

Pokémon Trading Cards reveal visual stereotypes of natural minerals

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Abstract. Popular media influences public understanding of the natural world, yet its representation of minerals has rarely been quantified. To address this gap, this study analyzed 223 mineral illustrations from the Pokémon Trading Card Game (PTCG) between 1999 and 2026. Statistical analyses of visual features identified a dominant "universal crystal template" characterized by large, transparent, highly symmetrical prismatic crystals in cave environments. This template contrasts sharply with natural mineral occurrences, where minerals commonly form irregular rock-forming aggregates. Inferred mineral identities are heavily restricted to just six species, with Multiple Correspondence Analysis demonstrating that these dominant species share highly overlapping visual traits. Consequently, current AI models struggle to identify these stylized illustrations due to obscured diagnostic features, an inability to resolve three-dimensional geometry in artwork, and a lack of contextual environmental integration. These findings quantify how entertainment media constructs a shared visual stereotype of minerals. While such stereotypes distort geological reality, their global familiarity and mass appeal offer a unique opportunity for science communication. By critically decoding these media-driven biases, educators can leverage these widely accessible cards as engaging visual hooks to stimulate active inquiry into authentic mineralogy and geological processes.

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). Consequently,

systematic biases in visual representations may also shape public expectations of how minerals naturally occur. However, media portrayals often lead the public to expect idealized crystals rather than the variability observed in natural settings (e.g., McGowan & Alcott, 2022; Calvo & Lucha, 2024). Evaluating how accurately these representations reflect geological reality is therefore important for effective science communication (Osborne, 2014).

35 As one of the most globally distributed entertainment brands, the 30-year-old Pokémon franchise provides a large and consistent visual dataset linking popular culture with natural imagery (e.g., Balmford et al., 2002; McGowan & Scarlett, 2021). Within this franchise, the Pokémon Trading Card Game (PTCG) serves as a particularly rich visual archive. PTCG illustrations combine fictional characters with nature-inspired backgrounds, often featuring minerals as part of the scenery. This global distribution makes the PTCG an ideal proxy for examining visual mineral representation. Although previous studies have
40 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.

Because these illustrations were created for entertainment rather than scientific communication, they provide an unusually unbiased record of how minerals are visually imagined in popular culture. This research offers three principal contributions: (1) statistically identifying a shared "universal crystal template" within this globally recognized medium; (2) demonstrating
45 how this template obscures diagnostic geological information through human-AI comparative analyses; and (3) providing practical strategies for leveraging these illustrations to enhance geoscience education and science communication.

2 Dataset and methodology

2.1 Dataset compilation and selection criteria

50 The dataset was constructed using illustrations from the English version of the PTCG. A total of approximately 20,000 cards released between the *Base Set* in January 1999 and the *Pitch Black* expansion in July 2026 were surveyed. To ensure comprehensive coverage and account for database inconsistencies, the manual screening process was conducted twice across all cards using two independent public online databases (both last accessed in July 2026): *Pikawiz* (<https://www.pikawiz.com/cards>) and *Pokellektor* (<https://www.pokellektor.com/sets>). Every card, including identical
55 artworks reprinted across different sets, promotional campaigns, or mini-sets like McDonald's and Trick & Trade, was individually inspected by hand. To further validate dataset completeness, targeted searches were conducted using Pokémon species strongly associated with mineral imagery (e.g., Sableye). However, to prevent statistical duplication, any identical illustration was counted only once as a single unique entry in the final dataset.

All cards were screened against predefined mineralogical criteria. Cards were included if they clearly showed features such as
60 crystal faces, repeating geometric clusters, identifiable gemstones (including cut and organic gemstones), or distinct geological formations like natural ice crystals. However, official game mechanics and lore items with crystalline appearances, such as the

"Terastal" phenomenon or "Evolution Stones," were systematically excluded because this study focuses on environmental geological backgrounds created by illustrators, rather than pre-defined, franchise-specific items.

65 Following this dual-database screening, this study finalized a mineral illustration dataset of 223 cards, organized by release year and set number (see Supplement [Excel](#) table and Figs. A2 to A4). 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.



70 **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; detailed source information is provided in**

the Supplement table. (a) The first instance of a mineral illustration (#1); (b) limestone cave (#3); (c) crystal face striations parallel to the c-axis (#26); (d) coexistence of natural crystals and cut gemstones (#27); (e) photographic image of fluorite (#57); (f) hexagonal columnar crystal with a bipyramidal termination (#75); (g) suspected conchoidal fracture (#82); (h) representation of freezing plants (#96); (i) paragenetic growth of multicolored minerals (#133); (j) self-luminous (glowing) crystals (#137); (k) opalescence and play-of-color (#152); (l) intergrowth of polymorphic columnar crystals (#158); (m) earthy luster in a monoclinic system (#170); (n) coexistence of tetragonal and hexagonal prisms (#179); (o) spinel twin (#180); (p) octahedral crystal habit (#182); (q) octahedral habit with an adamantine luster (#185); (r) amethyst geode (#186); (s) alluvial (placer) deposit (#189); (t) photographic image of amber (#190); (u) hexagonal beryl (#191); (v) rough ruby crystal (#195); (w) coexistence of natural and cut gemstones with stratigraphic layers (#196); (x) orthorhombic topaz (#205); (y) octahedral magnetite with metallic luster (#208); (z) Pokémon moves and background context used for mineral identification (#210). (Card artwork © Pokémon/Nintendo/Creatures Inc./GAME FREAK Inc. Reproduced under fair use guidelines for scientific critique and educational research.)

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, dominant 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 inferred 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 facilitates the quantification of recurring visual combinations and identifies dominant representation patterns in the dataset (see Appendix B2 for details).

2.3 Comparative mineral identification

Inferred 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).

105 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. Similarly, Rock Identifier was chosen because, as of June 2026, it was the most downloaded geological application across mobile platforms with highly positive user reviews. This selection effectively represents the primary tools an average collector would likely use to identify a mineral on a card.

110 The AI models and the rock-scanning app 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 visually consistent with the crystal.

3 Quantifying visual mineral features in the Pokémon Trading Card Game

115 3.1 Visual homogenization of mineral occurrence and crystal geometry

Historical statistical results indicate that PTCG publication rates accelerated from approximately 1.4 cards to 4.0 cards per day by 2023 (Fig. A1). The first clear mineral illustration appeared in the 2000 Dark Dragonair card (Fig. 1a). Following this initial appearance, mineral artwork steadily increased to account for over one percent of all new releases since 2007 (Fig. A1). This creates a steadily growing mineral dataset that reflects visual trends over nearly three decades, ensuring that players entering the game during different periods all have continuous opportunities to encounter mineral-themed card art.

120

A total of 223 PTCG cards containing mineral illustrations, produced by 85 different artists, were included in the analysis (Appendix A3). Although six artists each contributed more than ten mineral-themed illustrations (accounting for 29% of the dataset), most artists produced only one or two cards. Despite this diversity of illustrators, the statistical results reveal remarkably consistent patterns in both the geological settings and crystal features depicted in the artwork. To identify these recurring visual patterns, the environmental settings and crystal characteristics illustrated in the card backgrounds were quantified.

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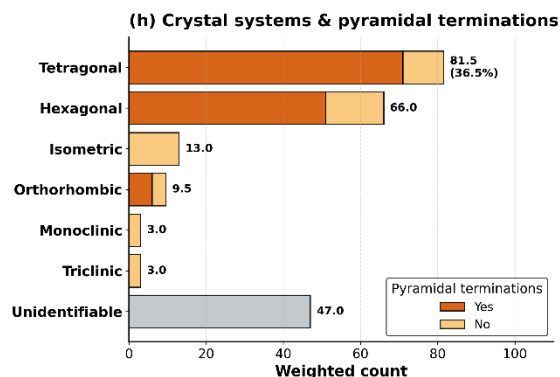
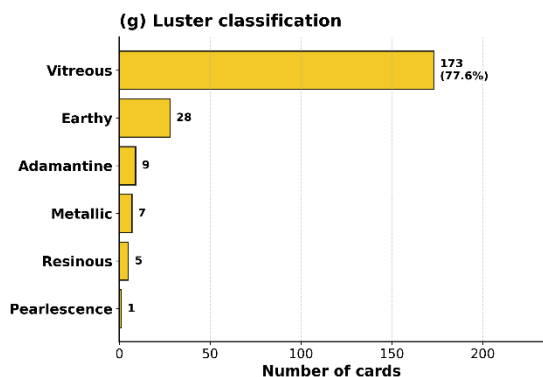
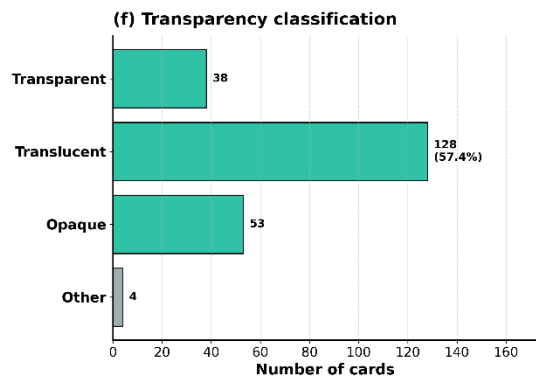
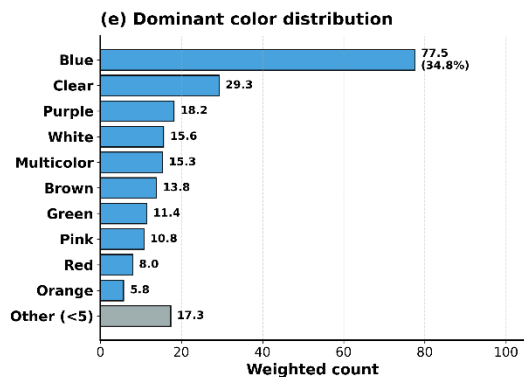
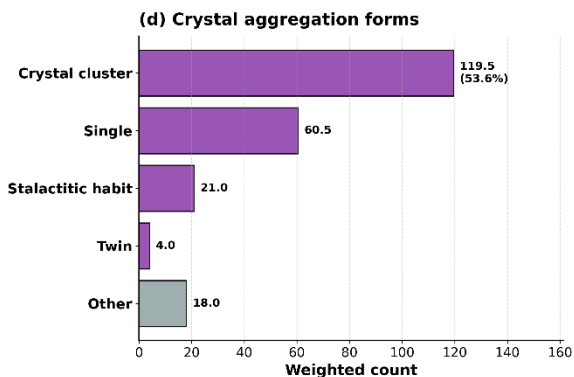
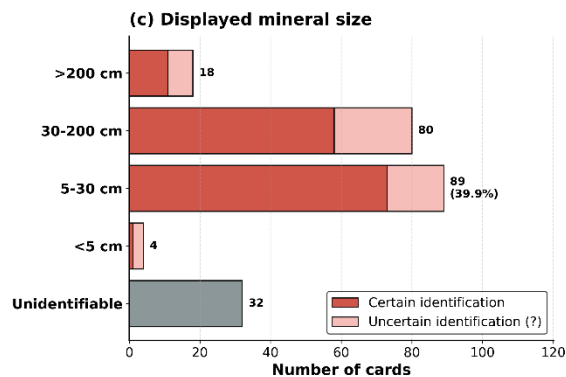
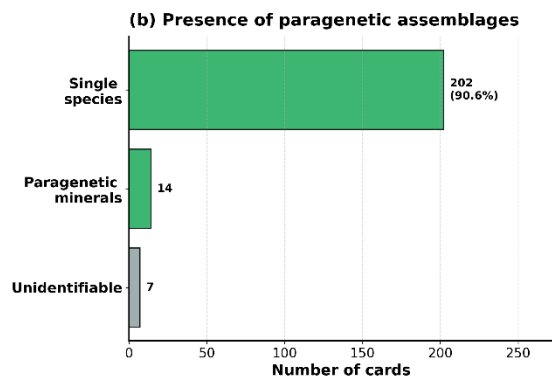
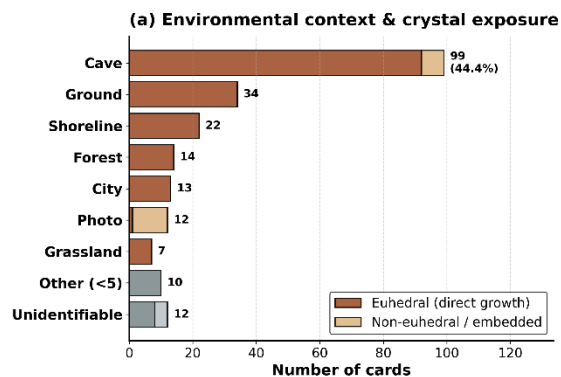
Nearly half of the illustrated minerals occur in caves (99 cards, 44%, Figs. 1d and 2a). Most are shown fully exposed (202 cards, e.g., Figs. 1f and 2a) rather than embedded in host rock (e.g., Fig. 1k), and when host rocks are present, they lack sufficient petrological textures for lithological identification.

130 Based on the theoretical heights of the depicted Pokémon, over half the illustrated crystals exceed 30 cm along the c-axis (Fig. 2c). These crystals are typically well formed (euhedral), pristine, unweathered, highly symmetrical (e.g., Fig. 1f), and terminate in elongate prismatic habits. Most occur as crystal clusters (e.g., Figs. 1a and 1n), whereas twinned crystals are uncommon

(Fig. 1o and Fig. 2d). At the assemblage scale, the vast majority of illustrations depict only a single inferred mineral species (Figs. 1c, d, l, u, w, and Fig. 2b), while coexisting mineral assemblages are rare (e.g., Fig. 1i).

135 Because microscopic features such as inclusions, cleavage, and growth striations are absent, crystal system classification is necessarily based on two-dimensional geometric outlines. The dataset is dominated by tetragonal and hexagonal systems (e.g., Figs. 1f, u, v), which together account for approximately 84% of the identifiable crystal systems (Fig. 2h). 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
140 (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).

These highly repetitive environmental and crystallographic characteristics provided the basis for inferring the most likely mineral species represented in each illustration. Consequently, 22 mineral groups were manually inferred across the dataset. Varieties were consolidated into broad species groups; for example, amethyst (Fig. 1r) was classified under quartz. The inferred
145 mineral diversity was highly uneven: the six most frequently inferred groups—ice, quartz, calcite, zircon, corundum, and fluorite—account for 84% of the entire dataset (Fig. 3). Within this subset, ice and quartz overwhelmingly dominated, accounting for approximately 32% and 28% of all inferred minerals, respectively.



150 **Figure 2. Quantitative analysis of geological environments and physical features in fictional mineral cards. (a) Geological settings and growth habits (dark brown: euhedral crystals; light brown: embedded forms; gray: unspecified environments). (b) Occurrence of single-species versus paragenetic associations. (c) Size classifications (dark red: confident interpretations; light red: uncertain interpretations). (d) Weighted frequency of crystal aggregation patterns. (e) Dominant mineral colors (rare colors grouped as “Other”). (f, g) Transparency and luster based on visual light**
155 **interaction and background visibility. (h) Crystal systems and pyramidal terminations (dark orange: with pyramids; light orange: without pyramids; mixed crystal systems calculated using weighted values).**

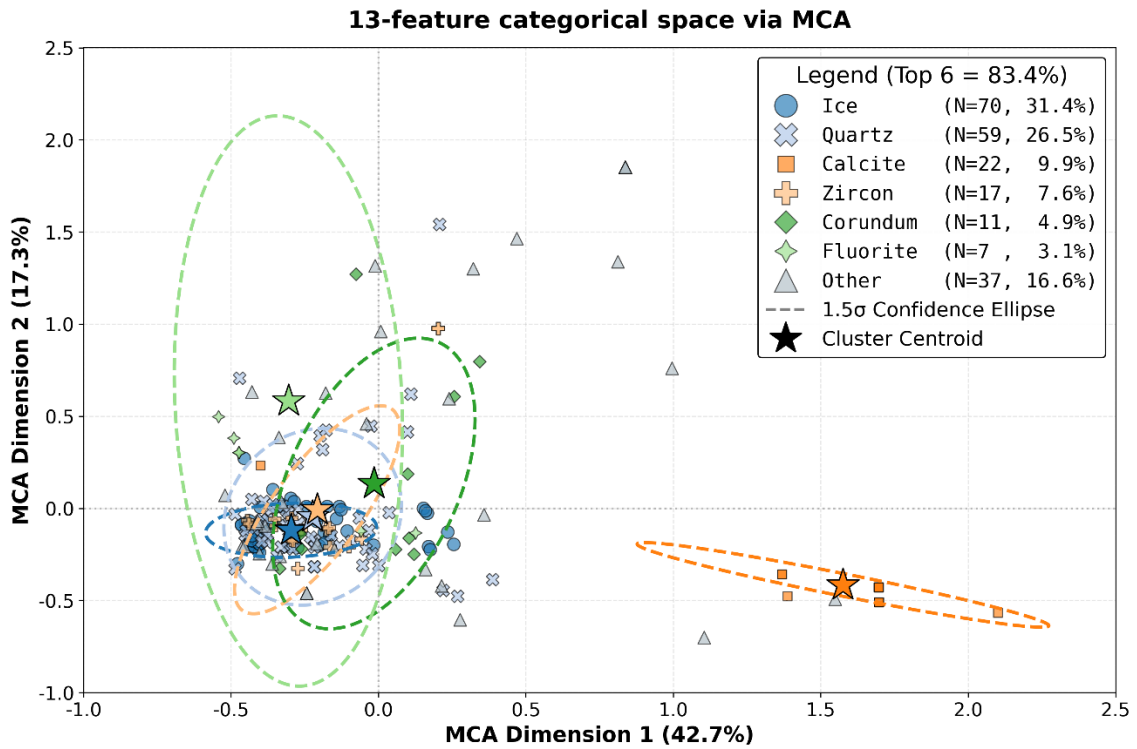
3.2 Constructing the universal visual template and human-AI discrepancies

To statistically validate this simplified visual template and examine the relationships among these characteristics, MCA was
160 performed. A Benzécri correction was applied to avoid underestimating the variance of categorical variables (Appendix B2). The resulting ordination reveals three distinct patterns (Fig. 3). Calcite forms a clearly isolated cluster along the primary axis, whereas the confidence ellipses of ice, quartz, corundum, and zircon overlap extensively, indicating highly similar visual characteristics. Fluorite occupies a broader area of the feature space, suggesting greater morphological variability.

To compare human and machine interpretation of these stylized illustrations, three AI systems were applied to the complete
165 dataset of 223 cards. Before analyzing the artwork, a control experiment using 43 photographs of real mineral specimens was conducted to verify that the AI systems could reliably identify realistic mineral images. Overall accuracies ranged from 74% to 95%, demonstrating strong baseline performance on natural mineral photographs (Appendix C).

Across the 223 card illustrations, agreement between manual interpretation and AI ranged from 45% to 56%, whereas the
specialized rock-scanning application achieved only 12% agreement (Fig. 4a). Agreement between ChatGPT and Gemini was
170 likewise limited (42%), indicating considerable variation among AI interpretations of stylized artwork.

Agreement also varied substantially among mineral groups (Fig. 4b). Approximately half of the illustrations contain fantasy
elements, including giant crystals growing through urban environments or floating rock masses. Human–AI agreement was
consistently lower for these fantasy-style illustrations than for more geologically realistic depictions (Fig. 4c). Compared with
the manual baseline, AI systems systematically overidentified quartz while underrecognizing tetragonal minerals (e.g., zircon,
175 Fig. 4d).



180 Figure 3. Multidimensional visual feature distribution of fictional minerals. Results are based on Multiple Correspondence Analysis (MCA) of the 13 categorical features detailed in Appendix B1. Eigenvalues were adjusted using the Benzécri correction to accurately reflect explained variance, with Dimensions 1 and 2 explaining 42.7% and 17.3% of total inertia, respectively. Dashed confidence ellipses (1.5 standard deviations) outline core distribution ranges encompassing approximately 68% of samples per mineral group. Star symbols represent centroids in the feature space.

185 Legend indicates absolute frequencies and relative percentages for each mineral group.

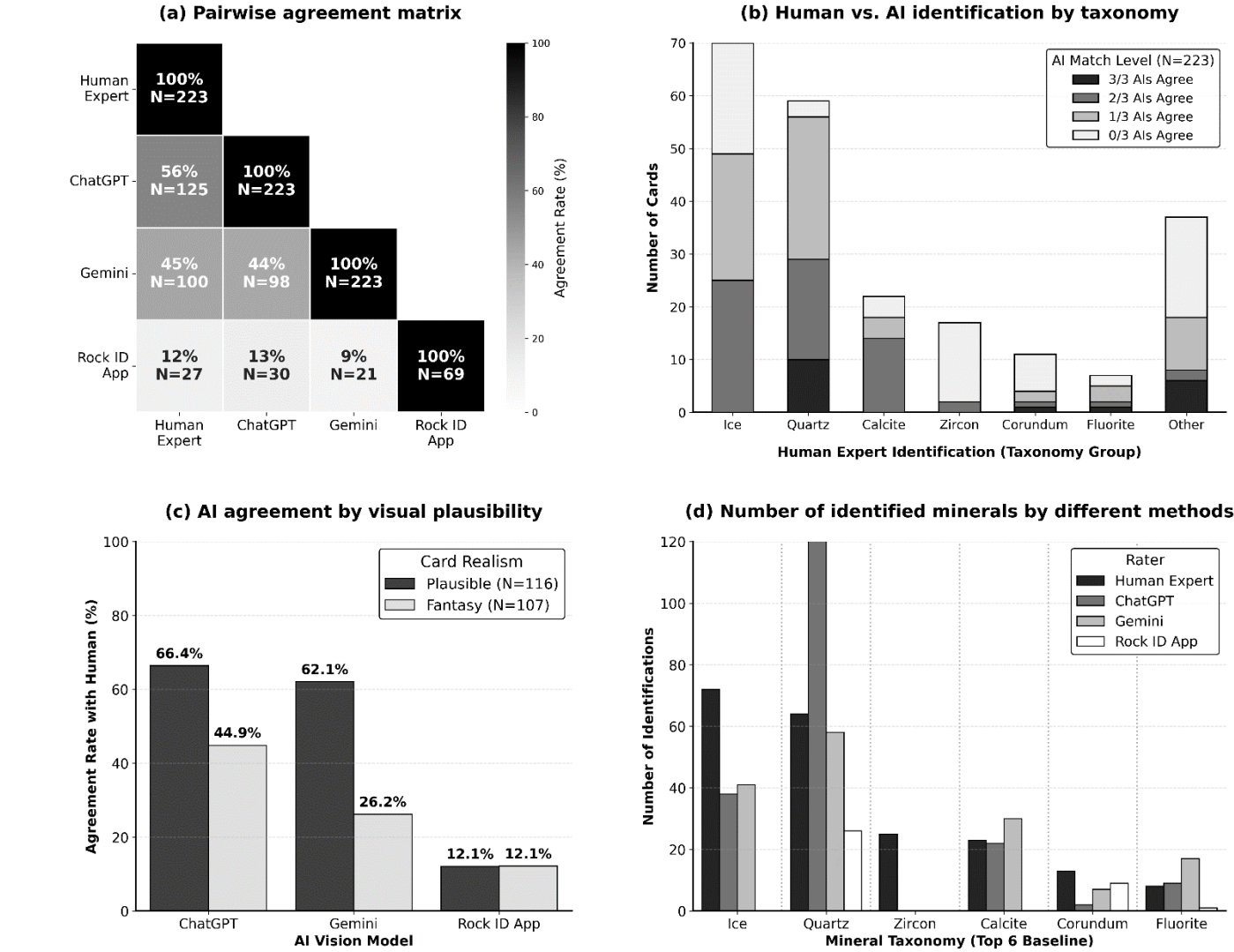


Figure 4. Comparative analysis of AI and human mineral identification. (a) Pairwise agreement matrix among human evaluation, two large language models (ChatGPT and Gemini), and a geology-specific app (Rock Identifier). Values indicate the agreement percentage and matching sample counts (N). (b) AI identification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

4.1 The universal template as a shared public image

The quantified morphological patterns reveal a substantial divergence between PTCG representations and natural geological systems. In the PTCG, minerals are typically depicted as giant (>30 cm), pristine, and perfectly symmetrical crystals isolated in caves (e.g., Fig. 1d). In contrast, most real-world minerals exist as interlocking grains, veins in igneous or metamorphic rocks, or 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 requiring exceptionally stable geochemical conditions, such as those in the Naica Mine, Mexico (Fig. 1l; García-Ruiz et al., 2007). Likewise, minerals in natural systems commonly occur as paragenetic assemblages rather than isolated crystals. For example, quartz and feldspar are ubiquitous companions in many rock types, yet only 6% of the dataset depicts multiple mineral species. PTCG illustrations clearly favor visually simplified geological scenes over realistic mineral occurrences.

The same idealization extends to optical and physical properties (Fig. 2). The dataset shows a severe scarcity of dark-colored minerals, earthy luster, opaque crystals, and fractured textures (Figs. 1g, m). Instead, minerals are consistently portrayed with bright color, glassy translucency, vitreous luster, and high geometric symmetry. These idealized characteristics closely match the commercial image of crystal 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 dataset shows a dominant preference for vibrant blue (Figs. 1f, j), further reinforcing the stylized visual identity of fictional minerals.

The environmental and optical biases observed above are driven by a broader geometric homogenization. As these illustrations prioritize artistic expression and aesthetic impact over scientific documentation, they rely on a limited visual vocabulary of crystals drawn from museum displays and commercial specimens. Consequently, crystal symmetry is treated as a flexible design aesthetic rather than a strict diagnostic feature.

This reliance on familiar visual templates 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). Unexpectedly, tetragonal prisms dominate as the most common shape, sharply contrasting with the global abundance of hexagonal forms (e.g., quartz, calcite) in both natural environments and commercial markets. This discrepancy suggests that media representation is driven by visual impact rather than geological sampling. Furthermore, illustrators occasionally mix fundamentally incompatible crystal systems within a single illustration (e.g., Fig. 1n), inadvertently violating crystallographic laws.

4.2 The universal template transcends mineral identity

These morphological biases extend beyond geometry to influence inferred mineral identity. Ice provides a robust test of this hypothesis because, unlike most other minerals, its identification relies primarily on contextual evidence (Pokémon types, move names, cold environments) rather than crystal morphology. If artists faithfully represented diverse minerals, ice should exhibit distinct morphological characteristics. Instead, MCA shows ice forms the most tightly clustered group (Fig. 3), indicating remarkably consistent visual representation. Crucially, more than half of the inferred ice crystals are drawn as tetragonal prisms, despite terrestrial ice (ice Ih) crystallizing almost exclusively in the hexagonal system. This firmly demonstrates that illustrations prioritize a culturally familiar "crystal" archetype over actual crystallography.

Even excluding ice, the inferred mineral distribution remains highly concentrated. Among the remaining 153 cards depicting minerals stable under ambient conditions, nearly 40% were inferred as quartz, while most of the remainder were assigned to stalactitic calcite, zircon, corundum, or fluorite. Collectively, these six dominant mineral groups account for 83.4% of the inferred mineral diversity, indicating that only a limited range of mineral identities is repeatedly represented. In contrast, common rock-forming silicates (feldspar, pyroxene, amphibole, mica) are almost absent. This pattern likely reflects their limited visual familiarity and their lack of traditional crystalline aesthetics. Likewise, gemstones such as diamond, beryl, and chrysoberyl are rare, probably because the public most commonly encounters them as polished gems rather than natural crystals. Although this limited diversity does not diminish the artistic appeal, incorporating a broader range of geological materials could substantially enhance their value for science communication by presenting a more representative picture of Earth's mineral diversity.

The MCA results provide quantitative evidence for this 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 primarily reflects 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, it remains the only clear exception, highlighting how rarely illustrators depart from the dominant crystal archetype.

Finally, many illustrations 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).

4.3 AI misclassification as evidence of media-driven mineral stereotypes

To explore how modern AI interprets stylized mineral illustrations, this study incorporated AI evaluations as a comparative analytical tool. Because PTCG artists employ diverse styles ranging from hyper-realism (e.g., Figs. 1e, t) to heavy fantasy abstraction, AI serves as an objective machine-vision baseline to quantify exactly which diagnostic geological features are lost during artistic stylization. When processing photographs of real minerals (Appendix C), the AI tools and manual evaluations yielded consistent and scientifically accurate answers. This demonstrates that modern AI is fully capable of identifying minerals when they follow natural geological principles. However, when evaluating highly stylized hand-drawn cards, AI outputs diverged significantly (Figs. 4b–d). This analytical limitation reflects the visual simplification and fantasy art styles prevalent throughout the dataset, where many illustrations intentionally prioritize symbolic crystal forms over geological realism (e.g., Calvo & Lucha, 2024).

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 geologically trained observer recognizes that the environment is inconsistent with quartz formation and identifies it as ice (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, quartz becomes the most commonly identified mineral 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. These observations suggest that current AI should be used for geological reasoning rather than definitive identification when interpreting stylized 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 fundamental disconnect between the inferred mineral species and the depicted morphology, leading models to repeatedly misclassify clear tetragonal prisms as hexagonal quartz (Fig. 4d). Dedicated rock-scanning applications perform worst, as their training on photorealistic specimens renders them unable to interpret artistic abstractions. Ultimately, these illustrations preserve the cultural image of a "crystal" while actively omitting the geological characteristics required for reliable identification.

4.4 Implications for science communication and public perception

The analytical results show that widely circulated media often simplifies geological reality into a standard visual template, creating an expectation that minerals typically occur as isolated, large, translucent, and perfectly formed crystals (e.g., Calvo & Lucha, 2024). Recognizing this discrepancy provides an opportunity for geoscience communication. Rather than simply correcting misconceptions, educators can use these familiar images to discuss how popular media shapes public perceptions of minerals and geological processes.

PTCG illustrations are well suited for this purpose because they are freely accessible through public online databases, internationally recognizable, and familiar to many children before they receive formal geology education. Educators can leverage these illustrations as engaging visual hooks during school science workshops or museum guided tours, effectively transforming media-driven stereotypes into active discussions on mineralogy and geological environments.

The visual template identified in this study likely reflects the influence of commercial gemstone markets, curated museum displays where aesthetically perfect crystals are preferentially showcased (Francek, 2013), and the artistic backgrounds of Pokémon illustrators. Most illustrators are professional artists rather than geologists and intentionally adopt highly stylized visual languages, making simplified crystal imagery an expected artistic convention. This shared convention provides valuable insight into how popular culture collectively constructs the public image of minerals.

Although this stereotypical representation has remained consistent throughout nearly three decades of PTCG publications, future illustrations could incorporate greater mineralogical diversity without sacrificing artistic appeal. For example, illustrators could draw inspiration from museum collections, mineral markets, and geological references to depict a wider range of crystal habits and geological occurrences. Collaboration with mineralogists could further introduce scientifically recognizable features, such as calcite birefringence or fluorite fluorescence (e.g., Fig. 1j). Additionally, depicting realistic mineral assemblages and deposit environments, such as characteristic pegmatite parageneses, would further improve educational value.

Nevertheless, PTCG is a creative medium, and scientific realism should never constrain artistic expression. The Pokémon Company is entirely justified in prioritizing aesthetic appeal over scientific accuracy. Stylized and fantastical illustrations are central to the franchise's imaginative appeal, and their popularity demonstrates that scientific accuracy is unnecessary for successful visual storytelling. However, with over 1,000 new cards released annually, embedding occasional scientifically accurate "Easter eggs" would provide educators with highly engaging teaching materials while preserving the game's creative identity, proving that entertainment media can simultaneously inspire curiosity and broaden public engagement with the Earth sciences.

5 Conclusion

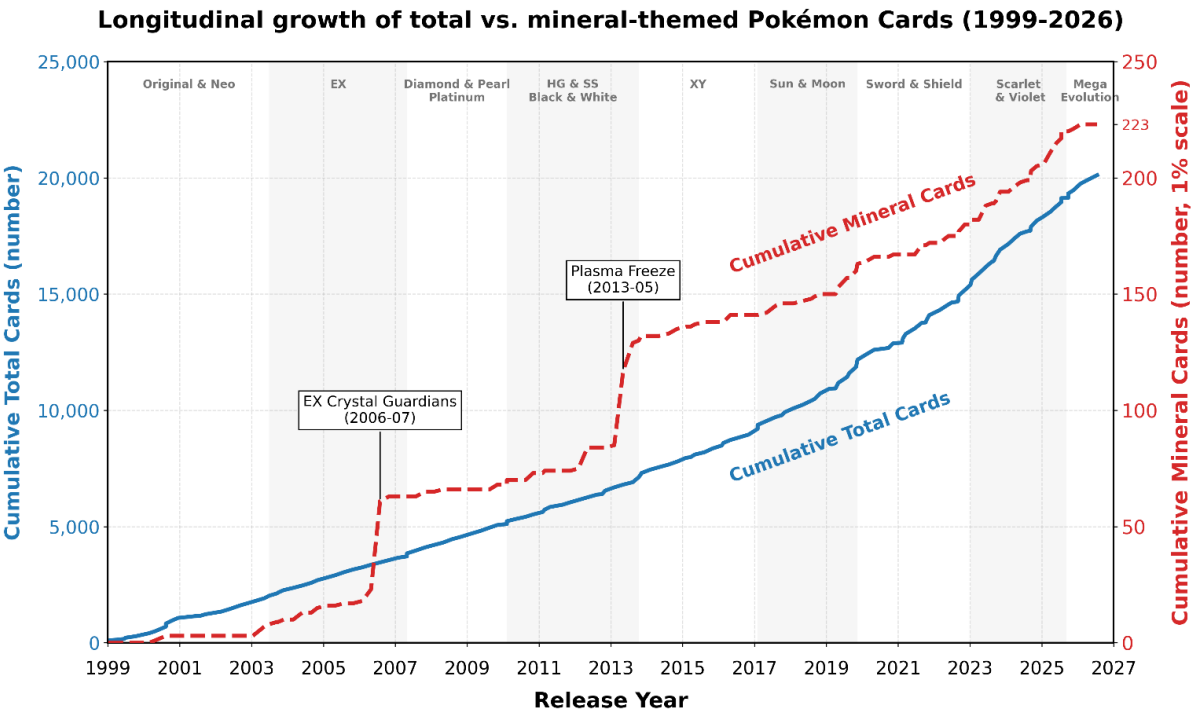
The Pokémon Trading Card Game provides a nearly three-decade global visual archive reflecting shared cultural assumptions about minerals. The results reveal a dominant “universal crystal template” favoring large, euhedral, transparent, and highly symmetrical specimens isolated in caves, restricting inferred minerals to just six species. Furthermore, the unnatural dominance of tetragonal crystal forms, even applied to hexagonal terrestrial ice, demonstrates a widespread disregard for crystallographic

320 rigor. By emphasizing visually striking anomalies, this template systematically excludes the irregular, fine-grained, and
paragenetic textures that dominate natural systems. Consequently, current AI systems struggle to interpret these stylized
illustrations because they rely on oversimplified visual features, cannot infer three-dimensional crystal symmetry, and lack
contextual geological reasoning.

Recognizing these visual conventions offers valuable opportunities for science communication. Rather than dismissing media-
driven stereotypes as mere misconceptions, educators can utilize popular media like the PTCG as engaging entry points to
discuss authentic mineral diversity, geological environments, and solid Earth processes. Ultimately, as visual media continues
to shape public scientific perception, critically decoding these existing illustrations and incorporating scientifically informed
325 elements into future artwork provides a compelling bridge between popular culture and Earth science education.

Appendix A: Supplementary Materials

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



330 **Figure A1. Cumulative total number of cards (blue) and mineral-illustrated cards (red) released between 1999 and 2026, respectively (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. Background colors denote distinct official Pokémon game generations.**

A2 Mineral-illustrated cards analyzed in this study



335 **Figure A2. Mineral-illustrated cards analyzed in this study (Nos. 1 to 70). 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 in July 2026). To strictly adhere to copyright policies and prevent unauthorized high-resolution reproduction, all artwork presented in this figure has been intentionally**

340 **blurred. (Card artwork © Pokémon/Nintendo/Creatures Inc./GAME FREAK Inc. Reproduced under fair use guidelines for scientific critique and educational research.)**



Figure A3. Mineral-illustrated cards analyzed in this study (Nos. 71 to 150). 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 in July 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.)



Figure A4. Mineral-illustrated cards analyzed in this study (Nos. 151 to 223). 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 in July 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.)

A3 Distribution of Mineral-Themed Pokémon Trading Card Game Illustrations Among Artists

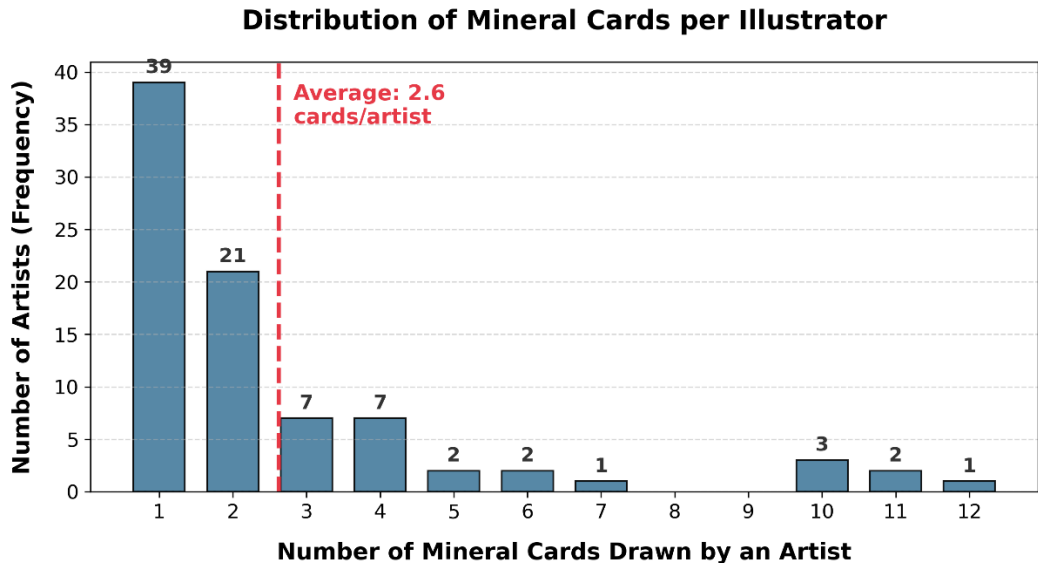


Figure A5. Distribution of mineral-themed Pokémon Trading Card Game illustrations across 85 identified artists. The dataset comprises 223 mineral-themed cards with an average of approximately 2.6 cards per artist. Approximately 70% of artists contributed only one or two cards, whereas six illustrators produced ten or more cards each, collectively accounting for 29% of the dataset.

Appendix B: Methods

B1 Classification criteria for visual features of fictional minerals

Beyond basic metadata, thirteen categorical variables were manually interpreted for each card. These are grouped into four domains (see Supplement table for the complete dataset):

1. Environmental context

- Growth setting: Environments were categorized based on background geomorphology. Examples include Cave (broadly covering various underground spaces like karst limestone caves and mines), Forest (wooded areas), Shoreline (boundaries between water and land, including lakeshores and riverbanks), Ocean, Ground (general land surfaces), Grassland, City (including artificial structures), and Sky. Some common natural landscapes, such as magmatic or volcanic areas, were grouped into more objective categories like Cave or Coastal because defining volcanic processes visually can be subjective. Similarly, wind-formed and glacial landscapes were grouped into broader and undisputed areas like Coastal or Ground.

- Crystal exposure: The crystal relationship with the host rock was recorded as "Y" if the mineral exhibits clear geometric crystal faces protruding from the host rock, or "N" if it is anhedral or buried. If the mineral or gemstone in the illustration has been artificially cut or processed into jewelry, tools, or ornaments, it was designated as "N/A" (Not Applicable).
- Major rock type (host rock): Classified petrologically based on visual texture. "Sedimentary" includes cards showing distinct stratification, bedding planes, clastic components, or internal cave formations. Specifically, an underground environment was inferred to be a "Limestone Cave" and classified under Sedimentary if it concurrently exhibited visual markers like downward-hanging stalactites, upward-growing stalagmites, dripping water textures, and basal pools, typically colored in earth or brown tones. "Igneous" includes cards showing columnar jointing, active magmatic flow structures, or distinct volcanic environments. "Metamorphic" includes cards showing clear foliation, banding, or structural deformation textures. "Unidentifiable" includes cards lacking sufficient background rock detail or textural clarity for confident petrological assignment.
- 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 co-occur together.

2. Intrinsic morphological traits

- Displayed mineral size: The official heights of the depicted Pokémon species, retrieved from the *Bulbapedia* database (https://bulbapedia.bulbagarden.net/wiki/Main_Page), were used as reference scale bars to estimate the longest visible axis of each crystal. To ensure consistency across the dataset, variation among individual members of the same Pokémon species was ignored, and only the official species height was used for scaling. When multiple crystals of different sizes were present in a single illustration, the predominant crystal size was used as the representative value. Categories include XS (<5 cm), S (5–30 cm), M (30–200 cm), and L (>200 cm). Interpretative uncertainty due to perspective distortion was denoted with a question mark (e.g., L?).
- 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 striations, cleavage, or fracture (e.g., conchoidal fracture) are visible. Perfectly smooth, idealized geometric bodies without these features were recorded as "N."

3. Physical and optical properties

- 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, [Pearlescence](#), or Earthy. The presence of specular highlights (e.g., starburst reflections) resulted in a higher luster grading.
 - 415 • 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
- 420 • Real-world plausibility: "Plausible" indicates that the crystal geometry, environment, and physical laws (e.g., gravity) align with natural possibilities. [This means the occurrence and growth state of the mineral are reasonable in an actual geological setting.](#) "Fantasy" indicates violations of geological norms. Examples include crystals floating in the air, [abnormally giant crystals growing directly on artificial city streets, deep ocean or unsuitable ground surfaces](#), or mutually exclusive crystal systems on a single body.
 - 425 • 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. [Standard MCA applied to an indicator matrix often generates artificial dimensions. This inherently inflates the total inertia and heavily underestimates the actual variance explained by the primary dimensions \(Abdi & Valentin, 2007\).](#)
- 430 [To rectify this mathematical distortion, Benzécri's correction \(Benzécri, 1979\) was applied. This procedure recalculates the eigenvalues by discarding those below a specific mathematical threshold. This effectively filters out the artificial variance, providing a much more accurate estimation of the explanatory power for the dominant visual axes.](#) For spatial visualization, confidence ellipses set at 1.5 standard deviations were plotted to delineate the core 68% feature space for each mineral
- 435 taxonomy.

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.

440 "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.

445 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).

450 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.

455 **Appendix C: AI Baseline Performance on Real Mineral Specimens**

C1. Sampling strategy

To validate the baseline identification capabilities of the AI models and ensure that misclassifications in the main study were driven by artistic stylization rather than algorithmic limitations, a control experiment utilizing photographs of natural mineral specimens was conducted. A proportional stratified sampling approach was designed to mirror the frequency distribution of the minerals identified in the PTCG dataset.

460 The control group consisted of 43 photographs. For the seven most frequently occurring minerals (ice, quartz, calcite, zircon, corundum, fluorite, and amber), four distinct photographs were selected per species. For less frequent minerals, photograph counts aligned with their proportional abundance: beryl (3), garnet (2), magnetite (2), spinel (2), topaz (2), diamond (1),

465 feldspar (1), mica (1), and tourmaline (1). To maintain scientific rigor, all 43 images were sourced from the Wikimedia Commons database and selected for exhibiting clear euhedral or subhedral crystal habits. URL links and attributions are detailed in the supplementary Excel file.

C2. Testing procedure and results

470 The 43 photographs were randomized to prevent sequential bias. Each image was processed by three AI tools (ChatGPT 5.3, Gemini 3.0, and Rock Identifier v2.19.2) using the identical standardized prompts applied to the card illustrations. Each

photograph was tested twice per software application, and the response most accurately identifying the correct species was recorded as the model's optimal capability.

The baseline experiment confirmed that all three tools possess high proficiency in natural geological pattern recognition. Gemini achieved the highest accuracy at 95%, followed by ChatGPT at 86%, and Rock Identifier at 74%. Rock Identifier's relatively lower success rate was attributed to the absence of ice crystals and limestone cave formations in its training database; excluding these materials raised its accuracy above 80%. Given the small sample size, these percentages serve strictly as a general baseline reference. The complete evaluation matrix is provided in the supplementary Excel file and summarized in Figure C1.



Figure C1. Performance evaluation of three AI tools (ChatGPT, Gemini, and Rock Identifier) on 43 real mineral photographs used in the control experiment. Photographs of actual mineral specimens were sourced from Wikimedia Commons under Creative Commons licenses or public domain designations. Detailed attributions, including license types and author names, are listed in the supplementary Excel file.

Data availability.

The dataset containing the coded variables for the 223 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 two independent public online databases (both last accessed in July 2026): *Pikawiz* (https://www.pikawiz.com/cards) and *Pokellector* (https://www.pokellector.com/sets).

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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