

Singapore Management University

Institutional Knowledge at Singapore Management University

Research Collection School Of Computing and Information Systems

School of Computing and Information Systems

3-2015

Personal visualization and personal visual analytics

Dandan HUANG

Melanie TORY

Bon Adriel ASENIERO

Lyn BARTRAM

Scott BATEMAN

See next page for additional authors

Follow this and additional works at: https://ink.library.smu.edu.sg/sis_research



Part of the [Graphics and Human Computer Interfaces Commons](#)

Citation

HUANG, Dandan; TORY, Melanie; ASENIERO, Bon Adriel; BARTRAM, Lyn; BATEMAN, Scott; CARPEDALE, Sheelagh; TANG, Anthony; and WOODBURY, Robert. Personal visualization and personal visual analytics. (2015). *IEEE Transactions on Visualization and Computer Graphics*. 21, (3), 420-433.

Available at: https://ink.library.smu.edu.sg/sis_research/7996

This Journal Article is brought to you for free and open access by the School of Computing and Information Systems at Institutional Knowledge at Singapore Management University. It has been accepted for inclusion in Research Collection School Of Computing and Information Systems by an authorized administrator of Institutional Knowledge at Singapore Management University. For more information, please email cherylds@smu.edu.sg.

Author

Dandan HUANG, Melanie TORY, Bon Adriel ASENIERO, Lyn BARTRAM, Scott BATEMAN, Sheelagh CARPEDALE, Anthony TANG, and Robert WOODBURY

Personal Visualization and Personal Visual Analytics

Dandan Huang, Melanie Tory, Bon Adriel Aseniero, Lyn Bartram, Scott Bateman, Sheelagh Carpendale, *Member, IEEE Computer Society*, Anthony Tang, and Robert Woodbury

Abstract—Data surrounds each and every one of us in our daily lives, ranging from exercise logs, to archives of our interactions with others on social media, to online resources pertaining to our hobbies. There is enormous potential for us to use these data to understand ourselves better and make positive changes in our lives. Visualization (Vis) and visual analytics (VA) offer substantial opportunities to help individuals gain insights about themselves, their communities and their interests; however, designing tools to support data analysis in non-professional life brings a unique set of research and design challenges. We investigate the requirements and research directions required to take full advantage of Vis and VA in a personal context. We develop a taxonomy of design dimensions to provide a coherent vocabulary for discussing personal visualization and personal visual analytics. By identifying and exploring clusters in the design space, we discuss challenges and share perspectives on future research. This work brings together research that was previously scattered across disciplines. Our goal is to call research attention to this space and engage researchers to explore the enabling techniques and technology that will support people to better understand data relevant to their personal lives, interests, and needs.

Index Terms—Taxonomy, personal context, interaction design, mobile and ubiquitous visualization

1 INTRODUCTION

WE are surrounded by data in our everyday lives. Many times these data relate to our professional interests, but increasingly we have access to data that has little to do with our work. For instance, we now have access to immense data stores about our communities (e.g., census data). Due to commercial availability of sensors, data describing our health and fitness (e.g., exercise logs, pedometer data) and even our resource usage (e.g., utilities such as water, electricity use) are easily available to us. These data are relevant to our personal lives—they enable us to explore information about ourselves, our communities, and issues that are personally relevant and important to us. Furthermore, existing commercial systems are making visual exploration and reasoning more widely accessible for use in personal situations.

However, research into the use of visualization (Vis) and visual analytics (VA) in personal contexts has been distributed across several different research communities. This means that many common lessons, findings, issues and gaps may be missed even though these research communities actually share many common goals. In this paper we unify much of this previous work and establish a common

research agenda for visualization tools and studies that seek to empower everyday people through exploring data. To do this we describe previous and future work as being part of a new field and research community called personal visualization (PV) and personal visual analytics (PVA).

Personal visualization involves the *design of interactive visual data representations for use in a personal context*, and personal visual analytics is the *science of analytical reasoning facilitated by visual representations used within a personal context*. The difference between the two areas is analogous to the difference between Vis and VA—Personal Visual Analytics involves both visualization and automatic computer assisted analysis, whereas Personal Visualization focuses on visual data representations. We note that in normal conversation and writing we expect that people will use either PV or PVA, but not both terms together. However, for the purposes of our current review and summary of the areas, in this document we will refer to the two areas collectively as PV&PVA.

The main question that PV&PVA is concerned with is: *How can the power of visualization and visual analytics be made appropriate for use in personal contexts—including for people who have little experience with data, visualization, or statistical reasoning?* There is enormous potential for us to use data to make positive changes in our personal lives and the lives of others, but as visualization and visual analytics experts are well aware, greater availability of data does not on its own lead to new insights. Data must be accessible, understandable, and interpretable before interacting with it can lead to insights or actionable knowledge. Adoption of PV&PVA technologies also depends on how well those technologies fit into people's daily environments and routines.

PV&PVA builds on work in visualization and visual analytics and aims to empower everyday users to develop insights within a *personal context*. Personal context implies non-professional situations, in which people may have quite

- D. Huang and M. Tory are with the University of Victoria. E-mail: dhuang@uvic.ca, mtory@cs.uvic.ca.
- B.A. Aseniero, S. Carpendale, and A. Tang are with the University of Calgary. E-mail: {b.aseniero, sheelagh, tonyt}@ucalgary.ca.
- L. Bartram and R. Woodbury are with the Simon Fraser University. E-mail: {lyn, rw}@sfu.ca.
- S. Bateman is with the University of Prince Edward Island. E-mail: sbateman@upe.ca.

Manuscript received 14 Feb. 2014; revised 24 May 2014; accepted 4 Sept. 2014. Date of publication 22 Sept. 2014; date of current version 30 Jan. 2015.

Recommended for acceptance by M. Agrawala.

For information on obtaining reprints of this article, please send e-mail to: reprints@ieee.org, and reference the Digital Object Identifier below.

Digital Object Identifier no. 10.1109/TVCG.2014.2359887

different motivations, priorities, role expectations, environments, or time and resource budgets as compared to professional situations. Because of these differences, PV&PVA designs necessarily have new requirements and challenges that bring new opportunities for Vis and VA research.

By defining the area of PV&PVA, we hope to provide common ground for research. PV&PVA unites research that is current distributed across visualization, human-computer interaction (HCI), ubiquitous computing, and personal informatics (PI) communities. A successful research agenda for PV&PVA really relies on this unification: PI informs the collection and management of personally relevant data, HCI and ubiquitous computing help us to design effective sensing devices and interactions that fit into people's everyday environments, and visualization helps us understand how to support visual data exploration and analysis activities.

In this paper, we review existing PV&PVA literature across several fields to identify common approaches, findings and gaps. Through our review we establish an initial set of design dimensions to characterize this space and provide a common vocabulary that will make it easier to relate and share information between fields. Our goal is to explore the emerging interest in this field and offer a new perspective on the challenges that arise when designing for personal contexts. We see this work as a new starting point for different fields to learn about one another, thereby unifying a larger community.

In the following sections, we first define the space of PV&PVA (Section 2). We then describe our methods and present a taxonomy of design dimensions based on our literature review (Section 3). Following this, we summarize recent research trends (Section 4) and use our taxonomy to identify interesting topics that have been explored to date (Section 5). Finally, we discuss design challenges and share our perspectives on future research in PV&PVA.

2 DEFINING THE SPACE OF PERSONAL VISUALIZATION AND PERSONAL VISUAL ANALYTICS

We have defined personal visualization and personal visual analytics in terms of *personal context*: PV&PVA tools are designed for and used within personal contexts. So what exactly is personal context? In activity theory, Nardi [66] argued that context is “both internal, involving specific objects and goals—and, at the same time, external to people, involving artifacts, other people, and specific settings”. This concept has been already applied in HCI practice. Internally, context could be “abstract artifacts” [1], such as goals, skill sets, preferences, experience, etc. Externally, context could be either physical constraints (e.g., physical environments or devices) or social influence (e.g., norms in a community or division of labor).

We distinguish personal context from *personal data* (i.e., data about oneself). While PV&PVA applications often involve personal data as well, it is not a requirement of our definition. For example, a person might be interested in exploring census statistics that do not necessarily have personal relevance and are not directly their own data; our definition of PV&PVA is inclusive enough to encompass this type of application.

Our focus on personal context leads to some differences from traditional Vis & VA and some new and interesting research challenges. Most traditional visualization applications focus on supporting expert analysts with respect to their occupational roles, which means typical systems (except perhaps those for situational awareness) presume that analysts will have long periods of time to do deep analysis of the data, using workstations with substantial computing power and large screens.

In a personal context, by contrast, people may look into their data with different goals, backgrounds, and expectations (i.e., internal context). While these differences may not exist in every case, our point is that they *very often* exist and are therefore worthy of design and research attention. People may have a lower priority and time budget for performing analytical tasks when they are not part of a work-role expectation, and their motivations may differ from those of people in professional contexts, as discussed by Sprague and Tory [76]. The vast majority of people are not visualization or data analytics experts, so analytic tools will need to be accessible. Memories, skills, knowledge, values, and culture impact how people perceive visualizations and interpret data, and this may be particularly true when people perceive the world from a self-centered perspective (i.e., reasoning about things with respect to oneself). In some cases, data may be meaningful only to the individual. External factors that may characterize personal context include devices, use context and social influence. People may use a wide variety of different devices according to the situation, such as mobile devices on the go and ambient displays in their homes. Meanwhile, social influence may impact their behaviors and decisions (e.g., sharing information or experience, setting group goals, or comparing one's performance with peers).

Interactions in a personal context could be different as well. While some people may actively execute deep analytical tasks indistinguishable from most traditional visualization tasks (e.g., Quantified Self or performance training for fitness activities), other tasks could involve passive attention [83] (e.g., ongoing monitoring or ambient awareness facilitated by mobile devices and ambient displays). These passive attention activities need to fit seamlessly into other aspects of people's lives. The point here is not to draw a perfect boundary between PV&PVA and traditional Vis & VA, but rather to highlight a set of new challenges and opportunities that arise when we explicitly consider designing for a personal context.

As PV&PVA research broadens the scope of visualization and visual analytics, it also subsumes many related fields, including casual InfoVis [69], InfoVis for the Masses [21], persuasive computing [30] and personal informatics [56], [59]. Personal Informatics has become an established research area, and PI tools have been applied to a number of domains, such as health and environmental conservation. However, PI tools and research have largely focused on data collection rather than data presentation and interaction. With their definition of casual infovis, Pousman et al. [69] brought attention to “InfoVis edge cases”. However, while their focus was to identify high-level categories of systems that were outside of traditional InfoVis, our focus here is to articulate a taxonomy of design dimensions that characterize PV&PVA.

Further, we note that we consider “traditional InfoVis systems” to be part of PV&PVA when they are used in a personal context. Similarly, InfoVis for the Masses [21] encouraged the Vis community to reach a broader audience, a philosophy we also support. However, they had a somewhat narrow focus, primarily on infographics and news media, that forms only a small part of PV&PVA.

The past work in these fields provides much of the foundational knowledge needed for PV&PVA, and addresses many individual aspects of design, but research in these fields has been isolated. We are intentionally inclusive in our definitions to support our aim of uniting research that currently spans several fields.

3 RESEARCH METHODS AND DESIGN SPACE

In this section, we describe our research method, which we used to articulate a set of design dimensions characterizing the design space of PV&PVA research. These dimensions relate to data, context, interaction and insights (Table 1). Later in the paper, we use the dimensions to identify clusters of work in PV&PVA and discuss future challenges.

As part of our iterative process, we conducted an extensive literature survey of PV&PVA designs. We systematically identified relevant papers from TVCG (including VIS papers), CHI papers and notes, UBICOMP, INTERACT, AVI, EuroVis, and PacificVis from 2008-2012, plus CHI 2013 since those papers were available at the time. Relevance was based on meeting all of the following criteria:

- Data were about oneself, one’s family or community, or relevant to personal interest or needs.
- Designs were intended to help people develop insights within a personal context (system design goal). Visualizations designed to support occupational roles or tasks were excluded (e.g., those specifically designed for domain experts or analysts in an occupational role).
- Designers intended the visualizations to be viewed from a non-professional perspective (e.g., from a self-centered viewpoint). Visualizations intended for use from an analyst’s perspective or that required professional training were excluded.
- Research focused on visualization and interaction design or their evaluation. Papers that focused on system architecture, system optimization or algorithms were excluded.

This resulted in a set of 59 papers. We complemented this list with an additional seven papers that we had encountered elsewhere (but which still fit in the selection criteria); these were typically reported in domain-specific venues or beyond the time range of our search. Together, these formed the collection of PV&PVA papers (see the summary in Table 2) that we read in detail and used to develop and refine our dimensions.

We developed our taxonomy of PV&PVA design dimensions using an iterative, bottom-up approach. Our objective was to develop a set of dimensions that could adequately describe and distinguish among PV&PVA tools in the literature as well as those that we had created or encountered through our own research. The dimensions evolved much like a process of open coding, where we developed a set of

dimensions and levels, mapped the literature to it, and then adjusted the dimensions and levels when one or more tools did not fit well. We considered our set of dimensions and levels to be complete when we reached consensus and could adequately represent the unique attributes of PV&PVA tools in our collection.

Our dimensions focus on design attributes that are important to PV&PVA applications, that are not well characterized by existing taxonomies, and that can distinguish among the tools that we encountered in our literature review. We did not attempt, for example, to come up with a new taxonomy of visualization tasks, since those are already well characterized by others and are probably very similar in PV&PVA applications, at least at a low unit task level. Instead, we categorize the design space based on aspects of the data, context, interaction, and insights that characterized the papers we reviewed. Secondarily, we also coded each paper’s evaluation method and venue type.

We note that our taxonomy is intended as a starting point to foster PV&PVA research and thus should not be considered complete and definitive. As PV&PVA becomes established as a field and research within it evolves and expands, these design dimensions will need to grow and adjust.

To reduce redundancy while discussing the design dimensions (Table 1), when more than one paper was based on the same visualization tool we refer only to their latest version of the tool (thus the following seven were removed: [13], [17], [19], [27], [46], [47], [48]). This reduced the set of 66 papers to 59 designs that we coded and mapped to a parallel plot of design dimensions. Exploring the plot helped us to identify design trends and research interest to date. The most prevalent characteristics of existing PV&PVA tools can be observed by looking at the sizes of the boxes (representing levels within the dimensions) in Fig. 1.

We would also like to acknowledge the rapid growth in industry practice related to PV&PVA, most notably the quantified self movement. Wearable devices are widely used to collect daily activities in an unintrusive way, e.g., Fitbit, Nike Fuelband, Jawbone, etc. People also have access to health measures (e.g., sleep quality) with devices like Body-Media and Zeo. Mobile apps that connect to sensors embedded in smartphones provide similar functionality. In addition, applications such as open.sen.se and Exist help individuals integrate and manage data from all their devices and apps. The substantial industry interest in PV&PVA suggests promise for future growth in this field. Obviously, these industry tools share common ground with academic work and also fit our search criteria. As we refined our design dimensions, we considered whether they could also describe and distinguish the commercially available tools that we were familiar with. However, for tractability, our comprehensive review focuses on the academic literature.

4 CURRENT RESEARCH TRENDS

Research attention in PV&PVA has been steadily increasing over the past five years (Table 2) and the greatest number of papers has come from the HCI community. The papers cover a variety of applications that address most aspects of daily life, e.g., residential energy consumption, fitness, personal health, social networks, politics, residential environment,

TABLE 1
Design Dimensions, Levels within Each Dimension, and Examples from the Literature

	Dimensions	Definition	Levels	Examples
Data	Data Scope	Who the data is about	self family peers community	Sleep quality [7] Internet bandwidth shared at home [14] Relationship with friends [37] Hang-out patterns on campus [75], online conversations [29]
	Data Effort	Amount of effort that is expended in data collection	none sensor manual mixed	Online search history [6] Nonobtrusive sensing devices, e.g. wearable sensors [31] Manual logging pictures and annotations [62] Combination of sensor recording and manual input [58]
	Data Agency	The degree of control a person has over what data is collected, and when and how it is collected	no control partial control total control	Online conversation logs [29] Users have control of whether or not to collect the data, but cannot customize what data they would like to collect [31] Manually recorded children's photos and growth progress [45]
Context	Design Context	Who designed and developed the application	self group participatory third party	Visualization designed by oneself Tools designed by a study group to chart their progress Using an online survey to get feedback on early visual design concepts [31] Visualization of music listening history designed by the researcher [9]
	Settings	In what situation the tool is used and how it is used	personal domestic mobile shared public mixed	Personal laptop (mostly non-mobile but used by oneself) [65] Ambient display at home (mostly non-mobile) [32] Used on a mobile phone while on-the-go [31] Visualization of physical activities viewed by co-workers [60] Visualization to promote energy conservation presented in a public space [41] Combination of above, e.g., visualization of residential energy on a personal computer and a mobile phone [5]
	Influence Context	Who the application is intended to inform	self family community mixed	My physical condition [19] Children's growth progress [45] Inform public about elections [84] Encourage water drinking for peers and oneself [16]
Interaction	Attentional Demand	How much attention is required to interact with the tool	low mixed high	Cell phone wall paper [7], ambient display [32] Pedometer counter on a cell phone and the historical data on a desktop [58] Exploration of music listening history with focused attention [9]
	Explorability	The ability to explore the data	low mixed high	Visual metaphor representing one's physical activities [31] Data overview on a cell phone and exploration of history data on a client service [5] Exploring historical data with dynamic queries [9]
Insight	Actionability	Degree to which the insight gained from using the tool can guide future actions	low mixed high	Does not inform further action, e.g., supports reminiscing about the past [68] Smartphone app that gives reminders about when to exercise and enables reflection on progress via historical records [58] Engages a certain behavior, e.g., encourage energy conservation [50]
	Automated Analysis	Data mining or other automated analysis methods are employed	Yes/No	Classify physical activities to types of transportation [31]

life logging, personal finance, and recycling. In 56 out of 66 papers, researchers evaluated their designs using one or more methods (details in Table 3). We also found that most designs published in the VIS community in our selection were either not evaluated (three out of 10 cases) or were evaluated only in a controlled lab study with a focus on efficiency and errors (four out of 10 cases). Conversely, in papers published in HCI venues, researchers most often deployed the tool in the field (33 out of 49 cases). These field studies were

usually for a short period ranging from one week to one month (Fig. 2). Deployments for more than six months were rarely considered. We further discuss evaluation of PV&PVA designs in Section 6.7.

Our parallel plot visualization (Fig. 1 and supplemental material, which can be found on the Computer Society Digital Library at <http://doi.ieeecomputersociety.org/10.1109/TVCG.2014.2359887>) reveals that most PV&PVA tools were designed to help individuals explore their own data (i.e.,

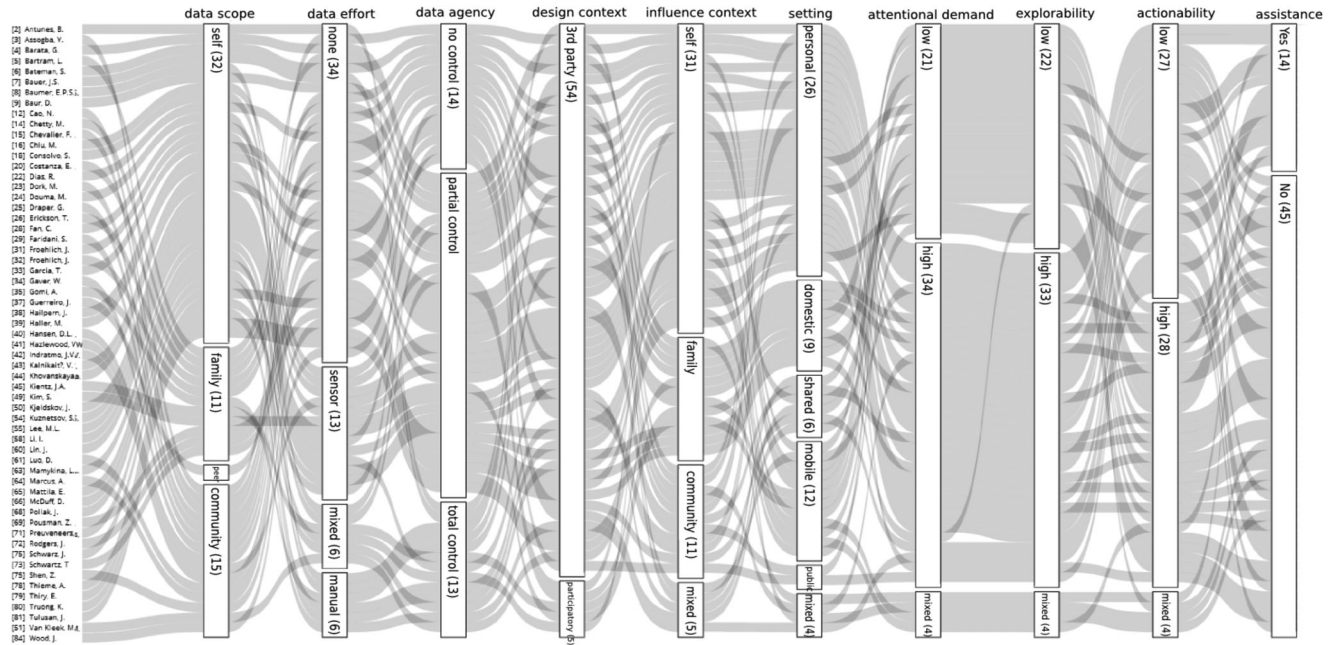


Fig. 1. PV&PVA design dimensions (parallel axes) and surveyed tools (first axis). Box sizes indicate the number of tools with each classification. Linked highlighting enables cluster exploration. (See the visualization tool itself and additional images in the supplemental material, available online.)

data about themselves, see the large box for Data Scope: Self). From a data effort level, the most common situation was that data were either provided, requiring no effort (e.g., by web servers or system logs) or non-intrusively collected by sensors (with partial personal control). If data collection required no effort or people had little control over the data collection, the tools mostly had low actionability (34 out of 45 cases, seen by hovering the mouse over “no effort” or “no control” in the interactive visualization). We also found that people could achieve total control over data collection (what, how and when to record) only when they manually recorded or organized data; this occurred mostly in applications for personal health (nine out of 13 cases). Much less control was provided if data were collected through public channels such as social networks.

From the perspective of context, most of the tools were intended to develop insights for one’s family or oneself. We observed that nearly all PV&PVA tools were designed by third parties (we reflect on this design perspective in Section 6.5). However, the literature suggests that involving participants in the design process (participatory design) might be related to higher actionability (all five

participatory designs achieved high actionability). Meanwhile, the tool set in our selection covers most use contexts: ambient displays at home, mobile devices on the go, personal computers or laptops used in a personal space, shared views with others, and displays for the public. It seems that applying mobile devices and shared views aimed to achieve higher actionability (14 out of 16 cases).

PV&PVA designs also covered a wide range of interactions, facilitating diverse attentional demands and explorability. Many of the tools, mostly with mobile devices or ambient displays, did not require focused attention (25 out of 59 cases).

From an insight perspective, not all PV&PVA designs were intended to reveal actionable knowledge (low actionability: 27 out of 59 cases). People also used these tools to satisfy their curiosity (e.g., exploring census data), to reminisce about experiences, or to share with others (e.g., exploring activity traces at home). Interestingly, although automated computational assistance (e.g., classification algorithms) is common in visual analytics generally, this type of analysis was not common in tools that we surveyed (14 out of 59 cases). Examples included sentiment analysis and classification of physical activities. This issue is discussed in Section 6.6.

TABLE 2
Summary of Surveyed Papers

	VIS Community	HCI Community	Other	Total
Before 2008			2	2
2008	2	6	1	9
2009	1	7	0	8
2010	3	6	3	12
2011	2	8	0	10
2012	2	16	1	19
2013		6		6
Total	10	49	7	66

TABLE 3
Summary of Evaluation Methods Showing the Number of Papers that Included Each Evaluation Type

Evaluation	VIS Community	HCI Community	Other	Total
None	3	6	1	10
Lab study	4	11	0	15
Interview	2	2	1	5
Survey	1	2	0	3
Field Study	0	33	5	38

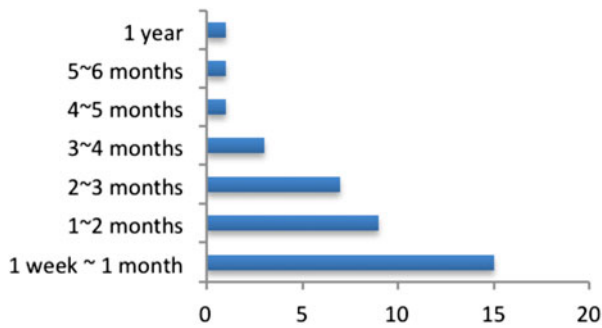


Fig. 2. Histogram showing duration of field studies.

5 RESEARCH INTEREST TO DATE

In this section we describe interesting clusters that we observed by exploring our interactive visualization of the design space (Fig 1). (See the supplemental material, available online, for the interactive visualization itself and for additional details and images related to the clusters.) Our goal, given PV&PVA's nascent state, was to explore the emerging interest in this field (What have people been working on?) and identify possible gaps (i.e., research opportunities) rather than to systematically categorize the space.

At the beginning of each section, we highlight the main design dimensions that characterized each cluster. These dimensions were sufficiently correlated in the visualization to make the cluster stand out through exploration. Note that the clusters were not meant to be mutually exclusive; instead they illustrated interesting relationships between design dimensions and highlighted some research trends to date. In addition, there was no small subset of dimensions that was able to characterize the research trends to date, so each cluster was characterized by a different set of dimensions and levels.

5.1 Enabling Exploration for Curiosity

Attentional Demand (high), Explorability (high), and Actionability (mostly low): Designs in this cluster enabled people to explore data to satisfy their curiosity. They therefore usually required high attentional demand and supported a high level of explorability. Insights obtained from using the tools were typically not very actionable (i.e. the outcome might help me to better understand myself, but does not tell me how to change my life). Low actionability

also corresponded to the goal of using the tool, which was often to understand something rather than to support taking specific actions or making changes.

Tools in this category were similar to traditional visualization tools, but usually had a self-centered focus (“my documents” [2], “my computer usage” [4], “places I have been to” [43] or “my finance” [74]). These tools enabled user exploration facilitated by typical analytical tasks such as select, reconfigure, encode, elaborate, filter, connect, etc. For example, Baur et al. designed a tool enabling users to explore their music listening history from last.fm (Fig. 3a) [9]. With exploratory interactions (like traditional InfoVis techniques) people could investigate their listening patterns or re-experience a special life event in the past (as musical experiences are usually associated with events).

For many tools in this cluster, personal knowledge and experience played an important role in the data interpretation process. For example, whether or not someone listens to music on a particular date depends on daily routines and special events [9]. Spending data can be explained by relevant routine activities, e.g., coffee drinking habits [74]. This implies that effectiveness of tools in this category could be dependent on highly personal factors. Yet most evaluations of tools in this cluster (12 out of 16) involved lab studies measuring task efficiency and error rate on experimentally controlled tasks with “hard-coded” use contexts. While such laboratory studies are common practice in VIS and VA research, they have limitations for evaluating PV&PVA applications. The need for new evaluation approaches is discussed further in Section 6.7.

Interaction techniques for tools in this cluster supported exploration (high explorability) that may help people narratively develop stories from their data. This might be the first phase of adoption (see discussion in Section 6.1). We suggest that adding aesthetic and “fun” factors may attract attention and inspire curiosity, e.g., providing a quantitative view of a friendship [37], comparing searching performance with expert searchers [6], or metaphorically illustrating tweet streams [12].

5.2 Supporting Awareness for Action

Attentional Demand (low), Explorability (low), and Actionability (mostly high): Applications in this cluster aimed to provide in-the-moment or on-going awareness with respect to personal behaviors (e.g., avoiding activities that would

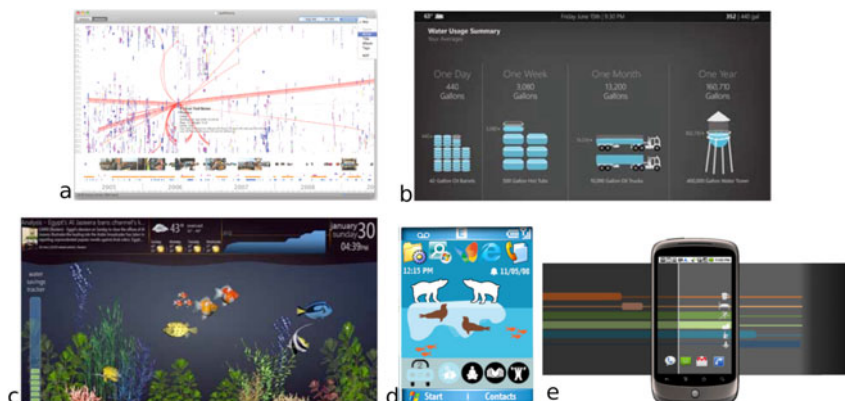


Fig. 3. Example PV&PVA tools (a. Streams of our lives; b. Metaphorical Unit views; c. Aquatic Ecosystem; d. UbiGreen; e. ShutEye).

harm sleep patterns, tracking blood sugar, or inducing green transportation habits). Designs usually supported continuous awareness (low attentional demand), enabled looking up data with a quick glance (low explorability), and provided in-the-moment feedback or suggestions for immediate action (high actionability).

Designs usually aimed to encourage behavioral change for personal health or energy conservation, and tried to fit into people's lives through a strategy of ambience (e.g., cell phone wallpaper). That is, by combining low attentional demand and just-sufficient salience, they avoided interrupting life routines. For example, ShutEye (Fig. 3e) provided sleep-related activity reminders through cell phone wallpaper [7]. It used simple bar charts to recommend a timeline for certain activities (e.g., avoid coffee 6 hours before bedtime). Interactions with tools in this cluster tended to be simple to fit in the on-the-go or ambient context and to efficiently provide key information as needed. Traditional desktop-based analytical techniques and interactions may be inappropriate here because of the high attentional demand they require.

Some tools in this cluster used machine learning or data mining algorithms to assist with data aggregation or disaggregation, e.g., classifying accelerometer data into physical activities [19] or disaggregating water consumption based on water use behaviors [32]. Additionally, some used metaphors to remind people of the potential impact of their behavior. For example, to remind people about global warming and encourage them to take green transportation [31], a polar bear on a piece of ice was displayed (Fig. 3d); the ice began to melt if the user's behavior was not environmentally friendly. This example also reveals some special PV&PVA requirements in terms of aesthetics (See discussion in Section 6.1).

In addition, social influence was often used as a persuasive strategy to engage behavior change (e.g., for drinking more water [16], staying physically active [60] or encouraging recycling [78]). In these examples, visualization was mostly used in a shared view among peers. For example, in Fish'n'Step [60], an individual's physical-activity level was represented by the size and color of a fish. Other fish in the same fish tank represented peers; thereby, the design used peer pressure and social competition to encourage healthy behavior. However, in some cases, inappropriate social strategies actually made the design less effective or caused undue stress. BinCam [78], which applied social surveillance to engage better recycling behavior, evoked feelings of guilt and shame. Meanwhile, viewing other people's personal data also brings up privacy concerns. We discuss these issues in Section 6.4.

5.3 Taking Care of Family

Data scope (family), influence context (family), and setting (domestic): Systems designed for families focused on data about family members or the home environment, and were used or deployed domestically. Some applications used decorative ambient displays to make the technology less intrusive and better fit in the home environment [32]; others ran on a personal computer, enabling close exploration and organization of family data to track progress [45]. Researchers also deployed visualizations on a TV system to enable people to view real-time energy use at home [73].

These applications mostly aimed to reveal actionable insights, e.g., for health [45], residential energy conservation [20], [26], [32] or resource sharing in the home [14]. A different example is tableau machine [68], a visualization of family traces that enabled family members to reminisce about their shared domestic life experiences.

Applications for family enabled some degree of control over data collection, either total control over how, when and what to collect (two out of 11), or partial control over when to collect (nine out of 11). Some designs also considered individual differences among family members. For example, "Aquatic ecosystem" views (Fig. 3c) may be more attractive and engaging to children [32], while some adults may prefer more traditional visual representations (e.g., line graphs or bar charts). Some designs aimed to provide additional contextual knowledge to help people interpret the primary data and achieve actionable insight; for example, one application linked energy consumption data to specific home appliances [20] and another represented measurement units using well-known quantities such as "hot tubs" and "oil trucks" to depict water usage (Fig. 3b) [32]. Sometimes complementary information from experts provided educational value or reference points (e.g., monitoring children's development in comparison to established developmental milestones [45]).

Inevitably, close interactions among family members can bring up issues of competition, cooperation and privacy. For example, a visualization of Internet traffic [14] was designed to educate family members about their shared Internet usage. Family members could view each other's online activities and bandwidth usage could be prioritized with respect to social roles. Here, some family members noted an unwelcome intrusion on privacy.

Based on the trends in these tools, we suggest that functionality and interaction design for "family" tools might need to focus on engaging family members and fostering communication between them. Visualization design and interaction techniques should also balance the diversity of users in a family, with respect to cognitive capabilities, skills, and social roles.

5.4 Reflecting on Communities

Data scope (community), data effort (none), data agency (no control), and influence context (community): Applications in this cluster demonstrated people's interest in data about their community. These designs were usually intended to inform the public or a certain social group, e.g., raising public awareness of elections [84], supporting easy exploration of survey data [25], or revealing topics evolving from social networks [23], [29]. The data were mostly from system logs or online portals, so little data collection effort was required (data effort: none), resulting in no control over the collection (data agency: no control).

These applications were mostly used for reflection purposes (e.g., exploring social patterns on campus [75], investigating how topics of tweets evolve over time [23], or comparing the vote rank of candidates in an election [84]). In a few examples, they were also used to encourage behaviors valued within the community. For example, Hazlewood et al. [41] deployed ambient displays in a department lobby to incite energy conservation in the building and encourage physical activity (using the stairs rather than the elevator).

Many of the papers in this cluster were published in the VIS community (six out of 10), perhaps indicating a similarity to other Vis and VA applications. Tools in this cluster mostly supported focused data exploration tasks; they employed many traditional visualization techniques to facilitate deep analysis, usually requiring high attentional demand. In several cases, automated computational analysis was used for mining large data sets from social networks (four out of 11), e.g., peak-finding [63] and sentiment analysis [23].

Traditional Vis and VA techniques may work well to support reflection on community data. However, since public data may not be too personally relevant, we speculate that such tools may benefit from employing additional engagement strategies to enhance interpretation. Examples include supporting exploration from different perspectives to capture relevant context [75] and employing non-traditional representations to compensate for the limited analytics skills of non-experts [25].

6 CHALLENGES

Now that we have described the kinds of research that comprise the PV&PVA field, hopefully the reader can see that PV&PVA brings forth a set of new design and research challenges. These new challenges arise because of the unique nature of personal context (e.g., role expectations, environments, and related activities). For example, PV&PVA systems may need to support people with limited visualization literacy and analytics experience, fit into personal life routines and physical surroundings, support fleeting and short term use, support recall of relevant events, and apply appropriate baselines to support reasoning about data. While some of these challenges are not completely new, PV&PVA introduces a unique perspective on these challenges, and emphasizes their importance. In this section, we articulate some of the key challenges that we consider important for advancing the field of PV&PVA. The challenges are a call to action: future research needs to address these issues to enhance PV&PVA tools and expand their impact.

6.1 Fit in Personal Routines and Environments

Any tool needs to be designed to fit within its physical environment and context of use. In a personal context, physical environments and activity routines can be quite different from those in professional contexts, leading to new design challenges. For example, we may wish to support fleeting use of a fitness tracking application without interrupting one's life routines, or customize a visualization's appearance so that it matches the aesthetic of a living room where it will be deployed.

Fitting into people's lives means that designers should consider availability, accessibility and ease of use for long-term adoption. Kim identified two stages of how people adopt everyday technologies [49]: in the early stage, interest is the main motivation; then gradually the tool is adopted into daily routines. In a later stage, people's practices with the tool become "rational reasoning rather than from an unconscious and habitual reiteration"; that is, using the tool becomes part of their routines. People's goals are mostly realized in the latter stage; however, the transition to this stage

takes time. Furthermore, whether the transition occurs at all depends on how easily the tool fits into the person's life.

There are many barriers that limit the adoption of PV&PVA tools. One way to reduce these barriers is to consider the context of use; for example, designers can reduce the effort required to collect and organize data, so tools can be used with minimal effort or at-a-glance. Visualization designs can be integrated with tools or devices that people use or encounter regularly in their daily routines. Examples include information appliances in the home, ambient wall "art", and mobile devices. For instance, a visualization integrated into mobile phone wallpaper would be frequently encountered as people use their phones.

Aesthetics of a PV&PVA tool (how it looks, how it is to be used, even its physical manifestation) must suit not only personal taste, but also its place context. Most notably, ambient visualizations that will be integrated into people's environments, especially their homes, present additional design challenges. A PV&PVA tool might expose its information as coloured lights in a kitchen backsplash rather than as a set of charts on a computer screen. Such a display would need to convey information to its audience and also be welcomed by the inhabitants of the house as part of their decor. Such displays probably need to emphasize visual appeal and customizability over efficiency of data interpretation.

In summary, PV&PVA tools need to naturally "fit" into people's lives in order to be successfully adopted. This includes not only physical environments but also human routines. Pre-design empirical research (e.g., ethnographic studies) can help designers gather information about these aspects of people's lives and ensure a proper fit for the final design.

6.2 Recall of Relevant Context for Reasoning

A challenge in PV&PVA is that the appropriate context for interpreting the primary data may not be in the form of data that is easily accessible. Activity theory [1] has recognized that people's understanding and use of information artifacts are strongly influenced by their internal context (experience, preferences, competencies, values, etc.) Relevant internal context for interpreting data in a PV&PVA tool might be the knowledge of one's own past activities, feelings, and interactions with others. From previous experience, a person may be aware that drinking coffee in the evening would cause insomnia [7]. Understanding their temporal patterns of energy use may be difficult without knowing what they were doing at certain times of the day. Some of this necessary context is in the form of memories that are recalled to explain past behaviors. Lee and Dey conducted a study with older people on pill-taking [55]. Participants tended to explain anomalies of pill taking (i.e., forgetting to take pills on time) with "routines and their subtle variations", mostly by digging into their memories. But memory is fallible and imprecise, particularly for older people in this case. Adding additional data from other sources (e.g., with help from context-aware technologies) may help to trigger people's memory and enable them to better make sense of the primary data. We found some encouraging examples in the literature, for example, cultivating actionable knowledge [73] or reminiscing about the past [79].

Overall, relevant context can relate to individual differences, personal experiences, view perspectives, and social

encounters. One challenge is that the appropriate context may vary for different people and in different situations. Identifying types of contextual data that will be more generically useful, and devising flexible mechanisms to enable people to recall or recognize contextual data that they consider relevant, may help to enrich the inferential knowledge that people bring when using PV&PVA tools, supporting richer insights.

6.3 Defining Appropriate Baselines

Making comparisons is a fundamental way to gain insights from data, and this is equally true for PV&PVA applications. For example, in Baby Steps [45], parents could compare their children's development to milestones provided by a pediatrician. Froehlich et al. [32] used a Metaphorical Unit view (see Fig. 3b), mapping systematic water-consumption units to commonly understandable everyday objects (e.g., jugs or oil trucks). For diabetes control, doctors could recommend the base insulin dosage plan. People could learn about nutrition from a national food guide. In other words, people often need a reference (or baseline) to understand and assess their current situation.

But what baseline should be used for comparison? One challenge is to understand what makes an appropriate comparison set. Should a person's energy usage data be compared to their prior usage levels? Should it be compared to a national average? Should it be compared to their peers' data or data from demographically equivalent people? What does "demographically equivalent" mean? "Appropriate baseline" is an elusive idea, mainly because it depends so heavily on the context of use, goals, and also on each person's values. For instance, many people may be interested in leading healthy lives. Yet, what constitutes "healthy" may differ—for one person, it may be the absence of stress; for another, whether he is sleeping well; for another, her adherence to a national food guide. It is unlikely that we could define a single baseline to satisfy all these goals and values. Moreover, the appropriate baseline is likely to change along with the questions the person is trying to answer. As a possible solution to this challenge, future designs might provide flexibility for a person to choose different baselines depending on their situation and goals or automatically present comparisons with a variety of baselines.

6.4 Sharing and Privacy

Sharing experiences and spaces with others (family, friends, social groups, etc.) is an important aspect of everyday life. Already there are many PV&PVA tools with an influence context beyond the self. Examples include tools for sharing memories and experiences among family members or friends [68], [79]. One intriguing space is to apply social interactions to enhance motivation or persuade behavior change, for example, setting group goals [60], comparing your own progress to others' [16], or even interfering with social surveillance [78]. However, this approach should be applied carefully, since social interactions may also evoke negative emotions such as stress or guilt. Moreover, because sharing may enable people to see each other's data (e.g., when using data from peers or the neighborhood as a baseline), privacy must be considered.

For displays of personal data (data about oneself), people may desire even more privacy. We believe that PV&PVA tools will frequently be used by a single viewer, interwoven throughout their day. In some situations we may actually want to have a display that *cannot* be easily interpreted by everyone; it may be important to deliberately design visualizations that are incomprehensible to everyone but the owner. Such designs may be particularly important when personal interest is intrinsic and where privacy may be a concern. In such situations, highly personal-data encodings may be an essential design feature. One example is UbiFit, which provided a view of one's physical activities over the past week on a mobile phone, but did so with an abstract visualization of flowers in a garden. This abstraction aimed to be evocative and personally motivating, and had the benefit of making the data difficult or impossible to read by any other person. This kind of approach is important, since our personal data may be in public view (here on a mobile phone, but perhaps alternatively as an ambient display), and we may want to be selective about to *whom* we reveal the meaning of the display. The possible focus on visualization that is both revealing and insightful to a single viewer and concealing or at least neutral to others is a design approach that has not previously been considered in Vis or VA.

6.5 Diversifying Design Perspectives

PV&PVA tools often aim to help people gain insight into their own lives. However, current designs are mostly devised by system designers, who seem to decide "what information to present" and "what metaphor should convey the message" without considering the unique perspectives of individuals. Although many systems in our survey involved users in the design process, nearly all of them were designed by a third party (see Fig. 1). Such designs could be fragile in the face of human and contextual diversity. The disjunction between users and designers may elicit feelings of powerlessness or stress, inhibiting long-term use. We found many comments to this effect in post-study interview results. For example, UpStream [54] was designed to encourage people to use less water for showering, but the countdown display "induced too much guilt, making showering unnecessarily stressful". BinCam [78], which adopted social surveillance to engage better recycling behaviors, similarly evoked feelings of being "guilty or ashamed." Furthermore, a survey of persuasive technology in sustainability indicated limited evidence for behavior change, particularly over the long-term [10]. Studies have also shown that negative emotions may cause stress and prevent lasting adoption [53].

The question of how much control people can and should have over their data and visualizations remains to be answered. In an inspiring study by Byrne et al., [11], participants were asked to design visualizations, assisted by a custom-designed storytelling application, to tell stories from others' life-logging data. It might be powerful to have a flexible framework that helps people design visualizations for themselves, when they have interest in doing so. Another consideration is the support for group design. Designing visualization tools for peers or groups could engage people in social interactions. For example, constructing one's life history together with family or friends [79] could improve the sharing experience. We consider this a realistic goal: with

the right tools, people should be able to customize a visualization enough that they feel that they have designed it themselves. (Even Wordle, a very simple word-cloud visualization, had enough personalization options to allow people to feel “creative” [82].)

Yet another way to diversify design perspectives is to apply variety of design strategies. Returning to the persuasive technologies discussion earlier in this section, recent critiques have argued that persuasive strategies might narrow people’s vision, because they are based on the assumption that human behavior can be measured and modeled [10]. What behaviors should change, and in what way, are predetermined by designers, and the systems try to actively encourage behavior change in these directions. An alternative design strategy could be to encourage reflection, enabling people to freely explore historical data and actively link current questions with previous experiences and context. For example, designs could help individuals understand their consumption data to cultivate energy literacy [73]. Reflective and persuasive technologies could be complementary, each providing value in different situations. While persuasive methods may encourage certain in-the-moment decisions, reflective tools may encourage people to actively understand their own behavior and set personally meaningful goals.

6.6 Integrating Computer Assisted Analysis

Often in large amounts of data, even with a good visual representation, patterns are not easily recognizable. In addition, some people using PV&PVA tools may spend limited time and effort on analysis of their data. Computer algorithms, on the other hand, are very good at identifying some kinds of patterns in large data sets. Computer assisted pattern recognition could relieve the burden on human attention and reveal interesting insights. Integrating automated analysis approaches with visualization has been at the core of visual analytics research. However, to date, these techniques have been much less prominent in tools designed for a personal context. In our survey, we found only 14 examples of automated analysis in a total of 59 tools. Techniques included clustering or classification [2], [3], [18], [31], [32], [65], layout optimization [2], [24], [75], text analysis [2], [23], [63], dimension reduction [29], and state recognition [70]. Khovanskaya et al. also explored data mining infrastructure for personal informatics [44].

Another promising direction could be to apply data mining and machine learning methods to support exploratory browsing. For example, people could investigate what-if experiments. Before making decisions, people could evaluate the impact of possible solutions [77]. For example, what if I change half of the bulbs into energy efficient ones? What if I change all of them? What if I modify settings of the programmed thermostats? By comparing the possible solutions and their impact, people could have flexibility to make decisions that are affordable or acceptable. Accordingly, in this what-if exploration, interactions would not be limited to visual components. People could also interact with the underlying mathematical models in an intuitive way.

Automated techniques inevitably have design trade-offs. These techniques could simplify the analysis process by modeling problems with expert knowledge. On the other

hand, computer models are likely to have flaws and may not consider all possible factors. For example, ubiGreen [31] could not recognize all physical activities, such as biking. Deep analysis is often a long-term process that involves building a mental model of the data; in these cases, automated techniques should facilitate the process of compiling evidence and producing insights rather than simply generating a conclusion. For example, user input could complement automated data collection [31], the same data could be represented and interpreted with different perspectives [32], or context could be provided to validate computer classification [65].

6.7 Evaluation

Evaluation of visualization and VA tools has been an ongoing research discussion for several years. PV&PVA is no exception, and in fact, presents some unique challenges for evaluation. Designers often aim for PV&PVA tools to integrate seamlessly into people’s life routines, physical environments, and social situations; these contexts of use would be very difficult to simulate in a controlled lab study. Moreover, we also need to re-consider the metrics that are typically used to assess VA or Vis systems. Time, error, and insights are not the only relevant metrics for evaluating PV&PVA tools, and often may not be the most important ones.

We see *ease* as a conceptual metric that could be used as one basis for evaluating PV&PVA tools. That is, how easily does the tool fit into one’s daily life, habits, and routine? Can one “ease” into the use of the tool without effortfully breaking from one’s current activities? Can one easily answer the questions they might have of their dataset? Can one easily interpret and understand a visual presentation? Can one easily grow with the tool, moving towards more sophisticated analysis as they gain experience? A flip side of ease is unease: what are the barriers to use that a system imposes [36], [52]? Only a few studies have addressed this adoption issue. In the latest study with Dubuque [26], 40 percent of the participants reported that they rarely used the system. Obviously, adoption barriers are critical to consider in PV&PVA research.

Note that our concept of *ease* goes far beyond the traditional “ease of use” metric. While ease of use is one relevant aspect, we think of ease much more broadly. Ease can be considered analogous to “comfort”. With our concept of ease we can ask whether a tool fits comfortably into people’s environments, routines, habits, and social experiences. We can also ask how that comfort level changes as people gain experience with the tool and as their life routines and relationships evolve and adapt over time.

While operationalizing this concept of “ease” is challenging, it should be clear that conventional metrics used to evaluate visualization tools (i.e., task completion time, task errors, and even insights [72]) are not only insufficient, they may be the wrong metrics to use altogether for many scenarios. One unique characteristic of PV&PVA tools is that they may be used to “fill the gaps” in time when one is bored, curious, or doing something else [79]. In contrast, our canonical view of VA tool use is one of a focused information worker actively seeking information or insights. While someone using a PV&PVA tool might be focused on discovering complex insights (e.g., tracking health symptoms), they might be equally likely to use it for

purposes such as fun or awareness. Appropriate evaluation methods and metrics for assessing PV&PVA tools are urgently needed to support future research.

7 CONCLUSION AND OUR VISION

In this paper we introduce Personal Visualization and Personal Visual Analytics, a field that aims to empower people to gain awareness of, explore, and learn from data in *personal contexts*. PV&PVA brings unique design requirements because in everyday life, data interpretation and insight development are mediated by personal context, including environments, settings, personal experiences, skill sets, prior knowledge, and social influences. We explored salient characteristics of PV&PVA tools in relevant conference proceedings from the past five years. Our resulting design dimensions should help designers and researchers better understand the unique characteristics and requirements in this field.

PV&PVA research is underway and growing. Our work is a call to the visualization community that it is time to begin exploring the potential of visualization and analytic tools that play a meaningful role in people's personal lives, interests and information needs. Our design dimensions provide a starting point for shared discussions and future research related to PV&PVA, but they are only a beginning. To be successful in personal contexts and environments, visualization and interaction techniques may need to be substantially revised to meet the unique design requirements. Similarly, existing sensemaking models may need to be extended in order to explain insight development and knowledge discovery with PV&PVA applications, particularly for tools with a low attentional demand. Furthermore, existing methods for evaluating visualization and VA tools are insufficient to understand how well a tool "fits" within a personal context; new metrics and methods need to be devised to enable a richer understanding.

This work is a call to arms. We believe that integrating techniques from a variety of areas (including visualization, analytics, ubiquitous computing, human-computer interaction, and personal informatics) will lead to more powerful, engaging and useful interactive data experiences for everyone. There is a definite future for the tools and systems that we have termed PV&PVA: they are already out there and are being actively used. This means that the need for more research is urgent. People are already visualizing their spending habits, exercise, and sleep patterns, but there is little knowledge about whether these endeavors are successful, how they might be improved, and how they will impact people's lives. We hope that we can engage others to explore the enabling techniques and technologies that will support people to better understand data relevant to their personal lives, interests, and needs.

ACKNOWLEDGMENTS

This research was funded by NSERC and GRAND.

REFERENCES

- [1] D. Allen, S. Karanasios, and M. Slavova, "Working with activity theory: Context, technology, and information behavior," *J. Amer. Soc. Inf. Sci. Technol.*, vol. 62, no. 4, pp. 776–788, 2011.

- [2] B. Antunes, T. Guerreiro, and D. Gonçalves, "This just in! Your life in the newspaper," in *Proc. 12th IFIP TC 13 Int. Conf. Human-Comput. Interaction*, 2009, vol. 5727, pp. 279–292.
- [3] Y. Assogba, I. Ros, J. DiMicco, and M. McKeon, "Many bills: Engaging citizens through visualizations of congressional legislation," in *Proc. SIGCHI Conf. Human Factors Comput. Syst.*, New York, NY, USA, 2011, pp. 433–442.
- [4] G. Barata, H. Nicolau, and D. Gonçalves, "AppInsight: What have I been doing?" in *Proc. Int. Working Conf. Adv. Vis. Interfaces*, New York, NY, USA, 2012, pp. 465–472.
- [5] L. Bartram, J. Rodgers, and R. Woodbury, "Smart homes or smart occupants? supporting aware living in the home," in *Proc. 13th IFIP TC 13 Int. Conf. Human-Comput. Interaction - Vol. Part II*, Berlin, Germany, 2011, pp. 52–64.
- [6] S. Bateman, J. Teevan, and R. W. White, "The search dashboard: How reflection and comparison impact search behavior," in *Proc. SIGCHI Conf. Human Factors Comput. Syst.*, New York, NY, USA, 2012, pp. 1785–1794.
- [7] J. S. Bauer, S. Consolvo, B. Greenstein, J. Schooler, E. Wu, N. F. Watson, and J. Kientz, "ShutEye: Encouraging awareness of healthy sleep recommendations with a mobile, peripheral display," in *Proc. SIGCHI Conf. Human Factors Comput. Syst.*, New York, NY, USA, 2012, pp. 1401–1410.
- [8] E. P. S. Baumer, S. J. Katz, J. E. Freeman, P. Adams, A. L. Gonzales, J. Pollak, D. Retelny, J. Niederdeppe, C. M. Olson, and G. K. Gay, "Prescriptive persuasion and open-ended social awareness: Expanding the design space of mobile health," in *Proc. ACM Conf. Comput. Supported Cooperative Work*, New York, NY, USA, 2012, pp. 475–484.
- [9] D. Baur, F. Seiffert, M. Sedlmair, and S. Boring, "The streams of our lives: Visualizing listening histories in context," *IEEE Trans. Vis. Comput. Graph.*, vol. 16, no. 6, pp. 1119–1128, Dec. 2010.
- [10] H. Brynjarsdottir, M. Hakansson, J. Pierce, E. Baumer, C. DiSalvo, and P. Sengers, "Sustainably unpersuaded: how persuasion narrows our vision of sustainability," in *Proc. ACM Annu. Conf. Human Factors Comput. Syst.*, New York, NY, USA, 2012, pp. 947–956.
- [11] D. Byrne, A. Kelliher, and G. J. F. Jones, "Life editing: Third-party perspectives on lifelog content," in *Proc. SIGCHI Conf. Human Factors Comput. Syst.*, New York, NY, USA, 2011, pp. 1501–1510.
- [12] N. Cao, Y.-R. Lin, X. Sun, D. Lazer, S. Liu, and H. Qu, "Whisper: Tracing the spatiotemporal process of information diffusion in real time," *IEEE Trans. Vis. Comput. Graph.*, vol. 18, no. 12, pp. 2649–2658, Dec. 2012.
- [13] M. Chetty, R. Banks, R. Harper, T. Regan, A. Sellen, C. Gkantsidis, T. Karagiannis, and P. Key, "Who's hogging the bandwidth: The consequences of revealing the invisible in the home," in *Proc. SIGCHI Conf. Human Factors Comput. Syst.*, New York, NY, USA, 2010, pp. 659–668.
- [14] M. Chetty, D. Haslem, A. Baird, U. Ofoha, B. Sumner, and R. Grinter, "Why is my internet slow?: Making network speeds visible," in *Proc. SIGCHI Conf. Human Factors Comput. Syst.*, New York, NY, USA, 2011, pp. 1889–1898.
- [15] F. Chevalier, S. Huot, and J.-D. Fekete, "WikipediaViz: Conveying article quality for casual Wikipedia readers," in *Proc. IEEE Pacific Vis. Symp.*, 2010, pp. 49–56.
- [16] M.-C. Chiu, S.-P. Chang, Y.-C. Chang, H.-H. Chu, C. C.-H. Chen, F.-H. Hsiao, and J.-C. Ko, "Playful bottle: A mobile social persuasion system to motivate healthy water intake," in *Proc. 11th Int. Conf. Ubiquitous Comput.*, New York, NY, USA, 2009, pp. 185–194.
- [17] S. Consolvo, P. Klasnja, D. W. McDonald, D. Avrahami, J. Froehlich, L. LeGrand, R. Libby, K. Mosher, and J. A. Landay, "Flowers or a robot army?: Encouraging awareness & activity with personal, mobile displays," in *Proc. 10th Int. Conf. Ubiquitous Comput.*, 2008, pp. 54–63.
- [18] S. Consolvo, D. W. McDonald, and J. A. Landay, "Theory-driven design strategies for technologies that support behavior change in everyday life," in *Proc. SIGCHI Conf. Human Factors Comput. Syst.*, New York, NY, USA, 2009, pp. 405–414.
- [19] S. Consolvo, D. W. McDonald, T. Toscos, M. Y. Chen, J. Froehlich, B. Harrison, P. Klasnja, A. LaMarca, L. LeGrand, R. Libby, I. Smith, and J. A. Landay, "Activity sensing in the wild: A field trial of ubifit garden," in *Proc. SIGCHI Conf. Human Factors Comput. Syst.*, New York, NY, USA, 2008, pp. 1797–1806.
- [20] E. Costanza, S. D. Ramchurn, and N. R. Jennings, "Understanding domestic energy consumption through interactive visualisation: A field study," in *Proc. ACM Conf. Ubiquitous Comput.*, New York, NY, USA, 2012, pp. 216–225.

- [21] M. Danziger, "Information visualization for the people," Master thesis, Dept. Comparative Media Studies, Massachusetts Inst. Technol., Cambridge, MA, USA, 2008.
- [22] R. Dias, M. J. Fonseca, and D. Goncalves, "Interactive exploration of music listening histories," in *Proc. Int. Working Conf. Adv. Vis. Interfaces*, New York, NY, USA, 2012, pp. 415–422.
- [23] M. Dork, D. Gruen, C. Williamson, and S. Carpendale, "A visual backchannel for large-scale events," *IEEE Trans. Vis. Comput. Graph.*, vol. 16, no. 6, pp. 1129–1138, Dec. 2010.
- [24] M. Douma, G. Ligierko, O. Ancuta, P. Gritsai, and S. Liu, "SpicyNodes: Radial layout authoring for the general public," *IEEE Trans. Vis. Comput. Graph.*, vol. 15, no. 6, pp. 1089–1096, Dec. 2009.
- [25] G. Draper and R. Riesenfeld, "Who votes for what? A visual query language for opinion data," *IEEE Trans. Vis. Comput. Graph.*, vol. 14, no. 6, pp. 1197–1204, Dec. 2008.
- [26] T. Erickson, M. Li, Y. Kim, A. Deshpande, S. Sahu, T. Chao, P. Sukaviriya, and M. Naphade, "The dubuque electricity portal: Evaluation of a city-scale residential electricity consumption feedback system," in *Proc. ACM Annu. Conf. Human Factors Comput. Syst.*, New York, NY, USA, 2013, pp. 1203–1212.
- [27] T. Erickson, M. Podlaseck, S. Sahu, J. D. Dai, T. Chao, and M. Naphade, "The dubuque water portal: Evaluation of the uptake, use and impact of residential water consumption feedback," in *Proc. ACM Annu. Conf. Human Factors Comput. Syst.*, New York, NY, USA, 2012, pp. 675–684.
- [28] C. Fan, J. Forlizzi, and A. K. Dey, "A spark of activity: Exploring informative art as visualization for physical activity," in *Proc. ACM Conf. Ubiquitous Comput.*, New York, NY, USA, 2012, pp. 81–84.
- [29] S. Faridani, E. Bitton, K. Ryokai, and K. Goldberg, "Opinion space: A scalable tool for browsing online comments," in *Proc. SIGCHI Conf. Human Factors Comput. Syst.*, New York, NY, USA, 2010, pp. 1175–1184.
- [30] B. Fogg, "Persuasive computers: Perspectives and research directions," in *Proc. SIGCHI Conf. Human Factors Comput. Syst.*, Los Angeles, CA, USA, 1998, pp. 225–232.
- [31] J. Froehlich, T. Dillahunt, P. Klasnja, J. Mankoff, S. Consolvo, B. Harrison, and J. A. Landay, "UbiGreen: Investigating a mobile tool for tracking and supporting green transportation habits," in *Proc. 27th Int. Conf. Human Factors Comput. Syst.*, New York, NY, USA, 2009, pp. 1043–1052.
- [32] J. Froehlich, L. Findlater, M. Ostergren, S. Ramanathan, J. -Peterson, I. Wragg, E. Larson, F. Fu, M. Bai, S. Patel, and J. A. Landay, "The design and evaluation of prototype eco-feedback displays for fixture-level water usage data," in *Proc. SIGCHI Conf. Human Factors Comput. Syst.*, New York, NY, USA, 2012, pp. 2367–2376.
- [33] T. Garcia, J. Aires, and D. Goncalves, "Who have I been talking to?" in *Proc. Int. Working Conf. Adv. Vis. Interfaces*, New York, NY, USA, 2012, pp. 481–484.
- [34] W. Gaver, A. Boucher, A. Law, S. Pennington, J. Bowers, J. Beaver, J. Humble, T. Kerridge, N. Villar, and A. Wilkie, "Threshold devices: looking out from the home," in *Proc. SIGCHI Conf. Human Factors Comput. Syst.*, New York, NY, USA, 2008, pp. 1429–1438.
- [35] A. Gomi, T. Itoh, and K. Zhang, "Meal—A menu evaluation system with symbolic icons in mobile devices," in *Proc. Int. Working Conf. Adv. Vis. Interfaces*, New York, NY, USA, 2012, pp. 772–773.
- [36] L. Grammel, M. Tory, and M. Storey, "How information visualization novices construct visualizations," *IEEE Trans. Vis. Comput. Graph.*, vol. 16, no. 6, pp. 943–952, Dec. 2010.
- [37] J. Guerreiro and D. Goncalves, "Visualiz'em: 'Show me more about him!'" in *Proc. Int. Working Conf. Adv. Vis. Interfaces*, New York, NY, USA, 2012, pp. 445–448.
- [38] J. Hailpern, N. Jitkoff, A. Warr, K. Karahalios, R. Sesek, and N. Shkrob, "YouPivot: Improving recall with contextual search," in *Proc. SIGCHI Conf. Human Factors Comput. Syst.*, New York, NY, USA, 2011, pp. 1521–1530.
- [39] M. Haller, C. Richter, P. Brandl, S. Gross, G. Schossleitner, A. Schrempf, H. Nii, M. Sugimoto, and M. Inami, "Finding the right way for interrupting people improving their sitting posture," in *Proc. 13th IFIP TC 13 Int. Conf. Human-Computer Interaction*, 2011, vol. 6947, pp. 1–17.
- [40] D. L. Hansen, B. Shneiderman, and M. Smith, "Visualizing threaded conversation networks: Mining message boards and e-mail lists for actionable insights," in *Proc. 6th Int. Conf. Active Media Technol.*, Berlin, Germany, 2010, pp. 47–62.
- [41] W. R. Hazlewood, E. Stolterman, and K. Connolly, "Issues in evaluating ambient displays in the wild: Two case studies," in *Proc. Annu. Conf. Human Factors Comput. Syst.*, New York, NY, USA, 2011, pp. 877–886.
- [42] Indratmo, J. Vassileva, and C. Gutwin, "Exploring blog archives with interactive visualization," in *Proc. Working Conf. Adv. Vis. Interfaces*, New York, NY, USA, 2008, pp. 39–46.
- [43] V. Kalnikaite, A. Sellen, S. Whittaker, and D. Kirk, "Now let me see where I was: Understanding how lifelogs mediate memory," in *Proc. SIGCHI Conf. Human Factors Comput. Syst.*, New York, NY, USA, 2010, pp. 2045–2054.
- [44] V. Khovanskaya, E. P. S. Baumer, D. Cosley, S. Volda, and G. Gay, "'Everybody knows what you're doing': A critical design approach to personal informatics," in *Proc. ACM Annu. Conf. Human Factors Comput. Syst.*, New York, NY, USA, 2013, pp. 3403–3412.
- [45] J. A. Kientz, R. I. Arriaga, and G. D. Abowd, "Baby steps: Evaluation of a system to support record-keeping for parents of young children," in *Proc. SIGCHI Conf. Human Factors Comput. Syst.*, New York, NY, USA, 2009, pp. 1713–1722.
- [46] J. A. Kientz, R. I. Arriaga, M. Chetty, G. R. Hayes, J. Richardson, S. N. Patel, and G. D. Abowd, "Grow and know: Understanding record-keeping needs for tracking the development of young children," in *Proc. SIGCHI Conf. Human Factors Comput. Syst.*, New York, NY, USA, 2007, pp. 1351–1360.
- [47] S. Kim and E. Paulos, "inAir: Measuring and visualizing indoor air quality," in *Proc. 11th Int. Conf. Ubiquitous Comput.*, New York, NY, USA, 2009, pp. 81–84.
- [48] S. Kim and E. Paulos, "inAir: Sharing indoor air quality measurements and visualizations," in *Proc. SIGCHI Conf. Human Factors Comput. Syst.*, New York, NY, USA, 2010, pp. 1861–1870.
- [49] S. Kim, E. Paulos, and J. Mankoff, "inAir: A longitudinal study of indoor air quality measurements and visualizations," in *Proc. SIGCHI Conf. Human Factors Comput. Syst.*, New York, NY, USA, 2013, pp. 2745–2754.
- [50] J. Kjeldskov, M. B. Skov, J. Paay, and R. Pathmanathan, "Using mobile phones to support sustainability: A field study of residential electricity consumption," in *Proc. ACM Annu. Conf. Human Factors Comput. Syst.*, New York, NY, USA, 2012, pp. 2347–2356.
- [51] M. Van Kleek, D. A. Smith, H. S. Packer, J. Skinner, and N. R. Shadbolt, "Carpe data: Supporting serendipitous data integration in personal information management," in *Proc. SIGCHI Conf. Human Factors Comput. Syst.*, New York, NY, USA, 2013, pp. 2339–2348.
- [52] A. J. Ko, B. A. Myers, and H. H. Aung, "Six learning barriers in end-user programming systems," in *Proc. IEEE Symp. Vis. Language—Human Centric Comput.*, Washington, DC, USA, 2004, pp. 199–206.
- [53] C. Kormos, "Anticipated changes to quality of life and the impact of divergent social normative information: A field experiment on sustainable transportation behaviour," Master thesis, Dept. Psychology, Univ. Victoria, Victoria, BC, Canada, 2009.
- [54] S. Kuznetsov and E. Paulos, "UpStream: Motivating water conservation with low-cost water flow sensing and persuasive displays," in *Proc. SIGCHI Conf. Human Factors Comput. Syst.*, New York, NY, USA, 2010, pp. 1851–1860.
- [55] M. L. Lee and A. K. Dey, "Reflecting on pills and phone use: Supporting awareness of functional abilities for older adults," in *Proc. SIGCHI Conf. Human Factors Comput. Syst.*, New York, NY, USA, 2011, pp. 2095–2104.
- [56] I. Li, A. Dey, and J. Forlizzi, "A stage-based model of personal informatics systems," in *Proc. 28th Int. Conf. Human Factors Comput. Syst.*, New York, NY, USA, 2010, pp. 557–566.
- [57] I. Li, A. K. Dey, and J. Forlizzi, "Understanding my data, myself: Supporting self-reflection with ubicomp technologies," in *Proc. 13th Int. Conf. Ubiquitous Comput.*, New York, NY, USA, 2011, pp. 405–414.
- [58] I. Li, A. K. Dey, and J. Forlizzi, "Using context to reveal factors that affect physical activity," *ACM Trans. Comput.-Human Interaction*, vol. 19, no. 1, pp. 1–21, 2012.
- [59] I. Li, J. Forlizzi, and A. Dey, "Know thyself: Monitoring and reflecting on facets of one's life," in *Proc. 28th International Conference on Human Factors in Computing Systems: Extended Abstracts Human Factors Comput. Syst.*, New York, NY, USA, 2010, pp. 4489–4492.
- [60] J. Lin, L. Mamykina, S. Lindtner, G. Delajoux, and H. Strub, "Fish'nSteps: Encouraging Physical Activity with an Interactive Computer Game," in *Proc. 8th Int. conf. Ubiquitous Comput.*, 2006, vol. 4206, pp. 261–278.

- [61] D. Luo, J. Yang, M. Krstajic, W. Ribarsky, and D. A. Keim, "EventRiver: Visually Exploring Text Collections with Temporal References," *IEEE Trans. Vis. Comput. Graph.*, vol. 18, no. 1, pp. 93–105, Jan. 2012.
- [62] L. Mamykina, E. Mynatt, P. Davidson, and D. Greenblatt, "MAHI: Investigation of social scaffolding for reflective thinking in diabetes management," in *Proc. SIGCHI Conf. Human Factors Comput. Syst.*, New York, NY, USA, 2008, pp. 477–486.
- [63] A. Marcus, M. S. Bernstein, O. Badar, D. R. Karger, S. Madden, and R. C. Miller, "Twitinfo: Aggregating and visualizing microblogs for event exploration," in *Proc. SIGCHI Conf. Human Factors Comput. Syst.*, New York, NY, USA, 2011, pp. 227–236.
- [64] E. Mattila, I. Korhonen, J. H. Salminen, A. Ahtinen, E. Koskinen, A. Säreälä, J. Pärkkä, and R. Lappalainen, "Empowering citizens for well-being and chronic disease management with wellness diary," *IEEE Trans. Inf. Technol. Biomed.*, vol. 14, no. 2, pp. 456–463, Mar. 2010.
- [65] D. McDuff, A. Karlson, A. Kapoor, A. Roseway, and M. Czerwinski, "AffectAura: An intelligent system for emotional memory," in *Proc. SIGCHI Conf. Human Factors Comput. Syst.*, New York, NY, USA, 2012, pp. 849–858.
- [66] B. A. Nardi, Chapter 4: "Studying context: A comparison of activity theory, situated action models, and distributed cognition," in *Context and Consciousness: Activity Theory and Human-Computer Interaction*, Cambridge, MA, USA: MIT Press, 1996, ch. 4.
- [67] J. Pollak, G. Gay, S. Byrne, E. Wagner, D. Retelny, and L. Humphreys, "It's time to eat! using mobile games to promote healthy eating," *IEEE Pervasive Comput.*, vol. 9, no. 3, pp. 21–27, Jul. 2010.
- [68] Z. Pousman, M. Romero, A. Smith, and M. Mateas, "Living with tableau machine: A longitudinal investigation of a curious domestic intelligence," in *Proc. 10th Int. Conf. Ubiquitous Comput.*, New York, NY, USA, 2008, pp. 370–379.
- [69] Z. Pousman, J. Stasko, and M. Mateas, "Casual information visualization: Depictions of data in everyday life," *IEEE Trans. Vis. Comput. Graph.*, vol. 13, no. 6, pp. 1145–1152, Nov./Dec. 2007.
- [70] D. Preuveneers and Y. Berbers, "Mobile phones assisting with health self-care: A diabetes case study," in *Proc. 10th Int. Conf. Human Comput. Interaction Mobile Devices Serv.*, New York, NY, USA, 2008, pp. 177–186.
- [71] J. Rodgers and L. Bartram, "Exploring ambient and artistic visualization for residential energy use feedback," *IEEE Trans. Vis. Comput. Graph.*, vol. 17, no. 12, pp. 2489–2497, Dec. 2011.
- [72] P. Saraiya, C. North, and K. Duca, "An evaluation of microarray visualization tools for biological insight," in *Proc. IEEE Symp. Inf. Vis.*, 2004, pp. 1–8.
- [73] T. Schwartz, S. Deneff, G. Stevens, L. Ramirez, and V. Wulf, "Cultivating energy literacy: Results from a longitudinal living lab study of a home energy management system," in *Proc. SIGCHI Conf. Human Factors Comput. Syst.*, New York, NY, USA, 2013, pp. 1193–1202.
- [74] J. Schwarz, J. Mankoff, and H. S. Matthews, "Reflections of everyday activities in spending data," in *Proc. SIGCHI Conf. Human Factors Comput. Syst.*, New York, NY, USA, 2009, pp. 1737–1740.
- [75] Z. Shen and K.-L. Ma, "MobiVis: A visualization system for exploring mobile data," in *Proc. IEEE Pacific Vis. Symp.*, 2008, pp. 175–182.
- [76] D. W. Sprague and M. Tory, "Motivation and procrastination: Methods for evaluating pragmatic casual information visualizations," *IEEE Comput. Graph. Appl.*, vol. 29, no. 4, pp. 86–91, Aug. 2009.
- [77] M. Sun, "Exploring aesthetic visualization for promoting consumer energy conservation," Master thesis, Simon Fraser Univ., Burnaby, BC, Canada, 2014.
- [78] A. Thieme, R. Comber, J. Miebach, J. Weeden, N. Kraemer, S. Lawson, and P. Olivier, "'We've bin watching you': Designing for reflection and social persuasion to promote sustainable lifestyles," in *Proc. SIGCHI Conf. Human Factors Comput. Syst.*, New York, NY, USA, 2012, pp. 2337–2346.
- [79] E. Thiry, S. Lindley, R. Banks, and T. Regan, "Authoring personal histories: Exploring the timeline as a framework for meaning making," in *Proc. SIGCHI Conf. Human Factors Comput. Syst.*, New York, NY, USA, 2013, pp. 1619–1628.
- [80] K. N. Truong, J. A. Kientz, T. Sohn, A. Rosenzweig, A. Fonville, and T. Smith, "The design and evaluation of a task-centered battery interface," in *Proc. 12th ACM Int. Conf. Ubiquitous Comput.*, New York, NY, USA, 2010, pp. 341–350.

- [81] J. Tulusan, T. Staake, and E. Fleisch, "Providing eco-driving feedback to corporate car drivers: What impact does a smartphone application have on their fuel efficiency?" in *Proc. ACM Conf. Ubiquitous Comput.*, New York, NY, USA, 2012, pp. 212–215.
- [82] F. B. Viegas, M. Wattenberg, and J. Feinberg, "Participatory visualization with wordle," *IEEE Trans. Vis. Comput. Graph.*, vol. 15, no. 6, pp. 1137–1144, Dec. 2009.
- [83] T. D. Wilson, "Models in information behaviour research," *J. Documentation*, vol. 55, no. 3, pp. 249–270, Aug. 1999.
- [84] J. Wood, D. Badawood, J. Dykes, and A. Slingsby, "BallotMaps: Detecting name bias in alphabetically ordered ballot papers," *IEEE Trans. Vis. Comput. Graph.*, vol. 17, no. 12, pp. 2384–2391, Dec. 2011.



Dandan Huang received the BEng degree from the University of Electronic Science & Technology of China in 2005 and the MSc degree from the University of Victoria in 2009. She is currently working toward the PhD degree and as a research assistant at the University of Victoria. Her research focuses on information visualization and human-computer interaction, with a particular interest in applying information visualization and visual analytics within everyday life contexts.



Melanie Tory received the BSc degree from the University of British Columbia in 1999 and the PhD degree from Simon Fraser University in 2004. She was a postdoctoral fellow at the University of British Columbia from 2004 to 2006 and is currently an associate professor of computer science at the University of Victoria. She is an associate editor at the *IEEE Computer Graphics and Applications* and *Papers* co-chair for *IEEE Information Visualization 2014-2015*. Her research focuses on collaborative visualization, sensemaking, PV&PVA, and empirical research to inform visualization design.



Bon Adriel Aseniero graduated with the BSc degree in computer science in 2012 from the University of Calgary, and is currently working toward the MSc degree from the same institution. He received the Alberta Innovates Technology and Futures (AITF) MSc provincial scholarship grant. His research interests include the design of information visualizations, personal informatics, and ubiquitous computing.



Lyn Bartram received the BA degree in political science degree in 1975 from UBC, the MMath degree in computer science in 1988 from the University of Waterloo, and the PhD degree in computing in 2001 from Simon Fraser University. She is an associate professor in Interactive Art + Technology at Simon Fraser University. Her research spans visualization, visual analytics, human-computer interaction and psychology, with a focus on the use of information and computing systems for improving sustainability in the built environment. In addition to numerous publications in the field of occupant behavior, energy conservation, and building technology design, she has led the development of interactive systems for two high-profile next-generation houses, earning awards in the architectural domain. She is the national leader of the Sustainability theme in the Canadian Network of Centres of Excellence in Graphics, Animation and New Media (GRAND).



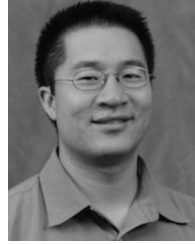
Scott Bateman received the BSc degree from UPEI in 2001, and the MSc and PhD degrees from Saskatchewan, in 2007 and 2012, respectively. He is an assistant professor of computer science at the University of Prince Edward Island, an adjunct professor at the University of Saskatchewan, and an associate editor with the *International Journal of Human-Computer Studies*. He received a Best Paper Award at CHI 2010. He is broadly interested in the area of HCI, and particularly interested in how the exploration of personal

data, especially in combination with social comparison, can lead to positive behavior change.



Sheelagh Carpendale is a professor of computer science at the University of Calgary, where she holds a Canada Research chair in Information Visualization and an NSERC/AITF/SMART Technologies Industrial research chair in Interactive Technologies. She has received the E.W.R. NSERC STEACIE Memorial fellowship; a British Academy of Film & Television Arts Interactive Awards (BAFTA), an ASTech Innovations in Technology Award, and the CHCCS Achievement Award, which is presented periodically to a

Canadian researcher who has made a substantial contribution to the fields of computer graphics, fields of computer graphics, visualization, or human-computer interaction. She is an internationally renowned leader in both information visualization and multi-touch tabletop interaction and has recently served in such roles as Papers, Program, or Conference chair for IEEE InfoVis, PacificVis, and ACM Tabletop and has received both the IEEE and ACM recognition of service awards. She is a member of the IEEE Computer Society.



Tony Tang is an assistant professor in the Department of Computer Science at the University of Calgary. His research interests are situated in Computer Supported Cooperative Work (CSCW)—the study of how people work together using technology—with a twist of Ubiquitous Computing—technology in everyday scenarios. His current research investigates the integration of mobile devices in large display environments, explorations into personal informatics, and telecommunication technolo-

gies for collaborative work.



Robert Woodbury Graduated with the bachelor of architecture degree in 1981 from Carleton University, MSc degree in 1982 and the PhD degree in 1988 both from Carnegie Mellon University (CMU). He has held academic positions at CMU, The University of Adelaide and Simon Fraser University. He received the Tee Sasada Award of the Association for Computer-Aided Architectural Design Research in Asia and the Award for Innovative Research of the Association for Computer Aided Design in Architecture.

He has published many scientific publications, including the recent book *Elements of Parametric Design*. His research interests include computational design, visual analytics and interactive systems.

▷ For more information on this or any other computing topic, please visit our Digital Library at www.computer.org/publications/dlib.