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In the eye of the beholder: A viewer-defined conception of online visual creativity

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Abstract
Despite substantial interest in developing theoretical models and technology for creativity enhancement, existing creativity research across various fields lacks a user-centered definition of creativity that can be operationalized in today's digital spaces. To address this, we conducted a mixed-methods longitudinal research on a study website mirroring content from Bēhance, a popular online platform for creatives. Specifically, we examined how content creators and consumers explored and reflected on online creative content through textual, visual, quantitative, and behavioral data. Analyzing and triangulating these multiple data streams, we conceptualize creativity from the perspectives of its genuine "users," the viewers. Collectively, we highlight (1) constructs of creativity that have not been emphasized in the existing literature, (2) the impact of users' roles on content exploration and conception of creativity, and (3) the difference between machine and human users' perception of creative content. We discuss theoretical and practical implications accordingly.

Keywords
Content curation, creativity, exploration, mixed-methods research

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Creativity is endemic to cultural expression. Indeed, creativity is highly valued in the cultural sector and seen by some as a uniquely human trait (Boden, 2004). In the face of increasingly powerful automation and machine intelligence, many hope to protect creativity as a final bastion of humanity (Moruzzi, 2020), claiming that computers will never be artists (Hertzmann, 2018). It is important to investigate the juncture between online platforms and creativity, as creative content powerfully incites human inspiration, disseminates avant-garde ideas, and facilitates cross-cultural communication. As online networks increasingly configure our social world, our cultural and artistic experiences enter digital ecosystems as well.

Before technology platforms release ill-formed, misguided solutions to creative access, it is imperative to understand what creativity *is* in the digital context. Without a clear understanding of online visual creativity, truly creative content may be minimized, hidden, or subverted in these digital spaces. In particular, visual artists may find their work rendered invisible to the public by algorithms or ranking systems that do not comprehend creativity. An understanding of creativity would also enable the production of cultural value: Creative pieces will be deemed valuable, enabling the adequate compensation of their creators, who may not have existing connections to elite cultural institutions. Furthermore, with an understanding of creativity, technologists would be able to improve the quality of creative tools and their respective outputs, thereby empowering digital artists with new technologies that enhance their practice. In many ways, creativity is a new frontier for emerging technologies: Instead of repetition, it prizes novelty; instead of optimization, it prizes transformation; instead of saturation, it prizes curation.

In this research, we approach a conception of creativity from the perspective of the "end user" of creative content: its viewer. After all, the newly formed creator economy is direct-to-consumer, enabling creator–audience interaction on an unforeseen scale. However, the digital audience is far from a monolithic entity: Each audience member brings their own personal experiences, beliefs, and cultural context to bear in their perception of creativity. Below, we sketch a multilayered portrait of digital creativity from the perspective of two groups of viewers: creators and the general population. Then, we attempt to translate between the emerging technologies (i.e. algorithmic models) that will platform this creativity and the human audience that will perceive it. As creativity is a particularly broad topic, we scope this research to focus specifically on visual creativity (i.e. visual art & design).

In our study, we utilize both qualitative and quantitative data, triangulating users' conception of creativity through text, images, and their online behavior (i.e. website usage data). We heed Crilly's (2019) call that creativity must be studied through a mixed methodology approach. This multifaceted methodology enables not the precise *measurement* of creativity but rather a *conceptual framework* through which to unpick creative perception. Furthermore, we discuss how different users interpret creativity as well as how different platform design choices influence creative perception.

Background and related work

Existing creativity research methods often rely on scholars' definitions of creativity and serve to validate theoretical constructs and/or domain-specific knowledge about creativity

(Kaufman and Sternberg, 2010; Sawyer, 2012). Given such approaches, insights from the actual "users" of creative content (i.e. content creators and consumers) are not accounted for. Therefore, these concepts may not be generalizable to a broader understanding of creativity in the modern digital landscape. Here, we review several areas in which scholars have previously studied creativity and the approaches they have applied.

Existing approaches to creativity research

Early psychometric research considered human creativity to be a form of intelligence (Haensly and Reynolds, 1989; Kim et al., 2010). Therefore, early studies examined creative individuals (e.g. artists, writers, and musicians) and explored commonalities among these figures. Another line of research views creativity as a form of problem-solving and analyzes idea generation processes (Kelley and Littman, 2001; Sternberg and Lubart, 1998; Treffinger et al., 2006). Accordingly, scholars have developed various metrics for creative functioning tests (see a review at Sawyer, 2012), such as the Torrance Tests of Creative Thinking (e.g. Kim, 2008; Runco et al., 2010) and remote association tests (e.g. Lee et al., 2014; Oltețeanu and Schultheis, 2019). Methodology-wise, researchers invited participants to produce creative work (e.g. draw a painting, write a poem) while recruiting domain experts to assess their working processes and products. Other researchers conducted the aforementioned creative functioning tests in laboratory settings. Finally, participants were sometimes asked to self-evaluate their own creative output.

Together, these methods have offered insights for several schools of thoughts in creativity research, such as Sternberg's (2006) definition of creativity as being "novel and functional" or the contrast between Big-C vs little-c creativity (Craft, 2001; Kaufman and Beghetto, 2009; Richards, 1990). Along similar lines, researchers have developed numerous models of creativity, ranging from the 4P (Rhodes, 1961) and 5A (Glăveanu, 2013) models through to the 7C (Lubart and Thornhill-Miller, 2019) and 8P (Sternberg and Karami, 2021) frameworks. While these models contain various permutations of key factors influencing creative judgments, they also exhibit various downsides. To begin with, these models are grounded heavily in existing creativity theories, maintaining a distance from authentic consumers of creative content. Besides, while viewers' roles and background (e.g. experts vs laymen) can lead to distinct points of view of creativity (see more in the Four-C Model of Creativity; Kaufman and Beghetto, 2009), the impact of individual differences is underexplored.

Furthermore, existing creativity models are generally united in their view of *product* (or "artifact" or "creation") as separate from *process* (or "action" or "creating"). Historically, creativity researchers seeking to evaluate creative *products*, as we are in this article, have controlled for the creative *process* (as well as other factors contributing to perceived creativity, such as the creator's reputation). In an ecologically valid situation, however, it is unreasonable to expect such information to be controlled. In seeking to understand real-world use cases for creative experiences, we acknowledge here the intertwined nature of process and product: Traces of the process may be contained within the product, while a process is executed for the goal of producing a given product. Indeed, a recent commentary (Glăveanu and Beghetto, 2021) has called for a "radical redefinition" of creativity that moves beyond person, process, product, and press (Rhodes, 1961) to an action-based approach of creativity as an experience. These researchers indicate that metrics focused only on outcome or process fail to consider the complex interplay between these vectors. Indeed, we have observed that when performing strict psychological evaluations of creativity, research may over-index on evaluations of the creative product; on the other hand, when designing technology to enhance creativity, research may over-index on evaluating the creative process. Instead, we follow Glăveanu and Beghetto's (2021) imperative to consider the creative experience as a person–world interaction embedded within an embodied context: the simultaneous engagement of person, process, product, and press.

Techno-social perspectives of creativity

Since computers arrived in our everyday life in the 1990s, researchers, particularly in the domain of human–computer interaction (HCI), have demonstrated increasing interest in the intersection of creativity and technology (Carroll, 2013; Edmonds, 2014). Specifically, they have focused on addressing two key questions: (1) how to improve the design of creativity support tools; (2) how to enhance creativity in collaborative work on computer-mediated platforms (Burleson and Selker, 2002; Lubart, 2005; Sawyer, 2012; Shneiderman, 2009). Compared to psychological creativity research, computer scientists and HCI researchers put less emphasis on the environmental or individual differences of creators. Instead, they are more interested in how technology can be applied to resolve creative challenges in practical scenarios (Carroll, 2013; Frich et al., 2019).

Despite key differences in research motivations, researchers and designers in the technology field often adopt conceptual constructs of creativity from the psychology literature. In fact, a recent review (Frich et al., 2018) reveals that less than a quarter of creativity research in the domain of HCI has made the attempt to formally define creativity; instead, researchers directly implement creativity measures from other disciplines. As the generalizability and ecological validity of these lab-based, in vitro approaches remain questionable measurements of creativity, there remains a gap between the user-centered motivations of technology researchers and psychological approaches to creativity research. Therefore, there is a need to address and conceptualize creativity from users' perspectives to design technology-enabled tools that facilitate both the creation and the consumption of creative content, resulting in our first research question:

> *RQ1: How do content creators and content consumers perceive creativity in the digital context?*

Next, we consider that technology-enabled tools are founded in models of perception and cognition that may not resonate for experiences of creativity. For instance, most image search and recommendation systems that are used to catalog creative content rely on algorithms to sort and organize images. In particular, these systems often use "style similarity" models to parse images (Anderson et al., 2020; Ruta et al., 2021; Wang et al., 2015). This computer vision approach detects consistencies in visual attributes between images, clustering images that it deems similar to one another. Then, algorithmic recommendation systems utilize these clusters to surface content they deem relevant. For instance, similar content is often recommended as "more like this" or "you may also like . . ." Across the board, algorithm-based image organization systems tend to group, suggest, and surface clusters of similar images together.

Another common approach to algorithmic exploration and organization is reinforcement learning (RL) (Chen et al., 2019; Tang et al., 2019). RL is a protocol developed based on psychological models of human learning, in which a person produces an understanding of a concept based on past experiences. In particular, RL models are founded in reward prediction errors: When an agent makes a choice that results in a better outcome than expected, the agent experiences a positive reward prediction error, reinforcing their choice; on the other hand, inferior outcomes and negative reward prediction errors drive them away from that choice in the future (Sutton and Barto, 2018). Therefore, positive experiences with a recommendation system encourage users to continuously engage in platform-selected content. In other words, there exists a trade-off between users' trust and reliance on algorithmic curation and their own attempt at exploration.

In this way, both style similarity and RL models restrict exploration to closely related objects. There is reason to believe that this may be antithetical to the expansive originality of human-perceived creativity. We thus propose:

RQ2: How does algorithmic curation (specifically, based on style similarity and reinforcement learning approaches) compare to human perceptions of creativity?

Another deficiency in creativity research to date is a lack of consideration of the many ways in which emerging technologies may be affecting creativity. More specifically, researchers have largely focused on how computer-mediated tools can facilitate the processes and outcomes of creative productions. However, they do not address whether users' interaction with these technologies—for example, algorithmically-bound search and recommendation systems—influences their perception of creativity. Therefore, it remains largely unknown whether the online experience of creative content changes users' perception of said content. In this regard, we posit our final research question:

RQ3: Do computer-mediated platforms influence users' (content creators' and content consumers') conceptions of creativity? If yes, how so?

Method

Participants and procedures

In the present research, we examined both content creators' (pro) and content consumers' (non-pro) conceptions of creativity. The pro participants are professional designers and artists recruited through professional networks, while the non-pros were non-professional individuals who regularly visit digital content platforms. In total, we recruited seven pro participants and nine non-pro participants. All participants were prescreened, and qualified participants then completed a prestudy interview, which further probed their personal perspectives on creativity and their practices of consuming creative content. Throughout a period of 4 weeks, participants received a prompt each week to

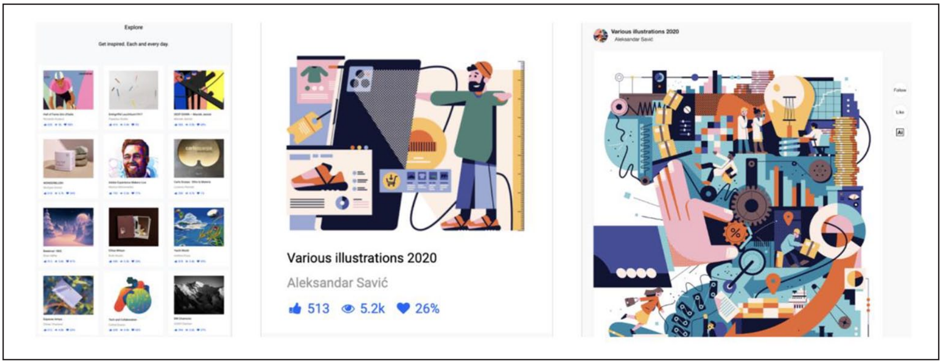

Figure 1. Homepage (left), a splash image (middle), and one of the content pages (right) of the study website.

seek relevant content on a study website created by the researchers. The prompts were explicitly designed to mimic realistic reasons one might search for creative content online. While looking for content in response to the given prompt, participants were also instructed to keep track of the most creative pieces they came across. Upon completion of each week's task, participants completed post-study questionnaires.

Study website and materials

We created a content website (https://exploretoday.site/) as a controlled sandbox for participant exploration. The website mirrors a popular source of creative content: Bēhance, a website that operates as a social-network-cum-digital-portfolio for creatives. We updated the website weekly to capture new content on the Discover page of Bēhance during that same week. The study homepage presents a gallery view of all content, from which participants could click on images to access individual content pages. The website contains embedded Google Analytics tracking, which records participants' page views and click actions (Figure 1).

Prestudy interviews

Prior to taking part in the longitudinal study, we asked participants to share their own perspectives on creativity and creative content. Participants were asked to define creativity and describe the role of creativity in their personal and professional lives. Finally, we asked participants what motivates them to seek out creative content and how they identify content of interest.

Post-task questionnaires

In each week's post-task questionnaire, participants would first share the three pieces of content selected in response to the weekly prompt and the three most creative pieces. They were then asked to rate each piece of selected content in terms of novelty, aesthetic value, likeability, and creativity using 5-point Likert-type scales and describe their reasons for selecting each piece. Next, participants described their exploration process and compared it with their expected experience.

Weekly prompts

We designed four prompts—one for each week of the study. We selected the four prompts based on three main considerations: theoretical synthetization (to adopt theoretical constructs based on existing creativity research), ecological validity (to mimic real-world situations in which users search for creative content online), and confirmation of preliminary findings (this consideration was applied to the prompts for Week 3 and Week 4 to further examine emerging themes from participants' responses during Week 1 and Week 2). Detailed descriptions of the weekly prompts can be found in Supplemental Appendix I.

Measurement

Qualitative measures. These include (1) visual content selected as creative responses (CRs, the pieces selected as the most creative) and prompt responses (PRs, the pieces selected in response to the prompt) and (2) rationales for evaluating creative content as well as exploration processes, recorded using text and audio in post-task questionnaires.

Quantitative measures. These include (1) self-report Likert-type scales to rate selected content; (2) participants' page views, clicks, and their corresponding time stamps, tracked by Google Analytics to analyze participants' exploration processes; and (3) visual and stylistic features of content selected by participants, extracted using computational methods (see more in *Analytic Approaches*). Descriptive statistics of all quantitative measures are reported in Supplemental Appendix II.

Justification for sample size

Despite the small sample size, participants' rich engagement with the study website throughout the 1-month period provides us with rich data for analysis. On average, each participant explored 44.09 content pages and spent 26.97 minutes each week on the study website. This results in 70 unique pieces of CR content and 185 non-CR pieces for visual analysis, as well as 1079 unique page views for behavioral data analysis.

Analytic approaches

We began our analyses by examining the prestudy interview to understand participants' current perspectives toward creativity. Next, we analyzed the longitudinal study data by examining the *processes* and *outcomes* of creative content exploration. We first investigated each type of data separately, including text/audio, visual, self-report Likert-type scales, and behavioral data. Finally, we applied triangulation approaches to synthesize across various data streams.

Analysis of prestudy interview data. The prestudy interview data, as well as participants' weekly responses, were analyzed using a qualitative and categorical coding scheme (Supplemental Appendix III). After initial categories were established, the data were coded from the bottom-up according to the content of the participants' responses. After a process of descriptive, in vivo, and simultaneous bottom-up coding, top-down codes were also applied to the data, drawn from relevant theories and previous research. Next, in the focused coding phase, we honed on areas of high convergence or recurrence. This led to a smaller set of codes that represented the majority of the data, and we began to elucidate key themes within the data. In this final stage, we also applied codes that were based on findings within other parts of this research program (e.g. responses to the weekly questionnaires). This enabled us to determine whether participants' prestudy reflections on creativity matched their discrete evaluations later in the study.

Analysis of self-report Likert-type scales. In addition to exploring descriptive statistics, we compared whether there were any differences in ratings for aesthetics, novelty, and likeability of CRs. In addition, we compared whether participants from the pro- and non-pro groups would rate their selected content differently.

Analysis of behavioral data. Using Google Analytics, we were able to record participants' step-by-step viewing processes while they were exploring content on the study website. We referred to the psychology literature on reinforcement learning and investigated whether participants' creative exploration processes simulate how humans "learn" a new item through exploration and exploitation (Schulz et al., 2019).

Analysis of visual data. We analyzed selected visual content through qualitative analysis, computational visual analysis, and computational stylistic analysis. First, we leveraged qualitative analysis methods from Rose's *Visual Methodologies* to deduce patterns within and between the images chosen as CRs. Second, we implemented algorithmic models from previous research (Lovato et al., 2014; Matz et al., 2019) to extract eight categories of visual features for each image (see Supplemental Appendix IV). We then examined any outstanding visual features specific to CRs. Third, we compared human perception to an algorithmic perception of the same content through computational stylistic analysis. Specifically, Bēhance uses a "style similarity" algorithmic model to sort and expose new content to users. We applied this style model (Ruta et al., 2021) to all of the images on our study website and produced a t-SNE diagram (i.e. a style map) of these images. That is, the style model processes the visual and artistic style of each image and represents how similar it is, in relation to all other images in the dataset, through physical distances (i.e. more stylistically similar images would locate more closely on the style map). Then, we compared the algorithm's image choices with those of our human participants.

Triangulation across data types. Given our mixed-methods approach, it was imperative to triangulate our disparate data streams. We began by comparing participants' prestudy interviews (i.e. their existing beliefs about creativity) to their weekly post-task questionnaire responses, including qualitative, quantitative, and visual data. Next, we compared participants' online behavioral data to their weekly self-reported description of their exploration processes. Finally, the algorithmically produced t-SNE cluster diagram was contrasted with participants' weekly responses and online behavior.

Existing beliefs toward creativity

Per our prestudy interviews, most participants consider creativity to be a part of both their professional life and their hobbies, and they seek out creative content regularly. Prior to the study, participants already exhibited recurring associations with creativity: "novelty," for example, is both a way that participants define creativity and a mechanism by which participants determine content creativity.

Interestingly, the concept of impact recurred throughout the interviews: Creative content is expected to have an effect on either individuals or communities. Indeed, even the participants' personal conceptions of creativity are founded in its "problem-solving" abilities, alongside creativity's "outlet," "wellness," and "fulfillment" offerings. The "expressivity" of creative content, in both professional communication and personal expression, also demonstrates the "usefulness" of creative content.

It is worth noting that creative professionals, specifically, highlighted the complexity of the creation process in determining whether or not something is creative; this finding aligns with insights from qualitative data from the weekly questionnaire responses (see more below). Content consumers (the non-pro group) were much less focused on the process by which content was produced, prioritizing instead the originality of the final outcomes.

Outcomes of exploring online creative content

Weekly qualitative responses

Overall, participants indicated that the most creative online content is novel, visually appealing, meaningful, and attention-grabbing. In addition, creative professionals alone prize the process of content production. PRs were categorically distinct from CRs, with participants prizing considerations such as personal attachment, societal trends, and aesthetic matching when choosing PRs.

Novelty. Regarding their rationales for selecting CRs, participants consistently cited a focus on novelty—also referred to as "unique," "never before seen" or "unusual." Indeed, the surprising nature of unique work seemed to draw users to select novel content: "It's never the first thing you'd expect, and the surprise factor makes it even more creative." Beyond what has been suggested by previous literature (Sawyer, 2012), participants indicated that "unexpected combinations" of subjects are considered novel, even when the individual visual elements are ordinary. Figure 2 shows a set of CRs selected due to their novelty, which illustrates participants' focus on surprising combinations of disparate elements, such as the recreation of a Ninja Turtle in classical sculptural form.

Visual elements and composition. Participants consistently highlighted visual boldness or unique compositional features in the CRs. They were drawn to CRs that were "visually

Figure 2. Selected images featuring *novelty* as a quality of creativity. Image credits (left to right): (1) Brand Illustrations for IV Studio by Hanna Rybak; (2) Illustrations for book covers by Eiko Ojala; (3) Emojinarium by Ana Miminoshvili; (4) Conceptual Illustrations Part. 4 by Francesco Bongiorni; (5) MONUMENTS (Chapter 1) by Benoit Lapray.

Figure 3. Selected images featuring *visual elements and composition* as the quality of creativity. Image credits (left to right): (1) Diver in the . . . by Kota Yamaji; (2) STUFF x bloom bloom FLEUR x Susan Fong | Oceania by CL. LO et al.; (3) MIDNIGHT JUNGLE by Chiron Duong; (4) Eyes: 2020 Visions. by Matt W. Moore; (5) LEGO by Rasmus Hjortshøj; (6) DEEP DOWN by Maciek Janicki.

compelling," such as one that was "realistically detailed yet surreal." Many participants emphasized colors, claiming "the colors and layering make the pattern pop" or "the usage of color is very thought-out and intentional." They found "the different patterns, colors, and textures to be alluring" and appreciated the "incredible amount of detail" in the visuals. Figure 3 shows CRs selected due to their expert visual effect. These pieces utilize well-known techniques for visual composition, such as the rule of thirds, abstraction, and symmetric and centered placement of visual elements.

Attention-grabbing. Many participants also highlighted eye-catching qualities and indicated that the CRs harnessed their attention. As one participant said, "This image immediately struck me. . . it draws my attention." Other participants mentioned, "I found that it drew my eye very quickly. . ." and "it caught my eyes at the very first glance." Indeed, this saliency directly contributed to viewers describing certain pieces as creative: "This piece is creative in that it captures the attention of an audience. . ." Previous literature has not emphasized saliency or the ability to grab the audience's attention as a key feature of creativity; this may be unique to the online realm. Figure 4 shows content that was considered eye-catching by participants, which often leveraged visually salient elements (e.g. high brightness or saturation) or combined various colors with high contrast ratios, allowing certain visual elements to "stand out."

Storytelling and meaning. There was also a component of storytelling that influenced viewers' selection of CRs, as explicitly highlighted by one participant: "[the piece] builds

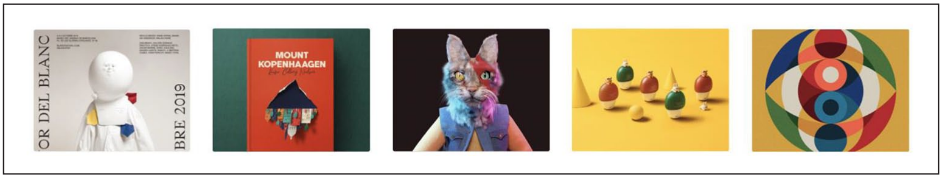

Figure 4. Selected images featuring *attention-grabbing* as the quality of creativity. Image credits (left to right): (1) University of Mississippi by Tobias Hall; (2) Illustrations for book covers by Eiko Ojala; (3) URBAN CATS by Bernat Casasnovas Torres; (4) SAVE THE FOREST by EUNJI D. LEE; (5) Eyes: 2020 Visions. by Matt W. Moore.

Figure 5. Selected images featuring *storytelling and meaning* as the quality of creativity. Image credits (left to right): (1) Trail of Water by Volvic by Yukai Du; (2) THE ADVENTURE OF GRANDPA FROG by Shishi Nguyen; (3) Hand-drawn Graphic Set | Personal Works | 2020 by Dzmitryi Kashtalyan; (4) Climate Activists by Luiza Kwiatkowska; (5) Maeklong railway market - Bangkok by Ashraful Arefin.

a good narrative . . .". Another viewer described a creative piece as ". . . allowing the viewer to entertain [a] narrative." In the same vein, participants appreciated content that conveyed a profound meaning. One viewer chose a given piece "because of the lasting impression it leaves on me. . .it is very thought-provoking. . .is a creative way to make the audience think." CRs often elicited emotions or actions on behalf of the viewers, emphasizing the underlying meaning or "story" behind the pieces. Interestingly, creative pieces that were selected due to their storytelling quality were often presented with visible main characters (Figure 5). We also see more hand-drawn characters and portrait photography in this category.

Process. Creative professionals demonstrated a particular focus on the mechanisms by which pieces had been constructed. Many professional participants expressed respect for processes that were difficult and laborious or for unique approaches to composing a given piece, such as "the usage of hidden/subtle silhouettes in these pieces are masterfully crafted." One participant described choosing a CR because, ". . . the process shown in developing the designs is really fascinating." Another participant mentioned: "the images are created in a way that creates movement, different focal points, and multiple levels of abstract forms." Although we did not find visual commonalities in CRs that were selected due to their process (Figure 6), participants often suggested that they were most impressed once they had clicked into the individual content page, where creators often illustrate their design process.

Figure 6. Selected images featuring *process* as the quality of creativity. Image credits (left to right): (1) Brand Illustrations for IV Studio by Hanna Ryback; (2) The Fall Comic - Issue 1 by Jared Muralt; (3) Illustrations 2020 by Simon Prades; (4) Design Engineering Handbook by Ranganath Krishnamani; (5) ADIDAS Y-3 _ RUNNER4D io by Aurélien Longo.

Figure 7. Selected images featuring *skills and styles* as the quality of creativity. Image credits (left to right): (1) The Ash Pond Series II by Tom Hegen; (2) MIDNIGHT JUNGLE by Chiron Duong; (3) War Horse - Michael Morpurgo by Tom Clohosy Cole; (4) The little question I love to ask: Sweet | 2020 by Le Thu; (5) The Fall Comic - Issue 1 by Jared Muralt; (6) Another day at the Rose Bowl Aquatics Center by Kremer Johnson and Jeff Whitlock.

Demonstration of skills and styles. Similarly, only creative professionals exhibited a focus on creative skills and artistic styles when selecting CRs. One participant stated this simply when explaining why he had chosen a certain CR: "Making something [like this]. . . takes great creative skill." Professionals valued creative skill particularly when it surpassed their own: "[this piece] struck me as an impressive manipulation of the medium and the material that I would not have thought of." Similarly, another participant remarked, "It's a lovely technique; one I'd like to learn from." CRs selected due to skill or style fell into two main categories: participants tended to select hand-made content (e.g. hand-drawn illustrations) and abstract forms (see Figure 7). Similar findings have been revealed in previous work, suggesting that professional creators may hold a different view to creative evaluation, placing a greater emphasis on pro-c (professional creativity; Kaufman and Beghetto, 2009) and technical execution (Jeffries, 2017).

Weekly quantitative data from post-task surveys

We performed independent sample *t* tests to examine differences in ratings for PRs and CRs. We found that participants' ratings of likeability $(t(352) = 2.00, p = .040)$ and novelty $(t(352) = 4.00, p < .001)$ are significantly higher for CRs (likeability: $M = 4.60, SD = .59$; novelty: $M = 4.12, SD = .93$) than PR images (likeability: $M = 4.45, SD = .71$; novelty: $M = 3.70, SD = .93$). Similarly, we compared whether ratings for CR images differed between pro and non-pro participants. We found that pro

Figure 8. Style similarity of all images used in the present study (left), CR images selected by non-pro participants (upper-right) and CR images selected by pro-participants (lower-right).

participants rated the likeability $(M = 4.69, SD = .49, t(352) = 2.00, p = .040)$ and aesthetics $(M = 4.53, SD = .73, t(352) = 2.00, p = .020)$ of CRs significantly higher than non-pro participants did (likeability: $M = 4.52, SD = .65$; aesthetics: $M = 4.26, SD = .80$), while there was no between-group difference in ratings for novelty and creativity.

Computational visual content analysis

Style similarity algorithmic clustering comparison. In this section, we examine the relationship between human users' perception and the platform's machine-based perception of creative content. After generating a t-SNE style similarity map of the website images, we marked out where CRs selected by pro and non-pro participants were "located" on the map. As shown in Figure 8, CRs selected by non-pro participants were scattered across the map without a clear pattern, while those selected by pro participants demonstrated two clusters. We calculated the kernel density with gaussian distribution based on where each CR was located within the map and compared the mean kernel density for images selected between the two groups. An independent t test suggests that images picked by pros showed stronger evidence of clustering $(t(352) = 7.497, p < .001)$.

Decomposing visual elements. With our visual data, we implemented methods from existing literature to perform computational visual analyses (Lovato et al., 2014; Matz et al.,

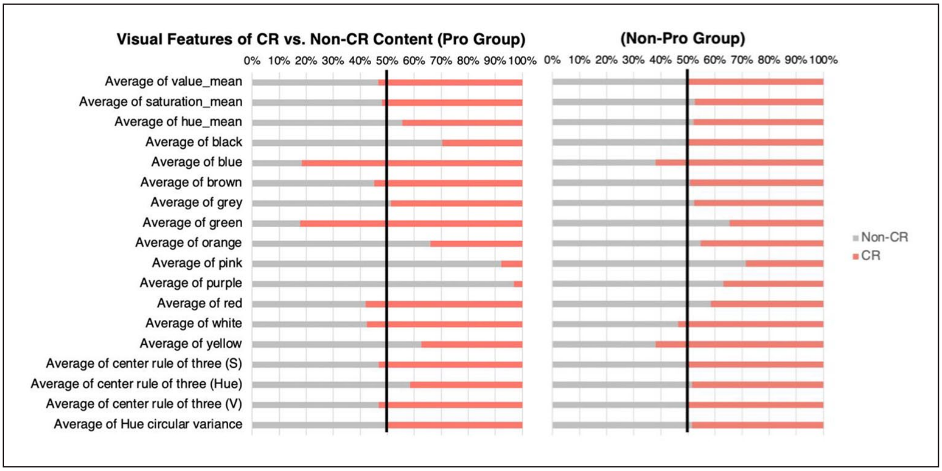

Figure 9. Comparing visual features of images selected as CRs versus non-CRs. Results were presented by non-pro (left) and pro groups (right). The vertical black lines denote the 50% baseline.

2019). We extracted eight categories of visual features for all images and calculated the mean values for each of these visual features of CRs and non-CRs (coded in pink and gray, respectively, in Figure 9). We then compared the visual features of CRs selected by pro and non-pro groups. As the values of different visual features are measured on different scales, we compared the results using 100% stacked bar graphs. That is, if there is no difference between CR and non-CR images for a particular visual feature, values for both categories would fall near 50%. As demonstrated below, pro-participants demonstrate strong preferences for specific colors when selecting creative images. Conversely, for non-pro participants, all indexes of visual features center around 50%.

We further investigated whether certain visual features of images predict participants' selection of CRs. We coded whether each image was selected as a CR piece or not (*no* = 0, *yes* = 1) and performed a logistic regression while controlling for the random effect of individual participant and time order (i.e. when the content was viewed). We found that images with higher values on the HSV (hue, saturation, value) color index (i.e. brighter images) as well as images with lower hues were more likely to be selected as creative pieces. Similarly, we constructed a linear regression model with the same control variables to examine the effect of visual features on self-reported creativity ratings. However, there was no significant effect of visual features on participants' subjective creativity ratings (Table 1).

Processes of exploring online creative content

Weekly qualitative responses

Participants began their exploration process by performing an initial scan of the entire content website, after which they honed in on images that grabbed their attention. In

Table 1. Effect of visual features on participants' selection of CRs and their self-report creativity ratings.

Outcome variable	Visual feature	β	*SE*	*p*
Selected as CR ($no = 0$, $yes = 1$)	Mean Value	0.876	0.421	.038*
	Mean Saturation	–0.316	0.370	.390
	Mean Hue	–1.134	0.457	.013*
Self-report ratings for creativity	Mean Value	0.125	0.171	.470
	Mean Saturation	–0.024	0.150	.880
	Mean -Hue	–0.176	0.216	.420

SE: standard error; CR: creative response.
$^{*}p < 0.05$; $^{**} p < 0.01$; $^{***} p < 0.001$.

some cases, the initial experience of the website was not driven by the weekly task *or* by seeking the most creative pieces; instead, participants simply sought out what was most salient to them before moving on to complete the task. Many participants made quick judgments from the visible thumbnails. If a piece of content caught their eye, they did open it separately; after a full pass through the content, participants would return to the separate pages they had opened. Some pro participants explicitly mentioned examining the creator's *process* on the individual project page. In particular, the pro participants exhibited confidence in their "taste" or "look"; the pieces that matched what they were looking for seemed to "pop out" to them.

Reinforcement learning through exploration processes

Exploration over time. Principles in reinforcement learning suggest humans tend to sample fewer new options when they gain more experiences in a behavioral domain (Sutton and Barto, 2018). Applied to the present study, this indicates that participants would be less likely to view unseen content throughout the study. Here, we found that the tendency to explore over time differs between the pro and non-pro groups. Specifically, non-pro participants' exploratory activities decreased significantly over time, resulting in a negative correlation between the likelihood of viewing a new content page and the number of pages explored (Pearson's $r = -.272, p = .006$). Conversely, for pro participants, the tendency to explore was not correlated with the amount of content they had consumed (Pearson's $r = .164, p = .200$) (Figure 10).

Learning over time. Per reinforcement learning theories, individuals would obtain more satisfying outcomes over time as their learning experiences accumulate (Sutton and Barto, 2018). Given this hypothesis, we expect to see increased ratings of CRs' creativity after participants have seen more content. However, only non-pro participants exhibited a positive correlation between the number of pages explored and their ratings of creativity (Pearson's $r = .187, p = .007$); among pro participants, we instead saw a negative correlation (Pearson's $r = -.189, p = .020$). This suggests while non-pro participants became more satisfied with their selected creative content, pro participants developed more stringent standards to evaluate content over time.

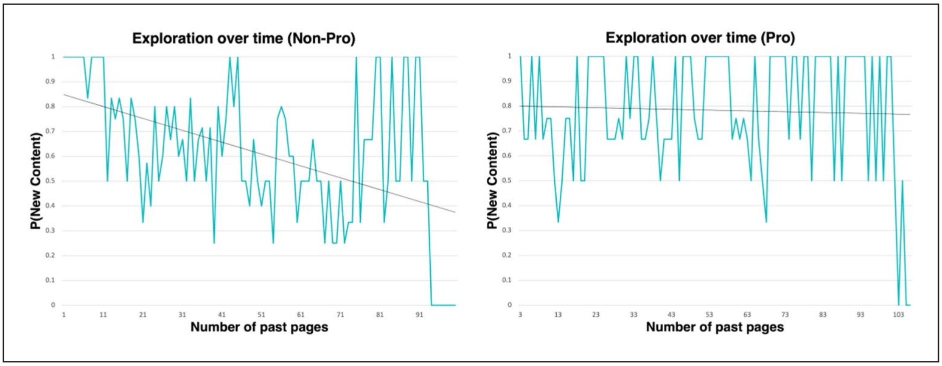

Figure 10. The probability of exploring new content over the number of content pages explored; results presented by non-pro (left) and pro (right).

Reward prediction guided by social metrics. Next, we compared participants' ratings of images' creativity with the images' mean social metrics (e.g. views and appreciations) on Behance. According to reinforcement learning theories, individuals are driven by outcomes that are more positive than their expectations (i.e. a positive reward prediction error). Hence, we would expect participants to select CRs in the context of positive reward prediction errors (i.e. when their own rating of the content exceeds the social metrics). Indeed, both non-pro and pro participants demonstrated a positive correlation between reward prediction error and the likelihood of CR selection (pro: Pearson's $r = .633, p < .001$; non-pro: Pearson's $r = .799, p < .001$). In particular, pro participants demonstrated smaller discrepancies between their ratings and the mean ratings on the public platform, suggesting that they were able to make more precise inferences about the public's creative perception.

Risk of exploration. Reinforcement learning literature suggests that the exploration of new options is accompanied by risks (Sutto and Barto, 2018). For the present study, this theory predicts that participants gave lower ratings to pieces that were more recently encountered. However, this trend was *not* found in our current data. In particular, non-pro participants' ratings for recently encountered CRs showed no significant difference from ratings for previously encountered content. Among the pro group, participants assigned higher ratings to more recently encountered content. This is likely explained by participants' emphasis on novelty, as highlighted earlier (Figure 11).

Visual features of content explored over time

We next examined the visual features of the content explored by participants within each week and throughout the course of the study period (i.e. across 4 weeks). That is, for each visual feature, we fit a linear regression model using view steps as a predictor (i.e. the first piece of content being viewed is coded as 1, the second piece of content being viewed is coded as 2, etc.) and controlling for the random effect of participants. Across

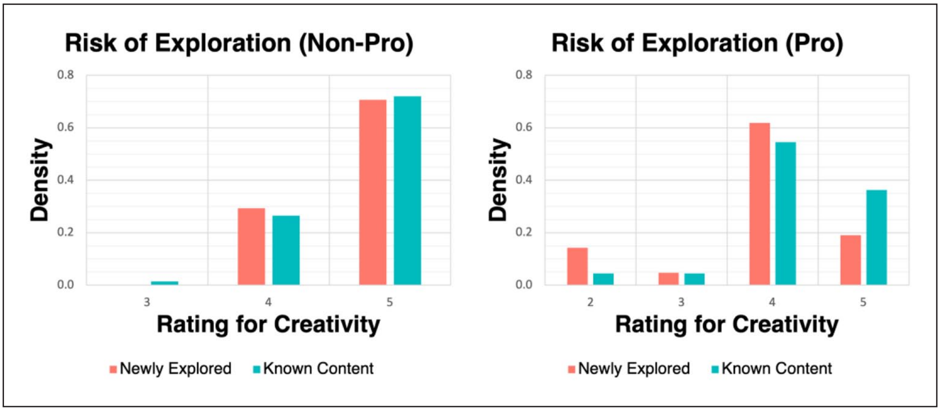

Figure 11. Risk of exploration by non-pro (left) and pro participants (right).

Table 2. Visual features of content explored over time.

Time scale	Visual feature	β	*SE*	*p*
Within each week	Mean Value	–0.0765	0.0272	.0051**
	Mean Saturation	0.0053	0.0297	.8600
	Mean Hue	0.0037	0.0255	.8900
	Center Rule of Three—Value	–0.0636	0.0257	.0130*
	Center Rule of Three—Saturation	0.0191	0.0289	.5100
	Center Rule of Three—Hue	–0.0025	0.0281	.9300
	Use of Black	0.0054	0.0026	.0380*
	Use of White	–0.0080	0.0036	.0250*
Across 4 weeks	Mean Value	0.0497	0.0228	.0300*
	Mean Saturation	0.0004	0.0002	.1100
	Mean Hue	0.0002	0.0002	.3300
	Center Rule of Three—Value	0.0005	0.0002	.8700
	Center Rule of Three—Saturation	0.0002	0.0002	.4300
	Center Rule of Three—Hue	0.0002	0.0002	.4000
	Use of Black	–0.0042	0.0022	.0540†
	Use of White	–0.0010	0.0028	.7300

SE: standard error.
†$p < .10$, *$p < .05$, **$p < .01$.

the exploration process for each week as well as for the entire study period, participants initially explored content with higher HSV values. This may be explained by the participants' self-reported exploration process, in which they initially sought salient content. As time steps increased, viewed content has incrementally lower HSV values, resulting in negative estimated coefficients. This result is also reflected in the presence of black and white in content explored over time; images get darker throughout the exploration process within a single week and throughout the course of the study (Table 2).

Figure 12. Images that participants were most likely to *start* their exploration processes with. Image credits (left to right): (1) Miscellaneous 2020 by Ana Miminoshvili; (2) The Journey. Digital paintings by Guenter Zimmermann; (3) GAP X Ken Lo Comfortable Hug Collection by Ken Lo; (4) Illustrations for the card game The Dragons by Marcin Minor; (5) TheBudies by Olivier Bucheron.

Triangulating multidimensional creativity results

Creative beliefs before and during the study

Comparing participants' prestudy interview responses with their weekly results throughout the study enables us to deduce key differences between users' creative beliefs prior to and throughout the experience. Generally, participants explored the study website in a similar manner to their existing content-seeking processes. Interestingly, several non-pro participants who described passively seeking creative content online for entertainment purposes all exhibited an outsize focus on attentional salience as a method of exploration. This is likely because they are accustomed to allowing the site to entertain them—experiencing content that is "pushed" onto them, rather than "pulling" content that they seek out.

We were also able to deduce if the attributes that participants thought would influence their perception of creativity aligned with their ratings of the creative pieces that they ultimately chose. Indeed, the participants who initially indicated that novelty (or newness, originality, unexpectedness, or uniqueness) was a core aspect of creativity rated their CRs high for novelty. Among all other attributes surveyed, novelty was most highly correlated with creativity for these participants. This finding also held for the reverse: If the "newness" of creative content was initially deemed important, lower creativity scores were given to content rated less novel. Generally, the attributes that participants mentioned in their pre-study interviews aligned with their content ratings.

Exploration processes and conceptions of creativity

Next, we triangulated participants' behavior on the study website with their self-reported responses to glean any differences in attitude and behavior. For instance, participants indicated that they tended to start with content that is sensorially salient and captures their attention. Indeed, web tracking data show that the degree of value and saturation of images being explored showed a decreasing trend over participants' exploration paths. As shown in Figure 12, images viewed at the start of exploration processes commonly included bright, intense, and warm color tones. In comparison, images viewed at the end had darker shades, lower tones, and cooler color schemes (Figure 13). Looking at

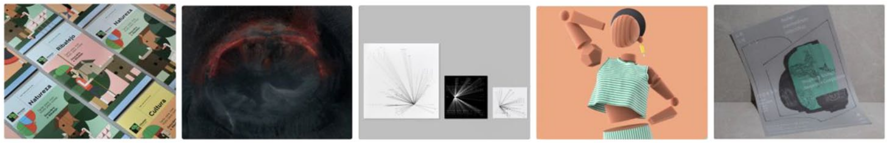

Figure 13. Images that participants were most likely to *end* their exploration processes with. Image credits (left to right): (1) Ribatejo, Viva a festa by Multiple Artists; (2) VOLCANIC REMNANTS – Iceland by Jan Erik Waider; (3) Ted Gärdestad by Stockholm Design Lab; (4) OPPO ColorOS 11 by Multiple Artists; (5) Dochwi: Superordinary Collectibles by Multiple Artists.

participants' behavioral data, we also saw that value levels of images' HSV metrics did decrease throughout the exploration process, suggesting that participants tended to start by focusing on content that quickly captured their attention.

On the other hand, some tendencies observed in the behavioral data were not mentioned in participants' self-report questionnaires, indicating that participants were unaware of certain inclinations or unknowingly making certain choices. For instance, none of the participants mentioned that their choices were guided by social metrics. However, the web usage data does suggest that images with more likes and views were more likely to be viewed and selected as CRs. Over time, participants also developed a more specific conception of creativity based on these social metrics.

Human versus machine perception of creative content

Finally, we triangulated the algorithmic results with those of our human participants. An analysis examined the style similarity clustering of images that were rated within the top 10% for novelty, aesthetic value, likeability, and creativity by participants. Images rated as highly novel by participants scattered across the t-SNE style similarity map without any outstanding patterns. Nonetheless, images viewed as highly aesthetic demonstrated strong evidence of clustering $(t = 5.836, p < .001)$ according to their kernel density. As shown in Figure 14, images with high aesthetic value formed a cluster, which contains mostly hand-drawn illustrations. Finally, images that were rated as highly creative followed the style patterns of both novel and aesthetic images. That is, while a considerable portion of creative images also centered around the same area, the evidence for clustering was not as strong $(t = 1.964, p = .054)$.

To compare style similarity clustering with participants' behavioral data, we standardized participants' view steps and examined when each image was seen throughout the exploration process. In Figure 15, we divide standardized view steps into three sections and show the images that were viewed during the first, second, and last portions of participants' exploration processes. As demonstrated by the clusters in each of the subfigures in Figure 15, participants tended to view similar styles during each part of the process, starting with photorealistic and graphic design content, then hand-drawn illustrations and geometric designs, and finally computer-generated graphics or photography.

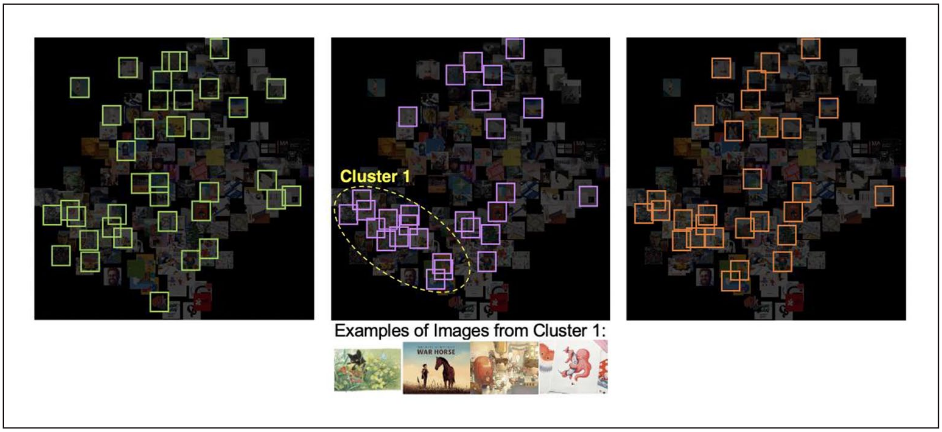

Figure 14. Style similarity of images with highest ratings for novelty (left), aesthetic value (center), and creativity (right).

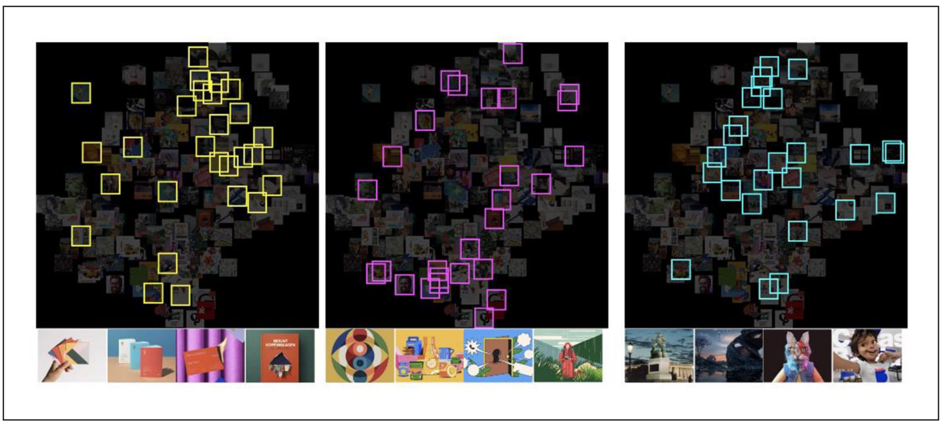

Figure 15. Style similarity of images explored during the first (left), second (middle), and last (right) portions of participants' viewed processes. The bottom rows presented examples of images viewed during the three stages of exploration.

Discussion

The present mixed-methods longitudinal research investigates users' conception of creativity through multiple data streams. Together, our findings suggest that adopting existing theories of creativity from other domains (e.g. psychology) may not be sufficient to capture the meaning of creativity for users of a specific computer-mediated platform. Even for constructs of creativity that have been proposed by previous literature (e.g. novelty and functionality), participants offer different interpretations of these factors in their responses. Perhaps the interaction of multiple variables—including some that have not been previously discussed in the literature—is necessary for online visual content to be perceived as creative. Therefore, it is important to take a multidimensional approach to conceptualizing creativity; we propose the need for a user-centered framework to study creativity in the domain of HCI. Specifically, we encourage scholars in the field to consider not only commonalities in users' approaches to creative content but also to consider differences in the roles and contexts of individual users. Indeed, when a viewer selects an image as a CR, they are indicating that the piece is creative in the context of their unique experience, rather than that there is something inherently creative about the image itself.

Commonality in user-centered creativity

First, we highlight commonalities in users' perceptions of creative content. Our results highlight two critical dimensions that influenced participants' perception of creativity. The first, vibrant visual elements, not only drive users' path of exploring creative content, but participants also tend to view such work as inherently creative. Indeed, as has been well-documented, social media's business model produces an "attention economy" (Simon, 1996) in which platforms vie for users' attention to claim profitable views, clicks, and so on. This has caused users to expect ever more salient content. To remain competitive, social websites have rewarded and prioritized attention-grabbing content. Such prioritization occurs by way of proprietary algorithms that take user behavior as input and optimize for human attention. This prioritization reinforces users' expectations for evermore vibrant content in online environments, and this may have caused the overvaluation of eye-catching pieces in this study. If users have a strongly developed habit of scrolling mindlessly through an endless array of content until a piece catches their eye, they seem to use that tactic to scope creative content as well.

Second, our results highlight the importance of context in evaluating creativity. For instance, participants' ratings of novelty— a key consideration for creative judgments—were not concerned with only "newness." Instead, participants deemed content novel when it was "creatively recombined" with other content in new and unusual ways. Similarly, the contextualized meaning of the content could make it "novel," even if the image itself was not. Here again, it is worth noting that one's previous experiences will inform the context within which they view content—determining whether it is deemed creative or not based on their personal priors. Applying traditional conceptions of creativity may not suffice for content consumers in this domain.

Different roles of content perceivers

By comparing the differences between how pro and non-pro participants explored and evaluated creative content throughout the course of 4 weeks, the present research offers particularly rich insights into the influence of content consumers' roles (e.g. artist/designer or general audience) on their conception of creativity. Furthermore, through triangulation, we further probed how machine perception of creative content conflicts with human users' behavior and perception.

Active content creators versus passive content consumers. The creative professionals focused on the process when making creative judgments. As described earlier, previous creativity research has delineated a sharp separation between product, process, press, and person (Rhodes, 1961), leading most creativity researchers to attempt to *control* for the process when evaluating creative products. In this way, many researchers will attempt to obscure or silence the process by which a piece was made when asking experts to evaluate the creative product. However, this finding in our research indicates that process and product may be inseparable, particularly for evaluators with creative experience, who mimetically intuit the process by which a piece was made—whether or not explicit process information is provided. This supports Glăveanu and Beghetto's reconceptualization of creativity to highlight the embodied, context-laden interplay between product and process in the overarching creative experience. Furthermore, the contextual process information that creative professionals intuit from the product directly impacts their creative evaluations: Products produced by seemingly more creative processes are rated as more creative. In this way, information about process should not be obscured—but, rather, made explicit—when judgments are being made regarding creative products.

The professional viewers' focus on process when evaluating creative output may be explained by theories of embodied cognition (Chiel and Beer, 1997; Frich et al., 2019; Wilson, 2002), in which one's perception is grounded in mimesis (Gebauer and Wulf, 1995; Zlatev, 2008). Previous neuroscientific studies have demonstrated that dancers will neurally "mimic" the dance when viewing the performance of other artists (Calvo-Merino et al., 2005). In a similar way, the pro participants were "experiencing" the process of creating the creative piece, developing physical empathy for the creator's process. If that process involved particular expertise, the pro viewer would find more value in the creative work. In this context, it is particularly interesting to consider the prioritization of hand-drawn and hand-made pieces by creative professionals. In these works, the creator's process is made visible through their use of the medium. The creative professional's physical empathy for the artist may be a more active extension of the oft-discussed "beholder's share" (Gombrich, 1972), in which a viewer's perception of an artwork is a necessary step of the creation process. Professional participants not only contribute by perceiving the work, but they also embody the creation process through mimesis. By contrast, the viewing experiences of the non-pro group had fewer concerns about the process by which content was created.

Human versus machine perception of creativity. Furthermore, by comparing the ordered manner by which the human participants explored the website images with the immediate clustering performed by the style similarity algorithm, it becomes apparent that algorithms are not "seeing" creativity in a way that mimics human perception. In this way, computer vision dissociates itself from human vision within the realm of creativity; while algorithms may be adept at performing human-like object recognition, they fall far behind in creative perception. Indeed, reinforcement learning is a common model by which both psychologists aim to unpack cognitive underpinnings and computer scientists aim to construct models replicative of human cognition. In the case of creative perception, reinforcement learning cannot be neatly applied, as a core viewer-perceived tenet of creativity is novelty—the antithesis of the repetition that reinforcement learning favors. However, reinforcement learning does demonstrate the ways in which social metrics and other contextual factors may influence creative perception over time. In addition to reinforcement learning, however, the results of this research call for new applications of psychological models that can better explain creative perception.

Impact of platform and interface design

It is interesting to note that not a single participant mentioned the social component of the study website; the website displayed a number of "views" and "likes" for each piece of content. It is possible that the participants did not consider this information in their decision-making processes. However, it is also possible that the participants were influenced by social information without realizing it, and therefore did not acknowledge this influence in their qualitative responses. Given their newfound role in prioritizing content, algorithms have become curators (Hogan, 2010) that operate according to metrics of attention. Recently, artists have indicated that they experience market pressures to optimize their creative work for saliency on social media. As artist Robert Saint Rich has described, this causes

> issues resulting in lack of depth, emotion, personality, and sincerity in the production of visual works [to] arise. If visual art is not captivating enough on a first glance, a "like" will not be granted from the audience, and the digital work will die.

This broaches broader questions regarding the future of creativity in the context of global broadcasting and minuscule attention spans. Indeed, recent months have been heralded as the birth of the "creator economy," in which digital spaces are used primarily to monetize creative content. This economy is direct-to-consumer, in which creatives interact directly with their audiences, thereby enabling creative success that is driven by viewers' decisions. It is apt, therefore, that this study has focused on the viewer-defined conception of creativity. Rather than relying on profit-driven algorithms, the creative landscape has the potential to be curated by its audience. In this way, creative value is democratized, minimizing creative judgments from elite institutions that previously wielded the power to "make or break" an artist.

Limitations and future research

Despite the various findings from our present research, we acknowledge several limitations of the current study and encourage future work to further address these shortcomings. To begin with, due to the longitudinal component of the current study, we settled on a relatively small sample size. While participants' deep engagement with the study website provided rich data for analysis, empirically testing key constructs of creativity found in our current research with larger samples would further deepen our understanding of these variables. Future research may also examine the generalizability of these findings to other domains of nonvisual creative work. It is also important for future work to address the effects of cultural differences and individual backgrounds on users' conceptions of creativity, rather than projecting a conception of creativity formulated only by the Global North. Such factors may also influence users' interaction with creative content platforms, a topic worth further investigation as well.

Indeed, as algorithms wield power in creative curation, they begin to influence the content that creative humans produce; in previous work, we demonstrated that creators begin to alter their output to pander to the algorithm (Herman, 2021). While algorithms maintain curatorial roles online, more creatives may produce pieces that are either (a) explicitly designed according to algorithmic priorities or (b) influenced by the algorithmically curated content that the creator receives as inspiration. Future research may investigate whether this produces a feedback loop by which algorithms influence what is created, curate creations accordingly, and thereby influence cultural tastes. If this is the case, artistic norms will be driven by what algorithms—rather than humans—deem worthy.

Another stream of future research may put these metrics of creativity into practice by measuring how they influence the creation of cultural value. Finally, we hope that others will apply our framework to evaluate the outcomes of creativity support tools–rather than relying on simplified metrics such as efficiency or the number of creative iterations produced–to produce tools that truly enhance online visual creativity.

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Supplemental material

Supplemental material for this article is available online.

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