“See the Image in Different Contexts”: Using Reverse Image Search to Support the Identification of Fake News in Instagram-like Social Media

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Abstract. Social media are an integral part of the daily lives of today’s young generation. In addition to the positive impact on learning through these channels, there are also risks related to toxic content like “fake news” on various social media. Fake news aims to change opinions based on disinformation or misinformation supporting conspiracy theories, e.g., related to the pandemic. Fake news creators use various multimedia artifacts, including images taken from serious and valid news sources, to attract the audience’s attention. Tracking images in different contexts can give social media users important clues to distinguish fake news from credible information. We report on the development of a web-based learning environment that includes a “virtual learning companion” to help learners improve their understanding, awareness, and critical thinking concerning such social media threats. The learning environment mimics Instagram and includes toxic and non-toxic content in a controlled way. The companion is implemented as a browser plugin that communicates with students via chat. The companion poses knowledge activation questions and answers according to an underlying script. The companion offers other sources with the same image identified through Reverse Image Search (RIS). The goal is to help learners find the same image in different contexts with different textual descriptions and keywords. For this purpose, we added basic NLP mechanisms to extract keywords from these contexts, including keywords that signal persuasiveness. Currently, we evaluate the impact of this tool and the provided support in distinguishing fake or credible news.

Keywords: AI-based learning support systems, Learning Companion Systems (LCS), Intelligent tutoring system (ITS), Recommendation, Awareness tool, Misinformation, Fake news, Social media, Chatbot, xAPI, Gamification, COVID-19.

1 Introduction

Besides positive and beneficial aspects of social media, like facilitating information sharing and co-creativity, there are also threats and risks that specifically affect young users. Fake news, impersonation and conspiracy theories that can impact users' views about events and news are such threats. This kind of misinformation is typically presented as authentic and credible in a persuasive way. For example, news posts on social media are usually presented as a combination of text and multimedia (especially images). The role of social media in the news ecosystem was highlighted in August 2017 in a report of the Center and Knight Foundation stating that two-thirds of U.S. adults obtain 67 percent of their daily news from social media, and 20 percent do so frequently [1]. Most U.S. Americans who see fake news reports are bound to believe in it [2].

The Virtual Learning Companion (VLC) assists learners in making judgments via a chatbot interface during the process of fact-checking. A specific type of support relies on "Reverse Image Search" (RIS) to retrieve and provide access to other instances of the same image in different contexts. Additionally, the VLC delivers keywords and phrases using natural language processing (NLP) from the other source websites. The companion also asks knowledge activation questions and motivates the learners to engage in fact-checking and to remain skeptical about the social media posts.

The following section provides relevant background from different areas. The first aspect is general human-oriented approaches to identifying and fighting fake news in social media. Such human-oriented approaches are to be distinguished from current AI-based techniques for the automatic detection of fake news. Given the educational orientation of our project, human-oriented approaches are particularly relevant. We also comment on systems supporting learners/users in fake news detection and the creation of awareness. Finally, we elaborate on the roots of our approach in the ITS tradition of learning companion systems. The specificity of our own approach lies in the provision of comparative contextual information using images as cues in combination with Reverse Image Search. We see this as a kind of learning from various contexts, which is a new approach to addressing fake news from an educational perspective.

2 Background

2.1 Human-oriented approaches to dealing with fake news

Victoria L. Rubin defines a conceptual model for fake news in the form of a triangle with the vertices Susceptible Host, Virulent Pathogen, and the Conducive Environment [3]. According to the model, fake news spreads if and only if the three causal factors occur simultaneously. Three interventions suggested interrupting the interaction of the mentioned factors: Automation to disarm the virulent pathogen, education to defuse the susceptible host, and regulation to make the conductive environment safe.

Automated, AI-based approaches can detect toxic features and add labels to the information items. One example of this approach is the LiT.RL News Verification

Browser, a search tool for newsreaders, reporters, editors, or information experts. The tool examines the language used in digital news websites to determine whether it is clickbait (to 94% accuracy on a test set of 5670 texts for an offline experiment), satirical news, or fake news. LiT.RL visualizes the results by highlighting the content in color-coded categories. The classification provided by the LiT.RL is not perfect and is not always adequate for public usage. Multimedia formats are unsupported [4].

Automated news validation systems based on NLP techniques can be helpful to assist content creators in quickly verifying common characteristics of misinformation. Additionally, such systems could also help teachers to teach critical content assessment skills or help information experts to reduce information overload for news clients by filtering out and flagging suspicious narratives [5].

The labeling strategy that is currently used on social media is sensitive for any keyword that could potentially be fake news (e.g., COVID-19 or vaccine). On the other hand, it is cumbersome to track and detect fake content. For example, deep fake image manipulation makes detecting fake content hard for the machine and for humans [6].

Another strategy to defuse the susceptible host and to help learner develop their own mechanisms to recognize and counter such influences is to educate [3]. This approach can be divided into two main strategies: increase the awareness and improve the learner's prejudge. There are adventitious techniques to "improve prejudges and awareness". For example, by using games and techniques that show the learner how to seek the truth and credible information from different contexts by using libraries and search engines. Moreover, to improve the learner 's prejudge, we can deliver a series of games to show how the fake news content creators make the content on social media and what kinds of content are usually categorized as misinformation.

To improve the learner's critical thinking rather than working on their bias, we can equip learners with a "fact-checking awareness tool". Such tools are designed to motivate learners to practice fact-checking. According to the American Library Association (ALA), accessing accurate information from different contexts, without censorship and filtering, is the best way to counter misinformation and media manipulation [7].

The last point in the triangle is "Regulatory". Legislative work should be methodically proactive and robust as the global Internet society aims to eradicate these pathogenic "Fakes" in the conducive digital environment by preventing them from reaching and "contaminating" susceptible hosts. The EU commission warned that social media companies would face new regulations unless they urgently attack fake news[1]. Some programs were set up under the lead of the EU and international organizations to tackle disinformation related to the pandemic situation in June 2020[2]. The inventor of the WWW, Tim Berners-Lee, made this statement in a recent Web Foundation conference: "*The administrations must acclimate rules and regulations to the digital age. They must guarantee that markets remain competitive, innovative, and open. And they have a responsibility to protect people's rights and freedoms on the Internet*"[3].

1 Tech firms could face new EU regulations over fake news, https://bit.ly/3BqBBLw , Jan 2022
2 Fighting disinformation, bit.ly/EUDisinfoCOVID19, Jan 2022
3 30 years on, what's next #ForTheWeb, https://bit.ly/3LzacLS, Jan 2022

2.2 Awareness tools

There are games and tools to increase learner awareness rather than filtering for possible fake news in social media. *Harmony Square*[4] and *Bad News*[5] games are designed to teach the learner to understand the six common misinformation techniques involved in spreading disinformation by playing the role of Twitter Editor. These games expose players to fake news tactics, and they win by publishing headlines that attract the most followers. After learning each technique, they reward the player with misinformation badges. The result of an empirical study for *Bad News* indicates an enhancement in learner's ability to spot misinformation techniques compared to a gamified control group, boosts people's confidence in their judgment, and can also confer psychological resistance to common online misinformation strategies in different countries with various background cultures [8].

A serious mini-game platform and information booklet have already been prepared and distributed to help teenagers critically reflect on digital advertising by *Media Awareness Network (MNet) (Current name Media Smarts*[7]*)*[9]. MNet has provided several free games for teen learners, some of which are specifically designed to address the issue of bias and prejudice with lack of information and to promote critical thinking skills. Media Smarts mentioned in their agenda that their goal is to encourage teens to examine the information and seek alternative viewpoints to raise their awareness [10]. In the *Reality Check*[8] game, an awareness game of Media Smarts, students learn how to find evidence, such as where a story initially came from and how to check it against other sources. They also learn how to use tools, such as fact-checking websites and reverse image searches in the narrative form. *Reality Check* game and our approach have a common strategy of focusing on teaching fact-checking techniques and motivating learners to fact-check any dubious news to reduce their biases. Meanwhile, *Bad News* and *Harmony* games inoculate learners and improve prejudging about the information.

2.3 Learning Companion Systems

Learning Companion Systems (LCS) is a subset of Intelligent Tutoring Systems (ITSs). They are characterized by providing personalized support and adaptive feedback through an explicit agent or companion [11]. The companion, guides the learner gradually and commonly adopts a non-authoritative role. The agent environment interface may incorporate multimedia, interactive buttons, menus, text, voice, animation, diagrams, virtual reality, or other interactive techniques.

LCS usually includes machine learning and natural language processing (NLP) techniques to facilitate communication between the LCS and the learners. Logging and

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[4] Harmony Square: https://harmonysquare.game/en, Jan 2022

[5] Bad-news-game: https://www.sdmlab.psychol.cam.ac.uk/research/bad-news-game, Jan 2022

[7] Canada's center for digital and media literacy https://mediasmarts.ca/ 22-01-2022

[8] Reality Check: The Game https://mediasmarts.ca/digital-media-literacy/educational-games/reality-check-game, 12-02-2021.

tracking the student's interactions with an LCS is used in student modeling. One scenario for the LCS would be to ask the learner to describe the logic behind their answers as a reflective question about the controversy of probable fake news. Each step during their task might lead to more robust learning, in line with the work on self-explanation at the time. Learners might develop many answers and articulate the reasons behind their responses that distill their understanding (self-regulated learning strategies)[12].

Based on the definitions of adaptive systems, adaptability is one of the most important issues for a tutoring system that includes LCS. The system should adapt to the learner's responses and actions and be flexible depending on the context and previous responses of the learner.

The agent response can be implemented in the conversation as feedback to the learner's text input or provide an appropriate visual response to the learner's interaction in various ways, such as offering an educational video as a recommendation[13]. Modeling students as a foundation for adaptive feedback in LCS tutorial dialogs can immensely increase learning progress for students with low and high prior knowledge [14]. An LCS can involve numerous roles in an instructional context. For example, the role of a leader who suggests new ideas for learners or a critic who challenges learners' suggestions [15].

Concerning the question of how knowledgeable the learning companion agent should be to reach the learner's expectation and motivate the student to continue collaborating with the agent, *Hietala* and *Niemirepo* pointed out that the learners lose their motivation if they use a knowledgeable and robust companion all the time. Notably, in the beginning, a companion that makes mistakes like humans is more effective, still, for a challenging assignment or dealing with a new issue [16].

Our Virtual Learning Companion (VLC) supports features such as role-playing for learners, providing adaptive feedback based on previous learner interactions and responses. Plus, providing educational recommendations and analysis artifacts based on RIS links judging environmental images and asking knowledge activation questions. In addition, receiving input and displaying information are among the core functions of the VLC system.

3 Approach

3.1 System components and architecture

We have chosen the PixelFed open-source framework for social media for a controlled social network environment. This environment allows for providing content in a controlled way and facilitates basic social media interactions. PixelFed is similar to Instagram: it is suitable for images, captions, and comments. The VLC is developed as a Chrome browser plugin that interacts with PixelFed artifacts. It moderates through chat with questions and recommendations while the student engages with the environment's artifacts. Learners will interact with the environment guided by the tasks they obtain from the companion. As illustrated in technical architecture in (cf. Fig. 1), the companion system comprises two sections: first, a frontend (the Chrome extension that interacts with the PixelFed environment); second, the backend microservices with a middleware (NodeJS express[9]) that mediates the frontend communication through REST API.

As part of our middleware, we have implemented an API for connecting to a WIT.AI[10] module in the backend. According to the trained model, this module allows for extending the chatbot interaction with an AI-powered module that detects the user's intent for each free text conversation. However, this feature was not used in the current trial for the chatbot conversation besides the underlined script. We create and expand the metadata for each image on PixelFed environment and store it in the document-oriented database (MongoDB[6]). We use Learning Locker as Learning Record Store (LRS) to log the action records in the standard Experience API (xAPI) structure.

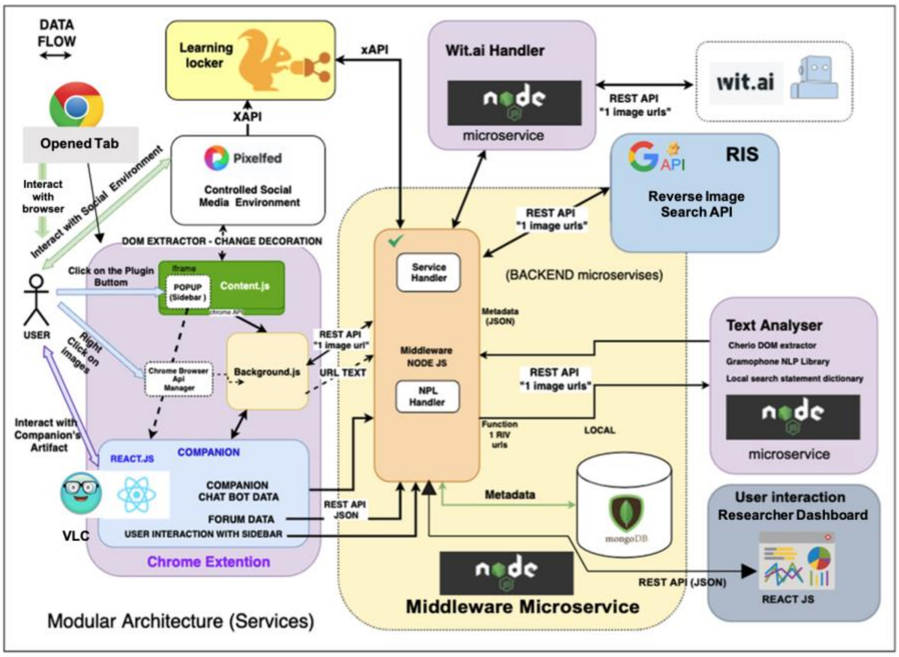

Fig. 1. The technical architecture and dataflow diagram for the companion system with service links (APIs)

A researcher dashboard module (see Fig. 1) has been implemented to analyze and visualize the user interactions.

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9 NodeJS is a JavaScript runtime built on Chrome's V8 JavaScript engine, 12-11-2021.

10 WIT-AI is a tool to Build Natural Language Experiences https://wit.ai, 12-11-2021

6 MongoDB, document-based, distributed database built for modern application, 12-11-2021.

3.2 Reverse Image Search Module (RIS)

In the front-end, the learner can select an image on the social media interface; then the companion system (as a chrome extension) sends the image URL to the middleware microservice. Associated with the extracted semantic keywords, it searches in the extracted text for the bold sentences corroding to the predefined dictionary, such as the sentences that contain words like “Claim”, “Fake,” etc. In the text analyzer microservice, we utilize the Cheerio library[12] to accomplish web scraping in JavaScript (Dom Tree extractor).

Moreover, to analyze the scrapped text of each RIS website, the Gramophone[13] module was used to extract the keywords based on term frequency and plus the filtering algorithm that we implemented on this service. The Gramophone can be configured to extract arbitrary length phrases (n-grams) of any length and not just keywords.

4 Scenario for trials

The learning environment uses a Chrome browser to access PixelFed with a prepared collection of fake/fact news images and captions. The actual companion (VLC) is implemented as an extension or plug-in of the Chrome browser.

Learners gain access to the common PixelFed environment by clicking on the provided unique, anonymous user-token link. Then, they are presented with brief instructions on how to open the Chrome extension. The companion image appears in the sidebar and guides them to select an image on PixelFed to activate the chatbot. After right-clicking on an image and selecting the VLC button, the companion automatically starts communicating with a chatbot-style conversation (e.g., “Hey, you made it!”) and asks some demographic questions (gender, age...), following up with knowledge activation questions that the learner has to answer as free text, e.g., ask the learner to express their opinion about the selected image in PixelFed. In the next step, the companion asks learner whether the Post on PixelFed Fake News or Fact is, and the learner has to vote/classify for only one of five categories (Fake, Probably Fake, Not sure, Probably Fact, Fact). Then, the learner must answer reflective questions to explain the reasons behind their answer.

The companion applies to stimulate reflection questions (e.g., “How sure are you?”). Next, the companion unlocks a “Recommended” tab that includes links from the Reverse Image Search (RIS). The same image is displayed in a different context and on websites in the extension's sidebar (cf. Fig. 2). Learners can visit these connections and compare each RIS link's keywords, metadata, bold phrases based on a predefined dictionary, and brief descriptions of each RIS link for the selected post. In this step, the companion motivates, and guides learners use an external tool to freely search on the Internet or perform and use reverse images tool themselves to get even more context on the topic.

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[12] https://zetcode.com/javascript/cheerio/, Cheerio module web scraping in JavaScript 02-2022

[13] https://github.com/bxjx/gramophone, Gramophone module keyword extractor 02-2022

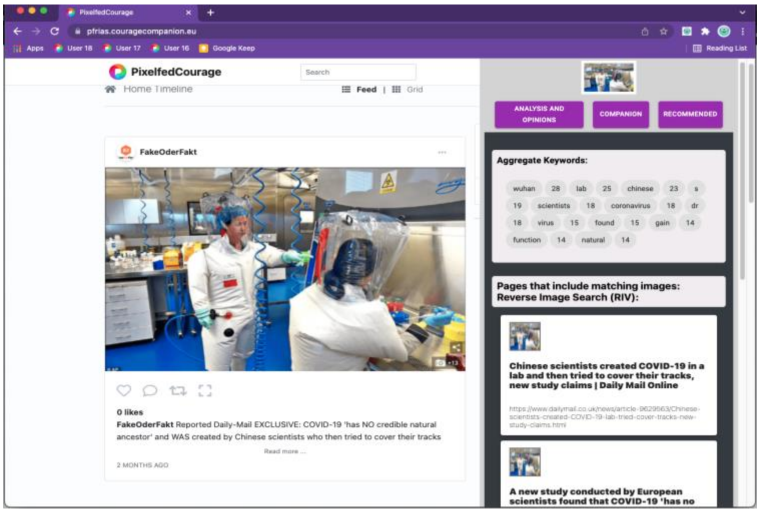

Fig. 2. The PixelFed environment (left side) with an image and the caption and the VLC add-on with contextual information (right side)

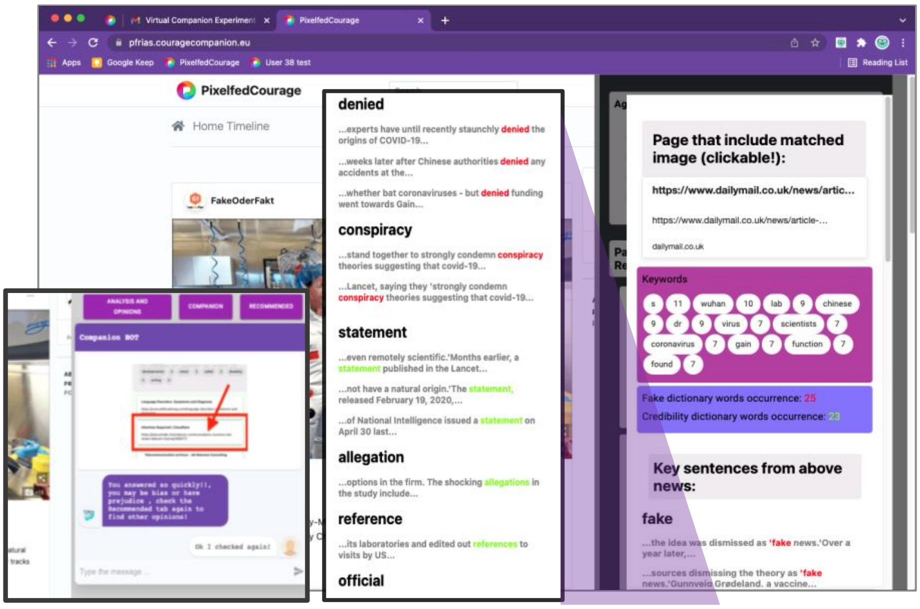

Fig. 3. Learner interactions with the VLC: Left – advice to check generated metadata more closely - after clicking on an RIS link, the corresponding keyword analysis is displayed (right); Center: learner scrolls down through "*key sentences"* with highlighted phrases.

Fig. **3** illustrates how learners can see each one of the retrieved RIS links in more detail. Learners can review the title and click on each link to see the bold sentences with the words highlighted, compare them, and compare them to the caption on PixelFed.

For example, learners will be able to see if the image is manipulated, the text is distorted, indicates misinformation, or is based on credible news from the well-known channels.

For researchers, it is interesting to know if learners change their minds after interacting with the additional artifacts provided by RIS or the recommended learning instructions. It is important to understand in which direction learners think and if their judgment changes after receiving feedback and interacting with the learning guide from the companion. Therefore, we log all meaningful learner interactions, timestamps, and any related websites that the learner visited during the conversation with the learning guide in the standard xAPI format during the test in LRS.

After interacting with the metadata for each image and returning to the chatbot conversation, the companion can provide a warning or feedback as a pedagogical intervention. Suppose learners quickly assess or respond without checking the recommended RIS. In this case, they receive a notification in the chat, e.g., “Be careful not to be biased!”. After browsing the RIS links, the companion then provides new (adapted) feedback and asks if they want to change their idea and vote again.

After the revision chatbot asks them to explain and justify their vote change, they have this conversation for all three established images in the PixelFed. In the end, the companion unlocks the “Analysis Tab and Collaboration” to check others’ votes as a bar chart.

The system also stores in the database learner’s responses, the companion's chat reactions, the learner interactions with environmental artifacts and the tab that learner opened in the browser during the experiment in its internal database. We are considering applying for the following school trials; for three selected images for the PixelFed environment related to pandemic situations. The images may contain fake or credible news and conspiracy theories that are used to teach critical thinking as a skill or to raise learner’s awareness. Also, teach them how to use the RIS tool to find the same image in different contexts to make better judgments from the signals. After interacting with three images, the companion gives some feedback from experts and their judgements over the provided posts and asks the learner if they were aware of this RIS method to detect fake news.

5 User Evaluation

In this first trial with the Chrome extension and PixelFed environment, forty-five invitations were sent to volunteer test users from the University of Duisburg-Essen to participate in the companion system. The invitations are accompanied by an anonymous, randomly selected user token with the instructional video and files. Twelve participants, aged 19-65, from different cultural backgrounds, actively participated in the study. The purpose of this preliminary, informal study was to test the practicability of the system (as a mainly technical test). Given this orientation, our user population was based on personal contacts, not striving for representativeness.

Test users were presented with three images in the control environment (PixelFed) that contained a fake, facts, or a controversial item about COVID-19. As mentioned in the example scenario, participants were instructed to interact with the companion

(Chrome extension) and finish the conversation for all three images. The results show that providing metadata from retrieved RIS links and instructing the companion motivate and help users to revise their initial judgments in a positive direction. After RIS and the companion instructions, one in four participants changed their judgment at least once for the provided social media post (6/24 votes).

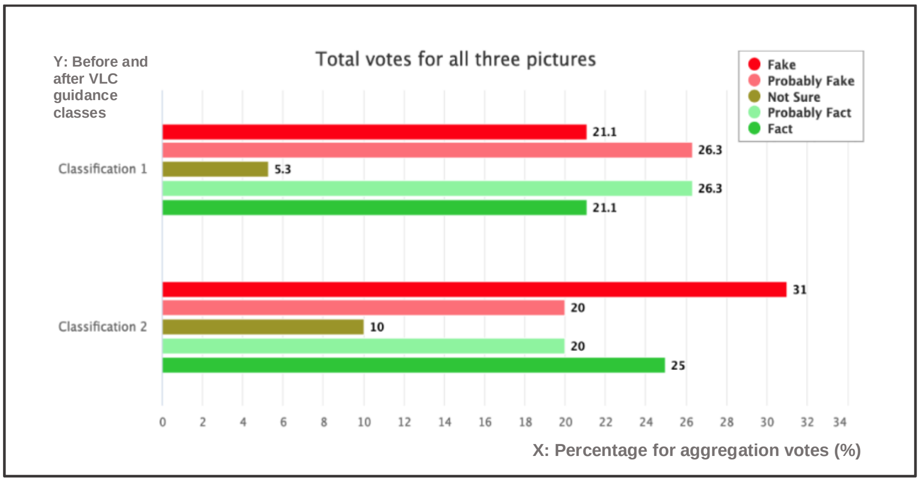

Fig. 4. Distribution of the votes for all three images before and after the guidance by the companion (classification 1, 2)

The above chart (Fig. 4), shows all votes aggregated over the three images by labels on a five-point scale. Classification 1 represents the votes before seeing and possibly taking into account the suggestions based on RIS and keyword extraction. Classification 2 corresponds to the judgements after provision of this information. One observation is that the deterministic classifications as a clear "Fake" or "Fact" have increased, but this is also true for the neutral category "Not Sure". The previously known expert judgements for the three examples were indeed one "Fake", one "Fact" and one "Not Sure". In addition, we have checked the individual votes and changes (per anonymous user-id): Five user judgements were changed after having received the additional information. Using a numerical scale between -2 and + 2 (i.e., -2 for "Fake" and +1 for "Probably Fact"), we could characterize these changes as increasing or decreasing the difference of the individual judgements to the expert judgement per item. Most of the changes (namely 3) led to decreasing the difference. Indeed, all these cases of "positive" changes resulted in the final judgement matching the expert judgement. There were 7 such matches in the initial classification 1 and 10 in the final classification 2.

The item with the least number of coincidences of user judgements with expert ratings was the item that had been classified as "Not Sure" by the experts. There was only one initial match (which was not changed) and additional one in a final judgement (change from "Probably Fake" to "Not sure"). In the dialog with a companion, this user commented: "There was some evidence that this is probably not fake - I think so." Another commented that the additional information was helpful to rethink the judgement more accurately. This user changed had the vote from “Probably Fake” to “Fake” on the item that was characterized as “Fake” in the expert judgment. The user explained this as follows: “Because the image’s caption is completely different from other resources. It seems that the image for this post is randomly picked from the web”.

6 Conclusion and Outlook

We have introduced a learning environment that consists of a virtual learning companion hooked up on an Instagram-like social media platform. The companion is implemented as a browser plugin that communicates as a chatbot on top of the social network. This companion interacts with learners via chat and triggers the user’s action with the environment artifacts. The companion exploits multimedia content (images) to provide adaptive feedback to learners and intervene with a pedagogical reflection.

This tool aims to motivate learners to sharpen their critical thinking and ask them to review other information items using similar (or the same) images in different contexts, rather than improving their prejudice (misinformation inoculation) in combating fake news. The companion application is equipped with a reverse image search tool that lists the most relevant websites with similar images to achieve this goal. Basic NLP techniques are applied to the textual content of the alternative sources to extract important keywords based on term frequency and filtering sentences according to the predefined dictionary. The metadata (keywords and phrases) extracted from the alternative sources are displayed in the application’s sidebar to help the learner in making their judgments.

An informal test with a small ad-hoc user group has confirmed the usability and practicability of the scenario. The test results indicate that delivering contextual metadata from retrieved RIS links and instruction from the companion motivates learners to revising and improving their initial judgments.

In the on-going and future development of the described learning scenario, we plan to include machine learning support in different ways: (1) Enhancing the chat interaction using WIT.AI for adaptive recognition of intents, and (2) using trained classifiers in the analysis of textual content around images to improve the identification and extraction of relevant keywords and phrases. Finally, we intend to apply the companion also to open social media platforms such as Instagram. This would not make a technical difference for the VLC as a browser plug-in, but it would require pedagogical control mechanisms to ensure responsible handling of information access. Additionally, we intend to enable social interaction between peers and of peers with moderators. By interacting with the same metadata for the shared content with images, the peers and moderators will be able to share their opinions about controversial content and present their different reasons and backgrounds.

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