the low literacy group shared no misinformation, they also did not flag problematic content. This aligns with their overall disengagement strategy: avoid action when uncertain. Their behavior implies a form of digital self-censorship where low confidence leads to inaction, not just in content sharing but also in corrective behaviors. This further supports the notion of epistemic paralysis, where users are overwhelmed by ambiguity and opt out entirely—not only from contributing but also from safeguarding the information space. It suggests that without procedural or civic empowerment, distrust can neutralize even protective instincts.

Finally, another relevant implication is found by participants ignoring many posts and content which they may have doubted, but didn't flag. The question behind this is whether this is detrimental or favourable to counter misinformation. Most literature suggests that a factor that allows the spread of misinformation to occur is the engagement users have with it, whether they believe it or not. And we know that RAs also gauge these interactions, and so if these help promote content, not interacting with them mitigate it? These reflections have broader implications that contrast current literature, and questions how corrective actions are measured.

5.4 Synthesizing Insights: Algorithmic Literacy, Misinformation, and Perception

This discussion chapter was structured to analyze the study's findings across three core components: the survey results, behavioral patterns during the simulated content feed, and interviews. These were each examined in light of relevant theoretical frameworks—particularly algorithmic literacy (Oeldorf-Hirsch & Neubaum, 2023), third-person perception (Perloff 1999) and broader misinformation engagement literature. The analysis moved from descriptive insights into participants' self-reported knowledge and beliefs, to observed behaviors and strategic choices, before culminating in a comparative literacy-based analysis that illuminated differences in discernment, skepticism, and civic action across the sample.

Across these sections, several key findings emerged. First, participants generally exhibited some awareness that algorithms shape their digital environments, but their understanding was often vague or incomplete. While some demonstrated competent, adaptive strategies (e.g., verifying sources or using visual heuristics), others displayed overconfidence or blanket skepticism, especially those with moderate or low levels of algorithmic literacy. Second, misinformation engagement was not solely a product of knowledge or awareness. Emotional, social, and reputational concerns played a central role in determining whether and how participants interacted with content, especially politically or religiously sensitive posts. Third, corrective behaviors such as flagging were almost entirely absent, regardless of literacy level, suggesting a systemic disconnect between recognition of misinformation and procedural or civic engagement.

So, how does algorithmic literacy influence users' behavior to counter misinformation? The findings show that algorithmic literacy has a decisive but complex influence. High algorithmic literacy correlates with more accurate content discernment and reduced misinformation sharing. Participants in this group demonstrated what can be described as "measured skepticism", or an ability to doubt content responsibly without falling into cynicism. However, even among these individuals, literacy did not translate into proactive correction; reporting and flagging were rarely used. This suggests that literacy alone is not sufficient to foster active moderation, it must be accompanied by platform trust and procedural empowerment.

In contrast, moderate literacy participants frequently overestimated their capabilities, leading to increased engagement with misinformation and poor classification accuracy. This overconfidence, highlighted in the literature as a risk of partial literacy, can be more damaging than low literacy, as it fosters confident but inaccurate behavior. Meanwhile, low literacy participants demonstrated the least engagement overall, often avoiding content or interaction altogether. While this minimized harm, it also reflected a form of epistemic withdrawal, where users disengage out of uncertainty or fear of making mistakes.

The Third-Person Effect (TPE) played a critical moderating role across all groups. Many participants believed misinformation was a problem for others, particularly older generations, and not for themselves. Contrary to initial assumptions, this self–other asymmetry undermines reflective practices and reduces the perceived need for deeper scrutiny or behavioral change. TPE thus dampens the motivational potential of literacy: even when individuals know how algorithms work or how misinformation spreads, if they see themselves as immune, they might because of over confidence be less likely to act.

In sum, this study reveals that algorithmic literacy is a necessary but insufficient condition for responsible digital engagement. It improves critical evaluation and reduces misinformation uptake, but without platform transparency, procedural familiarity, and reflexive self-awareness, it does not consistently lead to civic action. Moreover, third-person perception and emotional considerations further complicate this relationship, making clear that any intervention aimed at countering misinformation must address not just knowledge gaps, but also social dynamics, affective labor, and structural constraints.

The findings from this study, though rooted in the specific context of university students in Honduras, offer insights with potential relevance across similar digital ecosystems in the Central American region. Many of the behavioral patterns observed such as reliance on informal heuristics, ambivalence toward platform interventions, and affective barriers to engagement, are not unique to Honduras but reflect broader regional dynamics shaped by infrastructural limitations, political polarization, and distrust in legacy media.

Importantly, the affective and social dimensions of misinformation engagement, such as reputational risk, privacy concerns, and selective visibility, are likely to resonate across other digitally marginalized communities where social cohesion, cultural taboos, and platform distrust and or politization of mass media and information shape content interaction. The persistence of third-person perception (TPE) and partial algorithmic literacy further suggests that interventions designed for urban, highly connected populations in the Global North may not be directly transferable. Instead, these findings highlight the importance of designing region-specific media literacy programs that are sensitive to social trust structures, political sensitivities, and the emotional labor embedded in online participation.

6 Conclusion

This last chapter briefly summarizes the key research findings in relation to the central research question on algorithmic literacy and misinformation engagement among university students in Honduras. It then outlines the potential scalability of these insights to other digital and socio-cultural contexts. Finally, the chapter discusses the study's core limitations and proposes several directions for future research aimed at deepening our understanding of algorithmic competence, perception biases, and misinformation resilience in increasingly algorithmized information environments.

6.1 Summary

This study set out to answer the central research question: How does algorithmic literacy influence users' behavior to counter misinformation? Drawing from a mixed-methods approach involving surveys, a simulated content feed exercise, and follow-up interviews with university students in Honduras, the findings offer a multi-layered understanding of the interplay between algorithmic knowledge, digital behaviors, and socio-emotional constraints in the context of developing coutnries.

The results demonstrate that algorithmic literacy significantly shapes user engagement with misinformation, but not always in a linear or predictable manner. Participants with high algorithmic literacy displayed greater accuracy in identifying false content and exercised caution in sharing. However, even this group rarely engaged in proactive corrective behavior, such as flagging content.

Conversely, moderately literate users exhibited overconfidence in their ability to navigate algorithmic systems, leading to higher rates of misinformation sharing and false positives. Meanwhile, low-literacy participants refrained from sharing but often misclassified accurate content, pointing to epistemic insecurity and digital hesitancy. These behavioral typologies confirm the need for nuanced algorithmic literacy interventions that go beyond basic awareness and address procedural, critical, and civic dimensions.

An important layer across all literacy levels was the influence of Third-Person Perception (TPE). Many participants perceived misinformation as a problem affecting others, particularly older or less digitally literate users, more than themselves. This self–other asymmetry likely undercuts motivation to engage in countermeasures like fact-checking or flagging, reinforcing a complacent stance toward personal responsibility, rather than reinforcing previous literature suggesting it could foster and motivate corrective behavior. In developing country contexts like Honduras, where algorithmic literacy education is sparse and algorithmic systems are largely opaque, this combination of partial knowledge and perceived invulnerability presents a compounded risk.

6.2 Contribution to Literature

This thesis contributes to the growing body of work on algorithmic literacy by extending the framework of Oeldorf-Hirsch and Neubaum (2023) to a developing country context, where infrastructural, educational, and socio-cultural constraints create unique conditions for digital engagement. Introducing an empirical perspective on how TPE intersects with literacy to influence behaviors that either amplify or counter misinformation. Highlighting that literacy is not simply cognitive, but also situated and emotionally mediated, shaped by privacy concerns, social dynamics, and contextual ambiguity. This research furthermore challenges the assumption awareness automatically translates into action, thus calling for integrated literacy models that incorporate behavioral, emotional, and civic dimensions. This study also addresses a geographic and demographic gap in the literature by focusing on Honduran university students, an understudied group often excluded from global algorithmic governance and media literacy debates.

6.3 Scalability and Replicability of Research

The methodology adopted in this thesis, combining surveys, mock content feed tasks, and think-aloud protocols, provides a scalable and replicable model for studying algorithmic literacy in other contexts. The digital simulation was designed to mirror real-world interaction with social media content while allowing structured observation, making it adaptable across settings with varied platform use and literacy levels.

The use of thematically guided interviews and standardized survey questions also supports cross-cultural comparisons. Future applications could replicate the framework in other developing or digitally marginalized contexts, such as rural communities, older age cohorts, or secondary schools, to evaluate how algorithmic literacy manifests across the digital divide.

However, replicability would benefit from open-access tools (e.g., simulated feeds or evaluation rubrics), as well as collaboration with local institutions to ensure contextual relevance and ethical compliance.

6.4 **Limitations**

Several limitations should be acknowledged. For instance, the scope of platform analysis was limited. Although findings are grounded in user behavior on common social platforms, future studies could incorporate platform-specific data (e.g., backend analytics, algorithmic logs) to validate assumptions about personalization and amplification. In addition, although the study explored participants' stated intentions and behaviors, it could not fully capture private interactions, such as what they might share on closed messaging platforms or discuss offline. These "dark social" spaces, WhatsApp groups, DMs, or face-to-face conversations, are increasingly important in misinformation circulation, yet remain difficult to observe and analyze ethically.

6.4 Future Research Directions

This study opens several avenues for future inquiry, particularly in better understanding the intersection of algorithmic literacy, affective engagement, and misinformation within digitally marginalized contexts. While the findings provide a foundation for identifying key behavioral and perceptual patterns among university students in Honduras, they also raise critical questions that remain unanswered.

One important direction involves exploring the long-term impact of algorithmic literacy interventions. Future research should adopt longitudinal designs to assess whether increased literacy—through formal education or targeted training—results not only in improved conceptual understanding, but also in sustained changes in behavior, such as consistent fact-checking or increased use of reporting mechanisms. This would help assess whether the gap between knowledge and action identified in this study can be bridged over time.

The role of intergenerational dynamics in misinformation engagement also warrants closer examination. Many participants in this study externalized misinformation vulnerability to older relatives, a hallmark of the Third-Person Effect. Future work could investigate whether younger users serve as informal educators or gatekeepers for their families and how such relationships influence the spread—or containment—of false content within households.

Another line of inquiry involves the affective and social dimensions of misinformation engagement. Participants frequently cited reputational concerns, emotional exhaustion, and strategic visibility management as factors shaping their content interaction decisions. Future research should probe deeper into how these emotional and social cues interact with levels of algorithmic literacy to influence decisions around sharing, commenting, or flagging content. Additionally, questions raised in this study—such as whether these dynamics are more pronounced in developing regions due to politicized media environments or cultural norms—could form the basis of comparative cross-regional analyses.

Given the observed behavioral inconsistencies among participants with moderate algorithmic literacy, experimental studies could explore the causal relationship between perceived competence and misinformation engagement. For example, does overconfidence in one's literacy increase misinformation sharing? Can interventions that challenge this overconfidence improve both critical reflection and reporting behaviors?

Lastly, this study highlights the need to connect structural analyses of platform governance with user-level behaviors and perceptions. The interviews revealed a notable skepticism toward moderation tools and platform transparency—often resulting in inaction or disengagement. Future research should investigate how platform-level decisions, such as algorithm design, labeling practices, and user interface features, shape user trust and moderation participation, particularly in regions with low regulatory oversight and high misinformation exposure.

These questions are not merely academic—they touch on the core of how digital citizens understand their role within algorithmically curated environments. Addressing them will be key to advancing both theoretical models and practical solutions for navigating the complex, emotionally charged terrain of online information ecosystems.

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Appendix

A Survey

Survey on Algorithmic Literacy, Misinformation, and the Third-Person Effect
Section 1: Demographics

1. What is your age?
2. What is your highest level of completed education?
   - Bachelor's degree (currently pursuing or completed)
   - Master's degree
   - Doctoral (PhD) or Postdoctoral researcher
3. What is your field of study?
4. How frequently do you use social media?
   - Never
   - Rarely
   - Sometimes
   - Often
   - Always

Section 2: Algorithmic Literacy and Perceived Influence
To what extent do you agree with the following statements? (Scale: 1 = Strongly Disagree, 5 = Strongly Agree)

1. My social media feed is only influenced by my interactions (e.g., likes, shares, clicks).
2. I know how to adjust my algorithmic recommendations on social media.
3. Social media platforms use algorithms to decide what content appears on my feed.
4. I believe I can critically evaluate whether online content is promoted by an algorithm.
5. I understand how social media companies profit from algorithm-driven content.
6. How much do you think others understand how social media algorithms work?
   - Not at all
   - To a small extent
   - To a moderate extent
   - To a great extent
   - To a very great extent

Section 3: Fact-Checking Behavior and Perceived Influence

1. Have you ever verified the credibility of news before sharing it?
2. If answered “yes” in Q1, then: How often have you verified news before sharing it?
   - Always (Every time before sharing)
   - Often (Most of the time, but not always)
   - Sometimes (About half the time)
   - Rarely (Only a few times)
   - Never (I do not verify news before sharing)

3. Do you think your peers verify the credibility of news before sharing it?
4. When deciding whether to trust online news, which of the following do you consider? (Check all that apply)
    - The credibility of the news source (e.g., established media outlets, independent journalists)
    - The presence of multiple sources or perspectives (e.g., does the article cite different viewpoints?)
    - The author or publisher's reputation (e.g., known journalists, verified accounts)
    - The presence of fact-checking labels or verification indicators (e.g., third-party fact-checks, platform warnings)
    - The date of publication (e.g., ensuring information is current and relevant)
    - The use of supporting evidence (e.g., references, data, expert opinions)
    - Whether the content aligns with my pre-existing beliefs
    - The number of social media engagements (e.g., likes, shares, comments)
    - Recommendations or endorsements by people I trust (e.g., friends, influencers, experts)
    - The website's domain or URL structure (e.g., avoiding suspicious or misleading domains)
    - Other (please specify): _______

4A. Support for Regulation and Institutional Responsibility
Please indicate your level of agreement with the following statements (1 = Strongly disagree, 5 = Strongly agree):

1. The government should regulate how social media platforms handle disinformation.

2. Social media platforms should be responsible for moderating false or misleading content.

3. Digital platforms should be required to be more transparent about how they decide what content to show.

4. The state should require platforms to cooperate with authorities on disinformation issues.

5. Tech companies should be held accountable for the impact of algorithms on the spread of fake news.

4B. Perception of Current Measures and Need for Intervention
Please indicate your level of agreement with the following statements (1 = Strongly disagree, 5 = Strongly agree):

6. The current measures taken by platforms to combat disinformation are sufficient.

7. New measures are needed to curb online disinformation.

8. Fact-checking is effective in reducing the circulation of fake news.

9. Media and digital literacy should be an educational priority to address disinformation.
10. Users are also responsible for verifying information before sharing it.

B Mock Content Feed

Available at: https://xfvd-pa.github.io/el_observador/

Declaration of Authorship

I hereby declare that, to the best of my knowledge and belief, this Master Thesis titled "The role of Algorithmic Literacy in countering Misinformation in Developing Countries" is my own work. I confirm that each significant contribution to and quotation in this thesis that originates from the work or works of others is indicated by proper use of citation and references.

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