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Pokémon Trading Cards reveal visual stereotypes of natural minerals

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Abstract. Popular media often simplifies Earth materials into idealized forms, shaping public understanding of geology. To investigate this effect, this study analyzed 202 mineral illustrations from the Pokémon Trading Card Game between 1999 and 2026. By quantifying visual characteristics through Multiple Correspondence Analysis, a dominant "universal crystal template" was identified, defined by large, transparent, high-symmetry prismatic crystals in cave environments. This representation contrasts with natural systems, where minerals commonly occur as irregular, rock-forming aggregates. Comparisons between human interpretation and AI-based identification further show that these stylized images lack sufficient diagnostic information for consistent classification. While human interpretation incorporates contextual cues, AI models rely on simplified geometric features and exhibit strong anchoring bias. These results demonstrate that widely circulated media not only simplifies geological reality but systematically reinforces visual stereotypes of minerals.

Keywords: Mineralogy; Visual stereotypes; Popular media; Multiple Correspondence Analysis; Science communication

1 Introduction

Minerals are the primary constituents of the solid Earth, making a fundamental understanding of these materials essential for learning broader geological processes and natural resource management (Nesse, 2017; Okrusch & Frimmel, 2020). For many beginners, initial exposure to mineralogy occurs through popular science books, museums, commercial markets, and digital media (Calvo & Lucha, 2024). Repeated exposure to such imagery helps shape intuitive frameworks and spatial reasoning about geological materials (Tversky, 2005; King, 2008; Hut et al., 2019; McGowan & Scarlett, 2021). However, media portrayals often lead the public to expect idealized crystals rather than the variability observed in natural settings (e.g., McGowan & Alcott, 2022). Evaluating how accurately these representations reflect geological reality is therefore important for effective science communication (Osborne, 2014).

As one of the most globally distributed entertainment brands, the 30-year-old Pokémon series provides a large and consistent visual dataset linking popular culture with natural imagery (e.g., Balmford et al., 2002; McGowan & Scarlett, 2021). Pokémon Trading Card Game (PTCG) illustrations combine fictional characters with nature-inspired backgrounds, frequently depicting

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minerals as part of the background. This global distribution makes the PTCG an ideal proxy for examining visual mineral representation. Although previous studies have explored the educational value of such media (Balmford et al., 2002; Callahan et al., 2019; Naddaf, 2026), their role in shaping visual expectations of natural materials remains largely unquantified.

This study quantitatively evaluates how minerals are visually represented in popular media and how these representations diverge from natural geology. Two main contributions are presented. First, statistical analysis identifies a dominant visual template and quantifies its characteristics. Second, comparisons with AI-based identification show that these stylized images lack the diagnostic features required for reliable interpretation, further highlighting their departure from geological reality.

2 Dataset and methodology

2.1 Dataset compilation and selection criteria

The dataset was constructed using illustrations from the English version of the PTCG. A total of 19,875 cards released between the *Base Set* in January 1999 and the *Perfect Order* expansion in March 2026 were surveyed using the *Pikawiz* archive (a public online database: https://www.pikawiz.com/cards, last accessed March 2026) to ensure a complete timeline.

Historically, PTCG releases accelerated from approximately 1.4 cards per day to 4.0 cards per day by 2023 (Fig. A1). To ensure exhaustive coverage, all items were manually screened against predefined standards to identify every mineral-bearing card using specific mineralogical criteria. Cards were included if they clearly showed features such as crystal faces, repeating geometric clusters, identifiable gemstones, or distinct geological formations like limestone caves and natural ice crystals.

The first clear mineral illustration appeared in the 2000 Dark Dragonair card (Fig. 1a), after which mineral artwork steadily increased to account for over one percent of all new releases since 2013 (Fig. A1). This creates a steadily growing dataset that reflects visual trends over nearly three decades. This study finalized a dataset of 202 cards drawn by 84 different artists, organized by release year and set number (see Supplement table and Figs. A2, A3). Representative mineral illustrations from this dataset are shown in Fig. 1, reproduced strictly for non-commercial academic research and educational critique under fair use guidelines.

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Figure 1: Representative cropped images of mineral illustrations. Images are ordered by release year and digitally cropped to focus on mineral features. Parentheses indicate card numbers, while the Supplement table provides detailed

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source information. (Card artwork © Pokémon/Nintendo/Creatures Inc./GAME FREAK Inc. Reproduced under fair use guidelines for scientific critique and educational research.) (a) The first instance of a mineral illustration (#1); (b) limestone cave (#3); (c) crystal face striations parallel to the c-axis (#18); (d) coexistence of natural crystals and cut gemstones (#19); (e) photographic image of fluorite (#48); (f) hexagonal columnar crystal with a bipyramidal termination (#60); (g) suspected conchoidal fracture (#65); (h) representation of freezing plants (#79); (i) paragenetic growth of multicolored minerals (#116); (j) self-luminous (glowing) crystals (#120); (k) opalescence and play-of-color (#134); (l) intergrowth of polymorphic columnar crystals (#140); (m) earthy luster in a monoclinic system (#152); (n) coexistence of tetragonal and hexagonal prisms (#161); (o) spinel twin (#162); (p) octahedral crystal habit (#164); (q) octahedral habit with an adamantine luster (#167); (r) amethyst geode (#168); (s) alluvial (placer) deposit (#171); (t) photographic image of amber (#172); (u) hexagonal beryl (#173); (v) rough ruby crystal (#177); (w) coexistence of natural and cut gemstones with stratigraphic layers (#178); (x) orthorhombic topaz (#187); (y) octahedral magnetite with metallic luster (#190); (z) Pokémon moves and background context used for mineral identification (#191).

2.2 Multidimensional visual analysis framework

Illustrated background environments were treated as natural outcrops for geological analysis. For each card, 13 categorical variables were recorded by the author, a trained geoscientist, to describe the mineral setting, growth habit, and physical form (Appendix B1). These variables were grouped into environmental context (e.g., growth setting, host rock type, and crystal exposure types) and intrinsic mineral traits (e.g., crystal size, color, transparency, luster, optical effects, crystal form, crystal system, surface features, aggregation patterns, and the presence of paragenetic minerals). These parameters represent the fundamental diagnostic data used by geoscientists to identify mineral species and deduce formational environments (Nesse, 2017; Okrusch & Frimmel, 2020).

Multiple Correspondence Analysis (MCA) was applied to the categorical variables to identify patterns in visual feature associations (Benzécri, 1979; Abdi & Valentin, 2007). This technique converts categorical responses into geometric coordinates, creating a multidimensional spatial map where frequently co-occurring variables are plotted closer together. By mapping these associations without imposing numerical assumptions, MCA allows us to quantify recurring visual combinations and identify dominant representation patterns in the dataset (see Appendix B2 for details).

2.3 Comparative mineral identification

Mineral species were initially evaluated by the author independently of artificial intelligence (AI) results. Since assigning natural mineral names to fictional illustrations is inherently interpretive, ambiguous images were assigned two plausible candidates to minimize bias, as detailed in the Supplement table. All mineral names assigned in this study are documented in Okrusch and Frimmel (2020).

These human interpretations were compared against three automated tools: two large language models (ChatGPT-5.3 and Gemini 3.0; standard publicly available versions) and a specialized rock-scanning app (Rock Identifier v2.19.2). ChatGPT and

Gemini were selected as the most widely used AI platforms (Andreessen Horowitz, 2026), reflecting how the general public might apply unspecialized AI to scientific tasks.

AI models were prompted to identify the mineral type from full card images and explain their reasoning (Appendix B3). Because generative outputs can vary, each image was queried three times, recording either the majority result or the inference most consistent with the crystal's visual appearance. In contrast, the rock-scanning app produced consistent outputs when applied to cropped mineral regions, so these results were recorded directly.

3 Quantifying visual mineral features in the Pokémon Trading Card Game

3.1 Visual homogenization of mineral occurrence and crystal geometry

To identify dominant visual patterns, environmental settings and crystal features depicted in the card backgrounds were quantified. Nearly half of the illustrated minerals occur in caves (Fig. 1d and 2a). Most are shown fully exposed (e.g., Fig. 1f) rather than embedded in host rock (e.g., Fig. 1k), and when host rocks are present, they lack sufficient petrological textures for lithological identification.

Paragenetic analysis shows that the vast majority of illustrations feature a single mineral species (Figs. 1c, d, l, u, w, and 2b), whereas coexisting mineral assemblages are rare (e.g., Fig. 1i). In terms of scale, over half of the minerals are depicted as crystals exceeding 30 cm in length (Fig. 2c). These crystals are typically well-formed (euhedral), highly symmetrical (e.g., Fig. 1f), and commonly occur as clustered aggregates (e.g., Figs. 1a, n), whereas twinned forms are uncommon (Fig. 1o and 2d).

Optical properties are similarly constrained, with most minerals depicted as blue (Fig. 2e). Illustrations favor translucent crystals (Fig. 2f) with vitreous luster (Fig. 2g), and a notable proportion show self-luminous crystals in dark environments (e.g., Fig. 1j).

Because microscopic features such as inclusions, cleavage, and growth striations are absent, crystal system classification is based on two-dimensional geometric outlines (Fig. 2h). The dataset is dominated by tetragonal and hexagonal systems (e.g., Figs. 1f, u, v), which together account for approximately 85 percent of the identifiable crystal systems. These are typically illustrated as columnar crystals terminating in a single pyramid.

The remaining crystal systems are notably underrepresented. The isometric system appears as the third most common type, mainly as octahedra (Figs. 1e, p, q, y), whereas orthorhombic (Fig. 1x), monoclinic, and triclinic systems (Fig. 1m) are rare. A final category of unidentifiable forms consists primarily of massive crystals lacking distinct faces, as well as faceted gemstones (Figs. 1b, k, t, w).

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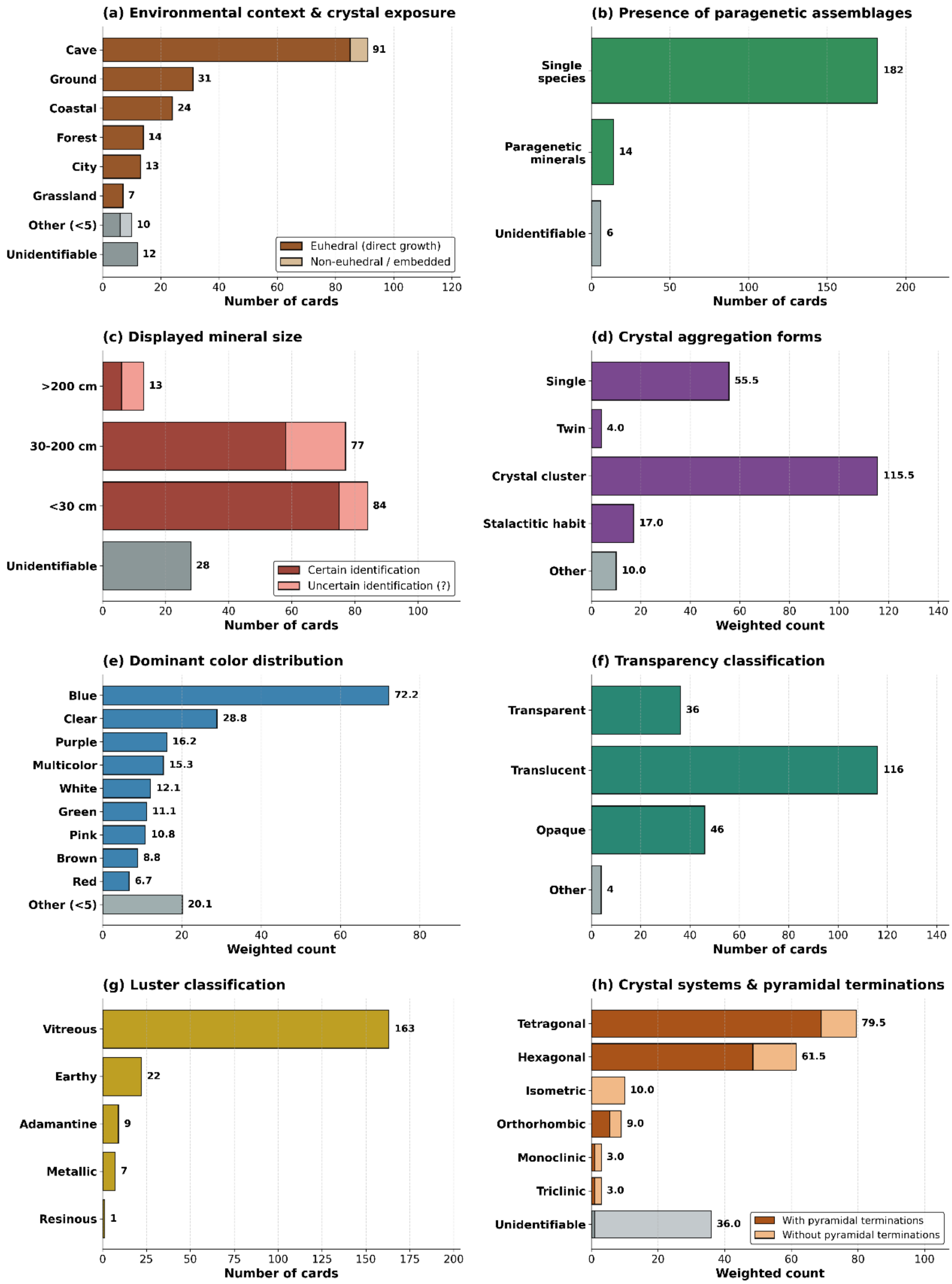

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Figure 2: Quantitative analysis of geological environments and physical features in fictional mineral cards. (a) shows geological settings and growth habits, where dark brown, light brown, and gray represent euhedral crystals, embedded forms, and unspecified environments, respectively. (b) compares single-species occurrences with paragenetic associations. (c) presents size classifications, with dark and light red indicating confident and uncertain interpretations, respectively. (d) shows the weighted frequency of crystal aggregation patterns. (e) illustrates primary mineral colors, using weighted averages for multicolored samples and grouping rare colors as "Other". (f) and (g) show transparency and luster based on visual light interaction and background visibility. (h) displays crystal systems and pyramidal terminations, with dark and light orange indicating crystals with and without pyramids, respectively. Mixed crystal systems are calculated using weighted values.

3.2 Constructing the universal visual template and human-AI discrepancies

To statistically validate this simplified template, the images were mapped to major mineral categories to establish a manual baseline. Varieties were consolidated into broad species groups. For example, amethyst (Fig. 1r) and citrine were grouped as quartz for this comparison. Manual identification shows that the six most frequently assigned mineral groups (ice, quartz, calcite, zircon, corundum, and fluorite) account for 84 percent of the dataset (Fig. 3), indicating a severe lack of visual diversity. MCA results reveal three distinct feature distribution patterns (Fig. 3). First, calcite forms an isolated cluster along the primary axis. Second, the confidence ellipses for ice, quartz, corundum, and zircon show substantial overlap, indicating highly uniform visual characteristics across these groups. Third, fluorite displays greater dispersion, suggesting higher variability in its representation.

Building on this identified visual homogeneity, this study introduced AI evaluations to test whether modern machine learning tools could accurately identify mineral species from these stylized illustrations. Overall, human and AI agreement ranged from 42 to 54 percent (Fig. 4a), while the rock-scanning app showed lower consistency. The agreement between ChatGPT and Gemini was only 42 percent, indicating that AI systems interpret stylized images inconsistently.

When examining the agreement across specific mineral categories, the results show that AI struggles to consistently identify even the most dominating taxonomy groups (Fig. 4b). Visual evaluation reveals that approximately half of the mineral cards incorporate fantasy elements that rarely occur in natural geological environments. Consequently, the results demonstrate that agreement between human interpretation and AI increased when the images were geologically realistic but decreased significantly for these fantasy-style images with unrealistic lighting and geometry (Fig. 4c). Unlike the human baseline, AI frequently overestimates the presence of quartz and struggles to identify tetragonal minerals (Fig. 4d).

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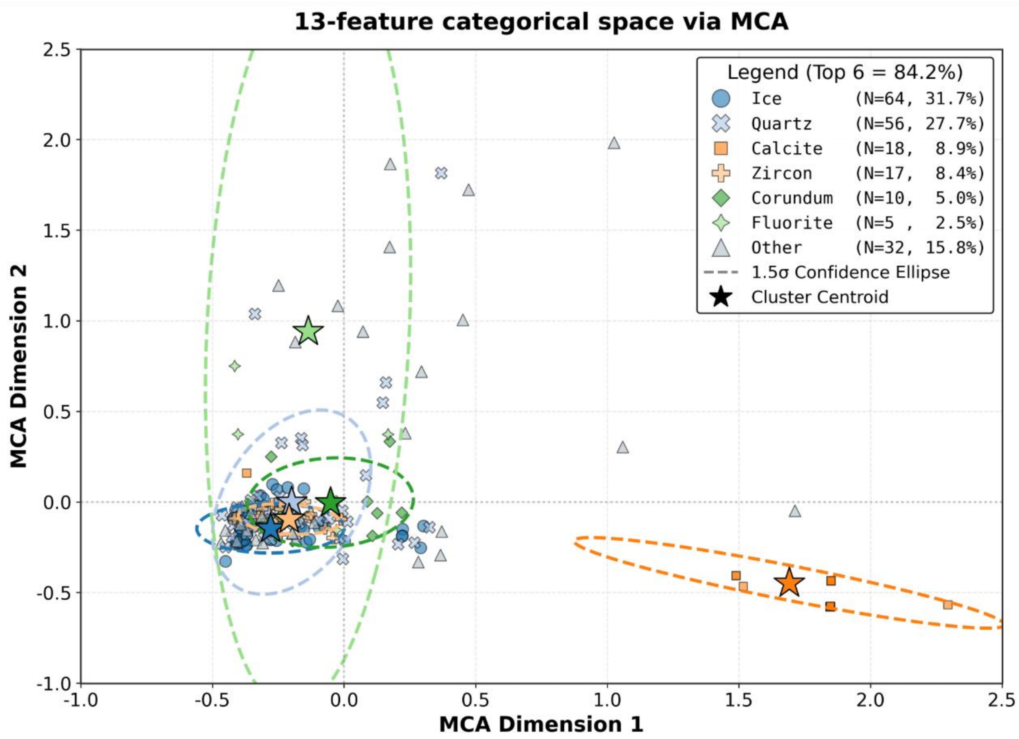

Figure 3: Multidimensional visual feature distribution of fictional minerals. MCA results based on the 13 categorical features. To accurately reflect the variance explained, eigenvalues were adjusted using the Benzécri correction, with Dimensions 1 and 2 explaining 68.8% and 31.2% of the total inertia, respectively. Dashed confidence ellipses (1.5 standard deviations) outline the core distribution range encompassing approximately 68% of the samples for each mineral. Star symbols represent the centroid for each mineral within the multidimensional feature space. The legend details the absolute frequency and relative percentage of each mineral group.

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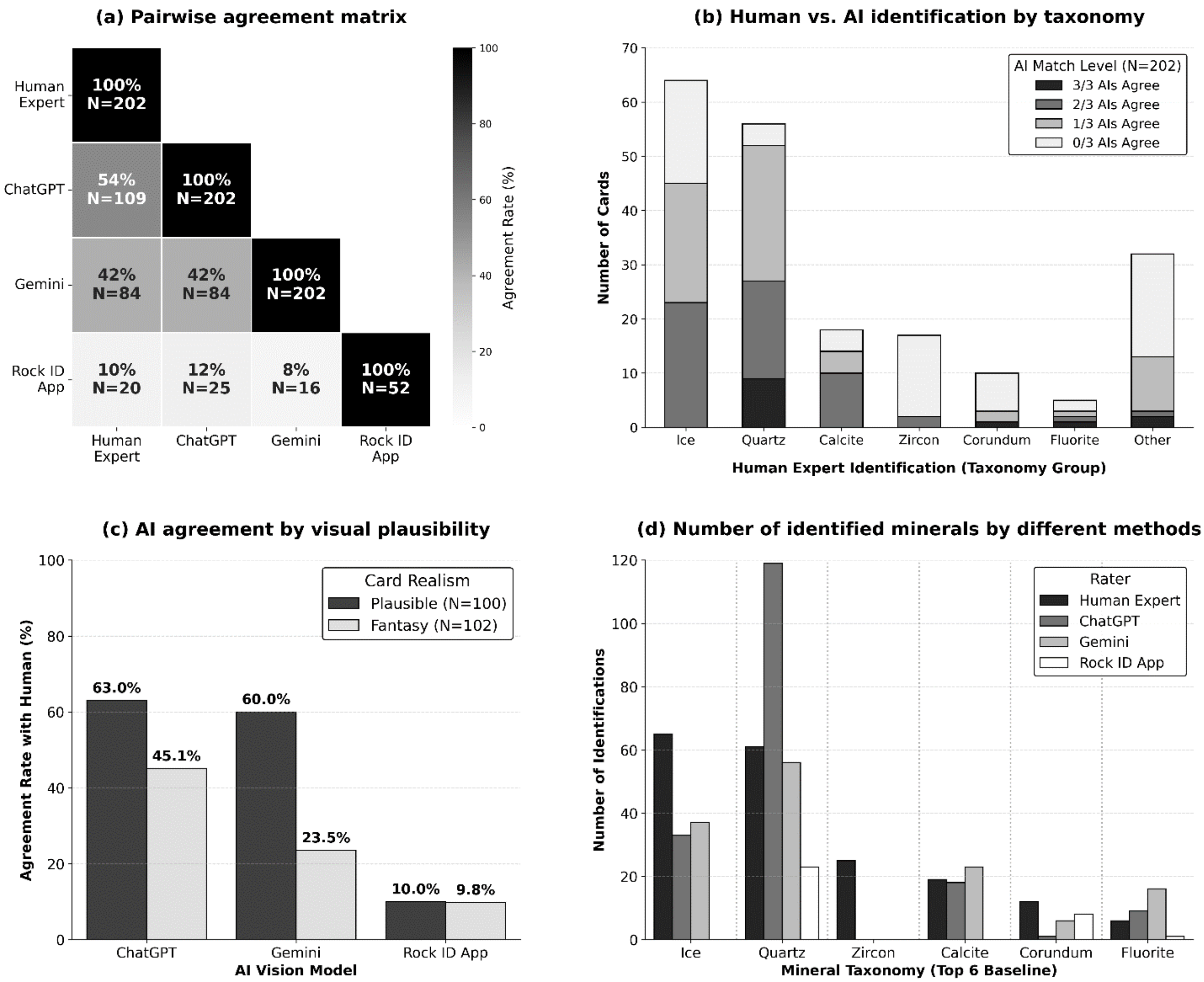

Figure 4: Comparative analysis of AI and human mineral identification. (a) Pairwise agreement matrix among human experts, two large language models (ChatGPT and Gemini), and a geology-specific app (Rock Identifier). Values indicate the agreement percentage and the number of matching samples (N). (b) AI identification consensus across major mineral taxonomy groups. Stacked bars illustrate the number of AI tools that successfully matched the human baseline. (c) The impact of illustrative realism (plausible versus fantasy) on the accuracy of each AI vision model. (d) Distribution of identification frequencies by each evaluator for the top six most common minerals, sorted by the number of human evaluations.

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4 Discussions

4.1 The universal template as a shared public image

Morphological analysis shows a gap between natural geology and popular media. In the PTCG, minerals are typically depicted as giant (>30 cm) and perfectly symmetrical crystals isolated in empty caves. In contrast, the vast majority of real-world minerals exist as interlocking grains or within veins in igneous or metamorphic rocks, or as weathered fragments in placer deposits (e.g., Fig. 1s; Nesse, 2017; Okrusch & Frimmel, 2020). While giant euhedral crystals do occur in nature, they are extraordinary anomalies confined to rare environments like hydrothermal caves (e.g., the Naica Mine in Mexico, Fig. 1l). In natural settings, minerals frequently occur in paragenetic associations; for instance, quartz and feldspar are ubiquitous partners in many rock types, yet only six percent of the dataset depicts multiple species. This lack of paragenesis and focus on rare crystals demonstrates that the media favors a simplified geological representation that diverges significantly from natural systems.

This media bias also extends to the extreme idealization of optical and physical properties to maximize aesthetic appeal (Fig. 2). The dataset shows a severe scarcity of dark materials, earthy luster, or opaque minerals, and an almost complete absence of fractured textures (Figs. 1g, m). Instead, illustrators prioritize visual perfection by depicting minerals with high geometric symmetry, glassy translucency, and a vitreous luster. These idealized characteristics closely match the commercial image of quartz in the gemstone market rather than raw ores found in the field. Furthermore, while common rock-forming minerals like quartz, feldspar, and calcite typically appear white, colorless, or gray in nature (Okrusch & Frimmel, 2020), the statistical results of the cards show a dominant preference for vibrant blue (Figs. 1f, j), further underscoring the shift toward high-impact visuals.

The environmental and optical biases observed above are driven by a broader geometric homogenization. Because the primary goal of these illustrations is artistic expression rather than scientific documentation, illustrators prioritize aesthetic appeal over crystallographic accuracy. Consequently, they often treat crystal symmetry as a flexible design element rather than a defining diagnostic feature.

This reliance on artistic shortcuts is reflected in the distribution of crystal systems, which are highly concentrated in tetragonal or hexagonal prisms terminating in pyramids along the c-axis (e.g., Fig. 1f). An intriguing finding is that tetragonal prisms unexpectedly emerge as the most common mineral shape. This proportion significantly contradicts the globally abundant hexagonal forms, such as quartz or calcite, that dominate both commercial markets and natural environments. Such a discrepancy confirms that media representation is driven by visual impact rather than geological sampling. Furthermore, observations suggest that some illustrators may not realize that crystal morphology is a diagnostic criterion, occasionally overlooking the rules of symmetry by mixing different crystal systems within a single illustration (e.g., Fig. 1n).

The identification of mineral species highlights a significant conceptual gap in public mineral recognition (Fig. 3). When excluding ice, 40 percent of the illustrated minerals align with the popular image of quartz, while other assignments are concentrated in stalactitic calcite, zircon, and corundum. Consequently, common rock-forming silicates like feldspar, pyroxene, amphibole, and mica are nearly absent because they lack the aesthetic appeal required for visual media. Notably, the high percentage of zircon may be a byproduct of the human geologist identifying the frequent tetragonal prisms rather than the artist's original intent. Intriguingly, common gemstones like diamond, beryl, chrysoberyl, and jadeite are largely absent, likely because the public primarily encounters these materials as polished jewelry, leading artists to neglect their natural growth forms.

The MCA results provide statistical evidence for this pattern through extreme visual simplification (Fig. 3). While natural quartz displays immense diversity from microscopic grains to banded agate, the cards restrict it to a single template of clear geometric prisms. The overlapping confidence ellipses for ice, quartz, corundum, and zircon strongly suggest that a single visual template dominates multiple mineral categories. The distinct calcite cluster is strictly due to its consistent depiction as limestone cave stalactites rather than common rhombohedral cleavage faces. In contrast, fluorite remains visually distinct because its unique cubic or octahedral habits are strong enough to resist the universal template. However, this remains a rare exception, proving how seldom illustrators depart from the standard prismatic mold.

Finally, many illustrations also introduce features that contradict natural physical laws. For example, some cards show faceted and gem-cut stones embedded directly in rock formations, blurring the distinction between natural growth and human polishing (e.g., Fig. 1d). Similarly, the common trope of self-luminous crystals ignores the fact that natural fluorescence requires external energy sources not present in dark caves (e.g., Fig. 1j).

4.2 AI misclassification as evidence of media-driven mineral stereotypes

To test whether modern machine learning could accurately identify stylized minerals, this study introduced AI evaluations as a comparative tool. When processing photorealistic mineral cards, the AI tools and manual evaluations yielded consistent and scientifically accurate answers (e.g., Figs. 1e, t). This demonstrates that modern AI is fully capable of identifying minerals when they follow natural geological principles. However, when evaluating hand-drawn cards, AI outputs diverged significantly (Figs. 4b–d). This failure reflects the visual simplification and the prevalence of fantasy art styles in the dataset because many drawings use general shapes without geological details.

Humans analyze these cards more comprehensively by integrating environmental context with crystal features. For example, when a transparent crystal emerges from snow, grass, or water, a human recognizes that the geological environment is inconsistent with quartz formation and identifies it as an ice crystal (e.g., Fig. 1h, z). In contrast, current AI models lack this contextual reasoning and suffer from anchoring bias, focusing solely on the isolated, stylized crystal shape (O'Leary, 2025; Takenami et al., 2025). Because these generalized shapes heavily mimic the universal template mentioned above, quartz becomes the most commonly identified mineral species across all AI platforms (Fig. 4d). By over-relying on this visual anchor instead of analyzing the entire scene, the models produce predictions that fluctuate wildly across different iterations. This exposes their fundamental instability when interpreting fantasy media.

Another critical limitation is that AI models struggle to infer three-dimensional symmetry from two-dimensional images (Zhang et al., 2024). Consequently, they rarely utilize crystal form and symmetry as diagnostic criteria. This causes a

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fundamental disconnect between the AI's inferred mineral species and the actual morphology depicted in the illustration, such as repeatedly misclassifying clear tetragonal prisms as hexagonal quartz (Fig. 4d).

Finally, specialized rock scanning applications face even stricter limitations. Because they are trained exclusively on realistic mineral photography, these dedicated tools are completely unable to process artistic abstractions, frequently yielding unidentifiable results when evaluating hand-drawn cards. Ultimately, the inability of advanced AI to interpret these illustrations is not merely a technological shortcoming but compelling statistical evidence of how deeply media-driven stereotypes have distorted authentic geological representation.

4.3 Implications for science communication and public perception

The findings from human and AI evaluations show that widely circulated media often simplify geological reality into a standard visual template. By omitting the irregular and opaque minerals that dominate the crust, media creates an expectation of isolated, large, and perfect translucent crystals. This template reflects a visual preference likely influenced by commercial gemstone markets and curated museum displays (Francek, 2013). Even with advancements in digital illustration over the past three decades, the PTCG continues to reproduce this selective imagery.

This visual trend gradually hides the true diversity of natural geological systems. These quantitative results highlight how visual culture prioritizes artistic impact over scientific accuracy, shaping public expectations of Earth materials. Recognizing this gap is beneficial for geoscience educators. To effectively communicate geological concepts, professionals might consider addressing these media representations to guide the public toward understanding authentic natural environments.

5 Conclusion

The Pokémon Trading Card Game provides a large visual archive reflecting shared cultural assumptions about minerals. The results identify a dominant “universal crystal template” characterized by large, euhedral, high-symmetry, and transparent crystals, typically isolated within cave environments. This template emphasizes visually striking but geologically uncommon features, while systematically excluding the irregular, fine-grained, and multi-mineral textures that dominate natural systems. Human and AI comparisons prove that these images lack the details needed for identification. The findings show that the media does not just simplify geology but also reinforces stereotypes. These patterns help us understand how media reshape science and affect how the public sees the solid Earth.

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Appendix A: Supplementary Materials

A1 Cumulative release trends of the Pokémon Trading Card Game and mineral-illustrated cards

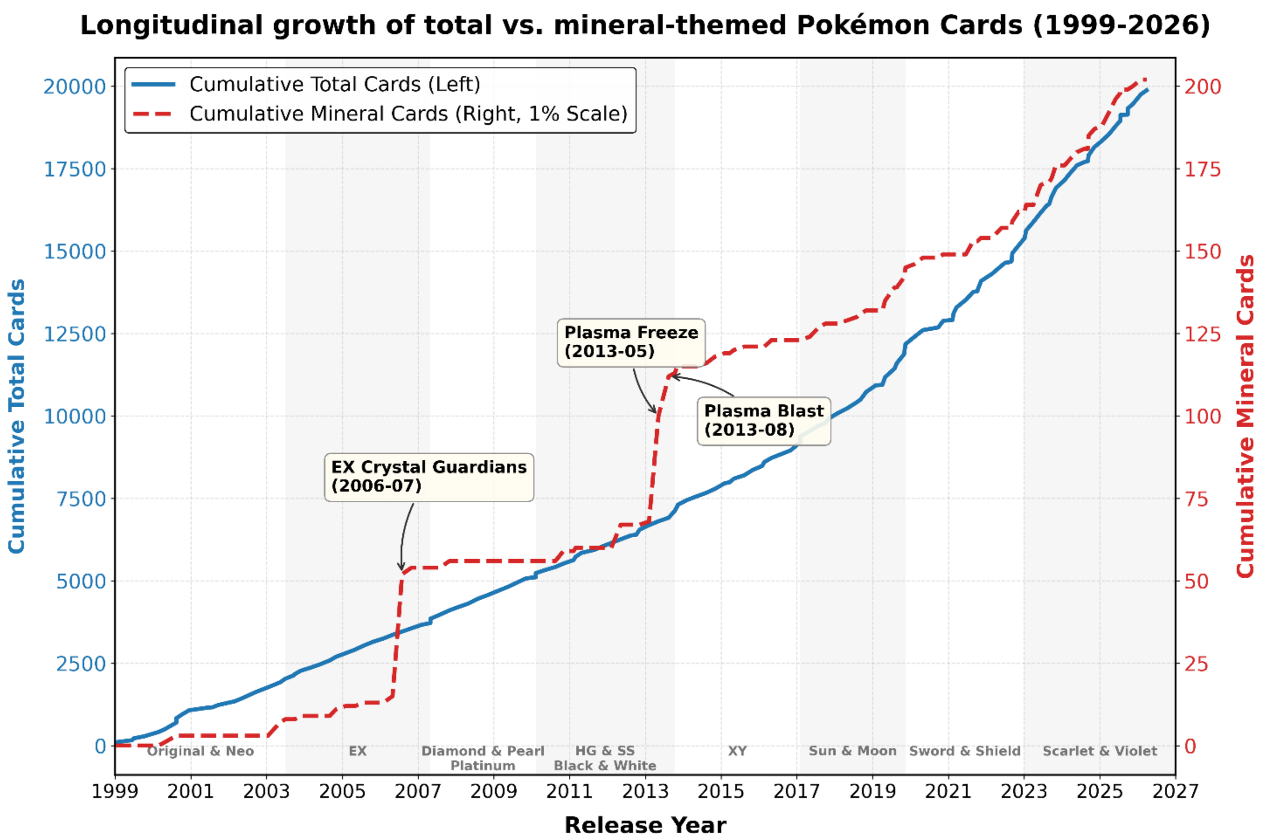

Figure A1: The blue and red curves represent the cumulative total number of cards and mineral-illustrated cards released between 1999 and 2026, respectively (see Supplement table). Periods where the red curve is positioned above the blue curve indicate that mineral-illustrated cards constitute more than one percent of total releases. Different background colors represent distinct official Pokémon game generations.

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A2 Mineral-illustrated cards analyzed in this study

Figure A2: Mineral-illustrated cards analyzed in this study (Nos. 1 to 100). Cards are numbered chronologically by release year. Cards outlined with a black border correspond to the original artwork used in Fig. 1 of the main text. Basic information for each card is provided in the Supplement table. Digital images of the cards were sourced from the Pikawiz database (https://www.pikawiz.com/cards, last accessed March 2026). To strictly adhere to copyright policies and prevent unauthorized high-resolution reproduction, all artwork presented in this figure has been intentionally blurred. (Card artwork © Pokémon/Nintendo/Creatures Inc./GAME FREAK Inc. Reproduced under fair use guidelines for scientific critique and educational research.)

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Figure A3: Mineral-illustrated cards analyzed in this study (Nos. 101 to 202). Cards are numbered chronologically by release year. Cards outlined with a black border correspond to the original artwork used in Fig. 1 of the main text. Basic information for each card is provided in the Supplement table. Digital images of the cards were sourced from the Pikawiz database (https://www.pikawiz.com/cards, last accessed March 2026). To strictly adhere to copyright policies and prevent unauthorized high-resolution reproduction, all artwork presented in this figure has been intentionally blurred. (Card artwork © Pokémon/Nintendo/Creatures Inc./GAME FREAK Inc. Reproduced under fair use guidelines for scientific critique and educational research.)

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Appendix B: Methods

B1 Classification criteria for visual features of fictional minerals

This study recorded various manually interpreted categorical variables for each card in addition to basic metadata. To ensure methodological clarity, these variables are grouped into four logical categories. Please refer to the Supplement table for the complete dataset.

1. Environmental context

• Growth setting & crystal exposure: Environments were categorized based on background geomorphology (e.g., Cave, Forest, Coastal, Ground, City). The crystal relationship with the host rock was recorded as "Y" if the mineral exhibits clear geometric faces or "N" if it is anhedral or buried.

• Major rock type (host rock): Classified petrologically based on visual texture. Recorded as "Sedimentary" if showing bedding, stalactitic structures, or clastic components; "Igneous" if showing columnar jointing, flow structures, or magmatic environments; and "Metamorphic" if showing foliation. Cards lacking identifiable rock details were marked as "Unidentifiable."

• Presence of paragenetic assemblages: Assesses whether the illustrator captured natural mineral diversity. Recorded as "Single Species Only" if only one mineral type is depicted, and "With Paragenetic Minerals" if two or more distinct minerals are shown growing together.

2. Intrinsic morphological traits

• Displayed mineral size: Official heights of depicted Pokémon were used as scale bars to estimate the longest visible axis of each crystal. Sizes were classified into three levels: L (Large, >200 cm), M (Medium, 30–200 cm), and S (Small, <30 cm). Uncertainties caused by extreme perspective or obstruction are denoted with a question mark (e.g., L?, M?).

• Crystal system & pyramidal terminations: Minerals were classified into Hexagonal, Isometric, Tetragonal, Orthorhombic, Monoclinic, or Triclinic systems based on geometric symmetry. Ambiguous crystals were assigned multiple possible systems using weighted calculations (e.g., two possibilities score 0.5 each). This study explicitly recorded the presence of "Pyramidal terminations" to quantify the abundance of pointed geometries. Crystals lacking symmetrical faces are marked as "Unidentifiable."

• Crystal aggregation: Growth patterns were categorized as Single crystal, Twin, or Crystal Cluster. The "Stalactitic habit" was classified independently to analyze biases tied to cave environments.

• Surface features of crystals: Evaluates microscopic realism. Recorded as "Y" if the illustration features striations, cleavage, or fracture (e.g., conchoidal fracture). Perfectly smooth, idealized geometric bodies without these features were recorded as "N."

3. Physical and optical properties

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• Dominant color: The primary color(s) of the mineral. Multicolored specimens were processed using weighted calculations. Minerals with more than four colors (e.g., opalescence) were recorded as "Multicolor."

• Luster: Classified as Adamantine, Vitreous, Metallic, Resinous, or Earthy. The presence of specular highlights (e.g., white starburst reflections) resulted in a higher luster grading.

• Transparency: Classified as Transparent, Translucent, or Opaque, determined by the visibility of internal inclusions, cleavage planes, or background objects behind the crystal.

• Mineral luminescence: Identifies exaggerated optical rendering. Recorded as "Y" if the mineral is drawn as a self-luminous light source (emitting halos) without a specific excitation source (like UV light). Recorded as "N" otherwise.

4. Analytical and educational metrics

• Real-world plausibility: "Plausible" indicates the crystal geometry, environment, and physical laws (e.g., gravity) align with natural possibilities. "Fantasy" indicates violations of geological norms (e.g., giant water-soluble minerals in the deep sea, anti-gravity floating, or mutually exclusive crystal systems on a single body).

• Mineral identification results: The inferred mineral species generated by LLMs (ChatGPT, Gemini), the Rock Identifier app, and the human expert baseline.

B2 Multiple Correspondence Analysis (MCA) and eigenvalue correction procedure

MCA served as the primary dimensionality reduction technique to uncover latent geometric relationships among categorical features. This study utilized the Prince library in Python to incorporate thirteen categorical variables. Because standard MCA applied to an indicator matrix inherently generates artificial dimensions, it severely inflates the total inertia and consequently underestimates the variance explained by the primary dimensions (Abdi & Valentin, 2007). To rectify this mathematical distortion and accurately evaluate the explanatory power of the dominant visual axes, we applied Benzécri's correction (Benzécri, 1979). For spatial visualization, confidence ellipses set at 1.5 standard deviations were plotted to delineate the core 68% feature space for each mineral taxonomy. This spatial mapping effectively illustrates the clustering and severe homogenization of diverse minerals into a single universal visual template within popular media.

B3 Standardized prompts for multimodal large language models (LLMs)

The study utilized ChatGPT and Gemini for mineral feature analysis between January and March 2026. The standardized prompt submitted to the models is as follows.

"You are a world-renowned mineralogist with an extensive background in geology and mineralogy. I will provide you with illustrations from Pokémon trading cards. Please visually disregard the Pokémon characters in the image and exclusively analyze the natural geological background features of the location. Based on these visual characteristics, deduce the most likely common mineral depicted in the background, and provide a rigorous scientific justification.

Please strictly adhere to the following format for your response:
1. Visual observation of mineral features: Detail the color, luster, transparency, crystal system geometry, and growth habit of the mineral in the card.
2. Final identification result: Synthesize the above features to provide a single, most likely common 'mineral' name (use standard mineralogical terminology).
3. Deductive logic and geological plausibility: Explain the reasoning behind your feature matching, and briefly assess the plausibility of this mineral occurring in the depicted geological environment."

In addition to data analysis, these AI tools were also employed to refine the manuscript's phrasing and structural clarity.

Data availability.

The dataset containing the coded variables for the 202 Pokémon cards and the detailed AI identification outputs is available in the Supplement table. The original illustrations of the Pokémon Trading Card Game used for initial screening are publicly accessible via the Pikawiz database (https://www.pikawiz.com/cards, last accessed: 25 March 2026).

Competing interests.

The author declares that there are no competing interests.

Ethical statement.

This research relies exclusively on the analysis of publicly available commercial media and AI models. No human subjects or sensitive data were involved; thus, formal ethical approval was not required. All artwork is properly credited and reproduced strictly under fair use guidelines for scientific critique.

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