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Visual narratives to edutain against misleading visualizations in healthcare

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ABSTRACT

We propose an interactive game based on visual narratives to *edutain*, i.e., to educate while entertaining, broad audiences against misleading visualizations in healthcare. Uncertainty at various stages of the visualization pipeline may give rise to misleading visual representations. These comprise misleading elements that may negatively impact the audiences by contributing to misinformed decisions, delayed treatments, and a lack of trust in medical information. We investigate whether visual narratives within the setting of an educational game support recognizing and addressing misleading elements in healthcare-related visualizations. Our methodological approach focuses on three key aspects: *(i)* identifying uncertainty types in the visualization pipeline which could serve as the origin of misleading elements, *(ii)* designing fictional visual narratives that comprise several misleading elements linking to these uncertainties, and *(iii)* proposing an interactive game that aids the communication of these misleading visualization elements to broad audiences. The game features eight fictional visual narratives built around misleading visualizations, each with specific assumptions linked to uncertainties. Players assess the correctness of these assumptions to earn points and rewards. In case of incorrect assessments, interactive explanations are provided to enhance understanding For an initial assessment of our game, we conducted a user study with 21 participants. Our study indicates that when participants incorrectly assess assumptions, they also spend more time elaborating on the reasons for their mistakes, indicating a willingness to learn more. The study also provided positive indications on game aspects such as memorability, reinforcement, and engagement, while it gave us pointers for future improvement.

1. Introduction

Daily, we generate and have access to a large volume of data within the domains of medicine, healthcare, and life sciences. This surge in data poses challenges for structuring and interpreting the generated health-related information to extract meaningful insights—for domain experts and laypeople alike [1]. In healthcare, visual communication of insights is essential for *supporting well-informed health-related decisions*. Yet, the corresponding data are specialized, heterogeneous, big, and often multi-scale. They are, thus, challenging to understand without appropriate visualizations—especially for laypeople without medical knowledge [2,3]. Numerous factors impact the effectiveness of visual communication of healthcare-related insights, influencing comprehension and translation into actions [4], while potentially misleading the intended audience.

Creating *misleading visualizations* is nowadays easier than ever [5]—also facilitated by generative technologies. Other — potentially unintentional — factors that contribute to creating misleading healthcare visualizations could relate to *uncertainties* manifesting at different stages of the visualization pipeline [6,7]. While not every uncertainty results in misleading elements and misleading elements may not exclusively stem from uncertainties, certain uncertainties are known to hamper the process of transforming raw (medical) data into visual representations, and into insights [6].

Misleading visualizations, whether they are intentionally or unintentionally created, can have significant *repercussions* on their target audiences [8]. In healthcare particularly, when individuals are exposed to inaccurate or misconveyed information, they can be led to poorly informed or misguided health-related decisions [1] and even underestimate a critical situation [9]. Encountering misleading healthcare information supported with visualizations online can lead to widespread misconceptions within the general population, especially during health crises. For example, Lisnic et al. [10] discusses the tweaked design of COVID-19 data visualizations on Twitter to deceitfully advocate vaccine ineffectiveness.

Educating the population about misleading visualizations is crucial for fostering informed decision-making [8,11] and — in the context of medicine — for *promoting health literacy* in broad audiences. By enhancing public awareness about potential pitfalls in visual representations of healthcare data, individuals can make more discerning judgments about health information, ultimately contributing to better

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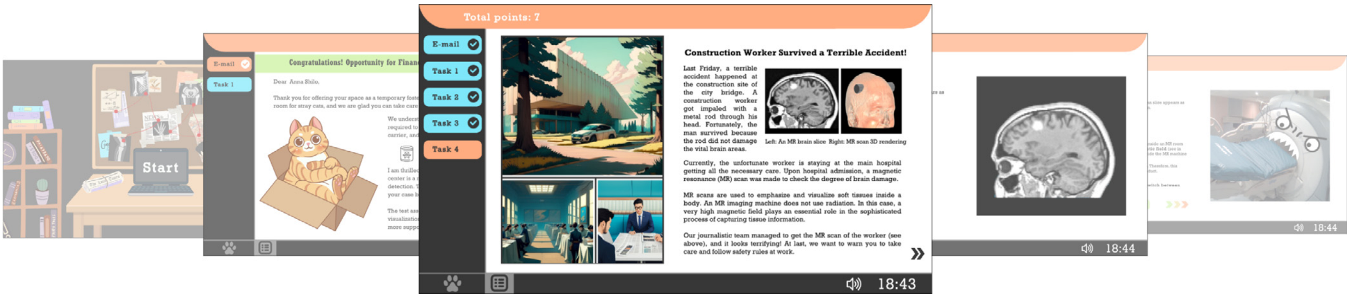

Fig. 1. The Unity game *DeteCATive* aims to edutain, i.e., to educate while entertaining, broad audiences about misleading visualizations in healthcare. The game comprises visual narratives to communicate elements of misleading visualizations, created by the introduction of different sources of uncertainty at the distinct steps of the visualization pipeline.

outcomes. To this end, games and visual narratives may serve as engaging and interactive educational tools, enhancing comprehension and retention by providing immersive and participatory learning experiences [12–14]. In this work, we decipher the role of uncertainties, as the potential source of misleading elements in healthcare data visualizations. We subsequently propose an interactive game based on visual narratives to investigate whether edutainment, i.e., education within entertainment, is a viable way to improve the healthcare literacy of broad audiences.

We design, implement, and assess an edutainment game that comprises visual narratives to raise the awareness of a broad audience about misleading elements in healthcare visualizations (Fig. 1). Our proposed game aims to enhance medical and public health literacy by equipping users with skills for the critical assessment of corresponding visualizations. Our interactive, on-screen game focuses on investigating visual narratives linked to healthcare data and their corresponding visualizations, which include a diverse set of misleading elements. These misleading elements may be the result of one or more uncertainties arising through the visualization pipeline. Our core *contribution* is the design process of the game. We start with a literature study that draws upon 66 papers to identify which elements can be misleading in healthcare/medical visualizations. We, then, create a set of visual narratives, where the integrated visualizations reflect the aforementioned misleading elements. Finally, we embed these visual narratives as investigations to be solved by the players within our game. As part of our work, we ultimately scrutinize whether our proposed edutainment approach supports the communication of misleading elements in healthcare visualization to broad audiences.

2. Related work

Misleading visualizations. Investigating the design of misleading visualizations and educating intended users against them are common topics in the visualization community. At the IEEE VIS conference, there is an annual event called VisLies, where participants discuss confusing and inadequate examples of such visual representations. Recent research by Lo et al. [8] delved into misleading visualizations, using the grounded theory method to collect and open code data. Their findings include a taxonomy of misleading elements containing 74 types of issues across five stages of the visual analytic (VA) process: input, visualization design, plotting, perceptions, and interpretation. Their process is based on a modified pipeline from McNutt et al. [11], who investigated mirages across the VA pipeline and emphasized the effects of choices made at each pipeline step on the final perceived message.

With the COVID-19 outbreak, the population's focus turned to healthcare and many misleading visualizations appeared on social media and information platforms. Lisnic et al. [10] explored how charts mislead audiences in practice, focusing on COVID-19-related posts with visualizations shared on Twitter in 2022. From the collected data a relevant sample was used for qualitative coding into a typology of misleading posting features: source of visualization, text polarity, visualization design violations, and reasoning errors. Their work showed that visualization design violations are not the actual way of spreading misinformation—confirming previous work that indicated that misinformation arguments usually follow design guidelines [15]. In the majority of cases, salient features of visualizations are used to weakly support a given idea. However, the facts that counteract this idea are purposely omitted.

These findings (including what elements make a visualization misleading [8], where they arise from [11], and how they mislead their intended audiences [10]) are central to our work. However, previous work (except for Lisnic et al. [10]) focuses on general data visualizations and not on visualizations within the context of healthcare. Healthcare visualization has specific characteristics with regard to the data, users, and tasks, as well as its scope and impact [16]. This requires a separate investigation into a common source of misleading elements across the medical visualization pipeline: uncertainties.

Uncertainty in the medical visualization pipeline. The field of uncertainty visualization is extensive. Surveys and new methodologies appear regularly [17–20], stressing the importance of uncertainty visualization in many domains. Specifically within the medical visualization pipeline, uncertainties — among others — can be responsible for misleading elements [6,7]. This is also evident for non-imaging data, for instance, when data quality problems such as missing data [21] and incorrect values [22] arise. Gschwandtner et al. [23] propose a taxonomy of dirty data, which is essential for understanding the quality and potential utilization of non-imaging medical data for misleading visualizations.

Yet, uncertainty is not encountered only at the data generation/ acquisition step of the pipeline. Ristovski et al. [7] initiated the taxonomy of uncertainties in the medical imaging data visualization pipeline. They identified sources of uncertainties in the medical visualization pipeline and described uncertainty types depending on spatial location, dimensionality, event types, and their sources. Moreover, depending on the uncertainty type, they proposed solutions for uncertainty-aware visualization. Recent work by Gillmann et al. [6] expanded the previous taxonomy. They separated the pipeline into image acquisition, transformation, and visualization, and investigated how categories like aleatoric (random) and epistemic (systematic) uncertainties arise in each of those steps.

Our work does not aim to provide another taxonomy—nor should it be seen as a meta-review of existing taxonomies. We solely employ the concept of uncertainties across the steps of medical visualization to investigate how they can contribute to the generation of misleading elements in visualization. For more details on uncertainty visualization for medical data, we refer the reader to the two published taxonomies by Ristovski et al. [7] and Gillmann et al. [6].

Visualization in healthcare education. *Storytelling* is a central component of many visualization approaches targeting large audiences within the context of science communication [24]. Within this context, storytelling often complements computer graphics solutions, used for processes like 3D modeling, animations, and rendering [25]. Narrative visualizations are often found at art exhibitions or museums because they convey messages effectively and build memorable experiences [26].

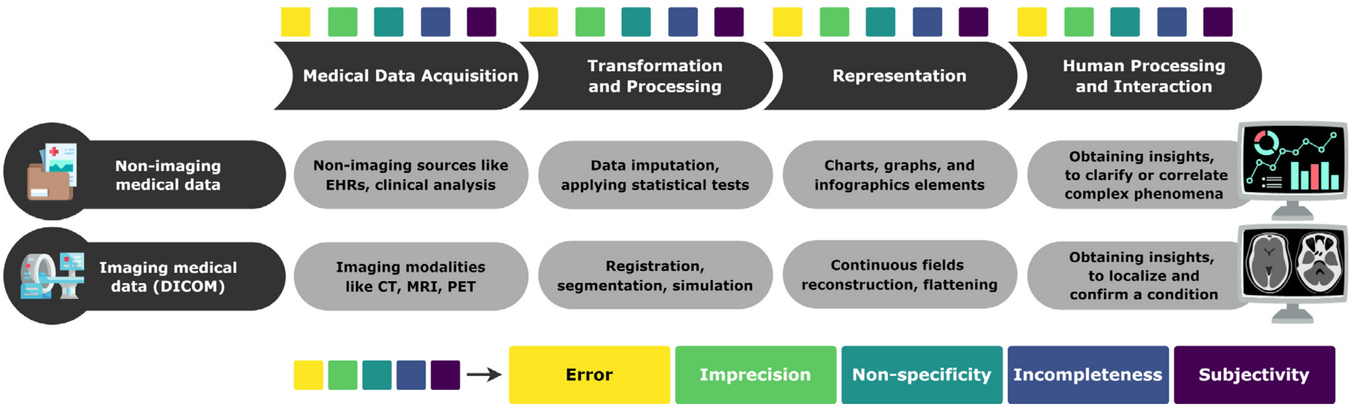

Fig. 2. The medical data visualization pipeline, inspired and adapted from several sources [6–8]. At the top, black blocks indicate the medical visualization pipeline steps. Grey capsule boxes contain processes or attributes describing each step of the two visualization pipelines (for imaging vs. non-imaging medical data). Please note that not all steps might be required in all cases. Colored boxes represent possible uncertainty types generating misleading elements at each step of the pipeline.

Sometimes, these solutions include virtual reality (VR) or augmented reality (AR) technologies to increase audience engagement [4]. According to Bach et al. [27], there are only three requirements when using narrative/storytelling design patterns: having a story, knowing your audience, and the effect the story should have on them. When it comes to complex concepts, effectively communicating stories to a large audience involves simplifying the message, emphasizing only key concepts, and omitting minor details [28]. In the medical field, storytelling is used to enhance the communication between a patient and a physician, for example, to explain the diagnostic or therapeutic procedure [2,4,29]. In the biological field, storytelling has investigated ways of communicating insights into biology [30,31].

In narrative visualization, Meuschke et al. [4] provided the first-ever implementation of data-driven narrative techniques to inform patients about pelvic fractures, brain aneurysms, and liver cancer. Additionally, they defined a seven-stage template to structure narrative medical visualization communicating disease data. In a continuation of their work, Meuschke et al. [2] improved the medical story design and summarized their insights into a research agenda for narrative medical visualization. A case study for narrative visualization in medicine was published by Kleinau et al. [29], where narratives were augmented with data-driven visualizations. This work aims to explain to broad audiences the impact of vortexes in an aortic arc using narratives enriched with data-driven visualizations.

Games vs. Gamification approaches. As opposed to games, which include a structured form of play, gamification approaches employ game elements to enhance engagement and motivation within non-game contexts. Gamification, as Landers et al. [12] note, motivates active participation and supports the learning experience with typical elements used in gaming, thus engagingly supporting the education process. Employing gamification is proven to be beneficial not only in educational fields like engineering [32] or preclinical training [33], but it also has supported post-traumatic stress disorder (PTSD) treatment [34]. However, its effectiveness is contentious [35,36]; some studies show no positive effects or even negative ones. For example, Toda et al. [36] identified which game elements can cause negative effects, including learner indifference and loss of performance, in the education process. A leaderboard, in particular, frequently caused all considered negative effects. Therefore, integrating gamification into education is challenging and requires careful design decisions. Conversely, games have also been used to promote visualization literacy, for example, through Bae et al.'s [37] do-it-yourself crafting game and Huynh et al.'s [38] (role-playing game) RPG-style game. The former engages younger children in interactive physical visualizations and the latter challenges older kids with visualization-based problem-solving. Yet, games targeting specifically medical or healthcare visualization literacy for broader audiences are not available.

3. Methodology

Investigating, understanding, correcting, and raising awareness about misleading visualizations is a continuous effort of our community. New categories of misleading elements are being identified and organized into taxonomies [8]. Novel methods to aid visualization design [39] and to detect and counteract misleading visualizations are also currently investigated [40]. However, research papers are expert-oriented and can be challenging for the average visualization consumer to process. Even more in healthcare, visualizations often contain information that might not be accessible to someone without prior domain knowledge.

Our goal is to raise awareness about misleading healthcare visualizations among broad audiences. We design and develop an edutainment game that offers an approachable, understandable, and enjoyable way to learn more about this topic. Inspired by experiential learning theory [41], our approach encourages active participation in judging the validity of healthcare data representations. Players are tasked with identifying deceptive elements and exploring the rationale behind each of those. Active experimentation occurs as users engage with the visualizations, make decisions based on their interpretations, and learn from the outcomes of their actions in the game. Experiencing and reflecting on mistakes is ultimately anticipated to contribute to a deeper understanding of the subject.

In the upcoming sections, we first analyze the theoretical background of *uncertainty as a potential source of misleading elements* in healthcare visualizations (Section 3.1). Subsequently, we use this as the basis for the design of our *visual narratives*, which are finally employed as part of the *game design* (Section 3.2).

3.1. Misleading elements in healthcare visualization

Sources of misleading elements in visualization have been previously summarized by existing taxonomies [8,11] with regard to the visual design of a non-healthcare-specific visualization pipeline. To investigate misleading elements within the entire medical visualization pipeline, we establish a link to uncertainty sources manifesting at the different pipeline steps. Prior to this, we provide an overview of the data types and characteristics in healthcare.

3.1.1. Data types in healthcare

Data in healthcare are heterogeneous and complex. They are obtained from different sources and stored in various formats. In our work, we consider two medical data types: imaging and non-imaging data (Fig. 2). Imaging data are acquired from medical imaging modalities. For medical imaging data, we mostly encounter representations such as volume renderings [42]. Under non-imaging medical data, we consider only tabular data coming from EHRs [43], clinical trial data, and public health data [1], including cohort and population studies. For non-imaging data, we commonly encounter information visualizations that, for instance, aim to represent the underlying data "statistically". These can be, for example, a bar chart indicating categories such as gender, age, and therapy within a cohort of cancer patients, or a chart with the annual number of fatalities attributed to cardiovascular diseases.

3.1.2. Uncertainty as a source of misleading elements

As discussed in Section 1, not every uncertainty leads to misleading elements and misleading elements may not solely arise from uncertainties. However, the presence of uncertainties has serious implications for the visualization design and the subsequent derivation of insights [6,7]. Therefore, we anticipate a link between uncertainty and misleading elements in visualization. Within this work, we define *uncertainty* as the multifaceted concept encompassing errors, imprecision, subjectivity, and non-specificity [44] and *misleading visualization* as a visual representation that may distort or misrepresent data, leading to misunderstanding the presented information [8].

To establish the theoretical basis for our work, we used an open coding approach [45]. We initially gathered and analyzed several misleading visualization reviews [8,11] and uncertainty visualization taxonomies [6,7]. We subsequently gathered additional relevant articles at the interface of generating misleading visualizations and uncertainty visualization in healthcare from the Web of Science and Google Scholar. The search keywords followed the formulation:

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(uncertainty OR error OR imprecision OR non-specificity OR incompleteness OR subjectivity OR misleading) AND (medical imaging OR EHR OR health-care) AND (visualization)
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(*incl. synonyms thereof*)

We excluded papers that were purely discussing uncertainty quantification, or uncertainty visualization—without any potentially misleading aspect attached. The final number of included papers is 66. After collection, we initially open coded these papers with regard to whether they involve imaging or non-imaging (EHR and public health) data. Then, we extended our open coding to include the medical visualization step where they belong to or manifest: medical data acquisition, transformation and processing, representation, or human processing and interaction (Fig. 2). Medical data acquisition is the step where data are collected, for example, from medical reports or scans. The next step entails processing the data and preparation thereof before visualization. The actual visualization of the prepared data happens at the representation step. The last step entails human interpretation of the ready visualization.

Subsequently, we also categorized the papers under different uncertainty types in the third open coding phase. For this, we followed the classification of uncertainties provided by Griethe et al. [44] augmented by an additional uncertainty type: incompleteness (otherwise known as missingness) [21]. In summary, we included these uncertainty types:

- *Error*, indicating outlier or deviation from a true value;
- *Imprecision*, when the data resolution differs from the needed;
- *Non-specificity*, meaning a lack of distinction for objects;
- *Incompleteness*, i.e., missing attributes;
- *Subjectivity*, i.e., degree of subjective influence in the data.

The final categorization of the papers includes misleading elements in relation to uncertainty types encountered throughout the visualization pipeline for both imaging and non-imaging data (Fig. 2). Detailed information about the open coding process (i.e., how many papers, and which, fall under each step/data type) can be found in our supplementary materials.

3.1.3. Examples of misleading elements

We have two distinct pipelines, as processes that utilize non-imaging and imaging data respectively (Fig. 2). These may entail different uncertainties and/or implications for the resulting misleading element(s) and the analytical process. For example, at the transformation and processing step, segmentation, which is the isolation of a specific region of interest, is applied to imaging data only. We hereby provide a few — commonly occurring — examples for all steps of each pipeline.

Non-imaging data. In the visualization pipeline of non-imaging medical data, we assume that the data are not fabricated and consider the source of misleading elements in the acquisition step to be due to problems with (self-) reporting [1,23]. Patients may lie to appear in a better light, to avoid embarrassment or negative consequences [1], and to achieve secondary benefits, like special medication or payments [46]. Uncertainty in reporting may also result from typos or entries into wrong fields, incorrect measurements, data format issues, or inadequate quality control [23]. Uncertainties in (self-) reporting may include errors (e.g., a patient claims they do not smoke; or a value is entered in the system erroneously), imprecisions (e.g., a patient claims they smoke two cigarettes a day, while they actually smoke 10; or a rounded value is entered instead of the precise number), non-specificity (e.g., vague self-descriptions of patient history), incompleteness (e.g., missing entries), and subjectivities (e.g., pain assessment). Such types of uncertainty have been extensively discussed by Preim et al. [1] and Gschwandtner et al. [23].

During transformation and processing, it is possible to make data fit within a theory, which can be used for falsifying research [47]. Using a more appealing imputation function (error) can add artifacts. The wrong statistical test can lead to incorrect conclusions and undermine the validity of research findings [47] (non-specificity). Inadequate extrapolation methods (imprecision) result in unreliable predictions and generalizations that may not hold in broader contexts [48]. Finally, data can be cherry-picked (subjectivity) [8].

At the representation step, misleading elements can distort perceptions, misinform audiences, and compromise the accuracy and integrity of the conveyed information [8]. Depending on the context of its use, a normal scale instead of a logarithmic (error) may distort the underlying patterns. Inconsistent binning size (imprecision) may give more emphasis to a specific bin and hide others. Data of a smaller magnitude can be obscured by larger values of another sample that is being simultaneously presented (non-specificity). The same way works with the use of a truncated axis (incompleteness), or setting an arbitrary threshold (subjectivity).

Finally, in the human processing and interaction step, design violations can influence the perception, for example, by a wrong choice of a colormap or by introducing artifacts [49] (error and imprecision). Additionally, hiding distributions within a bar chart (non-specificity) and text polarity (subjectivity) also can serve intentional purposes [10].

Medical imaging data. In the visualization pipeline of medical imaging data, imaging acquisitions adhere to approved protocols, and medical experts uphold medical ethics for the benefit of the patient's health. Despite the common presence of uncertainties in the acquisition step [6], which can sometimes be addressed post-acquisition, our focus lies specifically on those uncertainties that have the potential to mislead the audience, e.g., those that serve a specific agenda. For instance, medical imaging data can be vulnerable when transferred over the internet, due to increased risks of manipulation especially with the rise of generative artificial intelligence [50]. Manipulations in the transformation and processing visualization pipeline step include processes such as copy-move forgery or compression artifacts (error), blurry effects (imprecision), removing an area (incompleteness), adjusting contrast, sharpening, and brightness (subjectivity) [50]. More advanced methods use generative adversarial networks to mimic histopathological images [51] and inject specific pathological conditions in chest X-rays

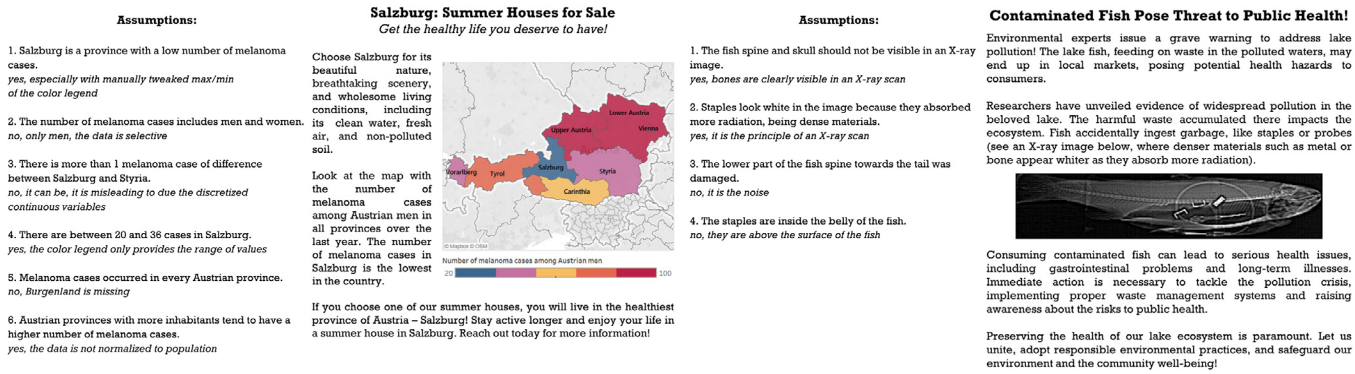

Fig. 3. Two of the eight visual narratives with their respective assumptions (indicated with the enumerations), employed as edutaining units in our game. The misleading visualizations are created by introducing different sources of uncertainty at the distinct steps of the visualization pipeline. Here, we depict one visual narrative with non-imaging public health data (left) and one with imaging data (right). The correct answers to the assumptions are italicized under each assumption.

and retinal images [52] (■ error). As discussed in the literature, the attackers' motivation can be political, ideological, attention-, revenge- or money-related [53].

In the representation step, creators of medical imaging data visualizations follow quality criteria: expressiveness, effectiveness, and appropriateness when representing data [54]. Still, misleading visualizations are not a rare phenomenon [8,11]. In the best case, a misleading visualization can originate from a designer's dilemma [8]. For instance, it could be the result of a design compromise during the flattening of an organ (■ non-specificity) [55].

For the human processing and interaction step, the use of improper color legend (■ error) is a common misleading element [49]. Also, the low resolution of the color legend can be used to conceal the exact values (■ imprecision), due to publication bias indicating that research with positive results has a higher chance of being published [47]. Another example is employing projection distortion that can influence the perception of distances like the diameter of vascular structures or tumor shape (■ non-specificity) [55]. Moreover, not communicating the data uncertainty (■ incompleteness) is used to present a visualization as accurate and true at all conditions [56].

3.2. Visual narratives to edutain broad audiences against misleading healthcare visualizations

We create an edutainment game, which we call *DeteCATive* (Fig. 1). Our on-screen game employs visual narratives to raise the awareness of a broad audience about misleading elements in healthcare visualizations. As such, the game course focuses on investigating visual narratives linked to healthcare data and their corresponding visualizations, which include misleading elements derived from uncertainty sources.

3.2.1. Target audience of *DeteCATive*

The target audience of our game is the general public, i.e., laypeople who do not necessarily have a background in medicine or healthcare. As evidenced also during the pandemic, this demographic is increasingly exposed to healthcare information on social media, where misleading visualizations may be prevalent [10]. Focusing on the younger population is strategic due to their active engagement with social media [57]. The primary knowledge gap of our audience stems from a lack of formal medical knowledge. This imposes several challenges—among which, simplifying complex medical information to ensure clarity and accessibility without compromising its educational value is the most important.

3.2.2. Designing the game course of *DeteCATive*

When conceiving the idea of our game, we imagined a private detective investigating newspaper snippets, advertisements, and social media posts to debunk healthcare-related "fake news". This inspired us to create an educational game, where a player can enjoy a similar atmosphere uncovering misleading elements—just like a detective would do. The player assumes the role of a detective solving investigation tasks that include misleading healthcare visualizations.

For each of the investigation tasks, we create a healthcare-related narrative revolving around open-source imaging or non-imaging data. The process of creating these narratives is discussed in Section 3.2.3 below, while the details of the narratives are presented later in Section 3.2.4. Every narrative is supported by a data visualization (see Fig. 3) that contains several deliberately introduced fallacies, such as those discussed in Section 3.1. We refer to this combination of a narrative with an accompanying visualization as a *visual narrative*. Two examples are shown in Fig. 3: one for non-imaging (left) and one for imaging data (right). Additionally, each visual narrative consists of a number of *assumptions* that provide clues about a corresponding number of misleading elements within the visual narrative (Fig. 3, enumerations in each narrative). These are suppositions or beliefs about certain facts or circumstances within the narrative. In *DeteCATive*, players are prompted to assess whether these assumptions are true or false to progress through the game. The assumptions are presented one by one to the audience. Progression through the assumptions and the investigation tasks follows a linear order, i.e., it is predetermined by the game designer. Free navigation is not allowed. This conceptual choice was made only to ease the implementation (and the evaluation, as we discuss in Section 4). For each correct assessment of an assumption, the players accumulate points. After each assessment, we also provide immediate feedback that aims to clarify the misleading element in the healthcare visualization at hand (Fig. 4). These *explanations* include both visual and text components. The textual explanations are short, precise, and unambiguous. The visual components supplement the textual components (Fig. 4). These are interactive and allow the user to understand the difference between the misleading vs. the correct alternative.

Solving riddles or puzzles activates problem-solving skills and increases motivation, thus improving the learning process [14]. However, it can be insufficient to sustain the motivation of players through the game. Positive reinforcement strategies, like a rewarding system, are used to increase player motivation [35,58]. We use two *rewarding systems*: score-keeping and achievements. The scoring system includes the points that the player achieves by correctly assessing riddles. One correct answer equals one point, and one incorrect answer provides zero points. These points are used at the end of the game to help the

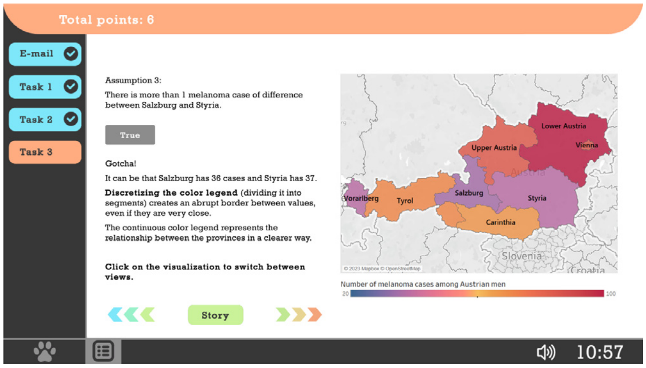

Fig. 4. Screenshot of the moment that a player receives feedback (textual and visual) for a wrongly assessed assumption of a non-imaging visual narrative. For the visual feedback, the player clicks on the visualization to interchangeably see the misleading vs. the correct alternative.

main character, who is also a "cat person", rescue stray cats. Only with a specific number of points, one or more cats can be saved at the end of the game (Fig. 5). Rescuing stray cats, despite not being essential to the mechanisms of the game, provides additional motivation for the player. The achievements also contain three versions of badges. When the player solves two particularly tedious riddles, the reward is the "*Eagle-eye*" badge. To get the "*Scholar*" badge, the player should get points for assessing correctly all the respective anatomical positions of the organs (Fig. 6). The most challenging badge is the "*Critical thinker*", for which all tricks with medical imaging data should be identified.

To enhance the gaming experience, we also integrate background music. Ambient music is preferred to complement the game's atmosphere and dynamics, supporting an immersive — yet calm — environment. For this, we commissioned a musician with extensive experience in composition. In the game, the track is looped and synchronized with the gameplay to provide a continuous backdrop for players, giving them the option to turn off the music at any time.

3.2.3. Designing visual narratives with misleading elements

To investigate whether an edutainment approach can support targeted audiences in identifying misleading elements in healthcare visualization, we create eight fictional visual narratives that can effectively demonstrate such misleading elements: four revolving around imaging and four around non-imaging public health data. Two of those are shown in Fig. 3. In some instances, we craft fictional visual narratives inspired by real cases, particularly within the realm of imaging data, where data for specific conditions might not be publicly available. For non-imaging data, we reproduce public health examples sourced from social media and other platforms. In all cases, we include visualizations with artificially introduced fallacies like those introduced in Section 3.1. These have been hand-picked as commonly occurring and indicative cases of uncertainty-related misleading visualizations in healthcare, i.e., they are cases that have been documented extensively in the literature. The visual narratives are described in detail in Section 3.2.4.

To make the narratives interesting while delivering our message, we used the *storytelling elements* of setting, characters, conflict, and message [59]. These elements were specifically employed to enhance the educational content within the constraints of our brief visual narratives. They serve the specific purpose of making complex information approachable, while still supporting the edutainment aspects of the game. For instance, one of our visual narratives was inspired by a 16th-century portrait of Gregor Baci located in Schloss Ambras, Innsbruck [60] and the accident of Phineas Gage, a 19th-century railroad constructor in the USA, who survived when an iron rod impaled his head at work [61]. This text of the narrative has been stylized as a newspaper snippet that conveys false information. This is accompanied

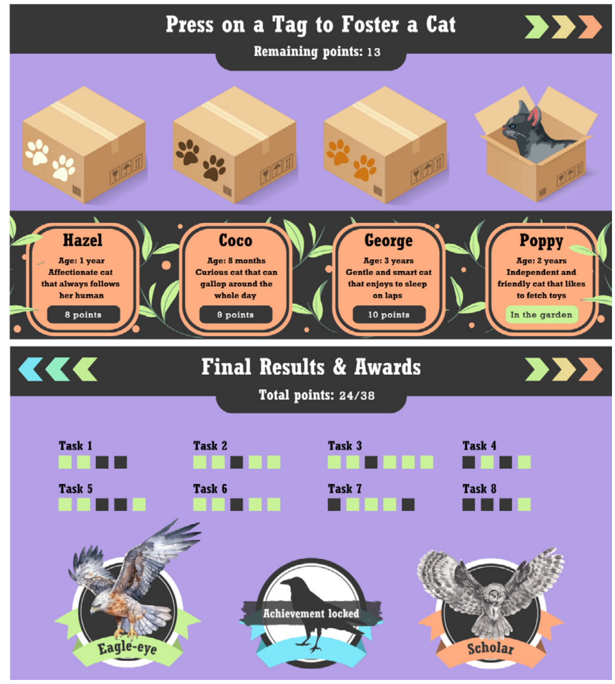

Fig. 5. (Top) Cats that can be rescued at the end of *DeteCATive* are used to create the game objective and to engage and reward the players. To rescue a cat the player must spend the collected points. (Bottom) At the end of the game, the player statistics are shown including the collected badges and correct answers in each investigation task.

by the corresponding visuals and looks like the following example (the `storytelling elements` are included within brackets for the reader, but were not shown to the audience):

Construction Worker Survived a Terrible Accident!

Last Friday, a terrible accident happened at the construction site of the city bridge (`setting`). A construction worker (`character`) got impaled with a metal rod through his head (`inciting incident, conflict`). Fortunately, the man survived because the rod did not damage the vital brain areas (`partial resolution of a conflict, the possibility of immediate death`).

Currently, the unfortunate worker is staying at the main hospital getting all the necessary care. Upon hospital admission (`resolution of a conflict by receiving care in a hospital`), a magnetic resonance (MR) scan was made to check the degree of brain damage (`false information`).

MR scans are used to emphasize and visualize soft tissues inside a body. An MR imaging machine does not use radiation. In this case, a very high magnetic field plays an essential role in the sophisticated process of capturing tissue information (`technological explanation`).

Our journalistic team (`building credibility`) managed to get the MR scan of the worker, and it looks terrifying as you can see in the picture (`imagery`)! At last, we want to warn you to take care and follow safety rules at work (`call to action/message`)".

As discussed in the previous section, for each visual narrative, we include a list of *assumptions*, the correctness of which should be

Fig. 6. Screenshot of the moment that a player achieves the "*Scholar*" badge for assessing all anatomical assumptions correctly.

assessed as part of the game (Fig. 3, left-hand side of each snippet). In the example of the construction accident above, a simple assumption would be "*A magnetic metal rod can be seen in the MR scan*". The audience should interpret the visual narrative to decide whether such an assumption is true. If the player answers incorrectly that the assumption is true, they will be reminded that the narrative states that MR machines generate powerful magnetic fields, therefore magnetic objects are prohibited in the scanning room. As a second example of a non-imaging case, we use a short narrative describing melanoma cases in the *Austrian population* (Fig. 3, left). The accompanying visualization would show the number of cases *just for the male population* (see the legend). A simple assumption would be "*The number of cases includes men and women*" and the audience should interpret the narrative and the visualization to decide whether such an assumption is true.

Within the text of the visual narrative, we hide (similarly to a real-life scenario) an intent, provide context, and give some hints or details about healthcare-related aspects that might be completely unknown to the target audience. For instance, we do not expect our audience to know that magnetic metal objects are prohibited in any MR room, as they are not familiar with the physics of the acquisition. Although such information is normally not present — or even worse, concealed — within a real-life visual narrative with an intent to deceive, we want to minimize (when possible) the players' potential knowledge gap. In the game, when providing solutions to the audience we explain the origin of the misleading elements and deliver the potential motivation for making such misleading visualizations. For this, we use plain language avoiding medical jargon, employ visual aids and interaction, and incorporate narrative elements.

3.2.4. The eight visual narratives of our game

For the *non-imaging cases*, we developed two visual narratives around a public health data set from COVID-19 patients. Two other visual narratives were centered around cancer statistics. In all four cases, we simulated misleading elements at different steps of the pipeline:

- The first visual narrative supports a public health initiative for continued mask-wearing in public transport, with intentionally introduced uncertainty types (■ typos, ■ bin issues, ■ data of different magnitudes, ■ wrong chart choice, and ■ misleading titles). The respective investigation task **(T1)** utilizes a stacked cumulative COVID-19 data representation, where failure to recognize its cumulative nature may create an impression of unceasing growth of COVID-19 cases.
- The next visual narrative falsely encourages real estate investment across a country, supported by intentionally introduced uncertainty types (■ color violation, ■ low scale resolution, ■ missing data, ■ normalization issues, ■ selective data, and ■ inappropriate axis range). The corresponding investigation task **(T3)** employs a color map displaying melanoma cases across the country provinces, where an adjusted color legend and values lacking normalization to province populations highlight a specific province as the healthiest (Fig. 3, left).
- The following visual narrative aims to draw media attention to rising breast cancer cases in all provinces while overlooking the decrease in the capital due to intentionally introduced uncertainty types (■ area encoding, ■ wrong chart choice, ■ clutter, and ■ inconsistencies). The respective investigation task **(T5)** employs a stacked area chart to falsely depict breast cancer incidence among women across provinces.
- The last visual narrative aims to capitalize on a perceived decrease in cases with several uncertainty types (■ bin issues, ■ data of different magnitudes, ■ missing data, ■ normalization issues, ■ selective data, ■ wrong chart choice, and ■ invalid comparison). The corresponding investigation task **(T7)** utilizes a stacked bar chart with COVID-19 data aggregated annually and concealing part of the time frame.

For the *imaging cases*, we simulated misleading elements at different steps of the pipeline for the following visual narratives:

- The first visual narrative aims to caution against alcohol consumption by introducing uncertainty types (■ under-segmentation, ■ non-specificity related to modality physics, ■ object orientation, ■ knowledge gap, ■ lack of guidance, and ■ subjective choice of transfer function). The corresponding investigation task **(T2)** utilizes a volume rendering of a human abdomen CT scan, simulating a fatty liver.
- The next visual narrative aims to create awareness about workplace safety based on several tweaked facts (■ artificially introduced noise, ■ non-specificity related to modality physics and tissue visibility, and ■ incompleteness arising from a knowledge gap of the audience). The accompanying investigation task **(T4)** features an MR scan and rendering of a head, simulating a magnetic metal rod impalement.
- The following visual narrative aims to boost newspaper sales through "click baiting" with a sensational title about a sportswoman's condition by introducing several uncertainties (■ non-specificity related to modality physics and tissue visibility, ■ incompleteness due to a knowledge gap, and ■ subjectivity arising from viewing properties). The respective investigation task **(T6)** employs a CT volume rendering, simulating dextrocardia, a condition where the heart is positioned on the right side of the body instead of the left.
- The last visual narrative aims to raise awareness about pollution by taking advantage of uncertainties (■ noise, ■ non-specificity related to modality physics and tissue visibility, ■ incompleteness due to spatial information loss, and ■ subjectivity from 2D projection perception). The associated investigation task **(T8)** uses a topogram of a fish CT scan (2D X-ray image), where foreign objects create an illusion of being inside the fish due to the loss of spatial information in 2D images (Fig. 3, right).

3.2.5. Implementation environment

DeteCATive has been developed in Unity2021.3.1f1 using C#, with images made in Canva and comics in online AI art generators such as Hotpot, Gencraft, and Canva AI image generator. The first author hand-drew digitally all the visuals of the game. The texts of the stories were additionally processed with ChatGPT3.0 to improve the fluency of the text. The accompanying visualizations were generated in MeVisLab 3.6.1.9 (2022-11-27 Release) for the imaging cases and in Tableau 2023.1 for the non-imaging cases.

3.2.6. Pilot trial

To evaluate the suitability and feasibility of the investigation tasks within the game course, i.e., to make sure that the visual narratives and assumptions were understandable and not too complex, a small focus group of five testers (without medical or visualization knowledge) was asked to conduct a pilot trial. Their feedback was valuable—mostly leading to changes in the formulation of some assumptions to increase clarity. Moreover, we got confirmation that some misleading elements were hard to recognize and in some cases, too difficult assumptions were simplified in the final game course.

4. Case study

We conducted a case study to gauge the effectiveness of our approach by evaluating player performance and aspects related to the value of the visual narratives to our method. This was intended to provide us with the first insights into the potential impact of the game and to inform the design of a larger-scale study in the future. In this user study, we let users interact with our game as they would do in a real-world scenario, while *(i)* focusing on *performance* by measuring their speed and error rates during gameplay, and *(ii)* investigating targeted aspects of the *value of our visual narrative approach*, such as memorability, reinforcement, engagement (aesthetics, cognitive involvement, captivation), and subjective likes and dislikes. For the assessment of performance, we relied on dedicated metrics [62] recorded from the game activity file. For the assessment of the value of the visual narratives, we drew from established evaluation frameworks and guidelines in the literature [2,62,63]. The order was deliberately non-randomized. Non-imaging and imaging investigation tasks have been arranged into an alternating pattern in ascending order of complexity. This was done to observe potential inter-task influences and to keep track of the point at which players exit the game.

4.1. User study design

Performance. We recorded the game activity file during each player's game course to collect the speed of investigation task performance and rate of errors with regard to the assessment of the assumptions in the eight visual narratives. These measurements can be used to assess performance [62]. To this end, a C# code was written for the Unity-developed game, which records the game activity. The data in the game activity file were:

- *Narrative reading time*, i.e., the time between the opening of an investigation task and the first switch to the assumptions.
- *Number of back-references to the narrative*, i.e., how often a participant returned to the textual narrative while analyzing an assumption or its explanation.
- *Accuracy of answers*, i.e., whether a participant correctly or incorrectly assessed an assumption during the game. This was measured by tracking points gathered during the game.
- *Assumption processing time*, i.e., the time between reading an assumption and submitting an answer. This indicated how long a specific assumption took for each player to process.
- *Explanation reading time*, i.e., the time required to read the explanation/clarification to an incorrectly answered assumption. This related to the player's level of interest in understanding and learning more about an incorrect answer.
- *Position of game exit,* i.e., after which investigation task a participant exited the game. This related to the willingness to engage more with the game and/or to learn more.

Value of visual narratives. We additionally evaluated game design decisions and subjective likes and dislikes [62]. The questionnaire included open-ended and multiple-choice questions, as well as 7-point Likert scales (from "Strongly disagree" to "Strongly agree"). To build our questionnaire, we drew from the work on narrative visualization evaluation by Meuschke et al. [2], where aspects such as memorability, aesthetics, and cognitive involvement are underscored. We additionally assessed the benefits of our twofold reinforcement strategy, while we also included the engagement aspect, using questions inspired by VisEngage [63].

For the *memorability* aspect, we asked "short-term memory" questions related to the user referring to the misleading elements at each investigation task or to previous tasks, to refresh the information delivered there. "Long-term memory" questions, instead, asked a participant to write a small paragraph about a misleading element that they remember/enjoyed solving the most. To evaluate these questions, we gathered and weighed several pre-defined key phrases about each narrative. When a player mentioned one or more of these key phrases, they gathered points that accumulate to a score of 100%. Within the *reinforcement* questions, we assessed whether our two reinforcement strategies (points and achievement badges) work for each player. The players were asked about their experience with the reinforcement strategy and also about the reasons why they continued playing until the end or exited the game early. The *engagement* aspect included the aspects of aesthetics [3], cognitive involvement [2], and captivation [63]. Finally, subjective likes and dislikes were also captured [62].

4.2. Case study and results

We conducted a case study on-site with 21 participants, who were recruited by snowball sampling [64]. This was conducted within our networks, including members of our research group and colleagues, and through a course announcement and word-of-mouth communication to generate interest. No remuneration was offered for the study participation. The study was entirely voluntary, as we sought individuals who were intrinsically interested in engaging in an educational game centered on the theme of healthcare and medicine. After a short introduction and after signing the necessary forms for potential revocation of data, we asked the participants to play *DeteCATive* as they would normally do in real-world circumstances. Out of the 21 participants, 14 are 20–29 years old, 5 are 30–39 years old, and the remaining 2 are older. Although more heterogeneous demographics would be preferable, younger people have higher chances of consuming visualizations in the wild (e.g., in social media) [57]. None of the participants possessed advanced knowledge or experience with medicine/biology, all indicating high school level knowledge. They also exhibited different educational backgrounds.

Performance. Regarding the *narrative reading time*, the game activity files indicated that the narrative with a misleading element of a cluttered stacked area chart to depict breast cancer incidences (**T5**, from the non-imaging cases) took the longest to read. There were no other noticeable differences between imaging and non-imaging cases. Looking at the *number of back-references to the narrative*, there was an evident decreasing trend for most of the participants. This may be an indication of increasing player confidence throughout the game, or of increasing fatigue and/or boredom. We observed varying *accuracy of answers* through the assumptions—with some consistently being answered correctly while others showed lower accuracy. For instance, most of the participants did not notice that one of the investigation tasks (**T3**, from the non-imaging cases) included a map with a missing province (see assumption 3.5 in Fig. 7). Interestingly, assumptions related to imaging investigation tasks demonstrated a relatively high accuracy rate, while some assumptions were found to be more challenging—either due to ambiguity or a lack of attention. The answers also indicated that players were more prone to rely on the visualizations accompanying the narratives, and potentially even ignore hints provided in the text. Furthermore, a Mann–Whitney U-test [65] indicated that the *assumption processing time* does not correlate to how easy or hard an assumption is, neither to the accuracy of answers. Conversely, the *explanation reading time* increased for the least correct assumptions (Fig. 8), as

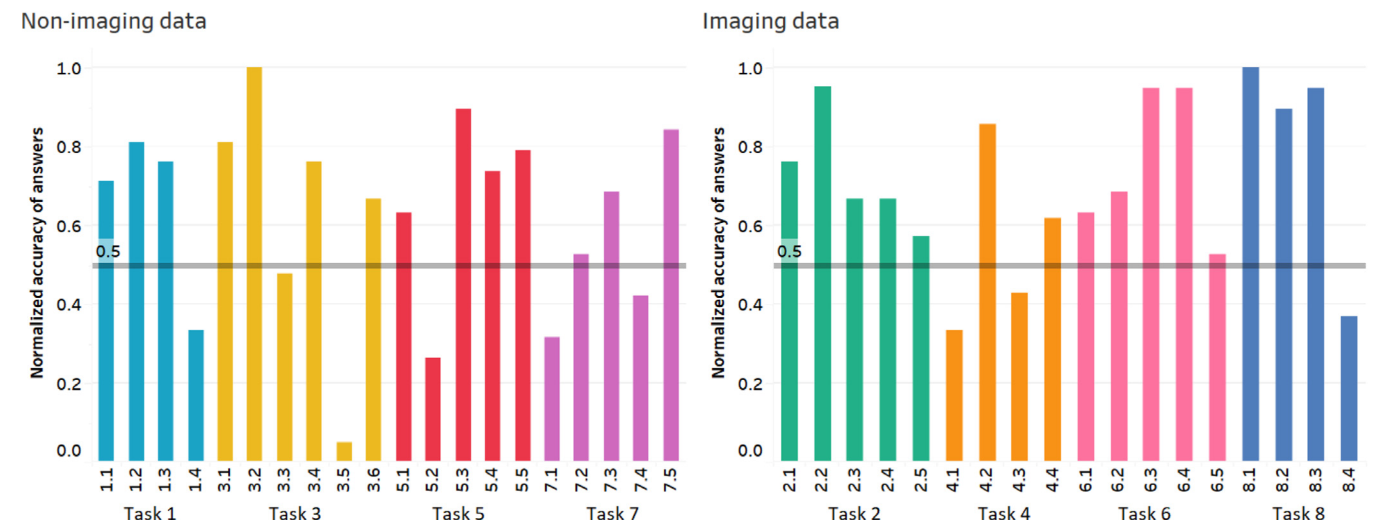

Fig. 7. Accuracy of assessing whether an assumption is true or false for all investigation tasks, separated into non-imaging (left) vs. imaging (right) cases. The gray line indicates 50% accuracy.

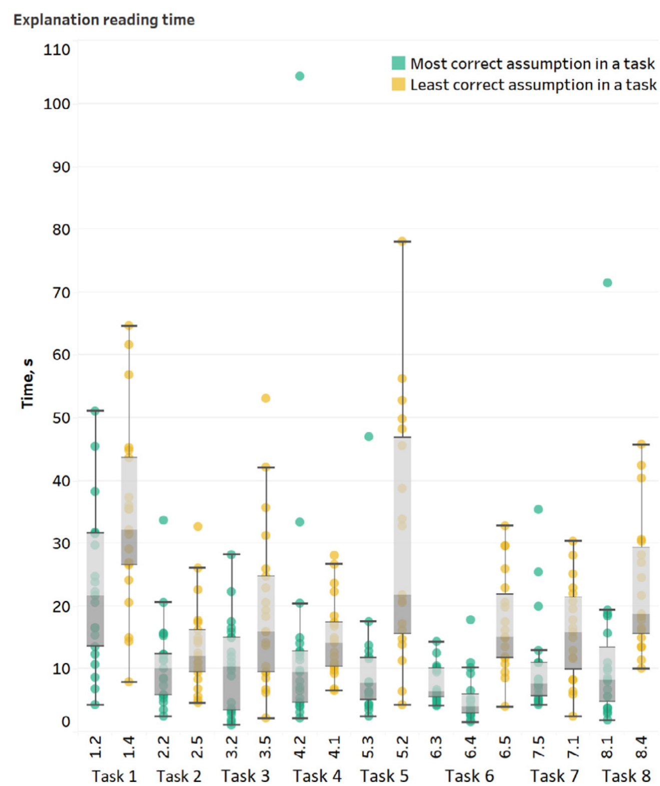

Fig. 8. Distribution of explanation reading time for most (green) vs. least (yellow) correctly answered assumptions in each investigation task.

anticipated. A Mann–Whitney U-test indicated that the explanations for the least correctly assessed assumptions were thought over longer than the most correct ones (<.05). This may be an indication of further interest or curiosity. Finally, about the *position of game exit*, only two players exited the game early—and one of them did so by mistake. It is essential to acknowledge the potential bias introduced by the freedom of exiting the game, as participants might be more inclined to complete all investigation tasks when being observed.

Value of visual narratives. As for *memorability*, the participants recollected mostly the medical imaging narratives (Fig. 9). The most correctly described misleading element was the one related to the non-imaging narrative of melanoma (**T3**). This is noticeably also the one with the lowest accuracy (Fig. 7). This might indicate that when the players made an error they might have spent some time reading the explanation, therefore, also remembering the assumption. *Reinforcement* results demonstrated that the players wanted to pursue the primary objective of rescuing as many stray cats as possible, but they also wanted to gain badges (Fig. 10(a)). All participants indicated that they continued playing until the end of the game because they were primarily curious to "investigate more stories"(i.e., visual narratives), while their second most frequent reason was to gain more points (Fig. 10(b)). This could indicate that the visual narratives were considered even more interesting than collecting points or badges. The game *engagement*, divided into aesthetics, cognitive involvement, and captivation got mostly positive feedback in all three categories. All participants agreed that the game interface was intuitive to use and that the aesthetics of the game were satisfactory. Most participants were strongly cognitively involved. For example, 19 participants agreed that they learned about misleading visualizations during the game, while 18 participants felt interested in learning more about the topics. Most participants (18/21) agreed that it was easy to focus on the game, but the background music was often turned down or off. Also, the ambiguity of assumptions (5/21) in the game was most commonly indicated as what they did not like. *Subjective feedback* indicated that the participants frequently praised the game art style (10/21) and described the user interface as "intuitive" and "not cluttered" (7/21). The educational aspect was well-received, particularly the game that presented new knowledge in a fun way. Finally, participants made mostly suggestions for a stronger reinforcement strategy through increased interaction with the game objective to boost motivation. For instance, one participant commented that they did not relate to the plot of rescuing stray cats, while other participants mentioned having difficulties navigating the game. Also, the music was sometimes considered distracting.

Study limitations and future goals. Our case study has several limitations that provide avenues for future research. Primarily, our current design has not considered the data visualization literacy of the target audience. When discussing our target audience, we identified a notable knowledge gap centered around medical or healthcare-related expertise. Yet, overlooking data visualization literacy limits the users' capabilities to understand and evaluate visualizations effectively. Ignoring this aspect may obscure insights and hinder the users' capacity to discern accurate medical information from misleading representations. Börner et al. [66] conducted a thorough investigation of data visualization literacy aspects and provided guidelines on incorporating such aspects in

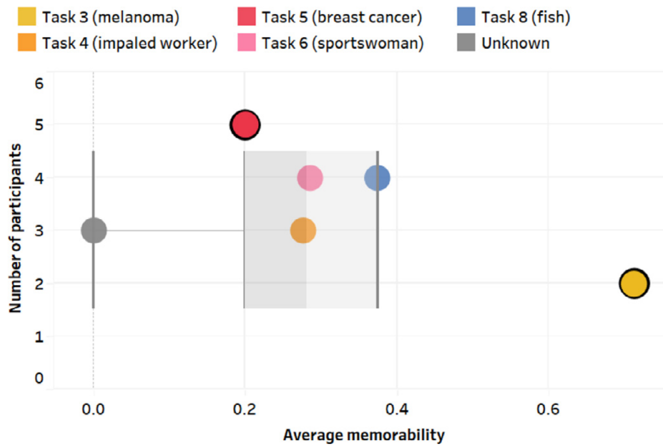

Fig. 9. Box plot of the average memorability score of each investigation task (horizontal axis) vs. the number of participants recollecting it (vertical axis). The glyphs with a black outline indicate non-imaging cases, and the rest are imaging cases.

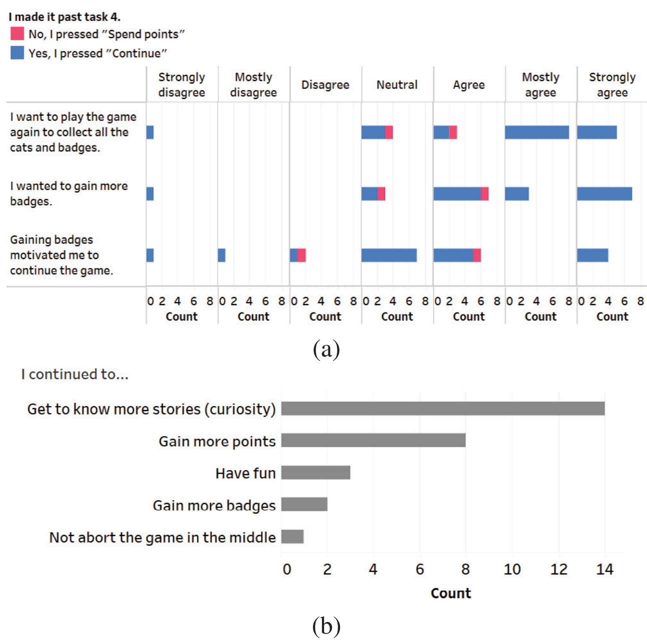

Fig. 10. (a) Distribution of answers regarding our reinforcement mechanisms (collecting badges and rescuing cats). (b) Distribution of answers indicating the reasons for continuing the game (beyond investigation task 4, which was the middle of the game).

visualization designs and evaluations. Considering these aspects would allow us to go beyond the limited investigation of healthcare-related literacy, providing significant enhancements to our preliminary work.

Moreover, we recognize the lack of long-term data on information retention and skill acquisition through the game, due to our focus on short-term engagement and learning. This calls for a follow-up larger-scale study—potentially in the format of a case-control study against other traditional educational methods. Investigating further the usability of the approach and delving deeper into its engagement potential, e.g., through the Player eXperience Inventory (PXI) [67], would also be interesting avenues for the future. Being an initial exploration, our study involves a participant pool that is rather limited and lacks diversity, e.g., in age and background. To enhance the robustness of our preliminary findings, a more comprehensive study with a larger and more diverse (in age, educational background, and health literacy level) population is essential. Including a larger variety of visual narratives would allow us to investigate whether there is a correlation between the type of uncertainty or misleading element and how easy it is to identify. A larger study would also include a need for accessibility improvements to include people with limited technology skills or different learning styles. Finally, it would be interesting to investigate how the requirements for a game (and also the derived insights) would differ when the target audience would include medical students or interested patients, instead of laypeople.

5. Conclusions

We proposed a game that employs visual narratives to educate and entertain broad audiences about misleading visualizations in healthcare. Our methodology involved an open coding of 66 papers to identify misleading elements in healthcare data visualizations. Informed by the literature, we developed eight evidence-based visual narratives to include in our edutainment game *DeteCATive*. A case study with 21 participants demonstrated high engagement and increased awareness about "dirty data" [23]. Future directions in our work prioritize a more comprehensive user study with generalizable insights.

CRediT authorship contribution statement

Anna Shilo: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Renata G. Raidou:** Writing – review & editing, Writing – original draft, Supervision, Project administration, Methodology, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.cag.2024.104011.

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