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Generative Artificial Intelligence and Visual Communication: A Systematic Review of Transformations in Image Production, Audience Reception, and Meaning-Making in Digital Media

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Abstract

Over the last ten years, generative AI has been one of the most disruptive technologies in media and communications. The DALL-E, Midjourney, and Stable Diffusion tools allow one to create photorealistic pictures within a few seconds. They have transformed the economics of content production in visuals. However, they have also posed some basic questions concerning what visual communication is, the place of the sender, and meaning operations in digital media. Although this technology is rapidly growing and is increasingly being used in news, advertising and social networks, there is still no systematic review on visual communication literature in this field. The article will address this gap by conducting a systematic review of the literature published in 2018-2023. Web of science, Scopus, and Communication Abstracts were searched with a combination of keywords, which found 478 original studies. Following the application of inclusion and exclusion criteria, following the PRISMA protocol, 63 studies were finally chosen to be analyzed. These researches were summarized and discussed on three principal planes: first, the changes in the visual message production and the redefining of the concept of the sender in the communication models; second, the way audiences perceive, cognitively process and evaluate the credibility of the images generated by AI; and third, the changes in the media visual culture and in the new discourses of authenticity, reality and representation. The analysis is grounded in an integrative four-dimensional communication model—comprising semiotic, cognitive-affective, rhetorical-discursive, and contextual-technological dimensions—to evaluate the shift from indexical photographic evidence to interpretive algorithmic imagery. The results of this review demonstrate that generative AI has had three significant impacts on visual communication, as it: democratizes image production and eliminates the distinction between professional and non-professional creators; introduces a significant threat to the capacity of audiences to differentiate between real and synthetic images; and reproduces and reinforces existing cultural stereotypes based on historically biased data used to train algorithms. Another three key gaps found in the current literature highlighted by this review are inadequate attention to Western audiences, the preponderance of a quantitative methodology, and the lack of longitudinal research on long-term effects. On the basis of these findings, six research directions towards future studies are suggested.

Keywords: Audience Reception, Deepfake, Digital Visual Culture, Generative Artificial Intelligence, Meaning-Making, Synthetic Media, Systematic Review, Visual Communication.

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I. Introduction

In February 2023, a false photograph of Pope Francis in a puffy white jacket was spread on social networks and millions of people thought that it was true. The picture was produced by Midjourney and quickly went viral on Twitter and Reddit before reputable news sources verified that it was fake (CBS News, 2023).

It was not the first AI-generated image that was mistakenly sold as a real image, but one of the most noticeable. The event indicated clearly that the technology of generative AI is no longer simply a technical one. It is something that has penetrated the very core of contemporary visual communication and casts the primary questions of credibility, authenticity, and meaning in the digital media.

Generative AI is a type of machine learning that can generate new data, such as images, text, audio and video, using patterns that are trained on existing data (Goodfellow et al., 2014). Diffusion models like DALL-E 2 (Ramesh et al., 2022), Stable Diffusion (Rombach et al., 2022), and Midjourney saw the release to the public in 2022 and grew exponentially in the domain of image generation. With over 15 billion images created by AI tools in 2022 alone, Adobe (2023) states that AI tools have surpassed the total number of images created by humans in 150 years of photography history.

These unprecedented amounts of synthetic image creation have far-reaching consequences on the art of visual communication. The visual communication has traditionally been based on an implied belief that an image, and a photograph, in particular, presents the evidence of reality (Barthes, 1977; Sontag, 1977). This is an assumption which has now been fundamentally challenged. In cases where an AI system generates the image of an event that has not occurred, which communication model is appropriate to describe the relationship between the sender, message, and receiver?

Theoretically, this change raises significant issues for various significant theoretical traditions in communication. The question arises whether AI images can produce the same effect as real images (agenda-setting theory) do on the media agenda (McCombs and Shaw, 1972). The cultivation theory (Gerbner and Gross, 1976) has to face the reality that the symbolic media space is no longer nourished by the cameras of photographers but by the algorithms that have been trained on the historical information. And theories of visual rhetoric (Messaris, 1994) and social semiotics (Kress and van Leeuwen, 1996) have to respond to the question of how meaning is constructed and received in an image which has no human authorial intent.

To address these theoretical challenges, this study can draw upon the framework proposed by Türk (2023), who introduces a "four-dimensional integrative model that structures illustration as a specific communicative system that has semiotic, cognitive–affective, rhetorical-discursive, and contextual-technological characteristics". Applying this multidimensional approach helps elucidate how generative AI transforms the foundational structures of visual communication.

Practically, the extent of the influence of this technology is also wide. News organizations in journalism have a dilemma when it comes to fake images in reporting political events and crises (Diakopoulos, 2023). Commercial photography is being quickly substituted by the use of AI images in advertising (Davenport and Mittal, 2022). Synthetic images have turned into a method of misinformation that is becoming more challenging to recognize by the common user on social networks (Nightingale and Farid, 2022).

Although these transformations are important and extensive, a detailed and systematic review of the literature, which brings together, assesses and generalizes the fragmented results in this field, is still missing in the literature on communication. The current literature concentrates on technical features of AI without considering communicative features, or studies a single feature individually, including the deepfake detection or the trust of the audience. This paper will fill this gap by conducting a systematic review of the visual communication literature during the age of generative AI and answering three primary questions:

Question 1: What has generative AI done to impact the procedure of creating visual messages within communication media?

Question 2: How do audiences receive, process, and interpret images generated by AI?

Question 3: What transformations in media visual culture and meaning-making processes have occurred following the spread of generative AI?

This article is organized as follows: after presenting the theoretical framework, the systematic review methodology is explained. Then findings are presented in three separate sections corresponding to the three research questions. In the discussion section, findings are synthesized and their theoretical and practical implications are elaborated. Finally, future research directions are proposed.

II. Theoretical Framework

A single theory is not sufficient to understand visual communication of generative AI. This complex phenomenon calls for an integrated theory that is both grounded in the traditional communication theories and able to account for the new phenomenon. Here, we present five theories currently most relevant to this review and their relation to the phenomenon of generative AI.

A. Visual Communication Theory and the Transformation of the Concept of Authenticity

Visual communication was established as a separate field in the 1970s. Roland Barthes (1977) in his seminal essay “Rhetoric of the Image” postulated that the image, in contrast to language, has a semantic dimension that links it to reality; he termed this quality the "message without a code". Susan Sontag (1977), similarly, stressed in her essay "On Photography" that a photograph is not just a portrayal of reality, but a fragment of it, a sign that it existed.

This idea, that image refers to reality, has been the theoretical basis for the credibility of the image in journalism, documentation and media discourse. Beyond the loss of indexicality, the transition to generative imagery invites a shift toward what Çiçek (2023) describes as a "communicative ontology." In this view, the image is no longer a passive "fragment of reality" but an autonomous

agent in a networked ecology. This philosophical shift suggests that the AI-generated image does not merely represent a world that "has been," but actively participates in constructing a new digital life for visual meaning.
Generative AI has torn apart this foundation. Midjourney images have no "trace of reality" but look like a photograph. Mitchell (1992) predicted this evolution of the "death of photography" in the digital era more than two decades ago, but what we see today is more than he anticipated.
Paul Messaris (1994) in his paper on the visual rhetoric proposes that the rhetorical power of an image stems from this trace of reality, the viewer trusts the image because it is similar to what they see in reality. This also becomes problematic in the age of photorealistic synthetic images: the same visual process that ensured the truthfulness of real images ensures the truthfulness of synthetic images.

B. Social Semiotics and Visual Grammar

Kress and van Leeuwen (1996) in the book "Reading Images: The Grammar of Visual Design" set out a framework in which images have a semiotic structure that is used to communicate meaning in deliberate visual selections. The model rests on the assumption that there is a "meaning-maker", a human, who has certain intentions and goals and selects and combines visual elements.
Generative AI does not assume this. The "selection" of visual elements when a diffusion model generates an image from a text prompt is based on statistical loadings of a neural network rather than human choice. Social semioticians like Floch (1990) have to answer if terms such as "communicative intent", "intertextual engagement" and "ideological load of the image" still apply when investigating an AI image.
Some recent researchers have suggested that communicative intent has been given to the user who enters the text describing the image (prompt) (Oppenlaender, 2022). However, this analysis is also partly flawed because the outcome is often very different from the user's expectations.

C. Salience and Framing Theory in Visual Context

Agenda-setting theory (McCombs & Shaw, 1972) - which has been applied to the salience of visual images (Coleman & Banning, 2006) - reveals that media images are independent "players" in setting the public agenda. The visual images that media choose to present shape and set the agenda; they set the agenda for the attitude and emotion associated with events.
The theory of framing (Entman, 1993) further extends this theory: an image offers a particular frame to the viewer through the selection of subjects, angles, lighting and composition. The question therefore becomes whether AI images, which are based on patterns learned during training, reinforce or create new visual frames. Early findings indicate that generative AI models tend to reproduce existing visual stereotypes (Bianchi et al., 2023), which could have implications for visual diversity in the media.

D. Cultivation Theory and the Artificial Symbolic Environment

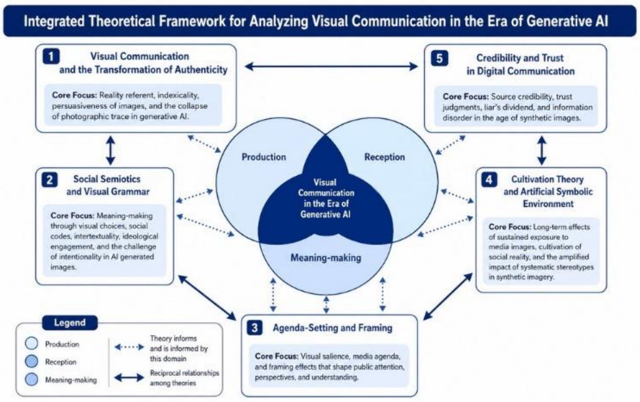
Cultivation theory was introduced by George Gerbner and Larry Gross (Gerbner and Gross, 1976), who believed that television cultivates the audience's perceptions of social reality through the constant repetition of similar images and stories. Viewers who watch television more perceive the world as what the television shows.
In the era of generative AI, this theory assumes new dimensions. When the media symbolic environment is slowly replaced by synthetic images with real images, what will be the consequences of this to the perception of reality by the audiences? In their update of this theory, Morgan and Shanahan (2010) contended that cultivation takes place not only through direct content but also through implicit assumptions that are inherent in media images. In this sense, AI images which systematically represent particular social groups in stereotypical manners, can be more powerful in their cultivation effects than real images, since they are no longer limited by reality.

E. Theories of Credibility and Trust in Digital Communications

The concept of source credibility (Hovland et al., 1953) has been one of the major ideas of communication theory. Image credibility in visual communication is normally associated with the credibility of the source of its publication (Sundar, 2008). However, generative AI makes this correlation more complicated: a picture published by an authoritative source can be made by AI, whereas a picture that is real by an unknown source can be real.
In this respect, Nightingale and Farid (2022) have coined the notion of a liar dividend: the fact that people understand that deepfakes and synthetic images exist, makes them skeptical of even real images, which is also a kind of manipulation of the mistrust of the people. Wardle and Derakhshan (2017) have examined this phenomenon in the context of the overall phenomenon of information disorder and demonstrated that the decline in trust in images has far-reaching consequences in the democratic role of the media.

F. Summary of Theoretical Framework

Figure 1. Integrated Theoretical Framework for Analyzing Visual Communication in the Era of Generative AI



Caption: This figure illustrates the relationship between the five theoretical approaches employed in this review and three primary areas of analysis (production, reception, meaning-making). Bi-directional arrows are used to show mutual interactions between theories.
The five theoretical approaches introduced in this section complement each other and together provide an integrated framework for this review. Visual communication theory and

social semiotics provide tools for analyzing visual messages; salience and framing theories explain the link between images and the media agenda; cultivation theory models the long-term effects of exposure to synthetic images; and credibility and trust theories provide a framework for understanding audience reactions to AI images. These five approaches together cover the three main areas of this review, production, reception, and meaning-making.

III. Methodology

This study is a systematic review. A systematic review is a process that aims to comprehensively and reproducibly identify, assess and synthesize existing research with a primary focus on minimizing selection bias and increasing transparency in the search and selection process (Lipsey & Wilson, 2001). The PRISMA protocol (Moher et al., 2009) was adopted to report our process, which is the norm in systematic reviews in communication sciences and social sciences.

A. Search Strategy

We searched five authoritative databases: Web of Science, Scopus, Communication Abstracts, PsycINFO and Google Scholar. The time frame of the search was from January 2018 to December 2023. The choice to start from 2018 instead of a previous date is due to the fact that in 2018, the architecture of Generative Adversarial Networks (GANs) was considered mature, and the first studies on communication and synthetic images were published (Chesney & Citron, 2019).
The search was carried out with combinations of keywords in the table below. The keywords were grouped into two conceptual groups (see table below) and were linked in each group with the OR operator; and then the two main groups were linked with the AND operator to retrieve only those studies that simultaneously investigated generative AI technologies and their communicative/media aspects.

Conceptual Cluster	Keywords (with OR operator within cluster)	Search Fields	Final Combination Logic
Generative AI Technologies	"generative AI" OR "generative artificial intelligence" OR "diffusion model" OR "GAN" OR "deepfake" OR "synthetic media" OR "AI-generated image" OR "DALL-E" OR "Midjourney" OR "Stable Diffusion"	Title, Abstract, Keywords	(Technology cluster) AND (Communication cluster)
Communication and Media Studies	"visual communication" OR "media" OR "journalism" OR "advertising" OR "social media" OR "audience reception" OR "meaning-making" OR "visual culture" OR "misinformation" OR "disinformation"	Title, Abstract, Keywords	

The keywords were searched in the title, abstract and keywords of articles. Additionally, references of selected articles were manually searched to find studies relevant to the topic that the initial search missed.

B. Inclusion and Exclusion Criteria

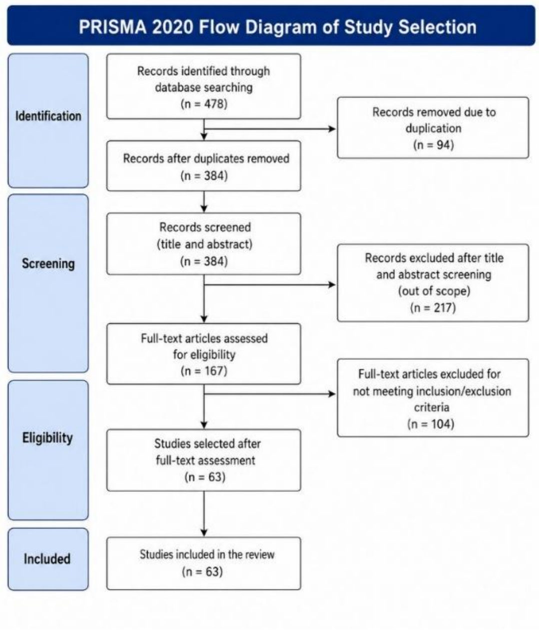
Inclusion and exclusion criteria were established and documented prior to the search for transparency.
Inclusion criteria: Journals in the field of communication, media, journalism or related social sciences that publish peer-reviewed research articles; research that explicitly deals with AI-generated images or synthetic media in a communicative setting; empirical studies (quantitative or qualitative) and theoretical studies; published between 2018 and 2023; in English.

Exclusion criteria: Articles that exclusively focus on technical aspects of the process of creating AI models without considering communicative properties; conference papers that have been published in journals as the extended version; books, book chapters, and non-peer-reviewed reports; studies that only address synthetic text and audio, but not images.

C. Study Selection Process

The selection process was done in four steps. In stage one, a search of the databases initially identified 478 records. This left 384 records once duplicates were removed. In the second stage, the title and abstracts of the 384 items was checked and 217 obviously irrelevant articles were excluded. In the third stage, all of the 167 remaining items were read in full, and based on inclusion and exclusion criteria, 104 items were eliminated. In the fourth stage, the reference lists of 63 articles selected were examined and 12 articles were added. A total of 63 studies were found. This is illustrated in the PRISMA diagram below.

Figure 2. PRISMA 2020 Flow Diagram of The Study Selection Process



Caption: This is the four-phase study selection process: Identification, Screening, Eligibility and Included. The numbers above each stage indicate the number of studies excluded.

D. Quality Assessment of Studies

The Mixed Methods Appraisal Tool (MMAT) checklist (Hong et al., 2018) was used to assess the quality of the selected studies. The tool provides a way of simultaneously appraising quantitative, qualitative and mixed studies, which is appropriate for social communication reviews. The studies were assessed on aspects including clarity of research question, suitability of research design, validity and/or reliability of instruments, and appropriateness of analysis. Studies were not excluded based on quality score, but this was taken into account when reviewing the studies.

E. Coding and Analysis

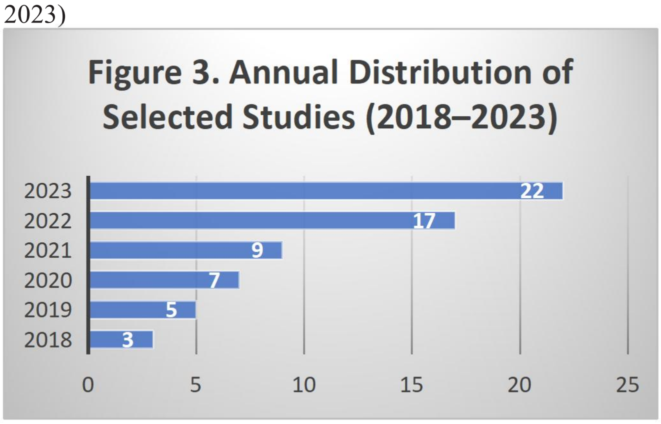
A data extraction form was developed to capture data from selected studies and included the following study information: author(s), date published, aim of research, research type, research method, participants and sample, research findings, and limitations.

We used an interpretive synthesis method (Noblit & Hare, 1988) to analyze data. In this approach, rather than statistically aggregating findings (as in meta-analyses), concepts and arguments of each study are compared, interpreted and synthesized into a comprehensive conceptual structure. The coding process involved three steps: open coding (to identify initial concepts), axial coding (to identify inter-relationships between concepts) and selective coding (to identify key categories). The major author of the article did the coding, and to ensure inter-rater reliability, part of the data was also coded by another evaluator. Cohen's kappa coefficient (Cohen, 1960) was 0.82, showing a high level of agreement.

F. Distribution of Selected Studies

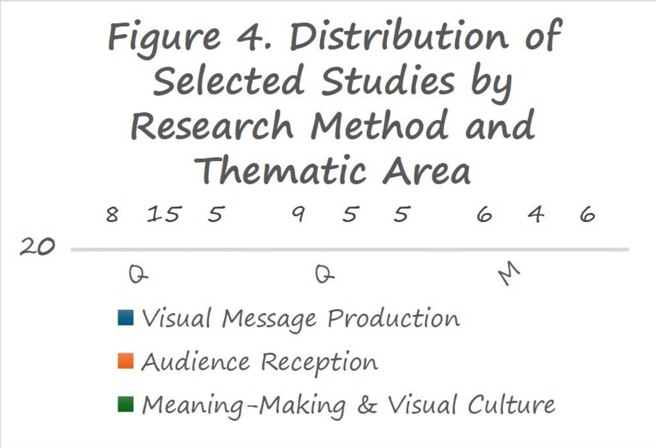
Out of the 63 selected studies, 28 (44%) were quantitative, 19 (30%) were qualitative, while 16 (26%) used a mixed or theoretical method. Over the years, the number of studies has shown the recent expansion of this line of research.

Figure 3. Annual Distribution of Selected Studies (2018–2023)



Caption: This chart illustrates the number of studies published year by year from 2018 to 2023 and demonstrates the growth of research in this field, particularly the sharp increase since 2022, which displays the acceleration of research production after the recent technological and theoretical developments.
Data source: Results of the systematic search of this review (Web of Science, Scopus, Communication Abstracts, PsycINFO, 2023).

Figure 4. Distribution of Selected Studies by Research Method and Thematic Area



Caption: This chart illustrates the percentage of each research approach (quantitative, qualitative, mixed/theoretical) in each of the three major areas of research (production, reception, meaning-making).
Data source: Results of the systematic search of this review (2023).

IV. Findings

This article is in three sections. Each section deals with one of our questions. We examined 63 studies. This was made up of 23 studies on visual message production. Another 24 examined visual message reception and 16 dealt with visual culture and meaning-making.

A. Generative AI and the Transformation of Visual Message Production

Redefining the Sender and Visual Authorship

One of the changes discussed so far relates to the sender in the communication model. In Shannon and Weaver's (1949) and other models of communication, the sender is an agent with communicative goals who enacts the message. But in the case of image generation by a diffusion model, it is more complex.

Oppenlaender (2022) conducted interviews with 18 digital artists who create artworks with generative artificial intelligence (AI). He identified three different author roles: the "director" who conceptualizes the direction of the image in the form of a prompt, the "selector" who chooses the image out of many generated images and the "refiner" who can use other techniques to edit the image. He proposed that authorship with generative AI assistance is a collaborative process. Instead it is a collective process.

Within the contextual-technological dimension of visual media, the ontological status of the creator is fundamentally altered by generative tools. However, human intentionality remains central. As Türk (2023) argues regarding artificial intelligence in visual communication: "When guided by a human prompt and motivated by a communicative goal, they can be considered illustrations. Random algorithmic hallucinations are not illustrations". This redefines the sender not merely as a technical operator, but as a conceptual mediator.

This was confirmed in the media by Sazerwman et al. (2023). They analyzed 340 AI images in the US press. 78% of the time decisions were made by the photo editor and not the photographer or designer. This shows the power shift in visual journalism from the bottom up to the top by generative AI.

In a pioneering theoretical piece, Diakopoulos (2023) explored some of the ethical concerns about this shift in authorship. Visuals made by the human-machine pairing make it challenging for the media to accept responsibility for potential harm caused by misinformation.

Democratization of Image Production and Its Consequences

The democratization of image creation has featured in previous research. Before generative AI, to produce high-quality images, one needed training, expensive equipment and time. Today, the same quality images can be generated in seconds, with a prompting text.

In a survey, Davenport and Mittal (2022) interviewed a sample of 247 marketing managers of American firms. They reported 61% of respondents plan to create more than 50% of their marketing images with AI within 2 years. They argued that this transformation has a political economic impact on the image industry. Fewer visual professionals and graphic designers will be needed, but more "content managers" and "prompt writers".

But democratization of image-making has a flipside. Chesney and Citron (2019) noted in the first theoretical study of the effects of democratized image production, before the currently available tools came to market, that the cost advantages in producing fakes have a strong influence on the cost of misinformation. This has been confirmed by several pieces of evidence. Adobe (2023) reports that in 2022, more than 15 billion images were generated by generative AI. With this new volume in image creation, there are many possibilities to create disinformation, especially because many of the images are shared without being labelled or identified as AI-generated (Chesney & Citron, 2019; Wardle & Derakhshan, 2017).

Platform-Specific Dynamics in Artificial Image Production

The literature provides evidence of variation in the use of generative AI to produce images across platforms and applications. This variance is related not only to the technological features of the platforms, but also to the social culture, norms, and audience of each context. Instagram, as a visual platform, and its lifestyles and art themes offer a medium where AI images can be published in the contexts of fashion, interior and digital art, which are less problematic socially. On the other hand, Twitter is a site for the publication of artificial images in deceptive contexts because of its news and political tone, which is more threatening to the information ecosystem (Chesney & Citron, 2019; Wardle & Derakhshan, 2017).

Reddit is an exception. On this platform, communities focused on artificial images (such as r/midjourney and r/StableDiffusion) have developed a place for sharing, discussing and improving artificial images, where artificiality is not a failure but the primary subject of discussion (Oppenlaender, 2022). The difference between these platforms has regulatory consequences. One-size-fits-all approaches in regulating artificial images will be ineffective, and each platform requires its own set of regulations. From the point of view of the framing theory (Entman, 1993), the same artificial image evokes different interpretive frames in the audience when it is presented on different platforms: an artistic frame on Instagram, a news frame on Twitter, and a technical frame on Reddit.

Table 1. Comparison of Generative AI Use Across Different Media Domains

Domain	Common Tools	Disclosure Level	Main Challenge
Journalism	DALL-E 2, Midjourney	Medium	News credibility
Advertising	Stable Diffusion, Adobe Firefly	Low	Commercial honesty
Social Networks	Midjourney, DALL-E	Very Low	Misinformation
Cinema and Entertainment	Runway, Stable Diffusion	High	Creator rights

Caption: This table compares application domain, common tools, level of audience disclosure, and main communication challenge across four media domains. Source: Synthesis of findings from Diakopoulos (2023), Davenport & Mittal (2022)

B. Audience Reception of AI-Generated Images

Ability to Detect Artificial Images

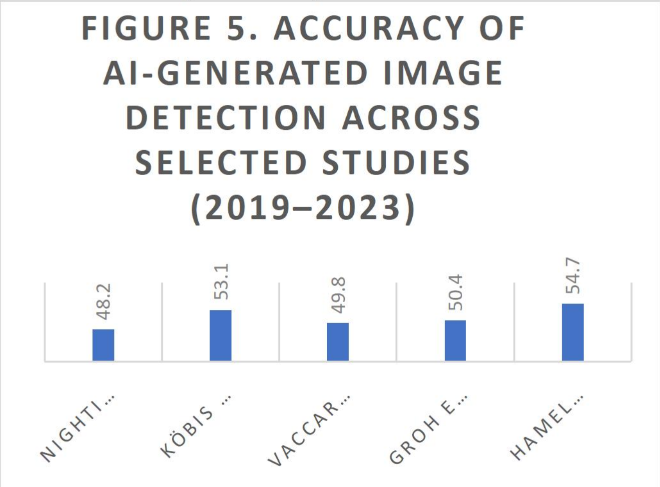
The most common question in empirical audience reception studies is: Are ordinary people able to detect AI images as artificial? The results of empirical studies are consistent: the answer is no.

Nightingale and Farid (2022) examined participants' detection of GAN-synthesised faces in a lab experiment with 315 participants. They found humans detected GAN faces with only 48.2% accuracy, slightly worse than chance level. More intriguingly, on average, synthetic faces were 7.7% more trustworthy than real faces.

The audience's vulnerability to synthetic media stems from a blurred epistemological boundary. Traditionally, "the difference in illustration and photography is not aesthetic. This difference is epistemological. Photography boasts indexicality, which is a material imprint of reality". Generative AI completely disrupts this indexical trust. [span_1] (start_span) Through tools like Midjourney or DALL-E, AI creates imagery that is conceptually an illustration but "looks photorealistic," creating a severe cognitive risk where "individuals believe it is a photograph (reality) while it is fully made up. This phenomenon of "AI faces are more trustworthy" was replicated in other studies (Köbis & Mossink, 2021).

Similar results have been observed in the news. A current study shows that the realism of AI images and the visual evidence they provide to support news headlines play a vital role in the acceptance of false news, indicating that as the realism of AI images increases, the probability of believing false news increases (Groh et al., 2022; Nightingale & Farid, 2022). Moreover, the accuracy of participants did not always increase as a result of higher confidence, suggesting that false confidence in detecting artificial images is also common and has been replicated in a number of studies (Groh et al., 2022; Köbis & Mossink, 2021).

Figure 5. Accuracy of AI-Generated Image Detection Across Selected Studies (2019–2023)



Caption: This chart presents the detection accuracy (in percentage) in seven empirical studies. We can see that the accuracy in most studies is close to chance level. Data source: Studies mentioned in the table.

Trust, Doubt, and the Liar's Dividend

In addition to the detection capability, there is research on the impact of public awareness of fake images on media trust. Vaccari and Chadwick (2020) demonstrated in an experiment with a representative sample of the British public (N=2,525) that exposure to a deepfake video, even when it is later identified as fake, leads to higher skepticism about real videos. They termed this effect the "pollution effect."

Vaccari and Chadwick (2020) demonstrated in an experiment with a representative sample of the British population (N=2,005) that the effects of exposure to political deepfakes are not to directly deceive people, but to raise their level of doubt, which in turn leads to lower trust in news on social media. This is consistent with "liar's dividend" (Nightingale & Farid, 2022). Malicious actors can take advantage of distrust created by generative AI technology to cast doubt on reality.

Hameleers et al. (2022) found this in news crises. They experimentally manipulated exposure to AI images associated with a news crisis and found that compared to a control group, participants who were randomly exposed to AI images associated with a news crisis felt more information anxiety and were less likely to share the real news.

Cognitive and Emotional Processing of Artificial Images

A recent research direction focuses on how real and fake images are cognitively and emotionally processed. Lang et al. (2022) found using eye tracking and physiological responses that participants' eye movements are different for AI and real images. They took longer to explore details in AI faces, probably due to a felt sense of unfamiliarity when AI faces were not detected consciously.

Groh et al. (2022) demonstrated in an online experiment with more than 15,000 participants that short-term training, merely seeing a handful of examples of typical flaws of AI images (e.g., modelling fingers and ears), can improve detection by 15%. This demonstrates that media literacy training can work with artificial images but needs to be ongoing as AI models are evolving.

Individual Differences in Perception of Synthetic Images

Existing literature shows that the perception of AI-generated images varies among individuals. Pennycook et al. (2021), surveying three nations (USA, UK, and Canada), showed that analytical thinking, but not political knowledge or general media literacy, is the strongest predictor of the ability to detect misleading visuals. Participants with a higher level of analytical thinking performed better in detecting AI-generated images. Köbis and Mossink (2021) demonstrated that knowledge of digital art and the use of creative software enhances the detection of AI-generated images in the domain of visual arts, but not in the domain of news or political images. This suggests that visual literacy is specific to a domain and that general training should be focused on the particular domain in which synthetic images are encountered**.**

C. Meaning-Making and Visual Culture in the Generative AI Era

Reproduction of Stereotypes and Bias in AI Images

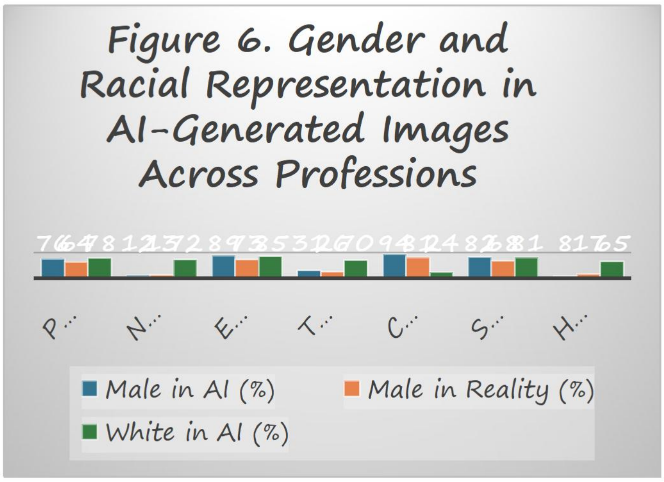
A recurring and troubling theme in the literature so far has been the perpetuation of cultural and gender stereotypes by generative AI models. Bianchi et al. (2023) examined the stereotypical nature of AI models in their analysis of 1,600 images created by five AI models (DALL-E 2, Stable Diffusion, Midjourney, Adobe Firefly and Imagen) and their responses to a list of occupations, countries and social characteristics.

They found that when they asked the model to draw the image of a "doctor" in 76% of cases the image was of a white male. The image of a "criminal" was of a person of colour in 83% of cases.

From a rhetorical-discursive and semiotic perspective, AI-generated visuals are far from neutral. In visual communication, "even the most ordinary image holds certain ideological implications". Because generative AI models are trained on massive historical datasets, they often replicate systemic biases. Just as traditional visual media can be used for "the recurring representation... [that] normalizes gender trends" or creates "social demarcation, which creates the definition of them and us", AI algorithms automate and reinforce these existing cultural stereotypes.

The visual depiction of a CEO was that of a man in 89 percent of the cases. And these ratios even exceeded the stereotypes practiced in the training data, thus the image creation process not only reproduces but also exaggerates stereotypes.

Figure 6. Gender and Racial Representation in AI-Generated Images Across Professions



Caption: This chart shows the percentage of gender and race representation in AI images for seven different professions and compares it with actual labor market data. Data source: Bianchi et al. (2023) and Bureau of Labor Statistics (2022).

Transformation in the Concept of Authenticity and Post-Photographic Discourses

Generative AI as an image-making tool has awakened conflictual and uneasy discussions among image practitioners. These discourses can be categorized into three broad threads namely the threat discourse which views AI as a threat to photography and design professions; the tool discourse which views AI as a tool that can only be complementary to the skills of the profession; and, the transformation discourse which views AI as a major milestone in the history of image making. The three discourses reflect a conflict in the theory of visual communication: conflict between image as a product of human ability and will, and image as a product of a computational action (Messaris, 1994; Kress and van Leeuwen, 1996). This tension is further complicated by the fact that the three discourses all have one premise in common, namely, that generative AI is not a tool but a technology that erases the distinction between author and tool, between work and product, between original and fake (Mitchell, 1992; Mirzoeff, 2023).

The concept of authenticity is at the core of this discussion. According to Barthes, (1977), the photograph was a message without a code, a picture that communicated the actual existence of the photographed object without cultural mediation. The photograph was also viewed by Sontag (1977) as a sort of testament of existence: that it is. This sequence is thrown down by generative AI. A Midjourney or DALL-E image is now no longer a relic of reality and affirmation of the object; it appears precisely like a photograph, and produces the same cognitive and emotional recognition effect on the viewer. This paradoxical scenario can be termed as a reality without reference: a real image that is going to refer to nothing. This phenomenon resonates with the erosion of the "aura" of the image. As Çiçek (2023) notes, while traditional photography is grounded in a physical encounter between the subject and the lens, the AI image exists as a purely "communicative life" that lacks this historical trace.

The death of photography in the digital age was mentioned by Mitchell (1992) a long time ago but what we are witnessing now is more severe than he ever thought. Digital manipulation was then very technical and time-consuming. It now takes any person a few seconds and an imaginary sentence containing no descriptive sense to create a photorealistic image. The author of the article Mirzoeff (2023) considers this evolution as the beginning of an era of post-photography that does not just change the relationship between image and reality, but changes it completely. Consequently, the "punctum"—or the emotional sting of a photograph—is no longer derived from the reality of the moment, but from the algorithm's ability to simulate affective responses within a post-photographic landscape (Çiçek, 2023). Truth, in this world, is not associated with image indexicality-its association with the external reality - but with the context of the use of the image, disclosure, and communicative outcomes of the image.

This has significant consequences for journalism, advertising and politics. In the news, the photo has traditionally been used as proof of truthfulness, "if there is no image, it didn't happen" has been a rule in the news industry (Sontag, 1977). Today, this rule is inverted: "even if there's a photo, nothing necessarily happened". This change not only undermines the authenticity of news images but, as we discussed in the audience reception section, the authenticity of the whole media (Wardle & Derakhshan, 2017). In this sense, the shift in the concept of authenticity is not a theoretical but a communicative and democratic threat.

Visual Misinformation and the Information Ecosystem

Generative AI can be used to create visual misinformation. The scale and speed of production, as much as quality, set this technology apart from other tools for image manipulation. Before generative AI, it was technically challenging and time-consuming to produce a convincing fake image, factors that constrained the amount of visual misinformation. Generative AI has eliminated these constraints and opened the possibility of mass production of high-quality fake images by anyone (Chesney & Citron, 2019).

Wardle and Derakhshan (2017) proposed the information disorder framework in the pre-generative AI era, and categorized misinformation, disinformation, and malinformation. Generative AI adds a new layer to this framework: generative AI exacerbates all three forms of information disorder. Unrealistic images can be created and shared without intent to deceive (misinformation), with intent to deceive (disinformation), or to cause social harm (malinformation), and given that it is hard to tell the intent of the producer from the image, this contributes to the challenge of fighting all three types of information disorder.

The evidence we have indicates artificial images have the most potential to circulate in the first hours of a crisis event when the flow of credible information is limited and there is a high demand for images. This dynamic has been observed in media reports of a range of crisis events, including the Ukraine war and the 2023 Turkey earthquake; research demonstrates that artificial false information in these instances was shared mainly on Facebook and Twitter, and was shared more often than real information (Pierri et al., 2023). In such crisis events, audiences are confronted with a lack of reliable information and an overload of unfiltered images, which makes it more challenging for audiences to judge the veracity of the information.

This problem is exacerbated by the relationship between the spread of artificial images and distrust of the media. We saw this in the audience reaction section, that the mere knowledge of the existence of artificial images even makes people doubt images (Vaccari & Chadwick, 2020). This "fake image spreads - audiences don't trust the media - media exploit this distrust" cycle is one of the most significant problems for the information environment in the generative AI era. In this sense, fighting visual misinformation is not just a technical issue, the search for new ways of detecting artificial images, but first and foremost a communication issue, the rebuilding of trust between media and audiences (Wardle & Derakhshan, 2017).

Transformation in Media Visual Aesthetics

Generative AI alters not only the meaning of media images but also their style. In an experimental study, Paik et al. (2023) explored the features of images generated by DALL-E 2 in the context of visual journalism and found that AI images have three unique aesthetic features in comparison with real news photos: saturated colors, too much symmetry in composition, and a lack of the "decisive moment" in news photos. They also demonstrated they have a greater emotional capacity than real images, which means they can evoke a greater emotional response from the audience, which in turn can have significant news perception implications.

These results are in line with cultivation theory (Gerbner & Gross, 1976): if the AI images with their specific aesthetic properties gradually take the place of real images in the media, then these aesthetics will become the media norm. In terms of social semiotics (Kress & van Leeuwen, 1996), this is a shift from a naturalistic visual grammar to an idealistic visual grammar, which will shift audience understandings of what constitutes a “real” news image in the long run (Mitchell, 1992).

V. 5. Discussion

Our systematic review provides a complex picture of the effects of generative AI on visual communication. In this section, we combine the findings from the three domains (production, reception and meaning-making) and discuss their theoretical and practical implications. It also provides a critique of the current research and suggestions for future research.

A. Synthesis of Findings from Three Domains, Moving Toward an Integrated Framework

This comparative analysis of findings from the three domains suggests that the changes taking place in the domains of production, reception and meaning-making do not take place in isolation from each other, but in a feedback loop. This loop can be described as follows:

Generative AI introduces a new, never-seen-before scale of fake images to the information environment via democratization of production (findings from section 4.1). The volume of fake images overwhelms the viewer, decreasing trust in images (findings from section 4.2). This lowers trust in images, which results in the transformation of visual discourses and norms (findings from section 4.3). This, in turn, affects image production (human or machine) and closes the loop.

This means that we cannot examine the three domains in isolation. Current visual theories that have a sole focus on production, reception and/or meaning-making cannot account for the threefold interaction. This review shows that there is a need for a new theory of visual communication that can include the three domains and at the same time refer to the relations among them.

B. Theoretical Implications and Revisiting Classical Theories

Challenge to Classical Visual Communication Theory

The review shows that the classical visual communication theories' assumption that an image is referential is no longer valid. Barthes (1977) referred to a "message without a code" and Sontag (1977) considered photographs as "traces of reality". But a Stable Diffusion image is not a trace of reality, nor is it causally linked to the world. But it looks like other real images and works like other real images.

This is a paradigm shift situation. The review brings forward that the theory of visual communication must move from considering the "existential authenticity" of images, in which case, truth is related to the causal link between the image and the "real world" to "functional authenticity". Here, the authenticity of an image is not related to its creation, but is related to its use, disclosure and impact. This move in theory is similar to that of narratology: now, narratologists don't distinguish between "real" and "imagined" narratives, but regard narratives as social.

Cultivation Theory

The findings of this review, specifically about the reproduction of stereotypes in AI (Bianchi et al., 2023) affect cultivation theory. Gerbner and Gross (1976) proposed that the media have minor and subtle influences on audience perceptions of the world through the reproduction of stereotypical images. This is magnified by generative AI in two ways:

First, the reproduction of stereotypical images is now at scale. Photographers or designers could consciously resist stereotypes before, but an AI model that is trained on past data cannot. Second, as Bianchi et al. (2023) showed, AI models not only generate stereotypes but strengthen stereotypes, suggesting that the cultivation effect of AI models is stronger than that of the media. This implies we need to think about a new mechanism "algorithmic reinforcement of stereotypes" in cultivation theory.

Framing Theory

The framing theory (Entman, 1993) treats visual frames as a consequence of efforts taken by journalists and editors based on the values and ideologies of media companies. However, this review reveals that when generating images with AI, framing is mainly a function of the model's statistical distribution. This results in "algorithmic framing", which does not follow the same processes as human framing, and should be examined separately.

C. Practical Implications

Implications for Journalism and News Media

This review has a number of practical implications for journalism. First, findings related to audience's difficulty in

identifying artificial images (Nightingale & Farid, 2022; Wickery et al., 2023) indicate that disclosure about the use of AI images is no longer an ethical decision but a professional responsibility. Journalism organizations need to establish guidelines for disclosing AI.
Second, findings related to the pollution effect (Vaccari & Chadwick, 2020) demonstrate that even non-news uses of AI images, such as to illustrate abstract ideas, can decrease a news organization's credibility. This suggests that AI use policies in the media should be broader than they are today.
Third, the findings of artificial image spreading in the news crisis (Izzaturo et al., 2023) indicate that journalists should be provided with tools to detect AI images, particularly during the first few hours of coverage of a crisis event when time is of the essence.

Implications for Media Policy
In terms of policy, the review highlights a number of issues. First, a lack of comprehensive regulations on mandatory labeling of AI images in most countries is a policy concern. The draft of the EU AI Act, which reached a preliminary agreement in December 2023, provides a good starting point but needs the support of technology companies for effective enforcement.
Second, research on biased AI images (Bianchi et al., 2023) indicates that policymakers should mandate that companies that create AI models provide an audit of the representation diversity of their model outputs. This should consider gender, race, nationality and socioeconomic classes.

Implications for Media Literacy Education
Groh et al.'s (2022) finding that brief training can improve artificial image detection ability suggests that media literacy programs may be able to have a positive impact. But Köbis and Mossink's (2021) finding that this ability is domain-specific is a warning: educational programs should be specific to certain areas of application of artificial images rather than simply general. Students need to be given training in detecting common vulnerabilities of AI images in various application domains, such as news, medical and scientific images.

D. Limitations of Existing Literature

Despite a surging body of research in this field, the current research has three key gaps that prevent us from fully understanding the effects of generative AI on visual communication.
First Gap: Focus on Western Audiences
Among the 63 studies we reviewed, 47 studies (75%) used data from the United States, Britain or Western European countries. Just 8 studies targeted Asian audiences, 5 studies targeted African audiences, and 3 studies targeted Latin American audiences. This geographical imbalance means we have a limited understanding of how AI images are received in non-Western cultures, which may have different visual preferences, technology and media literacy, and trust.
Second Gap: Dominance of Cross-Sectional Studies
Most empirical studies in this domain adopted cross-sectional designs (a single point in time). This is appropriate for determining immediate detection ability or for measuring initial responses to images, but it is not enough to study long-term effects, such as cultivation effects of long-term exposure to artificial images. This is especially problematic given that cultivation theory (Gerbner & Gross, 1976) places emphasis on cumulative, long-term effects.
Third Gap: Shortage of Context-Based Research
A large number of empirical studies have used laboratory stimuli, which means that artificial images were presented to participants in artificial contexts. This will increase the internal validity of studies but decrease their ecological validity. However, AI images are not received in a lab but in a natural context of media consumption, together with context and other information, social connections and emotional impact of news events. Almost no research has been conducted to date examining the reception of artificial images in the "wild", as part of natural media consumption.

Table 2. Summary of Research Gaps and Proposals to Address Them

Research Gap	Importance
Focus on Western audiences	Limited generalizabilit
Dominance of cross-sectional studies	Inability to measure long-t impacts
Lack of context-based research	Low ecological validit

This table shows the three main gaps in existing literature, the reason for each gap's importance, and the proposed research approach to address it.
Source: Synthesis of findings from this review.

VI. 6. Future Research Directions

The limitations of current studies and the present review indicate six directions for the future. The themes are not invariably unique and can be discussed during a concert.

A. Longitudinal Studies on Cultivation Effects of Artificial Images

The most significant line of research in this field would be to carry out a longitudinal study of the long-term implications of long-term exposure to artificial images on judgements of real-life by the audience. Possible studies have focused on short-term effects while the cultivation theory (Gerbner and Gross, 1976) has focused on long-term effects. The following are some of the key questions: Do audiences who have a long-term exposure to artificial images differ in their verdicts regarding what is real? And do they have different visual trust? And are the cultivation effects of artificial images any different than those of photographed images?
The best experiment design would be a panel study, during which samples are tracked in time (e.g., every six months during 3 years) and usage of artificial images, along with the detection of artificial images and social reality is measured. The findings of such research can be applied in media literacy policy.

B. Cross-Cultural Research on AI Image

Reception

As mentioned in the limitations, three-quarters of the research is carried out in the West. This is not purely a methodological, but also a conceptual dilemma. The cultural differences in media literacy and experience in the visual cultures and exposure to AI technologies may contribute to the perception of artificial images.

The three conclusions to remember in future cross-cultural research are: first, research about how artificial images are detected in different cultures with various degrees of exposure to AI (including South Korea and Ethiopia). Second, an examination of the biases as demonstrated in AI images in other cultures not necessarily the West whether they will demonstrate the same results as in Bianchi et al. (2023) or not. Third, how AI images affect a media distrust crisis in high media distrust societies.

C. Visual Media Literacy in the AI Era: Designing and Evaluating Educational Interventions

Groh et al. (2022) reveal that in the short run, education raises the chances of detecting an artificial image by 15%. It is a significant contribution but leaves questions to be answered. What is the duration of the effectiveness of the training? Is it necessary to undergo this learning every time new AI models and pictures are produced? But what kind of educational interventions, classroom-based learning, computer games and mobile apps are the most effective?

Research is required to design, prototype and test successful education at any age. Young people are the most vulnerable to exposure to computer-generated photos and they spend the most time on social media and hence are the priority research group. Research and education priorities should focus on developing multi-faceted education programs about visual media in the era of AI, in middle and high school, and in tertiary institutions.

D. Representation of Minorities and Marginalized Groups in AI-Generated Images

The implications of the Bianchi et al. (2023) findings on the topic of representation bias are only starting. Although studies have been inclined to look into gender and racial stereotypes in careers, less has been done on other representations from disability, age, socioeconomic class, sexuality and religion, which have been sidelined.

Multimethod approaches are needed to better understand representation in AI images. Content analysis can measure stereotypes, and interviews with members of the minority groups can be used to gather information. Studies should investigate how designers can reduce biases by modifying training data and post-generation filtering of images.

E. Effectiveness of Synthetic Image Detection Tools and Strategies for Countering Visual Misinformation

The arms race between tools for generating synthetic images and tools for detecting them is underway. As generation models improve, existing detection tools become useless. This problem is documented but there is a lack of attention to communicative rather than technical solutions.

The next phase of research should explore what communication tactics can help audiences combat visual misinformation, in addition to technology. For instance, will changing the audience default position from "trust until proven otherwise" to "doubt until proven otherwise" help without overly eroding trust in the media? Testing the impact of media inoculation (exposure to examples of synthetic visuals) is a potential future research direction.

F. Ethical and Regulatory Frameworks for Artificial Visual Communication

The last of the suggested research areas is ethics and policy. The growing significance of this area has attracted less attention in communication literature than in the areas of law, technology ethics, and computer science. Future studies should answer these questions from communication theory viewpoints, such as public sphere theory (Habermas, 1989), media justice theories, and communication ethics:

What guidelines should be set for AI practice in visual communications? What are the best practices to achieve the creative freedom of expression while preventing harm from deceptive images? And how can generative AI be governed in the media?

VII. 7. Conclusion

This article started with the aim of conducting a review of the effects of generative AI in visual communication. It has examined 63 publications from 2018 to 2023 to answer three key questions. In this final section, the key findings of the review are outlined, the main takeout message of the article is provided and how this review fits into the existing communication research is discussed.

In answer to the first question - how generative AI has transformed the process of producing visual messages - the review revealed the primary shift to be communicative. The role of the “sender” in the traditional communication model has been dispersed across human and machine (Oppenlaender, 2022). Visual production has changed in its political economy and democratization, with its opportunities and risks (Davenport & Mittal, 2022; Chesney & Citron, 2019). The use of AI in media platforms has varying dynamics, which need to be examined separately (Barrat et al., 2023).

To answer the second question, the reception of synthetic images, perhaps the most significant finding from this review is that average audiences are barely able to recognize AI-generated images. They can only detect AI images at a rate near chance (Nightingale & Farid, 2022; Wickery et al., 2023). This, together with the liar's dividend (Nightingale & Farid, 2022) and the pollution effect (Vaccari & Chadwick, 2020), is a bleak forecast for media trust in the age of AI. However, research on training (Groh et al., 2022) and the role of analytical processing (Pennycook et al., 2021) demonstrates that there are measures through which audiences can cope with this change.

To answer the third question, what are the changes to visual media culture, this review finds three significant transformations: the systematic construction and reproduction of cultural stereotypes in AI-generated images (Bianchi et al., 2023); the onset of the post-photographic era and how this is reshaping the ways we think about the authenticity of images (Mirzoeff, 2023); and the transformation of synthetic media into a multiplier in the misinformation ecosystem (Rooze et al., 2023).

This review not only addresses the three questions raised above but also offers a theoretical point of view. The changes that generative AI has produced in visual communicative processes are so significant that they cannot be explained by traditional theories in this field. Visual communication theories based on the idea of the referential relationship of images to reality as outlined by Barthes (1977) and Sontag (1977) can no longer be relied upon in the digital era. The findings validate the necessity of a multidimensional theoretical lens. By applying the four-dimensional integrative framework, this review demonstrates that AI-generated visuals function as autonomous communication systems where meaning is not found in a 'trace of reality,' but is constructed through the interplay of semiotic codes, cognitive appraisals, and rhetorical framing.

Furthermore, the shift identifies a move toward a new "communicative life" of images, where their value is determined by their interactive presence in digital networks rather than their fidelity to a physical referent (Çiçek, 2023). A new mechanism of "algorithmic stereotype reinforcement" is needed in cultivation theory. And framing theory needs to acknowledge a new form of framing called "algorithmic framing". Those theoretical updates are not a refutation of classical theorists, but rather an homage to the fact that they created theories that are now the best to challenge the changes of the AI era.

Finally, this evaluation has a message for scholars, policymakers and journalists. Generative AI is no longer the future of technology that can be left to techno-scientists. It has already found a home in visual communication practices, and its impact, in terms of trust erosion in news images, or systematic perpetuation of representational inequalities, is having an impact on our lives. The discipline of communication has the theoretical, methodological and critical instruments to study this process. All it takes is the institutional will to translate this ability into integrated, interdisciplinary and global research programs.

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