

An Exploration of Practice and Preferences for the Visual Communication of Biomedical Processes

L. Garrison^{1,2} , M. Meuschke³ , J. Fairman⁴, N.N. Smit^{1,2} , B. Preim³ , and S. Bruckner^{1,2} 

¹Dept. of Informatics, Univ. of Bergen, Norway, ²Mohn Medical Imaging and Visualization Centre, Haukeland Univ. Hospital, Norway, ³Institute for Simulation and Graphics, Otto-von-Guericke Univ., Germany, ⁴Dept. of Art as Applied to Medicine, Johns Hopkins Univ., USA

Abstract

The visual communication of biomedical processes draws from diverse techniques in both visualization and biomedical illustration. However, matching these techniques to their intended audience often relies on practice-based heuristics or narrow-scope evaluations. We present an exploratory study of the criteria that audiences use when evaluating a biomedical process visualization targeted for communication. Designed over a series of expert interviews and focus groups, our study focuses on common communication scenarios of five well-known biomedical processes and their standard visual representations. We framed these scenarios in a survey with participant expertise spanning from minimal to expert knowledge of a given topic. Our results show frequent overlap in abstraction preferences between expert and non-expert audiences, with similar prioritization of clarity and the ability of an asset to meet a given communication objective. We also found that some illustrative conventions are not as clear as we thought, e.g., glows have broadly ambiguous meaning, while other approaches were unexpectedly preferred, e.g., biomedical illustrations in place of data-driven visualizations. Our findings suggest numerous opportunities for the continued convergence of visualization and biomedical illustration techniques for targeted visualization design.

CCS Concepts

- **Human-centered computing** → Visualization design and evaluation methods; Scientific visualization; Visualization theory, concepts and paradigms;
 - **Computer Applications** → Life and Medical Sciences;
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1. Introduction

New technologies exposing novel aspects of science and medicine have increased demand for visual methods and tools for both experts [NI19] and non-experts. While numerous visualization works have been inspired by biomedical illustration [RBGV08], the demand for science communication has driven an increasing convergence of these two respective disciplines. For example, Cell-Blender [SVB*96; SB*01; KBK*08], a molecular simulation plugin for Blender [Com18], can be used by both biomedical illustrators and visualization scientists for analysis and communication. Along with this increased demand for new visualizations and tools comes a need to understand their utility for different audience types. Differing values between audience types were apparent at the 2020 VCBM Workshop Image Competition, where the contest winner as selected by a jury of biomedical illustrators received one of the lowest rankings according to conference attendee popular choice. The two audiences clearly evaluated and prioritized different aspects of the visualizations in the competition. As a whole, our community lacks a clear understanding of the rationale behind differing audience preferences, and similarly lacks a complete view of the various scientific and illustrative techniques used to visualize biomedical processes.

Our goal is to gain insights into how visualization and biomedical illustration techniques are used and assessed by differing audiences for visual communication. In an interdisciplinary approach with biomedical illustrators and visualization scientists we explored the similarities, as well as differences, in common approaches to visualize biomedical processes. From this study we identify opportunities for further growth and convergence of techniques. The five topics we surveyed (signal transduction, constitutive activation, blood flow, aneurysm, and metastasis) span the micro- to macroscale and include patho- and physiological processes to serve as a proxy for the large space of representations of biomedical processes. For each topic, communication scenarios and assets are designed in conjunction with expert focus groups. This approach controls the design space while providing important in-depth insights on discipline-dependent visualization practices. Specifically this study contributes:

- Insights into the **design considerations** necessary to develop materials for communication of biomedical processes from both a visualization and biomedical illustration pipeline.
- **Curated assets** demonstrating typical techniques used to depict five common biomedical processes.
- A **qualitative survey** involving participants with diverse and

creative expertise to evaluate visualization preferences for scenarios targeting (1) expert and (2) non-expert audiences.

- Reflection on **patterns observed in preferences** between different audience types with suggestions for further research.

2. Related Work

Our work is rooted in visualization design principles to communicate science through illustrative and data-driven means. We draw on prior ideas of abstraction spaces, with aspects of our survey modeled on the existing body of qualitative visualization research.

Purpose of Visualization. A number of theoretical frameworks guiding visualization are largely *data and task-centric*. Both Tominski & Schumann [TS20] and Munzner [Mun14] frame the purpose of visualization as the exploration, description, explanation, communication, and/or presentation of data. For visualization task identification and validation, Brehmer & Munzner describe a multilevel task typology exploring the what, why, and how of visualization tasks [BM13]. Munzner’s nested model of visualization [Mun09] provides a means for visualization scientists to evaluate their design choices at four distinct levels, from domain characterization to algorithm design.

Several works [GJ07; JH14; JM12; Jen17] place an emphasis on visualization for communication, education, and outreach using *illustrative* techniques which often come from a practice-based perspective. Sousa et al. similarly include illustrative approaches in their illustrative visualization framework to help scientists approach and solve visualization tasks [SGG05]. This parallels a traditional illustration pipeline of first receiving and recording information, then sketching and refinement, followed by rendering and addition of labels. Similar to these works, we take a broader view of visualization that includes illustrative and data-driven techniques aimed towards communication.

Abstraction in Visualization. Abstraction is inherent to visualization. Viola & Isenberg provided a formalization of abstraction in visualization [VI17]. Their definitions and updated formalization [VCI20] of visual abstraction serve as the basis for the abstraction spaces in our study. Rautek et al. describe abstraction as a powerful visual communication tool which can lend additional insights to one’s data [RBGV08]. Andrews takes a similar view of abstraction from the perspective of biomedical illustration, discussing instances where illustration is an optimal medium to visualize certain concepts, e.g., to easily remove “visual garbage” or to superimpose structures [And06]. This discussion is reminiscent of the data-driven principles of visualization stated by Tufte, e.g., avoidance of “chart junk” [Tuf86]. Abstraction, when fit appropriately to the task, lays the foundation for a successful visualization that can be evaluated empirically.

Empirical Visualization Studies. While empirical studies are increasingly considered as core elements of visualization research [CE20], the challenges to conducting a good empirical study are numerous [ZCL*20; Wei20]. For example, use of expert reviews, rather than conducting a broader user study, is strongly dependent on the evaluated visualization and its development stage. Tory & Möller found value in conducting expert reviews particularly in evaluations of early prototypes [TM05]. Our survey tar-

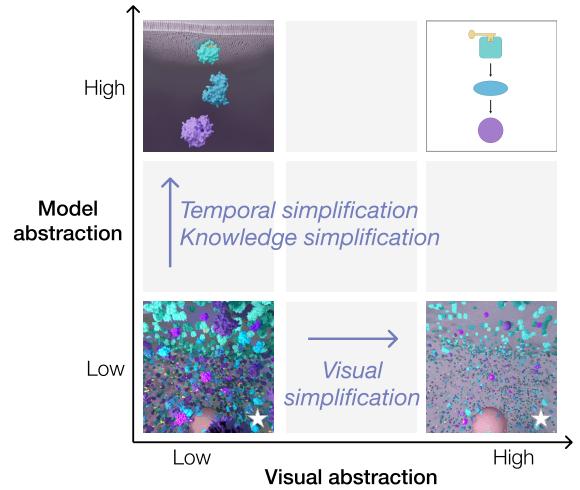


Figure 1: Conceptual abstraction space. Model abstraction spans the relative knowledge precision, i.e., the creator’s mental model, of the source data and its temporality, while visual abstraction encompasses the relative visual simplification of the model (stars denote animated assets).

geted experts from diverse domains in order to focus our participant pool to those with sufficient knowledge to understand and provide high quality feedback on all presented assets and scenarios. Empirical visualization research may be conducted to understand the field of visualization as a whole, e.g., studying visualization research keywords [IIS*16], or specific terms, such as memorability [BK*15; BVB*13; LC18]. Our survey design, and the use of keywords, is inspired primarily by the broader approach presented by Isenberg et al. [IIS*16].

Empirical studies on biomedical visualization are often controlled studies with narrow scopes, e.g., evaluating a specific technique. Such evaluation studies tend to focus on perceptual and cognitive aspects, e.g., Baca et al.’s study assessing efficacy based on usability, aesthetics, and iterability for a visualization of combustion [BCC*19]. Although we included both expert and non-expert audiences and also considered aesthetics as a variable, we took a larger, qualitative scope. Comparative studies may examine traditional illustration methods, e.g., pen and ink, relative to computational renderings that mimic the traditional style [INC*06]. Such an approach may also assess different computational techniques, e.g., semi-transparent structures in volume rendering [ER16], stylization and color adjustments to improve the aesthetics of surgical field imagery [BSB*19], or perceptually comparing aneurysm anatomy with embedded flow visualization [BGCP11]. Our survey focused on the comparison of assets produced using different visualization or biomedical illustration techniques. As Baer et al. [BGCP11], we asked participants to indicate personal preferences in their selections.

3. Abstraction Constructs

We apply two abstraction constructs to every asset: model and visual abstraction, as depicted in Fig. 1. This creates a common foun-

dation to compare audience preferences both within and between the five biomedical topics. We draw from the terminology and definitions of abstraction by Viola et al. [VCI20]. The authors discuss abstraction of data representations and abstraction of visual representations as two distinct phases in the visualization process, beginning with entirely non-visual data representations. Here, the authors conceptualize data abstraction as the steps to achieve a desired sparsity of the dataset after acquisition, cleaning, and filtering. We expand on this data-driven notion to encompass the data representation and abstraction process for biomedical illustrations.

Model Abstraction. Rather than thinking of data only in the context of its attributes, we additionally consider the knowledge precision, i.e., the creator’s *mental model*, of a given phenomenon. In addition, the temporal level of complexity plays a role in the level of abstraction in the resulting model. This accounts for understanding of the **details** and **dynamics** of a given biomedical process, e.g., signal transduction. These aspects constitute a generalized type of data abstraction that we term *model abstraction*. To illustrate model abstraction, consider the top-left and bottom-left assets in Fig. 1. The bottom-left asset, a rule-based stochastic visualization, requires a higher degree of knowledge precision to produce than the top-left asset. With regards to temporality, this asset is less simplified, as it captures the naturally dynamic process of signal transduction more than the asset above with a reduced and static molecular environment.

Visual Abstraction. Visual abstraction can preserve and emphasize the most salient information to allow the viewer to extract meaningful information. We consider visual abstraction as the extent to which the underlying model is visually simplified. This includes shape abstraction, e.g., a molecule visualized from x-ray crystallography data has a low visual abstraction (Fig. 1, left), relative to a shape primitive representation of the same molecule (Fig. 1, right). Visual abstraction also applies to environments, e.g., the removal or simplification of background elements to draw attention to the desired elements as on the top-right of Fig. 1. This is utilized in many focus+context techniques [RBGV08; Hau06].

Abstraction Space. We place each abstraction construct along an *abstraction axis*. Each axis describes a sequence of visual representations that incrementally depict degrees of reality [VCI20]. These axes produce the *abstraction space* depicted in Fig. 1 which provides the underlying basis for our survey design. We further segment each axis into non-expert relative categories from low to high abstraction. An asset that is high on both constructs is the most abstracted, e.g., Fig. 1, top right.

4. Study Design

Our primary goal was to understand the differences in preferences between expert and non-expert audiences in visualizations of biomedical processes. We summarize our process in Fig. 2. This study focused on spatial visual representations to enable a fair comparison of data-driven assets and illustrations. Prior evaluation studies in medical visualization have put less emphasis on illustrations, and have rather emphasized data-driven visualization works [PRI18]. Our equal emphasis of both visual representation types allowed us to consider audience preferences in an expanded

abstraction space. This approach included several challenges, the first of which was in establishing the boundaries of the design space with respect to visual representation and topic.

Design Space: Representation Constraints. The design space for depicting biomedical processes is enormous, and we do not intend our five topics to be comprehensive. They instead are meant to sufficiently cover the space of different criteria that an audience uses to evaluate a given topic representation. To constrain the design space, we first excluded interactivity; this has been explored elsewhere in a broader context [SBJ*14]. We included short animations to reflect the reality in our model abstraction construct that biomedical processes are highly dynamic. We included static elements that are often used to depict dynamic processes, e.g., glows and arrows [Jen17]. We excluded animations that were only viewpoint changes, e.g., turntable animations, and focused on motion of the biomedical assets themselves. We also limit the abstraction space to typical representations of each topic without delving into stylistic methods, e.g., line, grayscale, or full color. This aspect of abstraction has been touched on elsewhere [INC*06; Ise13; LVPI18].

Design Space: Topic Constraints. Topics in biomedical processes also span a massive design space. Our aim was to evaluate the smallest reasonable topic set. Biomedical processes occur at all levels of magnification, from micro- to macroscale. They can be normal or pathological. To narrow the design space w.r.t. topic, we performed a literature review as well as interviews with visualization and biomedical illustration experts from both academia and industry. We also reviewed the Association of Medical Illustrators Online Salon [oMed20] and several biomedical illustration portfolios to determine common topics visualized by both disciplines.

We chose two topics at the microscale: (1) signal transduction, a normal process whereby a signal is relayed between molecules in the body, and (2) constitutive activation, a process whereby one or more molecules in a signal chain is always switched “on” to create an never-ending signal relay. At the mesoscale we chose (3) normal blood flow and (4) an aneurysm. At the macroscale we chose (5) tumor metastasis, focusing on the movement of tumors from their origin site to other organs. The macroscale topic synthesizes concepts from both smaller magnification topics as it is driven through constitutive activation processes and travels through the bloodstream. Following topic selection we created audience scenarios for each topic that in turn guided asset production.

4.1. Survey Scenarios

We used scenarios to drive user comparison and selection, which we detail in Tables 1 and 2. This approach was inspired both by our expert interviews and by Lam et al.’s [LBI*12] findings that scenarios can effectively capture specific goals and research questions in a given domain. This corroborates well with biomedical illustration, where assets are most often created to fulfill the **communication objective** of a clearly-defined scenario. Our aim with these scenarios was to target relatively generic expert and non-expert audience use cases. We confirmed the validity of each described scenario with senior domain scientists, visualization scientists, and biomedical illustrators each with over ten years of experience. Our subsequent creation of visual assets was based on these audience scenarios.

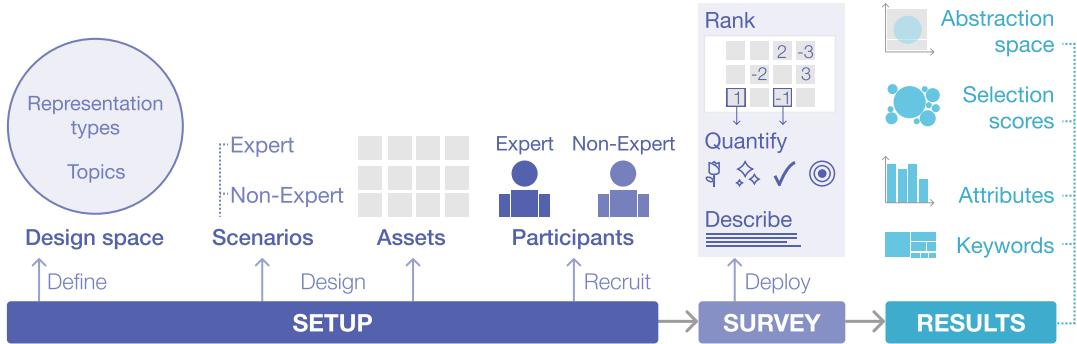


Figure 2: Three-phase study pipeline. **Setup:** define the design space, create audience scenarios and visual assets, and recruit survey participants, **Survey:** deploy survey asking participants to rank, quantify, and describe their top and bottom asset selections for each scenario, and **Results:** review survey results for patterns in selection abstraction space, scores, attribute rankings, and frequent keywords.

ios. This workflow mirrors the standard approach to visualization production while also further constraining the design space.

Table 1: Expert Audience Survey Scenarios

Topic	Scenario
Signal Transduction	An immunology researcher is publishing in an immunological venue on the newly-discovered pivotal role that a ligand plays in a signaling pathway. Their goal is to communicate the specificity of the activation pathway and its location in the cell with a visual supplement to their publication.
Constitutive Activation	An oncology researcher would like a visual supplement that demonstrates to the readership of an immunology journal the mechanism of disease in which a key molecule in the signal transduction chain is constitutively activated, which produces an unregulated positive feedback loop.
Blood Flow	A researcher studying vascular flow would like a visual to supplement their publication that explains the variation of laminar flow (i.e. smooth movement of fluid with no swirls), in normal hemodynamics (i.e., blood flow behavior).
Aneurysm	A researcher publishing in a medical venue would like to include a supplementary image or animation to describe the final shape of an aneurysm, resulting from abnormal hemodynamic forces (i.e., blood flow in helical or swirling patterns) and morphological properties of the vessel wall.
Metastasis	A radiation oncology researcher publishing in an oncology journal is focused on describing the metabolism and movement of metastatic tumors as the basis of validation for their novel radiation therapy approach.

4.2. Survey Visual Assets

We produced all assets via a series of topic-oriented focus groups to define the relevant design space and form consensus for each topic, following in part the framework for creative visualization-opportunities workshops described by Kerzner et al. [KGD*19]. Focus groups consisted of three to four people for each topic comprised of biomedical illustrators and/or visualization scientists. For each focus group we prepared sketches or concepts from our prior literature search and interviews to guide the discussion. Our interdisciplinary team of visualization scientists and biomedical illustrators enabled us to produce assets in-house to ensure consistency

Table 2: Non-Expert Audience Survey Scenarios

Topic	Scenario
Signal Transduction	An introductory biology student is studying for an upcoming exam. Their goal is to understand how a “message” is relayed through a series of messengers inside a cell.
Constitutive Activation	The same introductory biology student is tasked with identifying where in the signaling pathway a molecule is constantly activated when it should not be. This causes the entire signaling pathway to be always switched “on.”
Blood Flow	A person with little/no prior knowledge on the topic is interested in learning more about their body. They visit a popular health and well-being website, e.g. WebMD, to understand how blood moves and delivers nutrients throughout the body.
Aneurysm	A person has recently been diagnosed with a cerebral aneurysm. Their doctor shows them a visual to communicate what aneurysms are and why they must be closely observed.
Metastasis	A patient recently diagnosed with cancer has been told by their doctor that their cancer may metastasize, meaning that the cancer may spread to a different part of the body from where it began. To help them understand this concept, their doctor shows them a visual.

and to limit the number of variables in the survey. A key decision in our initial focus groups was to exclude labels and annotations, with the exception of occasional arrows when considered part of the model abstraction axis, from all assets. This decision was made both to limit the variable space and to prevent distraction from the actual interpretability of the assets themselves. Our production pipeline included the Adobe Suite (Illustrator, Photoshop, AfterEffects) [Ado21], Blender [Com18], and 3D Slicer [KPV14]. Animated assets were produced as short, looping GIFs. The following briefly details the driving design concepts for each of the five chosen topics. For high resolution assets we refer the reader to the asset directory in supplementary material.

Signal Transduction. Signal transduction describes a cellular communication process in the body by which a sequence of molecules are activated or deactivated in response to an initiating signal. Visual approaches range from static to dynamic, from basic shape primitives to realistic molecular shapes taken from the Pro-

tein Data Bank (PDB) [BWF*00]. The environment may be simplified to only the main molecules up to fully immersive scenes with all molecules engaging in stochastic reactions with complex biomolecular assemblies [FKRE09; BL18]. Glows, such as those utilized in CellPathway [RVM16], are frequently used in biomedical illustration and less frequently in visualization to indicate the concept of activation. For further details we refer the reader to Kožíková et al.'s survey of molecular representations [KKF*17].

We created 14 assets to represent common visualization options in this topic, shown in Fig. 4A. Half of the visualizations use realistic molecular models extracted from PDB, e.g., C11, the other half use simple primitive shapes as often seen in biology textbook and journal figures, e.g., C1. We use a key icon in the primitive shape assets following a focus group discussion and our review of such illustrations in visualization literature, where a key is often used to indicate the special status of a ligand [PGB*12]. We illustrated half of the assets in a simplified context while the others show the main molecules in complete isolation. We used MCell to simulate molecule movement and stochastic interactions with Cell-Blender [SVB*96; SB*01; KBK*08], a Blender plugin [Com18], to visualize our simulations. We excluded conformation changes in order to limit the design space. These scenes served as representatives for robust data-driven models of the stochastic interactions in a real molecular environment. Although the simulation with realistic-looking molecules and interactions (C14) is the least abstracted of the set, we note that even this scene is heavily abstracted, as we just show the main molecules and include only a basic cell nucleus and membrane. Our color choices for the glows reference contemporary biomedical illustration trends to use a saturated color in the same hue range as the molecule base color.

Constitutive Activation. Constitutive activation describes a signal transduction process that is always turned “on”, meaning that the factors that keep a signal flowing between molecules are always present in the cellular environment. Although a number of processes in the body are naturally constitutively activated, mutations can cause a signalling pathway that is normally only conditionally activated to be constitutively activated. If left unchecked this process can lead to proliferation of tumor cells through uncontrolled cellular division. We created a corollary pathological variant that represents constitutive activation for each of the original 14 signal transduction assets (Fig. 4B). We chose a generic mutation, showing a ligand that is not degraded or released from the first molecule in the chain after having activated the molecule. We followed conventions as indicated from our focus groups, showing the mutated molecule haloed in red with a red glow to indicate activation instead of the typical same-hue saturated color as in a normal signal cascade. We colored all other molecules and glows as in normal signal transduction, since they are not mutated. We kept all other scene aspects the same for assets C1-12. Since C13 and C14 included a more complex molecular environment with stochastic reactions, we factored in the effect of a constitutively-activated molecule where the result consists of many more activated molecules relative to normal signalling conditions.

Blood Flow. The flow of blood allows for delivery of oxygen and other essential substances to cells as well as the removal of waste products. While biomedical illustrators focus primarily on the ap-

pearance or on the constituents of blood cells, e.g., C4, C5, C11, and C12 in Fig. 3, visualization scientists focus primarily on visualizing fluid dynamics that are linked to the acquisition modality, e.g., Phase-Contrast MRI (PC-MRI). Oeltze-Jafra et al. [OMN*19] provide a comprehensive summary of visualization techniques that are applied to blood flow. Our data-driven assets included streamlines, particles, streamribbons, streamtubes, and arrow glyphs using data from Berg et al. [BRB*15]. While hemodynamics are the focus, we rendered the vessel structure itself as translucent with ghosting of the mesh as exemplified by Baer et al. [BGCP11]. For closer alignment with the color palette of the illustration assets we used the inferno matplotlib color palette to render quantities.

Aneurysm. An aneurysm is an extensively visualized pathology caused by changes in the arterial wall and/or abnormal hemodynamics [SPC09] with numerous methods developed to better understand aneurysm pathogenesis and rupture risk [OMN*19]. Unlike the microscale normal/pathological assets, the aneurysm/blood flow assets are not a 1:1 match. This was a conscious decision, as our goal for each topic was to produce the typical set of representations that would be used to convey the described scenario for an aneurysm. Some representations that are relevant for blood flow are irrelevant for communicating an aneurysm, e.g., the cellular composition of blood (Fig. 3, C4). The external shape of a blood vessel (Fig. 4C, C4) is a necessary and common visual representation to describe an aneurysm. While a number of the blood flow assets have an illustrative counterpart to the data-driven representation, in some cases such data are not available for aneurysms. For example, an aneurysm in the act of rupturing is difficult, if not impossible, to capture mid-rupture as in C6 of Fig. 4C. We confirm from focus groups that this is a common illustration created to educate a non-expert audience on the risk of an untreated aneurysm.

Metastasis. Metastasis, when visualized at the macroscale, offers a synthesis and continuation of the lower scale topics: tumor proliferation is driven through constitutively activated signaling pathways, and tumors metastasize, i.e., spread, to other organs through the bloodstream. While we discussed using angiogenesis in early focus groups to represent tumor growth, the other four strongly movement-themed topics made metastasis, with its strong sense of movement, a more consistent choice. Our focus on the depiction of tumor spread exposed a notable visualization gap: medical technology does not allow for detection of the actual movement of tumors, so we cannot directly visualize this process. The closest available option for human subjects uses PET/CT data. This multimodal imaging strategy indicates regions of high metabolic activity, and is frequently used by clinicians to track metastasis.

Our illustrative assets demonstrate four levels of visual abstraction for tumor metastasis—half with highly abstracted tumor shapes while the others show realistic tumor shapes. We only included those organs and circulatory elements critical to telling the story in the most complex of the illustrative assets (C10-12 in Fig. 4D), with gradual visual simplification of the organs at each step to the right of the visual abstraction axis until in C1-3 they are entirely removed. The scientific visual assets follow the typical visualization techniques outlined by Lawonn et al. [LSBP18] in their state of the art report on multimodal medical visualization.

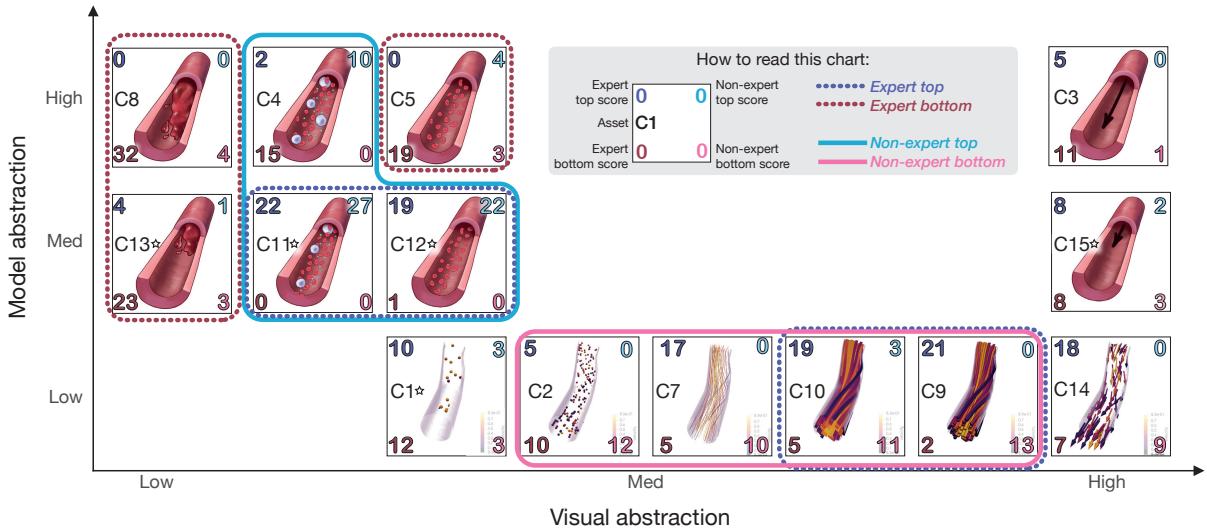


Figure 3: Blood flow abstraction space. Assets are arrayed in the space by degree of model (y-axis) and visual abstraction (x-axis). Animated assets are denoted with a star glyph to the right of the asset name. Values in the four corners of each asset represent a weighted score for its selection frequency as the first, second, or third choice for an expert or a non-expert audience scenario (see ‘How to read this chart,’ left). Encircled regions indicate assets with scores in the 20th percentile of each scenario (see ‘How to read this chart,’ right).

4.3. Survey Design Structure

We followed the principles for a comparative survey design laid out by Tory [Tor14]. Topics are organized so that a healthy/normal physiological topic precedes a corresponding pathological topic. This format provides the necessary context for the pathology. We asked participants to rank only their top three and bottom three choices for each scenario to keep the survey scope manageable. The bottom choices are just as valuable as the top choices, as encouraging participants to explore negative aspects of a visualization can be illuminating. For the top- and bottom-ranked choices we subsequently asked participants to assign quantitative rankings of four variables: aesthetics, scientific accuracy, visual clarity, and communication success. Our variable selection was guided by works of Abdul-Ramen et al. [ACL20] and by the judging criteria used for the Association of Medical Illustrators (AMI) juried salon. We additionally asked participants to select or enter their own keywords to describe the strengths and weaknesses of each of their ranked assets. We drew these keywords from the previously mentioned AMI salon judging criteria (see supplementary material). Lastly, we included an option for participants to add freeform comments.

We administered our survey via the Typeform [MO12]. Prior to deployment we conducted a pilot study with five participants to test our survey design. Following pilot study feedback we divided the survey into three segments by scale: micro-, meso-, macroscale to improve the overall completion rate. A second pilot study with three participants confirmed that the smaller segments kept average completion to 30 min.

4.4. Survey Recruitment

Our target participants included clinicians, biomedical illustrators, and domain and visualization scientists with familiarity in the se-

lected biomedical topics. Our aim was to collect at least 20 high quality responses for each topic to adequately create a picture of audience preference. We recruited participants via the authors’ respective professional networks. We collected only basic personal information, e.g., age, gender, and professional background. We additionally asked participants to report their expertise on each topic on a scale of 0 to 5, with 0 indicating “no knowledge” and 5 represents “extremely knowledgeable.” We used this information to create two audience groups: (1) expert and (2) non-expert, where experts reported a **4 or higher** and non-expert audience participants reported a **3 or below**. We used the reported professions and expertise as a secondary check on the validity of their self-reported expertise level.

5. Study Findings

The survey ran for approximately three months, with each segment available to participants for one month. Participation was roughly gender balanced (M=male, F=female) for each topic (signal transduction: N=32, 16M, 16F; constitutive activation: N=28, 15M, 13F; blood flow: N=36, 20M, 16F; aneurysm: N=34, 19M, 15F; and metastasis: N=22, 10M, 12F). Participant backgrounds were mixed and included MR physicists, clinicians, visualization scientists, molecular biologists, and biomedical illustrators with training and background ranging from professors and program directors to executives to medical journal and agency staff. Self-rated expertise (E=expert, NE=non-expert) per topic varied (signal transduction: 12E, 20NE; constitutive activation: 7E, 21NE; blood flow: 25E, 12NE; aneurysm: 19E, 16NE; and metastasis: 8E, 14NE). The microscale and mesoscale segments contained two topics each and averaged 34 minutes to complete. The macroscale segment contained only one topic and averaged 18 minutes to complete. Partic-

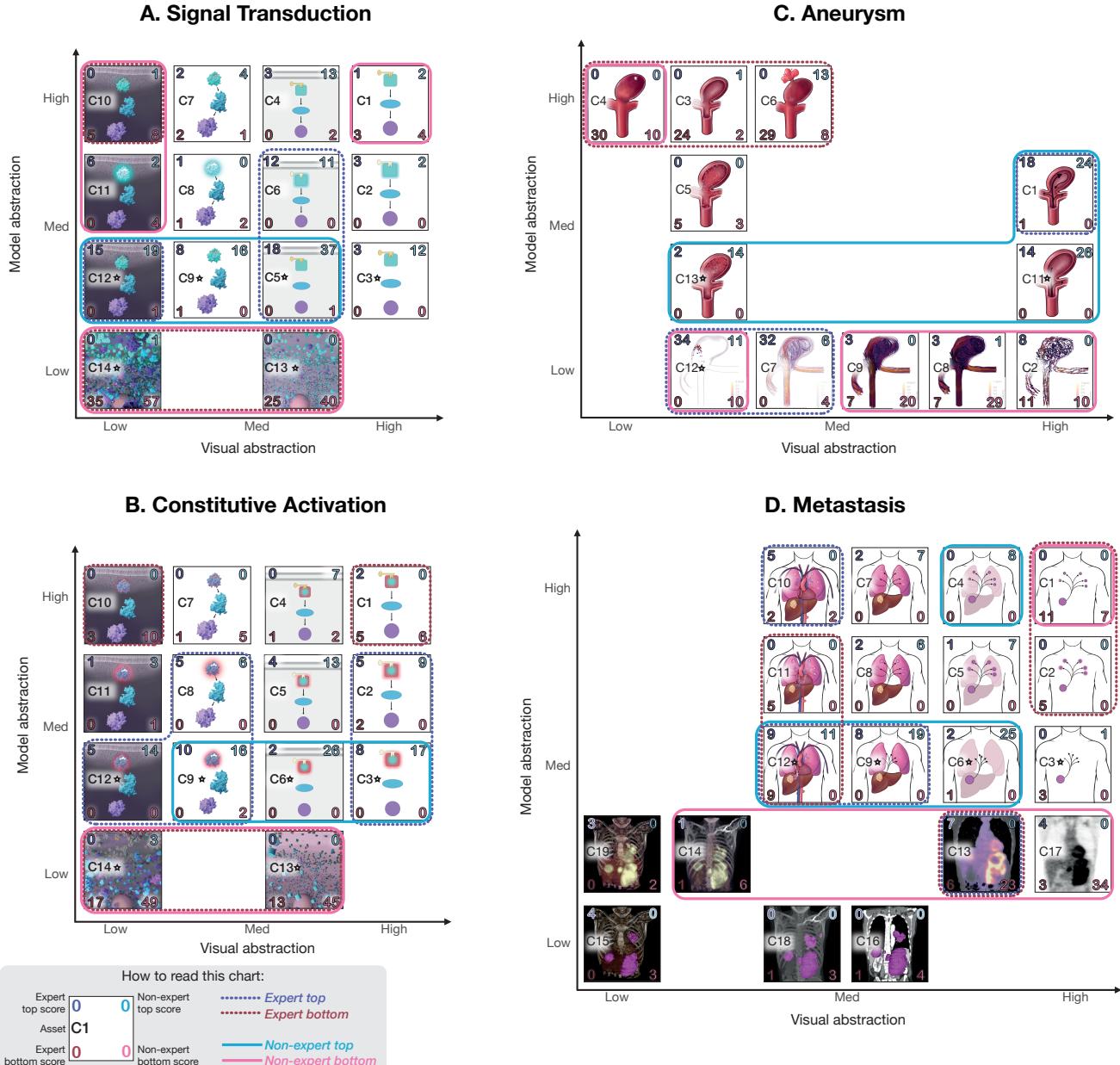


Figure 4: Abstraction spaces for (A) Signal transduction, (B) Constitutive activation, (C) Aneurysm, and (D) Metastasis. Assets are arrayed in the space by degree of model (y-axis) and visual abstraction (x-axis). Animated assets are denoted with a star glyph to the right of the asset name. Values in the four corners of each asset represent a weighted score for its selection frequency as the first, second, or third choice for an expert or a non-expert audience scenario (see ‘How to read this chart,’ left). Encircled regions indicate assets with scores in the 20th percentile of each scenario (see ‘How to read this chart,’ right).

ipation falloff ranged from 3 % to 26 % over the course of a given segment. Higher falloff rates were likely due to a higher percentage of time-constrained clinicians who were unable to complete the survey. We dropped responses from participants who did not complete all questions for a given topic to avoid artificial biasing of asset choices.

For each of the five surveyed topics we report the following.

with detailed per-topic results accessible at <https://public.tableau.com/profile/biomedsurvey2021>.

- **Asset scores:** Each asset received four weighted scores that represent the frequency that it was selected in the top or bottom three options in each scenario.
- **Average attribute ranking:** Average ranking values for aesthetics, scientific accuracy, visual clarity, and communication suc-

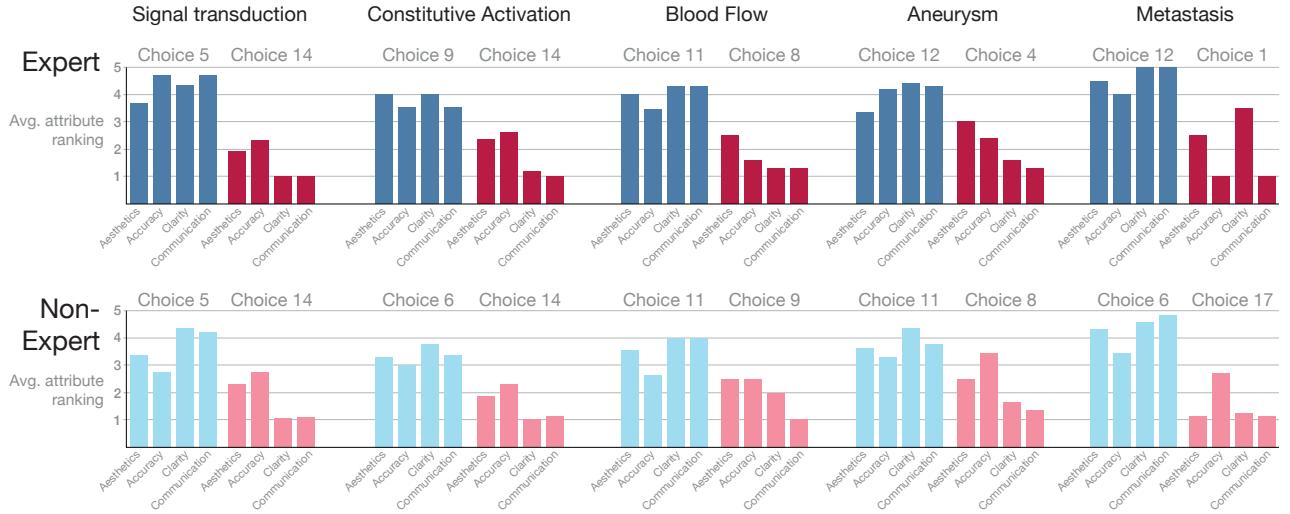


Figure 5: Expert and non-expert attribute rankings for top and bottom choices for all five topics.

cess for assets that were selected for each scenario (either as a top or bottom choice).

- **Keywords and comments:** Dominant keywords and representative comments used to describe the top- and bottom-scoring assets in each scenario.

Asset Scores. Asset scores are weighted such that $\text{final score} = 3s_1 + 2s_2 + s_3$, where s_1 , s_2 , and s_3 indicate the sum counts for an asset selected as 1st, 2nd, or 3rd for a given scenario. These scores are shown in the corners of each asset in Figs. 3 and 4A-D. We demarcate those assets falling in the top 20th percentile for expert top (dark blue), expert bottom (dark red), non-expert top (light blue), and non-expert bottom (pink) choice selections.

In all five topics we observe that the 20th percentile scores for both expert and non-expert top asset selections form clusters that often fall in the medium range of either one or both abstraction axes. We see a dislike of the most extreme ranges of the abstraction space, with a few exceptions. For example, in the lower left corner that denotes both low model and low visual abstraction of the aneurysm abstraction space (Fig. 4C), we see a cluster of expert top choices comprised of C12 (animated particle flow) and C7 (pathlines). For each topic selection, we see one or two clusters, or one cluster with one or more outliers. For example, blood flow in Fig. 3 shows two separate clusters of expert top choices. Interestingly, in this case the split in clusters seems to be associated with the different professions. Clinicians/biomedical illustrators most often selected C11 (animated blood constituents) and C12 (animated red blood cells), while visualization/domain scientists selected C9 (streamtubes) and C10 (streamribbons) more often.

In all topics we see an overlap in preferences between audiences in the 20th percentile of top selections. With respect to expert top selections, we occasionally see a slightly larger spread in the abstraction spaces, particularly along the model abstraction axis. This is apparent in the blood flow (Fig. 3), constitutive activation (Fig. 4B), and aneurysm (Fig. 4C) abstraction spaces. On the

other hand, non-expert top selections that do not overlap with expert selections often fall into a higher abstraction space region. We see this in blood flow C4 (static blood cell components) in Fig. 3, and in metastasis C4 (static abstracted tumors inside tinted organs) in Fig. 4D.

We similarly see frequent overlaps in bottom scenario selections. Their spread in the abstraction space is also similar between audiences, with two exceptions. In constitutive activation (Fig. 4B), we see a larger spread in bottom selections for the expert scenario, while in signal transduction (Fig. 4A) and aneurysm (Fig. 4C) the spread of bottom selections is larger for the non-expert scenario.

We additionally see occasional exceptions to top and bottom selection overlap for the expert and non-expert scenarios. For the aneurysm topic, C12 (animated particle flow) was selected as a bottom choice for a non-expert audience while also as the top choice for an expert audience (Fig. 4C). Other interesting cases show selection overlap within an expert audience. In metastasis, both C12 and C13 (CT slice with colored PET heatmap overlay) falls into both expert top and bottom scenario selections (Fig. 4D).

Attribute Rankings. Fig. 5 shows the average attribute rankings (aesthetics, accuracy, visual clarity, and communication) for the top and bottom choices for the expert (top row) and non-expert scenarios (bottom row) for each of the five topics: signal transduction, constitutive activation, blood flow, aneurysm, and metastasis.

We show top selections in a blue hue (dark blue for experts, light blue for non-expert audience) and bottom selections in a red hue (dark red for experts, pink for non-expert audience). Attribute rankings over all four attributes average at 4.1 for expert top selections while bottom selections average at 1.8. Average rankings across all four attributes are similar for non-expert audience selections, with 3.7 for the top selection and 1.8 as the bottom selection. We observe similar average ranking assignments between top and bottom choices in the non-expert audience evaluation of asset accuracy for signal transduction, blood flow, and aneurysm. This makes sense, as a non-expert audience is unlikely to have the necessary expertise

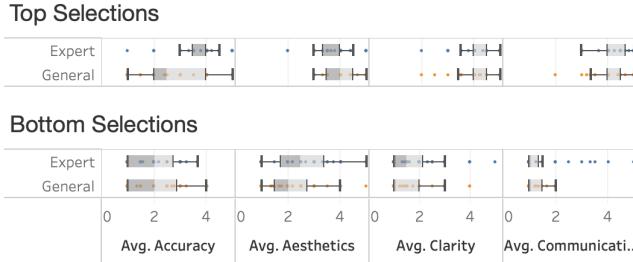


Figure 6: Average attribute rankings to assets selected as either top or bottom for an expert (blue) or non-expert scenario (orange) for accuracy, aesthetics, clarity, and communication success.

to determine the accuracy of a given asset. For the expert audience we see such similar ranking only in aesthetics in the top and bottom choices for aneurysm.

The assigned attribute rankings in Fig. 6 between expert and non-expert audiences are similarly distributed, although expert top selections often show a narrower distribution. Expert rankings for bottom choices show a long right tail, suggesting mixed perceptions of communication success for selected assets.

Keywords and Comments. Fig. 7 reveals similar keyword preferences for both expert and non-expert audiences in their top selections, with *informative*, *easy to read*, and *clear* in the 20th percentile for both audiences. The only difference between the two audiences is the selection frequency of these keywords: experts prioritized *informative* over *easy to read*, while for a non-expert audience this order is reversed. We see a stronger difference in the 20th percentile of preferred keywords for bottom selections between audience levels. Experts used *confusing*, *simplistic*, and *pretty* most frequently to describe bottom choices. In contrast, the 20th percentile of keywords for non-expert audience bottom selections included *confusing*, *distracting* and *excessive*. Also intriguing is experts' frequent use of *pretty* to describe their bottom choices.

Scenario comments indicated a strong preference for the inclusion of labels, legends, and captions. Feedback on the use of arrows was also positive, although many participants felt that the positive feedback loop in constitutive activation was not effectively communicated and that a different approach was needed, e.g., an additional arrow that looped back from the last to the first molecule in the sequence. Comments were generally positive w.r.t. animated assets, with several comments indicating a preference for animated arrows particularly in non-expert scenarios. Comments related to data-driven assets, e.g., metastasis PET/CT and blood flow visualizations, often stressed that such assets were overly abstract for non-expert audiences, e.g., blood should not be perceived as composed of wires and tubes. At times such assets lacked an aspect of the stated communication objective. These included the lack of nutrients for blood flow scientific assets, lack of visuals showing real-time spreading of tumors for metastasis, or the lack of vessel wall layers and thickness for aneurysm.

Conversely, participant comments on illustrative assets that were expert top choices often indicated a desire for additional realism, e.g., more accurate motion, more accurately-sized cell or molecu-



Figure 7: Word cloud of keywords chosen to describe top and bottom choices for expert and non-expert scenarios for all topics.

lar components. One participant noted in their selection of the animated blood constituents asset (C11 in Fig. 3), "The inclusion of multiple kinds of cells/molecules is helpful for accuracy. The animation could include more variability in flow among the objects for even more accuracy, but that could also potentially hinder the main communication goal if it becomes too distracting or hard to track." Other assets were selected as bottom choices for being too misleading for the topic scenario, e.g., blood flow fluid illustrations in Fig. 3 C8 and C13 "look too much like a clot," or the removal of organs creating too much uncertainty for where tumors had spread in metastasis, "without any anatomy underneath, you have no way of knowing what the dots represent, or how deep into the tissue they are. Is it a rash spreading? Unclear."

However, there was a clear limit to desired realism for either audience. Numerous comments focused on assets that were perceived as chaotic, noisy, and unnecessarily complex, e.g., the stochastic molecular interaction scenes included for signal transduction and constitutive activation (C13 and C14 in Fig. 4A and B). This complexity made meaningful interpretability regarding the achievement of the communication goal impossible for both audiences. Assets with excessive realism occasionally veered into "scary" for non-expert audiences, e.g., the greyscale PET scan image with high metabolic activity regions (C17, Fig. 4D).

6. Discussion

In the following we discuss the patterns we observed for audience preference and identify opportunities for improved visualization design for communication success, while also reflecting on the limitations of our study.

Preferred Abstraction. A meaningful visual abstraction eases visual processing and reduces cognitive load [VCI20]. Our results indicate for both audiences that preferred abstractions often reside in a middle space of visual and model abstraction. They dislike either extreme realism or extreme abstraction. Initially we thought that experts would have a higher preference for these extrema for

one of two reasons: (1) experts have such intimate knowledge of a subject that they do not need or want to see the complete picture, or (2) experts prefer completeness because their knowledge of a subject allows them to tolerate more complex information. Ultimately neither was consistently true. To some extent this corroborates previous works that found that the added value of dynamic visualizations is questionable and highly dependent upon the audience and communication objective [JM12; PM20].

Selection Criteria. Interestingly, participant keyword choices indicate different selection criteria for bottom choices, but similar selection criteria for top choices. This matches our observations of the degree of selection overlap between the two audiences: top choices overlapped more extensively than the bottom choices. This indicates that participants may place equally high priority on positive visual clarity and communication-related factors, i.e., *informative, easy to read, clear*. However, their criteria to identify a poor visualization differ, and as does their idea for what constitutes *confusing*. Experts consider oversimplification to be confusing, while a non-expert audience reacts against overly distracting or excessive visualizations. The non-expert audience preference against confusing or distracting visualizations makes sense—without sufficient subject background, information-rich visualizations are often incomprehensible. Such information overload is exemplified in the molecular simulation assets (C13 and C14 in Fig. 4A and B).

Aesthetics is not the only consideration in selecting a visualization. While the keyword *pretty* was selected often to describe both top and bottom choices, it was notably the third-most frequent keyword selected to describe expert bottom choices. For example, the bottom-most selection by experts to describe blood flow, C8 (static fluid visualization in Fig. 3), was most described as *pretty*, but additionally as *simplistic, inaccurate, and misleading*. Thus it seems that clarity and communication may carry more weight for this audience type. This prioritization makes intuitive sense, as experts rely often on visualizations for technical information exchange. A quantitative control study focused on aesthetics relative to accuracy as perceived by different audiences would be an interesting follow-on work.

Background Biases. Background expertise and training play a large role in asset preferences, and likely affect our perception and understanding of a visualization. For example, in the blood flow topic when both components and hemodynamics were identified as important, experts with mostly clinical or biomedical illustration backgrounds prioritized the visualization of blood components (C11 and C12, middle region in Fig. 3) over information encoding hemodynamic forces (C9 and C10, bottom region in Fig. 3). In metastasis, we saw a similar background-based selection split for the PET/CT heatmap asset (C13, bottom region in Fig. 4D). The experts selecting this as a top choice came from MR physics and visualization, while the experts selecting this as a bottom choice came from biomedical illustration or life sciences. The expert selection overlap with C12 in this topic is more difficult to explain. While background expertise likely plays a role, which we infer from one comment that it looks “too good to be true,” its selection as both a top and bottom expert choice requires finer-grained information than captured in our study.

Our backgrounds can also influence our perception of the mean-

ing of visual marks and channels, e.g., color. For example, while a clinician may be used to reading a PET/CT layered slice image with high metabolic activity regions as bright (C13) or dark (C17), someone without this background would interpret these differently, e.g., interpret the dark spots in C17 as dead tissue regions or the bright zones indicating a strange event in the body. A quick solution to disambiguate color meaning may involve labels and captions, but more immediately understandable solutions without this addition may be interesting to explore.

Stylistic Preferences. Stylistic elements are frequently used to emphasize a biomedical process. For example, while ubiquitously used in biomedical illustration, glows can mean many different things. Our focus group on metastasis discussed whether a tumor glow indicated pain, treatment application (radiotherapy), tumor metabolic activity, or was purely to draw attention. This lack of clarity became apparent in the survey, with one participant commenting, “It is unclear whether the glow in the tumors on the lungs is meant to denote a new growth or stylistic radiation treatment. If it is treatment, then perhaps there should be numbered steps or a device that provides the radiation.” At the microscale, the focus groups generally found glow indication to be meant to either draw attention or to indicate activity/aberrant activity. While this mixed meaning is convenient in our case, since we wanted to draw attention to areas of activity, it may quickly become problematic if that is not the communication goal. This suggests that glows should be used with care and their use reexamined in practice.

Study Limitations. We set a number of limitations and assumptions in this study given its large design space and broad topic range. For instance, our sampling of visualizations and topics was not comprehensive but representative of the massive space of creative and technological visualizations of biomedical processes. Additionally, the granularity of expertise in our survey is relatively coarse, and non-expert participants often had a higher basic scientific knowledge than someone from the broader public. A logical next step would be finer-grained surveys by expertise/target audience. This may introduce additional challenges in visual representation design, as many communication-oriented visualizations of biomedical processes that are aimed at the general public with no scientific background are heavily annotated or narrated, and often include multiple scales to orient the viewer, e.g., an initial view of the entire body is provided before diving inside an organ and on to the interior of the organ’s cell where a signal is passed between molecules in the cell. This type of visualization was out of the scope of our study, and given this we felt that including participants with a somewhat higher knowledge of biology would be beneficial for quality responses in some cases.

In choosing comparatively broad expert and non-expert scenarios our study favors those visualizations that are more flexible to interpretation. Even so, the visualizations for each topic naturally have different degrees of effectiveness based on the audience and the described scenario. Rather than identifying the single best visualization for a specific audience scenario, our overarching goal was instead to find general preferences and values for visualization selection.

7. Research Opportunities

This study opens a number of exciting opportunities for visualization research of biomedical processes. Gaps in biomedical illustration and visualization are readily apparent in all our topics. Illustration-driven works are currently filling in spaces in stories that cannot be easily told with data alone, e.g., aneurysm rupture, the cellular composition of blood, and the spread of tumors. These indicate that visualizing data is not always sufficient, and may in fact lead to a mismatch between audience and technique. However, data-driven visualization can offer a faster and realistic means to present phenomena that are laborious or impossible to create with current biomedical illustration workflows. While visualization research that applies illustrative techniques to patient data is relatively mature [LVPI18], illustrative techniques applied to represent a creator's mental model of a given phenomena or to represent a cohort are an open challenge [MGS*21].

Visualization research that intentionally considers layered messaging, e.g., one for communication targeted for a non-expert audience and one for analysis that targets an expert audience, may be interesting to consider. The overlapping preferences for assets between expert and non-expert audiences suggest that this may be amenable and more likely with increased demand for health communication. This layering may be achieved by superimposing visualization techniques in a manner similar to Pixar's storytelling approach: Pixar films are designed to entertain multiple levels of audiences, with numerous adult messages sprinkled throughout that do not affect the messages geared towards children. We imagine that this can be done with a thoughtful combination of data- and/or illustrative-driven assets. Linked juxtaposition may be another avenue to explore. For example, linking the process steps visualized in a highly abstracted asset, e.g., signal transduction with a basic glow sequence animation between primitive shapes, to a complex stochastic interaction visualization may help both experts and a non-expert audience to understand the sequence of a reaction framed in a realistic, complex environment.

8. Conclusion

The aim of our study was to better understand the development and evaluation process for visualizations of biomedical processes by different audiences. We particularly were interested in illuminating how visualization and biomedical illustration currently diverge and converge. Our findings show that both audience levels we surveyed place a high value on clarity and ability of a given asset to meet its stated communication objective. Moving forward, an optimal positioning for abstraction is likely in a middle space of both model and visual abstraction. We additionally found that some conventions are not as clear as we thought, e.g., glows can ambiguously indicate a call to attention, a pathological event, activation, etc., while other approaches were unexpectedly preferred, e.g., biomedical illustrations in place of data-driven visualizations. This latter preference occurred most often when the source data model was overly complex or did not capture the mechanism required to achieve the stated audience objective. Much of this study focused on communication. Future work that combines both biomedical illustration and visualization techniques in data analysis with domain experts also holds great potential.

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