EuroVis Workshop on Visual Analytics (2025)
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The Human-Data-Model Interaction Canvas for Visual Analytics

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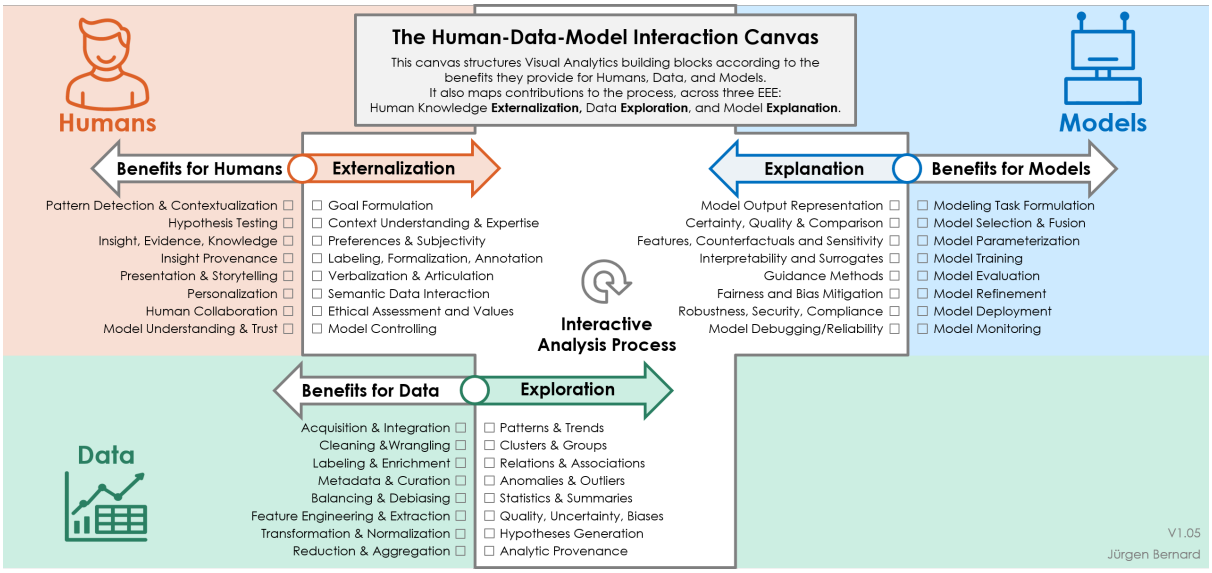


Figure 1: *The HDMI Canvas defines six lists of key VA building blocks that describe how humans, data, and models contribute to the VA process and benefit from the process. The canvas supports the characterization of existing approaches and the design of novel VA solutions.*

Abstract

Visual Analytics (VA) integrates humans, data, and models as key actors in insight generation and data-driven decision-making. This position paper values and reflects on 16 VA process models and frameworks and makes nine high-level observations that motivate a fresh perspective on VA. The contribution is the HDMI Canvas, a perspective to VA that complements the strengths of existing VA process models and frameworks. It systematically characterizes diverse roles of humans, data, and models, and how these actors benefit from and contribute to VA processes. The descriptive power of the HDMI Canvas eases the differentiation between a series of VA building blocks, rather than describing general VA principles only. The canvas includes modern human-centered methodologies, including human knowledge externalization and forms of feedback loops, while interpretable and explainable AI highlight model contributions beyond their conventional outputs. The HDMI Canvas has generative power, guiding the design of new VA processes and is optimized for external stakeholders, improving VA outreach, interdisciplinary collaboration, and user-centered design. The utility of the HDMI Canvas is demonstrated through two preliminary case studies.

1. Introduction

The evolution of Visual Analytics (VA) has been an exciting journey. Since its formal characterization as a successor of visual data mining about 20 years ago, VA has seen constant change, shaped by a series of external developments and trends like advanced statistics, big data, data science, (interactive) machine learning (ML), deep learning, large language models, and AI in general. Today, the three actors *Humans*, *Data*, and *Models* (including statistics, analysis algorithms, and ML) are more prominently discussed in society than ever before, signaling a prosperous era for VA research and practice, leading to enhanced data-, visualization-, interaction-, and AI-literacy. In the era of the digital transformation and data-driven decision-making, VA provides practical solutions to pressing challenge areas and emerging trends, including data exploration, scalability, complexity handling, multi-criteria decision-making, explainability, interpretability, transparency, bridging semantic gaps, domain-specific adaptability, cognitive amplification, and not least: human-AI collaboration.

Questions that inspired this position statement are: How well does our community sell its unique assets? Does the world know?

DOI: 10.2312/eurova.20251096

A latent concern is that VA undersells its immense benefits to the outside world. Or, more constructively: How can we enhance the visibility and adoption of VA assets? Which VA principles need to be included in a one-minute pitch to a real-world stakeholder? To what extent do VA research agendas, process models, and theoretical frameworks convey these key principles to society at first sight? Reflections within the VA community and experiences from applied, collaborative work have surfaced nine key observations:

Knowledge Generation beats Knowledge Externalization: Traditional process models in data mining, KDD, ML, and VA prioritize knowledge generation, supporting the flow from data to insights [FPSS96, WH00, PC05, CT05, KAF*08, SSS*14, ERT*17]. However, the human knowledge externalization process (from tacit into externalized knowledge through interactive interfaces) seems to be much less reflected. Deeply rooted in social sciences [KCM89], knowledge externalization was proposed for VA by Wang et al. and Federico et al. [WJD*09, FWR*17, CGM*16], leveraging van Wijk's influential value-of-visualization model. A fresh perspective may balance knowledge generation and externalization.

Feedback Loop++: The feedback loop [KAF*08, SSS*14, SSZ*16, SSZ*16] is one of VA's assets, beyond less human-centered Knowledge Discovery in Databases (KDD) [FPSS96] or Cross-Industry Standard Process for Data Mining (CRISP-DM) [WH00] processes. Initially focused on model selection, parameter steering, and quality assessment, human feedback now encompasses broader elements [EHR*14, ACKK14, HE24]. With the "human is the loop" scope [EHR*14], humans can influence similarities, dimension weights, item weights and relevance, group counts and contents, centroid landmarks, and labels. Additionally, distinctions exist between core knowledge and alternatives like domain expertise, contextual understanding, preferences, subjectivity, emotions, ethical assessment, and values [ACKK14, HE24]. Modern perspectives also ask about *how* feedback is elicited and formalized, including structured feedback [BSR*14, BZL*18], intervention [ACKK14, EHR*14], semantic interaction [EFN12], human-data interaction [MHH*14], and interactive adaptation [RMS*20].

Role of the Human: Many process models are highly abstract, or humans are only indirectly represented through visualization or knowledge components [FPSS96, WH00, PC05, KAF*08], obscuring the full spectrum of human involvement. A fresh, human-centered perspective may explicitly distinguish how humans *benefit* from VA processes [Rie19, Shn22, Rus22] and how they can *contribute* actively [RMS*20, ACKK14]. This approach can prioritize needs, expertise, and interpretability, with feedback mechanisms ensuring that processes remain effective, ethical, and aligned with real-world needs [Shn22].

Role of the AI: AI models have evolved from a passive tool that require manual selection, parameterization, and human oversight [FPSS96, WH00, PC05, KAF*08, SSS*14, SSZ*16, SSZ*17, SKKC19], to active (mixed-initiative) agents that more autonomously analyze data, learn, adapt, and collaborate with humans in decision-making [AGH99, Hor99, ACKK14, Rie19, SJB*21, Shn22, Rus22]. Treating models as actors, including their needs for improvement, but also their explainability, interpretability, and reliability [SSSE20, Hoh21, CMJ*20, RBB*23] would align VA with human-model collaboration perspectives [RM23, FDKN24, HE24].

Role of the Data: Data was long seen as a passive repository of gathered information that was processed, mined, and exploited for decision-making [PC05, Kit14]. However, recent frameworks reconceptualize data as socially constructed artifacts embedded with human values, biases, and context [DK23, Lup17, LAML22]. Rather than merely processed algorithmically with AutoML [RAB*24], data is increasingly understood to be engaged with both analytically and intuitively [MHH*14], inspiring exploration, insight formulation, developing "data hunches" [LAML22], and "spending time with data" [Lup17]. This VA perspective aligns with *data feminism*, exposing power imbalances in data [DK23]; *data humanism*, emphasizing emotional dimensions of data [Lup17]; and *personalized analytics*, prioritizing individual meaning-making over standardized metrics [MHH*14].

Goal(s) of a VA Process: A prominent perspective of VA is as a flow from data to knowledge, using models, visualizations, and interactions as tools [FPSS96, CMS99, PC05, CT05, KAF*08, SSS*14]. However, does this always match real-world scenarios [OM20]? What if, in some cases, data and knowledge are provided, so the goal is to benefit model enhancement [SKKC19]? Alternatively, knowledge and models may exist, yet data is lacking "AI-readiness". Like VIAL for interactive data labeling [BZSA18], VA may describe three simultaneous goals: benefiting human knowledge, model improvement, and data enrichment.

Three Types of Processes: In VA, three process models dominate. i) *Data transformation processes*, rooted in data mining and ML [FPSS96, WH00, CMS99, KAF*08, SSZ*16, SSZ*17, Hoh21], prepare data and ease pattern detection, executed mainly by developers. ii) *Knowledge generation processes*, emerging from information seeking and sense-making [Mar95, Shn96, PC05, CMS99, KAF*08, SSS*14], guide users in decision-making. iii) *Design processes*, mainly conducted by visualization designers [Mun09, SMM12, OM20], although VA-specific support remains scarce. A fresh perspective may present VA to the outside world in a unified framework, leveraging principles from data transformation, knowledge generation, and design.

Descriptive Power: Conceptual structures with descriptive power help to distinguish approaches, helping people to think–within the community and ideally beyond. Many VA process models outline essential characteristics and fundamental components that all VA approaches share [FPSS96, CMS99, WH00, PC05, KAF*08, SSS*14], much like a software interface or abstract base class. However, they do not necessarily help to differentiate between approaches and their VA building blocks. Enhanced perspectives may incorporate more detailed structure about human, data, and model factors to ease the characterization of applications.

Generative Power: Designing VA systems is even more challenging than traditional visualization systems, where methodological design support is more prevalent [Mun09, SMM12]. The generative power of traditional VA process models sometimes falls short in characterizing problems, identifying essential building blocks, and enabling the generation of novel, non-trivial VA solutions within a structured design space. A detailed VA design space could address these gaps and enhance interdisciplinary collaboration with external stakeholders in participatory and user-centered design.

The contributions of this position paper are as follows.

- It summarizes and values the strengths of 16 VA process models, conceptual frameworks, and design spaces, while identifying potential extensions, provided in the Supplemental Materials. Used to substantiate the nine observations presented in Section 1.
- It introduces a perspective on *Humans*, *Data*, and *Models*, as *ac-*

tors (as used in socio-technical contexts), to highlight their participation and interaction. The perspective analyzes how actors *benefit from* and *contribute to* VA processes, using the metaphor of three ingoing and three outgoing arrows, to show interaction directions. The three types of contributions to the VA process form the *EEE Framework*: *Externalization* of human knowledge, *Exploration* of data, and *Explanation* of models (Section 3).
- It presents the HDMI Canvas (Figure 1), an assembly of humans, data, and models, with 3×2 directed arrows representing actor contributions and actor benefits. For each of the six arrows, the HDMI Canvas defines key VA building blocks, enabling both the characterization of existing approaches and the design of novel VA approaches. The HDMI Canvas helps to break down the complexity of an analysis problem and to reveal human-data-model collaboration patterns, using a language suitable for external stakeholders (Section 4).
- First preliminary case studies demonstrate the practical application of the HDMI Canvas in concrete VA systems (Section 5).
- An online feedback mechanism before, during, and after the EuroVA workshop, to collect detailed feedback, validate the canvas structure, and ensure its adoption in the VA community.

2. Related Process Models, Frameworks, and Design Spaces

In addition to the nine high-level observations presented in the introduction that motivate the HDMI Canvas, supplemental material evaluates the strengths and remaining opportunities of 16 VA process models, conceptual frameworks, and design spaces–for reflection and for forming the fresh perspective.

3. Roles of Humans, Data, and Models in VA Processes

VA processes center around three key actors: Humans, Data, and Models. This section discusses how these actors *benefit* from VA (Section 3.1) and how they *contribute* back to the VA process (Section 3.2). The notion of benefits and contributions relates to traditional goal and task-based framings, where the VA process is tasked to benefit the actors, and actors are tasked to contribute to the VA process. Beyond tasks, benefits for and contributions by actors emphasize the bilateral nature of sending and receiving, as fundamental forms of communication. A main contribution is the "EEE" Framework, combining the **Externalization** of human knowledge, the **Exploration** of Data, and the **Explanation** of algorithmic models. This perspective supports the study of human-data-model collaboration, laying the ground for the HDMI Canvas in Section 4.

3.1. How Actors Benefit from Visual Analytics Processes

The benefit describes the ”centeredness” of VA processes for actors, i.e., what they take away. In human-centered VA, the output is knowledge, as a human benefit. Data-centric approaches enhance the data itself, while in ML, models benefit from VA processes.

Human-centered VA processes enhance data-driven decision-making by empowering users to explore complex data, derive meaningful insights, and make informed choices. Aligned with human-centered AI, and in contrast to fully automated approaches, human-centered VA prioritizes user involvement, interpretability, and adaptability. This ensures that data analysis remains intuitive, transparent, and actionable. Key benefits of this approach include:

- Pattern detection and data structuring
- Pattern contextualization of observations and findings
- Confirmatory data analysis to accept or reject hypotheses
- Insight, evidence, and knowledge generation
- Presentation, reporting, and storytelling
- Personalization of the analysis and insight provenance
- Collaboration and shared exploration among users
- Model understanding and trust

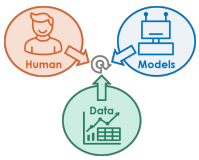
Data-centered VA processes help to transform raw data into representations that are usable by algorithmic models and useful for downstream analyses. Data can capture user interactions, feedback, and contextual nuances, enabling both humans and models to contribute to data improvement. Key benefits for data include:

- Data acquisition, integration, and connectivity
- Data cleaning and wrangling
- Data labeling, augmentation, and contextual enrichment
- Data curation and metadata
- Data balancing and debasing
- Data feature extraction and engineering
- Data transformations and normalizations
- Data reduction, and aggregation

Model-centered VA aligns with interactive ML: Based on a task formulation and ”AI-ready” data, model-centered processes focus on parameterizing, building, refining, evaluating, deploying, and monitoring models. Notable is the need for humans in essential process steps, e.g., for data labeling in supervised ML. Models benefit from human oversight, feedback, and contextual understanding, which help improve their accuracy, relevance, and ethical alignment. Benefits for models through VA can be described as:

- Modeling task formulation
- Model selection, model fusion, and ensembles
- Model parameterization
- Model building and training
- Model refinement
- Model evaluation and quality assessment
- Model deployment, monitoring, and performance tracking

3.2. How Entities Contribute to VA – The EEE Framework



VA processes can be structured by the contributions of the three key actors. Each actor brings unique strengths, enabling robust control, communication, and mutual guidance, forming the ”**EEE Framework**”: Human Knowledge and Preference **Externalization**, Data **Exploration**, and Model **Explanation**.

(Human Knowledge and Preference) Externalization transforms internal, tacit expertise into explicit, communicable knowledge or preferences. Capturing expert knowledge, expertise, feedback, and preferences tailors data analysis for strategic and/or personalized decision-making. Well-established in cognitive science, integrating externalization and interactive elicitation practices in VA can strengthen methodological support for data analytics:

- Goal formulation
- Knowledge and contextual understanding
- Domain expertise and experiential knowledge
- Preferences, subjectivity, and emotions
- Interactive data labeling, formalizing knowledge and preferences
- Annotation support and data hunches to capture tacit insights

- Verbalization and NLP interfaces enable user articulation
- Semantic interaction interfaces for direct human-data interaction
- Visual query systems and advanced facets for search and filtering
- Ethical assessment, creativity, and human values
- User control for modeling, parameterization, and validation
- Human collaboration environments for shared decision-making

(Data) Exploration is fundamental for actors in data analysis for knowledge generation, data-driven decision-making, and informed model-building. VA integrates human and model strengths to facilitate data discovery, navigating high-dimensional spaces using sophisticated VA methods to uncover latent structures and patterns. Key contributions of VA-driven data exploration include:

- Representation of patterns and trends in high-dimensional data
- Detection of clusters and groups of data items
- Relation and association discovery between attributes
- Detection of anomalies and outliers
- Statistics, summaries, and structuring
- Detection of quality issues, uncertainties, and biases
- Hypothesis generation based on explored insights
- Insight-based modeling and analytic provenance

(Model) Explanation goes beyond computational outputs through, pattern recognition, data processing, and automation. Model explanation involves activities designed to understand the reasoning behind model decisions, i.e., not only receiving what output has been generated by a model, but also why and how. It enhances interpretability through visualization and explainable AI methods, to foster a trustworthy, reliable, and safe AI experience. Main contributions of models and model explanations include:

- Model output visualization and interpretation
- Model certainty, quality assessment, and model comparison
- Guidance methods
- Feature importance and example-based explanations
- Model interpretability and surrogate models
- Counterfactuals, what-if scenarios, and sensitivity
- Visual, interactive, and verbal explanations
- Fairness and bias mitigation methods
- Robustness, security, and regulatory compliance
- Improved model debugging and continuous monitoring

4. The Interactive Visual Data Analysis (IVDA) Canvas

The HDMI Canvas characterizes *Humans*, *Data*, and *Models* based on the *benefits* they gain from VA processes and their *contributions* to the VA process. Section 4.1 discusses requirements, Section 4.2 presents the HDMI Canvas, and Section 4.3 discusses its use.

4.1. Requirements

The reflection on VA observations, process models, and other conceptual structures reveals key requirements for a fresh perspective.

- Describe VA for external stakeholders with actors, connections, and terminology that aid understanding and ease outreach.
- Highlight its core actors *Humans*, *Models*, and *Data* and their active roles: humans as decision-makers, models as collaborative actors, and data in an activated form to underline its importance.
- Associate actors with their *contributions* to and *benefits* from VA process to highlight interaction directions.
- Extend the diverse forms of human knowledge externalization to emphasize feedback-loop beauty.
- Make interpretable and explainable AI methods more present as model contributions (why), beyond model output (what).
- Focus on identifying differences between VA approaches rather than just commonalities, to strengthen its descriptive power.
- Visible forms of human-model communication should characterize mixed-initiative and human-AI collaboration methods.
- Aid the design of new approaches through enhanced structural guidance on VA building blocks, increasing its generative power.
- Visually, it should prioritize clarity, holistic and systematic thinking, and broad applicability beyond the VA community.

To achieve this, a *canvas* is used as a powerful strategic tool for structuring thoughts, analyzing situations, and supporting decision-making. Inspiration comes from established models like the SWOTanalysis matrix, the Business Model Canvas (BMC), and the Value Proposition Canvas.

4.2. Interactive Visual Data Analysis Canvas Overview

Figure 1 introduces the HDMI Canvas, a canvas structure that positions *Humans*, *Models*, and *Data* based on their *benefits* from VA processes (outgoing arrows) and *contributions* (ingoing arrows). It represents these actors as key elements in the canvas, focusing on their roles as key information hubs. The canvas highlights bidirectional information flow, characterizing forms of communication between actors, fostering control, interaction, and mutual guidance. By emphasizing dynamic interplay between actors, it reflects continuous dialogues and learning between actors, opening new avenues for human-data-model collaboration.

4.3. HDMI Canvas Usage with External Stakeholders

The HDMI Canvas supports communication with external stakeholders by making VA building blocks and interaction flows accessible to audiences unfamiliar with VA terminology. Many terms used in the canvas are already established in broader public and professional discourse, especially in the AI context. This allows practitioners, data scientists, and domain experts to engage with VA concepts without prior specialized knowledge. The structural depth of the HDMI Canvas enables transparent descriptions of VA approaches. The HDMI Canvas also serves as a generative tool for VA system design and supports user-centered development by offering a shared structure for discussing system goals and interaction-flow design. When all 3×2 flows are relevant, the design goal is a fully integrated VA "Supertool" for human-data-model collaboration. In summary, it provides a structured and an inclusive way to describe, analyze, and design VA systems, bridging disciplinary gaps and supporting effective collaboration with external stakeholders.

5. Case Studies

5.1. iPCA: Opening the Black Box of PCA Projections

The iPCA [JZF*09] VA approach enables experts to perform both exploratory data analysis and model analysis (Figure 2). It demonstrates white box model-steering and interpretation for the linear principal component analysis (PCA) projection, supporting better understanding and use. To facilitate data exploration, iPCA visualizes PCA results, using multiple coordinated views and a rich set of user interactions (1) (2). This helps experts to understand data characteristics and relationships between the data and the calculated PCA eigenspace, leading to a better understanding of the

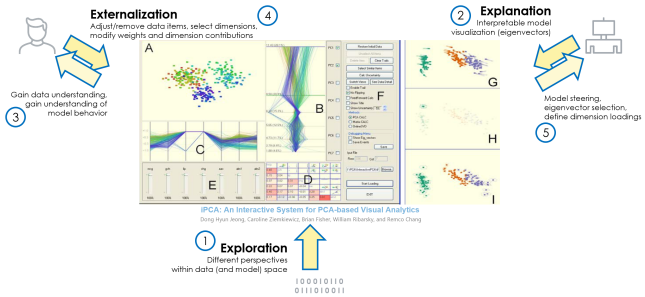


Figure 2: *The iPCA [JZF*09] white box approach leverages five out of six key information flows to enable performing both exploratory data analysis and model analysis (PCA).*

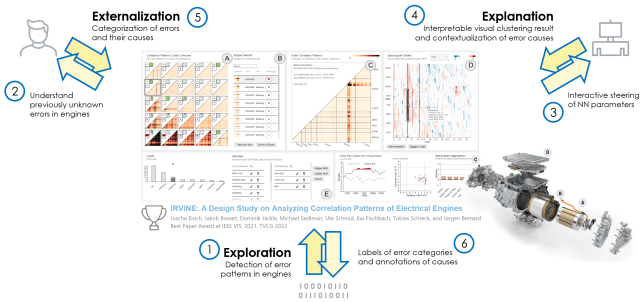


Figure 3: *The IRVINE [EBJ*22] VA system has "Supertool" complexity: to solve the analysis goal of the experts, all three actors want to benefit from and contribute to the VA workflow (steps 1-6).*

model and its internal analytics behavior (3). From an externalization perspective, several interaction techniques enable experts to engage with data values and model characteristics, including adjusting/removing data items, selecting dimensions, and modifying weights and dimension contributions (4). Model-centered interactions lead to model steering through parameterization, weighting, and dimension contributions (5); direct feedback reflects changes back to the user. This allows users to explore how and why PCA results respond to different inputs supporting more accurate analysis and improved model transparency. Overall, iPCA offers human, model, and data contributions to the VA process, with benefits for humans and models, i.e., five out of six key information flows are supported with this pioneering white box approach.

5.2. Analyzing Correlation Patterns of Electrical Engines

BMW uses acoustic data analysis to improve the manufacturing of its electrical engines by detecting and understanding previously unknown errors. With IRVINE [EBJ*22], expert engineers apply a comprehensive data exploration (1) strategy to identify subtle error patterns (2) across engine components (Figure 3). An interactive visual clustering algorithm, a neural network-based approach, allows dynamic paramete fine-tuning (3). Interactive steering enhances anomaly detection and facilitates a deeper understanding of underlying issues. The model explanation component builds trust by providing interpretable visual representations of clustering results and contextualizing potential error causes, easing insight generation (4). Experts engage in knowledge externalization by systematically categorizing errors and annotating potential causes (5). This process enriches the underlying data repository by contributing well-defined labels for error categories (6), which in turn strengthens future analysis and diagnostics. Overall, this integrated approach empowers BMW's experts to transform raw acoustic data into actionable intelligence, improving engine manufacturing and maintenance strategies. This innovative process not only mitigates production risks but also enhances overall product quality.

6. Discussion and Limitations

What is Knowledge?: Unlike many VA process models and conceptual structures, the HDMI Canvas does not treat knowledge as a main entity. First, because humans are an entity directly. Second, because knowledge is not the only human value worth considering. Third, because defining knowledge is difficult, what information artifacts it includes, and what not. Depending on the research context, different notions exist, such as in strong connection to epistemology in philosophy, or evidence in empirical research. The HDMI Canvas uses knowledge and preferences as a tandem to highlight the need for both objective and subjective information.

Data Actors?: The role of data as an independent actor in VA processes remains debated. At its most passive, data is merely an information state. At its most active, it interacts with the VA system, receiving inputs and generating outputs—like a database responding to a query ("bring the algorithms to the data"). For designers and developers, key questions arise: What responsibilities would data actors have in a VA process? How should data interact with humans and models? What goals should it pursue? To function meaningfully, what must it receive from human and model actors, and what does data contribute to the overall VA objectives? These reflections challenge the passive perception of data, opening avenues for treating it as a more dynamic actor–be it in the design process or during data analysis–an idea for future work.

VA Outreach: Part of the goal was to create a canvas that also helps to communicate essential building blocks of powerful VA systems to external stakeholders, using a form of communication that helps external people to on-board easily, without the need to internalize VA-intrinsic methodologies. For that purpose, the HDMI Canvas is already in use, and qualitative feedback from external stakeholders is positive, indicating its utility, and valuing VA as a central research field in the human-model-data spectrum. However, empirical data does not yet exist to back up the utility claim made.

7. Conclusions

This position paper reflects on VA process models and community observations, motivating a fresh perspective on VA, useful for collaboration with external stakeholders. Beyond the scope already nicely covered by state-of-the-art, it introduces the HDMI Canvas, which organizes humans, data, and models as actors in a VA canvas. The HDMI Canvas provides enhanced structural depth, clarifying how each of the actors can benefit from and contribute to VA processes more collaboratively. The descriptive power of the HDMI Canvas helps to distinguish existing approaches as demonstrated in two case studies, while the generative power can aid the design of novel VA approaches in collaborative and interdisciplinary settings.

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