Images Tell Stories

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Abstract

Images can enhance the interpretation of textual material and improve decision-making. We describe recent research on how images affect decisions, generally mediated through two channels: affect and cognition. Image characteristics capturing expressiveness, such as colorfulness, sharpness, etc., mainly engage emotions, whereas the degree to which image content either reinforces or adds to information embedded in accompanying text operates through the cognition channel. Image metrics are associated with higher crowdfunding investments, smaller analyst forecast errors and dispersion, and lower market risk. We discuss the role of generative AI in image generation and analysis and illustrate using text from GE's 10-K filings.

Keywords: Images; Generative AI; Visual Characteristics; Content Reinforcement; Visual Expressiveness; Machine Learning; Analyst Forecast Accuracy; Analyst Forecast Dispersion.

1. Introduction

Images tell stories. Beyond storytelling, images contain information that affects decisions across diverse areas. For example, it has been documented that characteristics (such as colorfulness) and information content of pictures contained in crowdfunding project proposals contribute to increased funding. Images in annual reports included in websites or filings submitted to the Securities and Exchange Commission give rise to more accurate analyst forecasts of earnings-per-share and decrease the dispersion across analyst forecasts; moreover, these images appear to affect long-term financial returns and other performance measures.

More impressively, information content contained in images, to the degree it adds or reinforces the textual content included in the documents that contain the images, appears to magnify the effects of images on decision-making. For example, images that add information to the textual material increase the crowdfunded amount. Information embedded in images that reinforce the textual content in annual reports magnifies their positive effect on analyst forecast accuracy, the decrease in analyst dispersion, and the increase in other financial measures.[1] The degree to which images reinforce textual content in ESG reports further contributes to increased ratings.

Beyond the information content contained in images, the features and characteristics of images are also a contributing factor. For example, elements such as colorfulness, sharpness, non-complexity, asymmetry of objects contained therein, and other features that together can be referred to as "expressiveness" contribute to the amount of crowdfunding.

[1] We are not aware of a definitive source regarding the process through which images are chosen for inclusion in financial documents such as annual reports. Specifically, does the personnel engaged in writing the report also decide on what images to include, such as to facilitate information assimilation by readers? This is a fascinating question that we intend to explore in future research.

This paper offers a glimpse into how images can make a difference in how stakeholders may adjust their reactions to written material when carefully selected images are included. This pioneering research is in its infancy and has a way to go. It is evident that it is worthwhile pursuing in light of the promising beginnings. Specifically, in light of the initial results (based on Ronen et al. 2023 and Ben-Rephael et al. (2024)) alluded to in the above paragraphs and further elaborated upon below, we believe that tackling the intricacies of image effects will allow investors to better assimilate the written information to an extent that improves decisions.

2. The two channels that mediate the effects of images

Why and how do images influence decisions? Affect (emotion or feeling) and cognition (mental processing) provide two channels through which images impact behavior and decisions. First, consider the 'affect' channel. Intimately related to perception, affect informs about the consequences of anticipated actions without deliberate thinking about such consequences. Affect shapes how the environment is perceived and acted upon. Findings in psychology and neuroscience highlight the role played by affect in decision-making. Intimately related to affect, perception governs how a particular image or a portion of an image attracts attention. For example, visual salience (by which we mean eye-catchiness) has been shown to direct readers' eyes to photographs or specific photographic elements such as sharpness, the number of objects in an image, and their size. Thus, visual salience should impact investment decisions if salient objects within an image elicit affective responses. Therefore, it is reasonable to expect that the content of images, mediated through perceptual effects and image characteristics mediated through affect, influence financial decisions, engaging the audience in the intricate process of perception and decision-making.

Images also influence decisions through their mediation of cognition. The presence of an image can significantly impact cognitive constructs such as memory, opinion, and intention. For instance, it has been documented that images typically substantially impact opinions more than text in the press media. Pictures are easier to remember because they are processed through different neural pathways. Images are also normally remembered better because they possess more distinctive features than text. The influence of images on cognition suggests that their content may either reinforce or add to cognitive processes created by the textual material contained in the documents within which the images are embedded.

In light of the above-described importance of images and their below-documented effects on financial decision-making, it is no wonder that they appear in communications directed at the investment management community. For example, Ronen et al. (2024) find that including a cover image on equity crowdfunding pitch sites is associated with an average funding increase of an economically significant 15%. Yet, while generally ubiquitous, images are underappreciated and understudied among investment community members, albeit commonly and purposefully embedded in disseminated material (investor relations communications, newsletters, performance reports, etc.).

3. Effects of Images Manifested through the Affect channel

A significant body of literature has focused on attributes of textual material. Terms such as readability, sentiment, and fog have popped up in academic writings documenting the systematic effects of such textual attributes on various decisions, notably market outcomes (Breuer, Knetsch, and Sachsenhausen 2024; Serafeim 2020). Only recently, increasing attention was directed to images' role in decision-making. Drawing on the psychological concepts of affect and cognition, Linkages between image characteristics and human reaction were conjectured. Using primarily experiments, marketing and entrepreneurship scholars considered, for example, the effects of videos on funding success in entrepreneurial ventures. Finance and accounting scholars explored how visual manipulation, like graphs, aids impression management.

Venturing beyond, Ronen, Ronen, Zhou, and Gans (2023) proposed seven key visual characteristics of images that shape investor responses: asymmetry, colorfulness, non-complexity, numerosity, self-similarity, sharpness, and softness. The authors combined these characteristics into a single expressiveness metric, which they found to be positively associated with the amount of investment in crowdfunding campaigns. The constructed expressiveness metric is believed to impact investor behavior by shaping perception and eliciting affective responses, highlighting the importance of visual design in investment decisions. Descriptions of the seven individual visual metrics computed using objective measures follow below. Additional mentions of the seven expressiveness components that occur in the broader literature, including, but not restricted to, psychology, marketing, computer science, medicine, and art, are provided in the Appendix.

The computations used to derive these metrics are detailed in Ronen et al. (2023).

3.1 Image Characteristics

3.1.1. Asymmetry

Asymmetry in images refers to visual imbalances in composition, structure, or element distribution. Precisely, asymmetry measures the extent to which an image's content is unevenly distributed across its central axes, highlighting a lack of balance or uniformity in visual composition.

Asymmetrical designs and patterns often elicit specific psychological and perceptual responses influencing decision-making. These effects can vary based on context, emotional associations, and individual preferences. While symmetry can predict positive aesthetic evaluations, especially in complex patterns and faces (Arnheim 1988; Fink et al. 2006), asymmetry is preferred in simple images for its ability to create a focal point (Bapna and Ganco 2021; Bertamini et al. 2019; McManus 2005). In Ronen et al., asymmetry is seen as directing attention and generating interest, thereby positively influencing the amount of funding raised for crowdfunds.

Illustrative Examples. To illustrate how asymmetry plays out in actual images, consider the panel below. It is evident that the top image, where feet are incoherently stacked to the right of the beautiful landscape, is more *asymmetric* (with a higher asymmetry score) than the bottom image, with its neat placement of cars.

Source: Images from crowdcube.com. Top: Vivobarefoot. Bottom: Whitecar.

3.1.2. Colorfulness

Colorfulness is linked to affective behavior and perception. Studies show that greater colorfulness enhances preference and positive affect across contexts, including learning outcomes (Kumi et al. 2012), and food (Genschow, Reutner, and Wänke 2012; Harrison, Reinecke, and Chang 2015; Paakki, Sandell, and Hopia 2019; Reinecke et al. 2013). Color significantly influences decision-making by eliciting emotional, cognitive, and behavioral responses across various contexts such as marketing, art, education, finance, and legal environments.

These influences are based on both psychological associations with colors and cultural perceptions. In general, red triggers urgency, risk avoidance, and heightened attention, while blue encourages calm, trust, and rational choices (Elliot 2019; Hill and Barton 2005; Pazda and Greitemeyer 2015; Wilms and Oberfeld 2018). This can vary across cultures. In Western cultures, red can symbolize warning or loss, whereas in China, it often represents prosperity and luck. In financial decision-making, red stimuli increase risk avoidance (Bapna and Ganco 2021; Chan and Park 2015; Gnambs, Appel, and Oeberst 2015; Kliger and Gilad 2012).

Illustrative Examples. To illustrate color variations in images, the top image, with its bright and appetizing displays, has a higher *colorfulness* score in the panel below than the somber and gloomy bottom image.

Source: Images from crowdcube.com. Top: Witt Energy. Bottom: The Baobab Network.

3.1.3. Non-complexity

Non-complexity in images is characterized by visual simplicity (reduced visual information), clear layouts, and minimal elements. Noncomplex images are generally preferred in decision-making as they necessitate less cognitive load and convey critical information quickly (Henderson and Cote 1998). Research shows that non-complexity enhances soothing qualities (Berlyne 1970) but reduces fascination, increasing preference when paired with order (Van Geert and Wagemans 2021). Processing fluency theory suggests simpler visuals are easier to process, are more pleasing, and generate positive affect (Alter and Oppenheimer 2006; Reber, Schwarz, and Winkielman 2004).

Illustrative Examples. In the panel below, the top image with its neatly displayed power vault has a higher *non-complexity* score than the chaotic bottom image.

Source: Images from crowdcube.com. Top: Powervault. Bottom: Oriental Rugs of Bath.

3.1.4. Numerosity

Numerosity represents the quantity of elements an image presents, influencing perception, cognition, and decision-making. Visual numerosity impacts the interpretation of information, the allocation of attention, and making choices, especially when accuracy and cognitive efficiency are required. Bagchi and Davis (2016) suggest that people infer greater quantity from higher numerosity, often ignoring other information. Park et al. (2016) find that numerosity is more salient to the human brain than other visual properties. Studies also show that images with more elements improve preference and performance, such as in annual reports (Townsend and Shu, 2010) and crowdfunding (Yang et al., 2020).

Illustrative Examples. In the panel below, the top image, replete with plasterboard fixings, has a higher *numerosity* score than the bottom image, displaying a single gel package.

Source: Images from crowdcube.com. Top: Gripit Fixings. Bottom: Notpla.

3.1.5. Self-Similarity

An image is self-similar if the same repeating visual pattern (or shape) is revealed when zooming in and out (Mayer and Landwehr 2018). Self-similarity can influence decision-making processes in contexts ranging from visual perception to social judgments, depending on how individuals process and interpret these visual cues.). Self-similarity has been shown to increase preferences (Robles et al. 2021; Taylor 1998) and evoke positive affect (Brielmann et al. 2022). Whether derived from nature, art, or computer-generated designs, self-similar images are consistently preferred (Spehar et al. 2003).

Illustrative Examples. In the panel below, the top image with repeated and somewhat similar sketches has a higher *self-similarity* score than the bottom image, with incoherently placed diverse objects.

Source: Images from crowdcube.com. Top: Open Energy Labs. Bottom: The Halal Dining Club.

3.1.6. Sharpness

Images' sharpness (lack of blurriness) enhances the visibility of details, improving perceptual accuracy and cognitive processing. In contrast, blurriness ushers ambiguity and degrades decision quality in advertising and medical diagnostics fields. Sharpness directs attention to the more apparent areas of an image (Enns and MacDonald 2013; Loschky et al. 2014; Marchesotti, Murray, and Perronnin 2015; Veas et al. 2011) and is generally preferred over blurry or grainy images (Virtanen, Nuutinen, and Häkkinen 2022).

Illustrative Examples. In the panel below, the top image, which displays cleanly discernible and crisp objects, scores higher on the *sharpness* score than the indistinct and fuzzy bottom image.

Source: Images from crowdcube.com. Top: Glovebox Direct. Bottom: iNeed.

3.1.7. Softness

Softness in images, engendering smoothness of textures, and diffused edges influence emotional and cognitive decision-making processes, especially in consumer behavior and perceptions of quality. Fortmann-Roe (2013) examined Twitter users' preferred profile appearances, finding that the combination of low brightness and low saturation (high softness) is preferred. This result is partially reinforced by Wilms and Oberfeld (2018) and Guterman et al. (2010), who focused on brightness.

Illustrative Examples. In the panel below, the top image displaying the ambient glow of an urban landscape has a higher *softness* score than the bottom image with harshly illuminated and delineated handbags.

Source: Images from crowdcube.com. Top: Feast Limited. Bottom: Handbag Clinic.

3.2 Impact of expressiveness on crowdfunding

Ronen et al. (2023) document the effect of the above-described image characteristics on the money raised in crowdfunding appeals. They find that the seven visual characteristics are positively associated with the amounts of funds raised at crowdfunding projects. Furthermore, *Expressiveness*, constructed as the combined measure to examine the overall effect of an image by summing the seven individual characteristics, is also positively associated with funding. An additional unit of *expressiveness*, controlling for many other factors, corresponds to an economically significant 10% approximate increase in funding. Thus, pitch images play a vital role by complementing, supplementing, or even replacing textual information, thereby enhancing pitch persuasiveness.

Section 3 delved into the effects of images mediated through the affect channel. In the next section, we explore how images influence decision-making through cognitive processes.

4. Effects of images manifested through the cognition channel

Cognitive effects manifest in images conveying information that reinforces content embedded in the textual material accompanying the images (*reinforcement*), or by contributing new information that supplements what the textual material transmits (*additivity*).

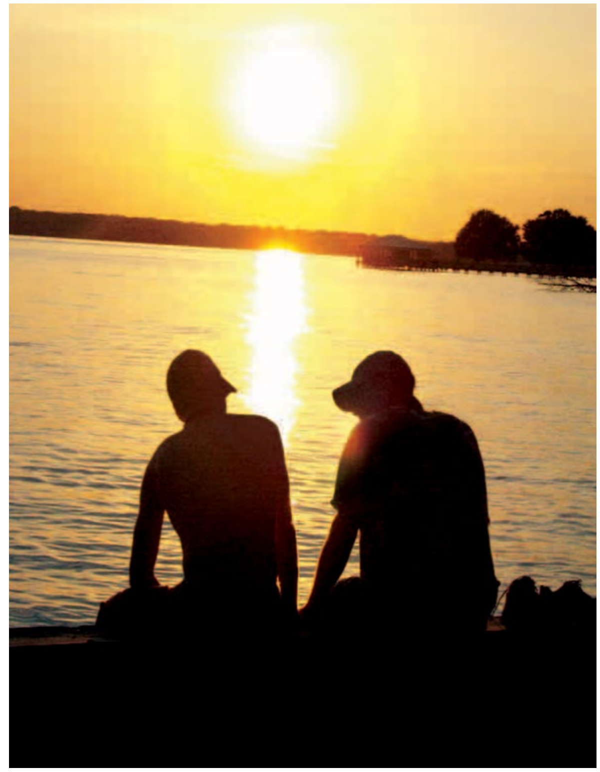
Whether images are positively associated with financial outcomes because they reinforce or because they are additive appears to depend on how prevalent visuals are in a report or other documents (relative to the amount of textual material the images accompany). In theory, image information can be repetitive, contradictory, additive, or neutral relative to textual content. In contexts such as the Crowdcube equity crowdfunding explored in Ronen et al. (2023), the textual and other nonvisual information disseminated about the private companies or projects is scarce, and the platforms allow only one large cover image in addition to some smaller thumbnail-size images elsewhere (in some limited cases). Here, one prominent image proved to be important in filling in the blanks for investors- either by grabbing attention or providing additional information.

Thus, where textual material is sparse, such as in crowdfunding, it is sensible to conjecture that images would help by adding information content to the text. Conversely, where textual information is plentiful but visual pages are relatively scarce, such as in the case of annual reports examined by Ben-Rephael et al. (2024) (briefly described below), the conjecture would be that images contribute by reinforcing the information content embedded in the text. Importantly, we surmise and confirm that the most desirable effects of *reinforcement* are exhibited when the reinforced text consists of salient sections or phrases. This is indeed what we find.

In Ronen et al (2023), we use Google Vision to obtain labels identifying objects or subjects portrayed in the image. Based on these labels and the pitch narrative, we construct the additivity measure to capture the extent to which the information contained in the image is additive to that conveyed in the textual description. We find that additivity contributes significantly. Evaluated at the mean level of expressiveness, funding increases by approximately 1.78% when the average image is one percentile point more additive. Two forces are at work: the affect channel, as reflected in expressiveness, and the cognitive channel, as reflected in *additivity.*

We now turn to the concept of reinforcement. Ben-Rephael et al. (2024) examine the effects of images on analyst forecast accuracy, dispersion, and other market measures. To construct the *reinforcement* measure –and the *additivity* measure referred to earlier in the context of Ronen et al (2023) -- we first classify image pages as *uninformative* if their top three Google Vision generated labels are not `meaningful' (such as "font," "circle," or "text.") We then process the labels for *informative* image pages (the complement of the *uninformative* image pages). Specifically, we classify an image page as *reinforcing* if at least one of its labels matches the corresponding textual narrative, and as *non-reinforcing* if there is no such match.

In the example below, the image page on the left is from the 2015 Astec Industries annual report; it is classified as *reinforcing* as it has labels such as "engineering", "gas", "industry", "infrastructure", "metal", and "silo" that can be found in the report. On the other hand, the image page on the right is from the 2006 Southside Bancshares annual report; it is *non-reinforcing* as the image has labels such as "evening," "horizon," "people in nature", and "sunrise," none of which matches text within the annual report.



Source: Images from company annual report. Left: NASDAQ_ASTE_2015, Page 35. Right: NASDAQ_SBSI_2006, Page 22.

In Ben-Rephael et al. (2024), we examine the relationship between visual informativeness, and analyst quarterly earnings forecast errors by constructing a within-analyst quarterly forecast accuracy measure based on forecast errors across stocks each analyst covers in a given quarter.

In addition to the analyst forecast error, we also examine the effect of visual informativeness on the dispersion of analyst forecasts.[2]

Among other metrics, we focus on our novel *reinforcement* measure, designed to capture the content reinforcement (cognitive) channel. While the main *reinforcement* measure reflects how content in images enhances the assimilation of textual information as calibrated by the degree to which image labels are congruent to the annual report textual narrative, we also consider

[2] For brevity, we omit the precise specification of the model predicting analyst forecasts dispersion.

reinforcement as targeted to text contained in the important and salient sections of the 10-K, such as the business description and MD&A section. We further examine the impact of specialized versions of reinforcement. For example, the *reinforcement* of the combined text of the business and MD&A sections.

We find that beyond the significant effect of the number of images (including all conceivably pertinent factors we control for in our regression model)[3], the effects of the above versions of *reinforcements* are all negative and statistically and economically significant, suggesting that *reinforcement* is associated with smaller analyst forecast errors. For example, a one standard deviation increase in the *reinforcement* of text contained in the 10-K's business description is associated with roughly a 1.8% increase in accuracy, measured in terms of the standard deviation of forecast error. Similarly, the *reinforcement* of the combined text of the business and MD&A sections, for example, is associated with roughly a 1.9% decrease in forecast dispersion. Also, this latter reinforcement measure is associated with lower risk, measured by the standard deviation of return, lower beta, and lower cost of equity.

5. Generative AI and its Usage in Financial Analysis

Revolutionary developments in image processing technologies, such as TensorFlow and Google Vision, now allow us to interpret information embedded in image datasets. These tools also make it possible to generate insights by interpreting complex data and presenting it in visually impactful ways. Such advancements can be of import to the investment management industry,

[3] We control for many factors: time between forecast and earnings announcement dates, textual readability, report pages, news articles, cumulative stock returns, return on assets, institutional holdings, advertising expenses, the firm's assets, book-to-market ratio, standard deviation of returns, average daily turnover, and stock market capitalization. Note that we include the daily standard deviation of returns over the fiscal year to proxy for risk that might impact the analysts' dispersion (See, for example, Campbell et al. (2014)).

given the pervasive and likely growing use of images in “corporate decks,” investor relations communications, newsletters, performance reports, etc.

This evolution is of great import to decision-makers, such as financial analysts who must navigate increasingly voluminous and complex data-driven datasets to evaluate trends, forecast outcomes, and make strategic recommendations (Rane 2023). Moreover, analysts must effectively interpret and present these data to stakeholders with varying financial expertise (Krause, 2023). Embedding such data in images may improve the data’s assimilation by the analysts’ clients.

Visuals and visual information can, therefore play a pivotal role in mitigating these challenges by bridging the gap between data complexity and human comprehension (Ronen et al. 2023)Well-designed visuals can help readers comprehend complicated text and data by offering images and other intuitive formats. This enables analysts to quickly highlight trends, anomalies, and critical metrics. Generative AI can enable the swift production and analysis of these aids.[4]

Indeed, AI tools can be applied in a variety of contexts in financial analysis (Fairhurst and Greene 2024; Krause 2023; Rane, Choudhary, and Rane 2024). For example, they can quickly process large datasets, whether textual or numerical, structured or unstructured, to identify patterns and provide visual aids such as images, dynamic dashboards (which can adjust visualizations based on user interaction and new data input), and predictive visualizations (DeJeu, 2024; Ye et al., 2024). In combination, these tools can simulate financial scenarios and facilitate the assessment of risks and opportunities for stakeholders.

[4] Whether analysts and other users of annual reports and other documents may be intimidated by the possibility that images they encounter are AI-generated is an open question that is a subject for future research.

In sum, generative AI can be effectively leveraged by financial analysts to integrate data analysis with the art of visual storytelling, potentially achieving higher engagement and efficiency and enabling analysts to convey complex financial narratives with greater clarity and impact. While the present state of generative AI is still in its infancy and the output is still inconsistent, future models will undoubtedly produce more impressive results.

In Section 5.1 below, we illustrate, using a simple example, how financial analysts can leverage AI tools to personalize visual content for different audiences, tailoring visuals to specific reports and stakeholders of varying levels of sophistication. For example, more sophisticated investors may prefer visuals emphasizing risk metrics, while crowdfunding audiences may respond better to emotionally resonant imagery. Customized visuals may help enhance communication effectiveness and financial outcomes.[5]

5.1. AI-Generated Images with Visual Reinforcement and Expressiveness

A simple example using ChatGPT-4o (DALL-E) and text from the MD&A section of GE's 10K 2023 illustrates how AI Tools can be used to create images with specific visual characteristics, such as the *expressiveness* and *reinforcement* measures described in Sections 2 and 3 above.

We ask ChatGPT to generate two images, both of which *reinforce* the following text derived from the MD&A Significant Trends and Developments section of GE's 2023 10K[6]: "Our results in 2023 reflect robust demand for commercial air travel and continued strength in services, which represents over 70% of Aerospace's revenue this year. A key underlying driver of our commercial engine and services business is global commercial departures, which grew high-teens

[5] Of course, one has to consider the nuances of publishing research/analysis, and the regulations and compliance processes involved. This is the subject of future research.
[6] This text also appears in the firm's 2023 Annual Report.

during 2023 compared to 2022. The air traffic growth trends vary by region given economic conditions, airline competition and government regulations. Consistent with industry projections, we estimate departures growth to decelerate to mid-single digits in 2024. We are in frequent dialogue with our airline, airframe, and maintenance, repair and overhaul customers about the outlook for commercial air travel, new aircraft production, fleet retirements, and after-market services, including shop visit and spare parts demand." The first image is constructed to reflect a higher value of *expressiveness*, based on the seven visual characteristics introduced in Ronen et al. (2023) and described in Section 2 above, and the second image is constructed to reflect a lower value.[7] The generated images are shown in Figure 1 and Figure 2 below.

[7] For image 1, we use the prompt: "Produce an image that reinforces the following sentences from the 2023 10k filing for General Electric Company. Make sure the image has high values for seven visual characteristics." We then feed ChatGPT the text and the definitions of the seven visual characteristics described in Section 2. For image 2, we duplicate this prompt but ask for low values instead of high values.

Figure 1: Image generated by ChatGPT based on GE text with a high value of *expressiveness*.

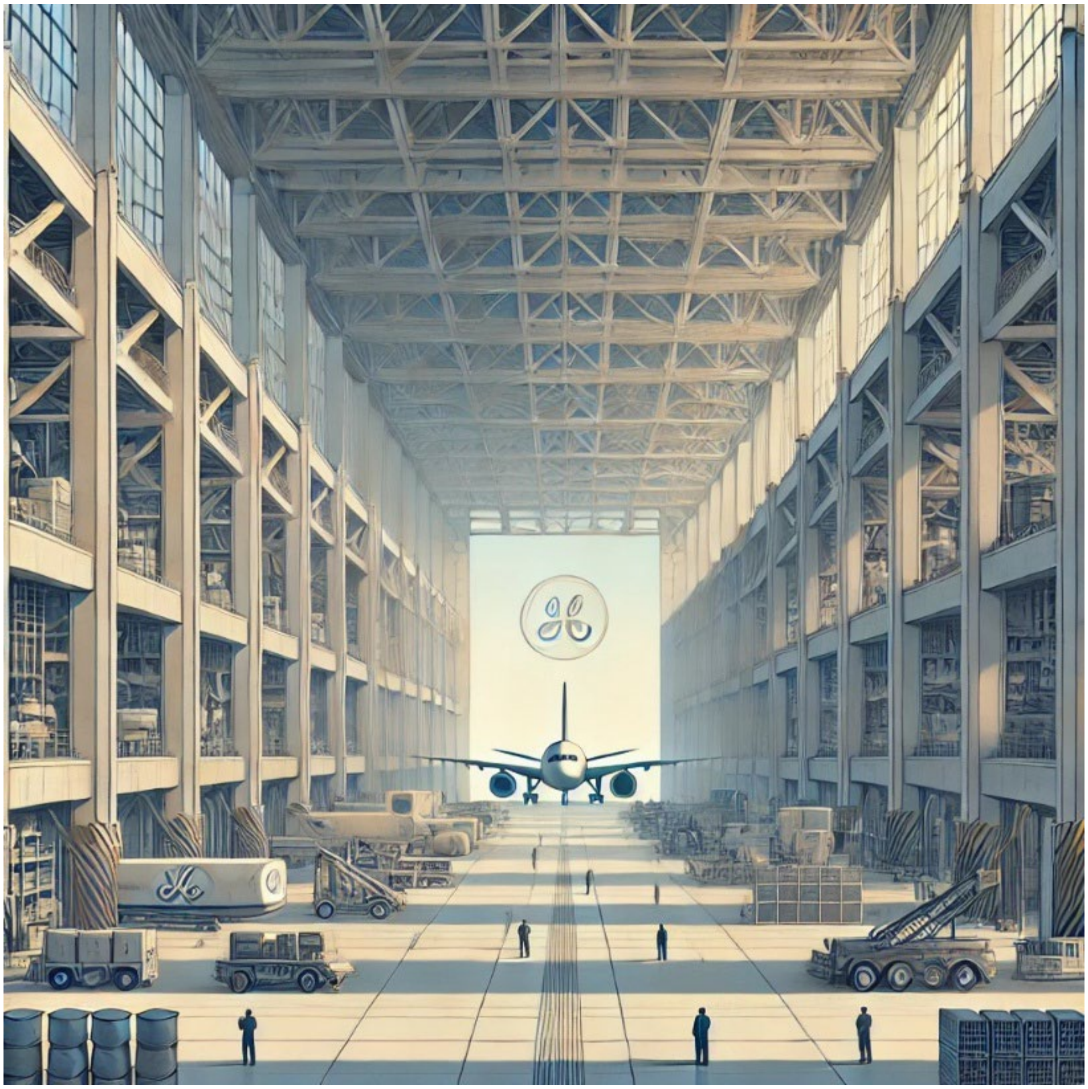


Figure 2: Image generated by ChatGPT based on GE text with a low value of *expressiveness:*

The combined Expressiveness measure of the first image is 2.36 as contrasted with 0.62 for the second image. Notably, the image with a higher *expressiveness* measure may be construed as more visually appealing (to most) than the one with a lower measure.

5.2. Tailoring Images – AI example

The simple example below illustrates how visual content can be tailored to specific reports and different stakeholders. ChatGPT was asked to produce three images (Figure 3, Figure 4, and Figure 5) to reinforce the concept that a toy company is expanding globally, with three distinct audiences specified each time:[8]

Figure3: Image generated by ChatGPT for *Retail Traders*.

[8] The specific prompts were: “Produce an image reinforcing the concept that a toy company is expanding globally that is designed to interest”, and the last part of the sentence was either: 1. “retail traders.” 2. “sophisticated investors such as a pension fund or a hedge fund”, 3. “unsophisticated investors such as crowdfund backers.”

Figure 4: Image generated by ChatGPT for *Sophisticated Traders.*

Figure 5: Image generated by ChatGPT for *Crowdfunding Backers*.

While the images tailored to the retail and sophisticated investors both highlight global expansion, manufacturing, and growth, the visual tone and focus appear to differ; vibrant, accessible visuals are presented to the retail investor versus a more muted, professional, and data-driven image to the sophisticated investor. The latter includes a focus on infrastructure. Image 3, designed for unsophisticated investors, is visually different, employing extremely cheerful, colorful, and engaging elements like dolls to showcase the company's products and global reach.

The charts indicating upward trends seem to be designed more playfully, to capture the company's excitement and potential for crowdfunding investors[9].

While these images do tailor the images to different audiences, the limitations of the visuals in both subsections are apparent. Visually the images are still rough, and cartoonish, and include odd textual elements. Moreover, current AI tools face many challenges in visual representation, including inconsistencies, limitations in the ability to interpret abstract prompts, and high variability across images generated from the same prompt across different executions. This notwithstanding, the prompts and images generated above illustrate promise in the potential of generative AI to visually communicate and tell stories, especially in the future. Research on AI is ongoing in full force. Future generations of AI will likely overcome the above-mentioned limitations.

6. Discussion and Conclusion

Ancient cave dwellers drew patterns on the walls of their bleak abodes; They were telling us things. Over the ages, painters and sculptors have whispered or shouted their inner musings through their artistic paintings, drawings, and sculptures. Surely, da Vinci, Picasso, and other giants of art history believed they were communicating with us mere mortals through their masterpieces. Is it any wonder that today's executives believe they can speak to us through images of all kinds?

This article explains and demonstrates how images inform. Image creators, like ancient cave dwellers and artists, believe they are conveying information to their audiences. Executives

[9] Tailored images are already being used on dynamic websites in other contexts (e.g., shopping, news, social media) to end-users based on different user profiles collected from browsing and other activity.

would not purposefully invest resources in creating and embedding imagery in their annual reports, ESG disclosures, prospectuses, patent applications, transcripts of conference calls, and the like had they not believed they were enhancing the ability of their constituent readers (investors, lenders, crowd funders, rating agencies, etc.) to assimilate valuable information they need for making informed decisions.

Indeed, using machine learning techniques, we have shown that images contribute to business constituencies' decisions by potentially reinforcing textual information conveyed to decision-makers or by adding to the information set available to readers of documents. In the case of crowdfunding, images contributed to an increase in funding through both an affect, emotional channel, or a cognitive channel by offering incremental information to what is provided in the textual material. In addition, we demonstrated that images contained in annual reports were associated with a decrease in analyst forecast errors and their dispersion—images also had a noticeable effect on measures of risk and other indicia of performance.

Much remains to be ascertained: what is the actual process of selecting images to be included in annual reports and other pertinent presentations? What are the potential implications, moral and practical, of exposing market agents to AI-generated images? It appears there are no serious legal impediments to using AI to generate images to be presented to the public as of now, but what about the future?[10] Questions proliferate, and answers must be offered.

[10] See https://openai.com/policies/row-terms-of-use/ and https://www.legalbrain.blog/post/are-chatgpt-generated-images-suitable-for-commercial-use
According to its Terms of Use, OpenAI assigns users all its rights to and titles and interests in the content generated by ChatGPT or its API. This suggests that users can use the content for any purpose, including commercial purposes such as sales or publication. The user is responsible for the generated content, including ensuring it does not violate any applicable laws. As a result, ChatGPT generated images are permissible for commercial purposes (including being sold) without violating any legal or contractual provisions. In addition, images created by ChatGPT do not need to be expressly attributed to AI, but if the user wishes to indicate authorship, then the OpenAI Terms contain recommended wording to be used for this purpose. Note that, according to the recently adopted EU AI Act users of an AI system

Despite these remaining questions, it is a tenable proposition that images can bolster financial analysts' ability to communicate effectively with their audience. Analysts can include images in their financial analysis reports to better convey their impressions of companies' financial health and prognostications of their future prosperity. To help analysts better communicate with their constituencies, further research focused on the role of images with implications for investment management is sorely needed.

In future work we intend to apply our methodology to a variety of reports and users. For example, we are examining the effect of images incorporated in initial public offering prospectuses on a variety of market microstructure variables, in ESG reports on ratings, in earnings conference calls on stock market measures, etc. We also plan to further investigate how firm executives decide what images to include and whether they design the images to match the written content in their reports. The legal aspects of including AI-generated images in financial analysts' reports and other presentations made to decision-makers are also important to consider. There is much to do, and the work is continuing. We are on it!

that generate or manipulate images, audio or video content that substantially resemble existing persons, objects, places or other entities or events and that would give a person the false impression that they are authentic or true ("deepfake"), must make it known that said content has been artificially generated or manipulated.

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Appendix

Mentions of the seven expressiveness components that occur in the broader literature, including, but not restricted to, psychology, marketing, computer science, medicine, and art, are provided below.

1. Asymmetry

Other examples of how image asymmetry beneficially affects various contexts of human experience includes: Visual Attention (Davis et al. 2006), Emotional Reactions – such as when purchasing products (Ravaja, Somervuori, and Salminen 2013); Aesthetic Preferences (Lewis 2017); heightened risk perception (Klatt, Ford, and Smeeton 2020); Brand Perception – influencing purchase behavior (Sebald and Vikander 2019); Neurocognitive Effects on Risk Preferences (Huang et al. 2017), Medical Imaging Decisions (Bayareh-Mancilla et al. 2023); and Consumer Responses (Ma et al. 2022).

2. Colorfulness

Other examples of how colorfulness affects human reactions include legal decision-making (Jacobson 2013); art auction bids (Ma, Noussair, and Renneboog 2022), product configurations (Deng, Hui, and Hutchinson 2010), voting (Garrett and Brooks 1987), financial decision-making (Ronen et al. 2023; Townsend and Shu 2010), consumer behavior in retail environments (Bellizzi and Hite 1992; Brengman 2002; Sliburyte and Skeryte 2014); cognitive effort (Shen, Shi, and Gao 2018); Impact on visualization (Bartram, Patra, and Stone 2017); and Managerial decisions (Cardinaels, Kramer, and Maas 2024).

3. Non-complexity

Other examples of how non-complexity affects human reactions include reducing cognitive load (Miniukovich and De Angeli 2014); influencing financial decisions (Ronen et al. 2023); focusing on essential elements (Honarpisheh and Faez 2013); trust inspiring (Mueller 2020); car purchasing behavior (Campino, Mendes, and Rosa 2023); marketing (Braun et al. 2013; Pieters, Wedel, and Batra 2010); in educational applications (Cuesta-Cambra, Niño-González, and Rodríguez-Terceño 2017); in navigation tools (Hashemi, Mirrashid, and Shirazi 2020); and in aesthetic preferences (Miniukovich and De Angeli 2014).

4. Numerosity

Other examples of how numerosity affects human reactions include its impact on visual attention (Anobile et al. 2020), neural selectivity (Cai et al., 2021), numerosity perception's effect on task context (Fornaciai, Farrell, and Park 2019), effects on the sense of time and quantity (Petrizzo et al. 2023), and consumer behavior (Sela and Berger, 2012).

5. Self-similarity

Other examples of how self-similarity affects human reactions include the impact on cognitive efficiency (Guo, Yan, and Qu 2015); the impact on visual attention (Maver 2010); the impact on memory recall (Moore et al. 2014); the impact on aesthetic preferences (Richter, Tiddeman, and Haun 2016); in medical imaging (Manjón et al. 2012; Zha et al. 2020); and in individual tasks (Turiel et al. 1997).

6. Sharpness

Other examples of how sharpness affects human reactions include the impact on visual perception (Lambooij et al. 2009); the impact on cognitive load in visual tasks (Zhang and Allebach 2008); the impact on trusted image perception (Mahdian and Saic 2007); in medical diagnostics (Gerig et al. 1992); the impact on perceived product quality (Rathee, Taylor, and Gupta 2024); the impact on engagement (Joshi et al. 2008); the impact on risk perception (Islam, Luo, and Sattar 2020); and the impact on brand perception (Fattal 2007).

7. Softness

Other examples of how softness affects human reactions include the contexts such as product design (Yu-Che and Ping-Hsien 2024); the impact on crowdfunding (Ronen et al. 2023); the effect on consumer behavior such as related to t-shirts and cars (Palmer, Schloss, and Sammartino 2013; Schloss, Strauss, and Palmer 2013); booking decisions (Lv, Li, and Xia 2020), the impact on haptic impressions (Ackerman, Nocera, and Bargh 2010); the impact in packaging design (Yazdanparast and Ketron 2023); in judgments of texture quality (Metzger and Drewing 2019); and in implications on purchasing (Wang et al. 2023).