An Emergent Design Study Methodology for Education: Reflections on the ROBIN System for Visualizing U.S. Migration Data

Alexander Bendeck*
Georgia Institute of Technology

Clio Andris†
Georgia Institute of Technology

John Stasko‡
Georgia Institute of Technology

ABSTRACT

The design study methodology is a standard approach for visualization researchers to build useful tools for domain experts in a specific field. While designing solely for domain experts is sometimes necessary, the standard methodology ignores the role that experts often play as educators in their field, especially when the data at hand may be of interest to broader audiences. In this paper, we discuss the iterative design process of the ROBIN visualization system for U.S. migration data, which was designed as an educational tool and communication aid. We also reflect on the differences between our approach and that of a traditional design study, and we outline opportunities for future work in designing visualization systems with both educator and student stakeholders. We believe that our work has the potential to promote further discussion about how to design visualization tools for education and communication.

Index Terms: Design studies, education, methodology, migration visualization.

1 INTRODUCTION

The design study methodology [49] is a common approach in the visualization community where researchers work with an expert or team of experts in a particular field to solve a domain-specific problem. Despite commonly resulting in powerful visualization systems, design study projects have been criticized as producing "one-off" or "bespoke" solutions that often fail to achieve broad or sustained use [1, 9, 24]. There may be no way around this limitation when, for instance, working with extremely complex or proprietary data. However, we believe it is fair to ask whether the design study methodology could be broadened to promote the development of systems for education and communication – especially when the experts additionally serve as educators, the dataset at hand is publicly available, and the data domain is relevant to society at large. Moreover, as underscored by research in learning sciences and human-computer interaction, designing systems for teaching and learning requires more expansive and participatory approaches to design studies [7, 14].

In this paper, we recount a "design journey" wherein an initial idea for a design study-like project led us to wonder whether we could create a visualization system for public migration data which supports educational scenarios and student engagement. After first setting out to build an analysis-focused system to visualize data on domestic migration within the United States (U.S.), we gradually modified the intended audience of our system through an iterative process, leading to an instructional focus. Along the way and especially as the project concluded, we were able to reflect on how and why we diverged from the traditional design study methodology as well as how these aspects of our project may apply in educational scenarios more generally.

*e-mail: abendeck3@gatech.edu
†e-mail: clio@gatech.edu
‡e-mail: stasko@cc.gatech.edu

The final version of our migration visualization system, called ROBIN, is the subject of another standalone paper which was published previously [3]. That main ROBIN paper covers more about the migration domain and contains further details about the system itself. In this work, we provide additional methodological detail and discussion, focusing closely on our design process involving two main sets of target users: experts in a specific domain who serve as teachers or educators, and their students who (for the time being) lack domain expertise. We also discuss our points of divergence from a typical design study, with differences stemming from our fundamentally different user group that both includes non-expert students and focuses on domain experts' role as educators.

In this workshop paper, we explore the methodological implications of designing a visualization system for education and communication around publicly-available demographic data. Our particular contributions along this vein are: (1) the provision of detail about the iterative design process of the ROBIN migration visualization system and instructional tool; and (2) a reflection on our deviations from a traditional design study methodology, including what generalizable takeaways could be applied for developing future education-focused visualization tools.

2 RELATED WORK

2.1 Design Studies

Sedlmair et al. [49] established the standard 9-step framework for the visualization design study methodology. Subsequent work has outlined modifications of the methodology for particular circumstances. The data-first design study methodology [36] is a refined framework for when acquisition of a dataset precedes identification of an expert collaborator. The design study "lite" methodology [55, 56] is an adapted approach which can simultaneously be used as a pedagogical process and a vehicle for community service. Others have discussed how to assess the rigor of design studies [33] and enumerated the types of contributions that design study projects can produce [48]. In this work, we discuss our own modifications to the traditional design study methodology through the lens of "visualization for education". We note that a few past design study projects have evaluated their tools with non-expert users [2, 53] or with both non-experts and domain experts [23]. However, these works say little about a general design process for catering to such audiences, especially in an educational context, and contribute minimal discussion or reflection on the design study methodology.

2.2 Visualization for Students & Non-Expert Users

Visualizations have been found to have educational benefits in science fields [57], as well as in computer science specifically [35]. While several interactive visualization tools for education have emerged [20], there has been little discussion of methodological reflections or approaches for educational system development. However, in a 2018 BELIV workshop paper, Wong et al. [60] did begin characterizing the traits of "non-expert" or "casual" users of visualizations, who lack expertise in the data domain much like students entering a classroom at the start of a semester. In our work, the distinction between experts (i.e., educators) and non-experts (i.e., students) is similarly based on each group's level of knowledge in the domain of migration, and we do not assume that members of either group have experience in visualization or data analysis. (However, we note that there is no consensus in the visualization literature on who constitutes non-expert users [5], and expertise in the data domain is sometimes conflated with experience in data analysis. We try our best to avoid ambiguity here.)

One type of visualization aimed at non-expert users is *narrative visualization* [50], which has gained steam in recent years as data-driven storytelling in journalism becomes increasingly prevalent. Researchers have argued that narrative visualization has the promise to expand the audiences of visualizations [4] and in doing so help share complex data insights with the general public [15]. Furthermore, recent work has expanded the space of narrative and storytelling visualization to investigate how audience annotations on charts can aid in collective storytelling [13, 27]. In our work, we explore how explanatory elements of visualization systems can support both domain expert users and non-experts simultaneously, taking inspiration from prior projects attempting to incorporate narrative elements into existing visualizations [17, 27] and design visualizations to convey stories [16, 31]. Also aimed at non-expert users are *casual visualizations* [40, 60] and similar visualizations designed for "broad audiences" [4]. Such visualizations often use ambient, artistic, or personalized components to be engaging and inclusive for a large target audience. However, these usually are not meant to have utility in an instructional setting.

3 Project Overview

3.1 Original Motivation for Project

This project was originally inspired by one of the paper author's prior work analyzing migration patterns in the United States, which found that migrants tended to move between U.S. counties with similar political preferences [32]. For instance, migrants leaving a county where the Democratic Party[1] candidate received a very high percentage of the vote in the last presidential election would likely move to another county that voted similarly. This effect was significant even after controlling for county-level attributes that impact migration patterns, such as income, distance, population size, and common resident occupations.

Domain experts studying migration (e.g., demographers, sociologists, etc.) are often interested in these types of relationships between migration and origin or destination demographics [21, 41]. Given the potential for migration patterns to impact society through, e.g., election outcomes [25, 46], these results are potentially of interest to the general public as well. This led us to consider leveraging visualization to allow interactive exploration of migration and demographic data. The main use case we had in mind was to allow both experts and non-experts to analyze this publicly-available data more easily. We also envisioned that a visualization tool for this data would enable effective visual presentation of findings from existing research, such as the political migration patterns mentioned above. Importantly, note that our focus on an educational use case emerged over time (as described in Sections 5.1 and 5.4.2), leading to several subsequent divergences from a traditional design study.

3.2 Data

We utilized the same migration data source from prior work by one of the authors [32], though we incorporated data from later years. This dataset contains **county-to-county migration data** within the U.S. between 2010 and 2019 and is accessible online via the Internal Revenue Service (IRS) [42]. We integrated the migration data with other publicly-available data on county-level metrics (which we call county "attributes") that are known to influence U.S. domestic migration patterns [32]. These county attributes are:

- **Voting in the 2020 presidential election** from Massachusetts Institute of Technology (MIT) [43].
- **Voting in the 2016 presidential election**, also from MIT.
- **Median household income** estimates from the 2019 American Community Survey (ACS) [45].
- **Educational attainment** (percent of adults with a bachelor's degree or higher) estimates, also from the ACS.
- **Urban-rural classification** (e.g., how urban vs. rural each county is) from the National Center for Health Statistics [44].

We would like to emphasize some key aspects of this data given our eventual focus of supporting education and communication. First, the data visualized in our system is all publicly available. This makes it feasible to share the data with a broad range of instructors and students in the first place, whereas this might not be permitted in a project centered around proprietary data. Second, while prior work has shown the utility of this data in a research setting, we argue that data about migration, election results, and so forth are of general interest to the public. In other words, while domain knowledge may help individuals conduct more informed or directed analyses of our data, expertise is not necessary to get started asking simple analytic questions out of curiosity. Though these aspects are not unique to our work and have been leveraged in previous projects related to education such as Gapminder [47], we emphasize their importance to our methodological approach.

3.3 Design Process Overview

Our iterative design process played out in three main phases (see Figure 1). Each phase is recounted and reflected upon in its own section of this paper.

Phase	Design Focus	Evaluation	Identified Next Steps
1	Support data analysis	Informal evaluation with visualization researchers (domain non-experts)	Assist non-expert engagement, understanding, & insight
2	Emphasize learning & communication	Lab-based studies with domain experts & non-expert students	Make small requested changes; Simplify & streamline UI
3	Refine final system	Lab-based studies with domain experts	Deploy & evaluate in a real-world setting

Figure 1: Summary of design phases.

In Phase 1, our aim (as described in Section 3.1 above) was to enable analysis of migration and demographic data by a broad audience of users. However, after conducting an informal evaluation of the preliminary system with visualization researchers in our research group (who lacked domain expertise), we found a need to add features aimed at supporting non-expert use of the system.

This led us into Phase 2, during which we implemented a subsequent version of the system with several features for non-experts and conducted a lab-based evaluation with both domain experts and non-experts. In this phase, we received valuable feedback on how to improve the system for both sets of users. We also began to better understand the challenges of designing an analysis-focused tool for users with vastly different levels of domain knowledge, which in part guided us towards a more educational focus.

Finally, in Phase 3, we refined the system further to produce the completed ROBIN tool. We firmly directed our system development efforts towards serving an educational purpose, identifying this as a good "middle ground" where domain expert educators and non-expert students could both benefit. We validated the final version of the system through lab-based studies with expert educators, leaving a real-world deployment (e.g., in the classroom) as a key next step.

[1] U.S. politics is a two-party system dominated by the liberal-leaning Democratic Party and the conservative-leaning Republican Party [39].

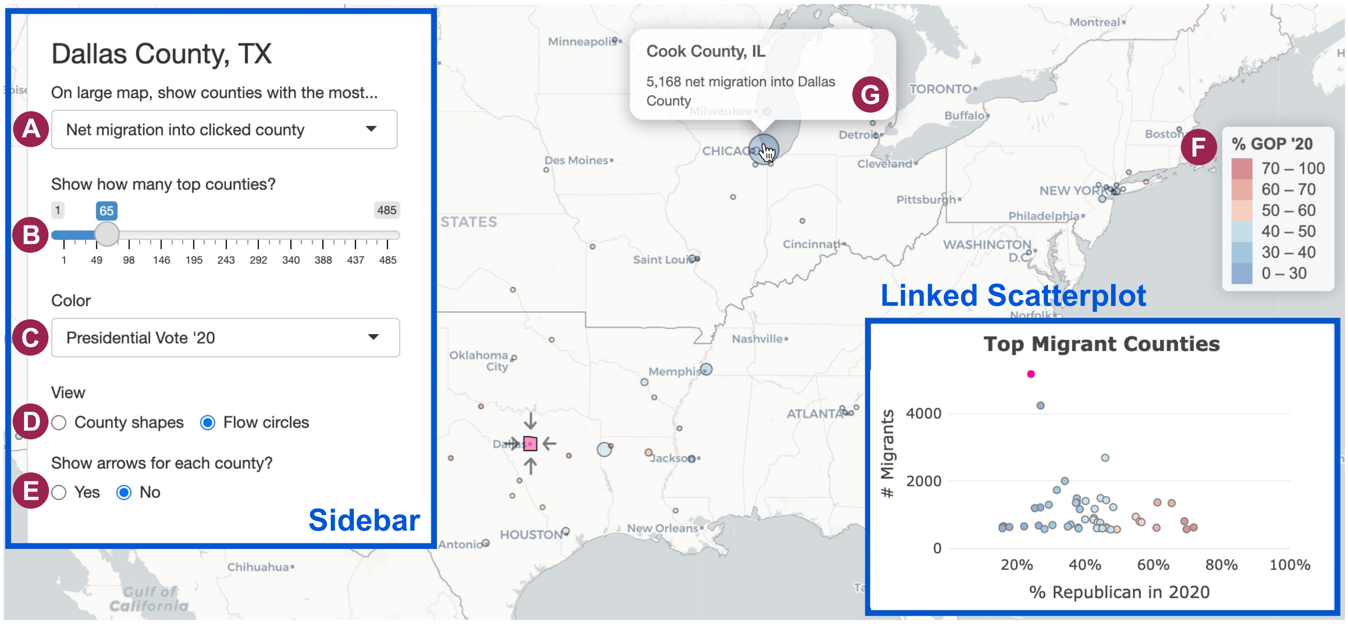

Figure 2: The preliminary system UI in individual county mode after clicking on Dallas County, Texas. The **sidebar** is on the left-hand side, the **linked scatterplot** is in the bottom-right corner, and the rest of the UI is occupied by the **main map**. After selecting a county, the sidebar houses the following dynamic query options: (A) the **migration flow option**, to select the migration direction and either raw or net migration; (B) the **number of top counties slider**; (C) the **color dropdown menu**, where the options are the county attributes introduced in Section 3.2; (D) the **view option**; and (E) the **show arrows** setting. Also note (F) the **color legend** and (G) a **pop-up tooltip** showing details for Cook County, Illinois, which is being hovered over on the main map. Cook County is correspondingly highlighted in pink on the scatterplot.

4 Phase 1: Supporting Data Analysis

4.1 Preliminary Design Requirements

Through brainstorming sessions among the authors and a review of relevant literature, we identified two preliminary design requirements for our initial analysis-focused system design. Input from the author with migration expertise was central to this process.

Given our multidimensional dataset, our first goal was to leverage the different attributes to elucidate interesting relationships in the data. In other words, we wanted our system to **visually show relationships between U.S. migration and other attributes (DR1)**. Secondly, we wanted to enable users to glean takeaways at multiple different levels of geography – for instance, focusing on an individual county of interest or alternatively on a group of similar counties. We thus wanted our system to **support both "one-to-many" and "many-to-many" migration queries (DR2)** (see examples below).

4.2 Preliminary Interface Design

In alignment with the two types of queries in **DR2**, we conceptualized two different "modes" for the system. The first mode, **individual county mode**, is meant for when the user is interested in answering one-to-many or many-to-one migration questions. An example of the latter would be "Which counties send the most migrants into DeKalb County, Georgia?" On the other hand, **attribute mode** can be used to investigate migration flows entering or exiting a group of counties that share some common attribute. A user could thus answer many-to-many migration questions for a set of counties defined by, for instance, voting behavior in the 2020 presidential election. An example question would be "Where do migrants from counties that voted over 70% Republican in 2020 move to?" Note that in answering questions like this, the user may want to visualize both (1) the counties are over 70% Republican and (2) the top destinations from these Republican counties. We deal with this by using a small inset map in attribute mode to visualize the former (see the left-hand side of Figure 3 below).

We initially designed the system's user interface (UI) to consist of three main components (Figure 2). The **sidebar** on the left-hand side is where the user can modify dynamic query widgets and change visual encodings on the map (**DR1**). The **main map** occupies most of the space in the UI and shows all counties returned by the current query parameters. The **linked scatterplot** in the bottom-right corner displays one point for each county on the main map. Position on the y-axis of the scatterplot represents the number of migrants moving to or from each county (depending on the query), and position on the x-axis depends on the county attribute chosen in the color dropdown. Hovering over a county on the scatterplot or on the main map makes a tooltip pop up on the map above that county, providing details-on-demand (following Shneiderman's mantra [51]) for the migration flows entering or leaving that single county (**DR2**). A text-based **tutorial** appeared on startup to provide the user with info on the UI.

(For a detailed overview of the system's UI and features, see the full Robin paper [3]. While that paper focuses on the final system version described in Section 6, most interface components are still easily mappable to those depicted in this subsection.)

4.3 Preliminary Evaluation

At this point, we believed that we had implemented sufficient querying functionality that would enable a broad set of users to visualize the types of insights hidden in the data. However, before evaluating the tool formally, we decided to conduct a quick and informal usability evaluation of our system with visualization research colleagues who lacked expertise in the data domain. We thus presented a half-hour demo of the system to a group of around a dozen visualization researchers and then sent a live link to each individual asking any interested volunteers to try out the system and provide feedback. Our goal was mainly to solicit feedback on the system's learnability and usability, though we welcomed input on how to improve any aspects of the system.

While feedback was generally positive, users' comments made clear that they did not have enough help to support them in effectively using the tool. Multiple users described the tutorial as *"helpful"*, but its style as a mostly static user manual did not seem to be sufficiently engaging. One user said she imagined that users would *"need to really spend time on doing data exploration"* to understand the tutorial content and asked if we had considered adding a demo video. Another suggested to *"keep the text briefer"* in the tutorial. Other comments indicated that the semantics of the views produced on the map were not always clear. One such response contained a screenshot of the map in individual county mode and a note that the user was *"not sure how to interpret"* it. Lastly, one colleague proposed that adding features to support social data analysis [59] could encourage deeper engagement and data exploration.

The feedback elicited through this evaluation led us to begin another cycle in our design process in which we focused intently on making the system easier to learn and use, especially for non-expert users. This subsequent phase is described in the next section.

5 Phase 2: Emphasizing Learning & Communication

5.1 Motivation

At this point, our motivation for leaning heavily into learning and knowledge communication as key design considerations began to emerge. Our preliminary evaluation (Section 4.3) revealed multiple usability and intuitiveness issues with the preliminary version of the system. We anticipated that several of these problems would also arise for domain experts using the system for analysis or teaching, even if such experts would more readily understand the data itself. We thus began brainstorming ideas for improving the system.

However, during this period we also did some additional reflection on the nature of our dataset and domain. Feedback during our preliminary evaluation indicated that non-experts found the data interesting and relevant, even if they requested additional assistance in understanding the data at a deeper level. We noted that the subjects of migration, demographics, and elections are of interest to the general public and not just domain experts. For instance, citizens are likely to be naturally interested in whether and how their communities are changing over time [22].

We ultimately decided to modify the focus of our system in the next design iteration. Rather than focus solely on more formal data analysis, we placed a greater emphasis on helping to support data exploration and domain-focused learning by non-experts, including students. This gave us a feeling of increased freedom to experiment with new system components (see Section 5.3) which we would likely not have considered otherwise.

5.2 Additional Design Considerations

Our first step in revising the system was to formulate concrete design considerations summarizing the main issues found in our preliminary evaluation. The considerations also aimed to better support users like students who are non-experts in the data domain. These were later distilled into a more concise design requirement: **Design the system for flexibility, learning, and ease of use (DR3)**.

- **Design engaging ways to familiarize users with the system and dataset.** Users reported that our tutorial was long and that its low-level instructions (e.g., "Change the view option") were disconnected from meaningful analysis. Our aim should be to make the tutorial more interactive, helping non-experts learn what types of questions the data can help them answer.

- **Provide information for users to situate themselves.** While dynamic query controls allow for quick and easy composition of analytic queries, user feedback suggested that the semantics of the resulting views were opaque. Users, especially students and domain non-experts, must be able to more easily keep track of the visualization views that they are creating.

- **Give shortcuts to finding insights.** Preliminary feedback suggested that non-experts in particular may feel unsure how to initiate their analysis, interpret views, and draw meaningful conclusions. We thus aim to help non-expert users more readily glean meaningful nuggets of knowledge from our dataset.

5.3 Revised System Design

In order to address our additional design considerations, we augmented the initial system to incorporate several new explanatory and textual components, which are described in detail below. (The core parts of the system's interface remained unchanged.)

Engage users with an interactive quiz. We trimmed the original user manual style tutorial down to a brief introduction of the system's features and added an **interactive quiz** meant as a more engaging means of teaching users how to operate the system. The quiz replaced rote and mechanical instructions (e.g., "Hover over the top points in the scatterplot") with a gamified walkthrough driven by data analysis questions. For example, users are prompted to click on Washington, D.C. in individual county mode and asked whether most migrants leaving D.C. are moving to counties close by. Users get instant feedback for each question, helping to assess their understanding of both the data and the tool's features. By implementing this new quiz, we aimed to leverage the previously identified benefits of "game-y" visualizations and infographics [10, 11, 12].

Provide situating information in a dedicated panel. We added a panel at the bottom of the main map for a new explanatory component of the UI. The **current view text** (Figure 3-C) is a natural language description of the currently displayed data based on the dynamic query settings. It is meant to serve as a sort of "title" for the current state of the system, addressing the issue of users getting confused about the semantics of the main map during analysis. For instance, after a user clicks on a county in individual county mode and changes the dynamic query settings, they could be looking at the "Top 100 counties with the most net migration from Fulton County, GA". Prior work has found template-based dynamic annotations for visualization system views useful for users with little experience doing data analysis [54] (see Law et al. [30] for a review of more work on automated insights). We posited that such annotations would be similarly helpful for non-expert users.

Enable social data analysis with "public snapshots". We were intrigued by our colleague's suggestion (see Section 4.3) to explore designs supporting social data analysis [59], given the potential to help users easily access others' prior data discoveries. This led us to implement a feature called **public snapshots** (Figure 3-A & B), which enables users to save the current system view along with a textual annotation. This view is then added to a library of saved "snapshots" which can later be loaded by other users. The feature is reminiscent of those in visualization systems intended to support asynchronous collaboration, like Many Eyes [58] and SenseUs [22], as well as more recent work using visualization annotations to support collective storytelling [27]. Our goal was to investigate how such features can be leveraged to support domain non-experts. We were particularly interested in the potential for the snapshots to serve as a way for domain expert educators to transfer their knowledge to students. To this end, we pre-loaded the system with some illustrative sample snapshots to help showcase the snapshot feature, the dataset, and example analysis queries and insights.

5.4 Interim Evaluations

Our next step was to conduct two interim evaluations: one set of user studies with migration domain experts (almost all of whom teach courses in a university setting), and another set with non-experts. In this subsection, we describe our basic approach and summarize key takeaways from these studies. We also include reflections on why we decided to strongly gear the final ROBIN system towards an educational focus.

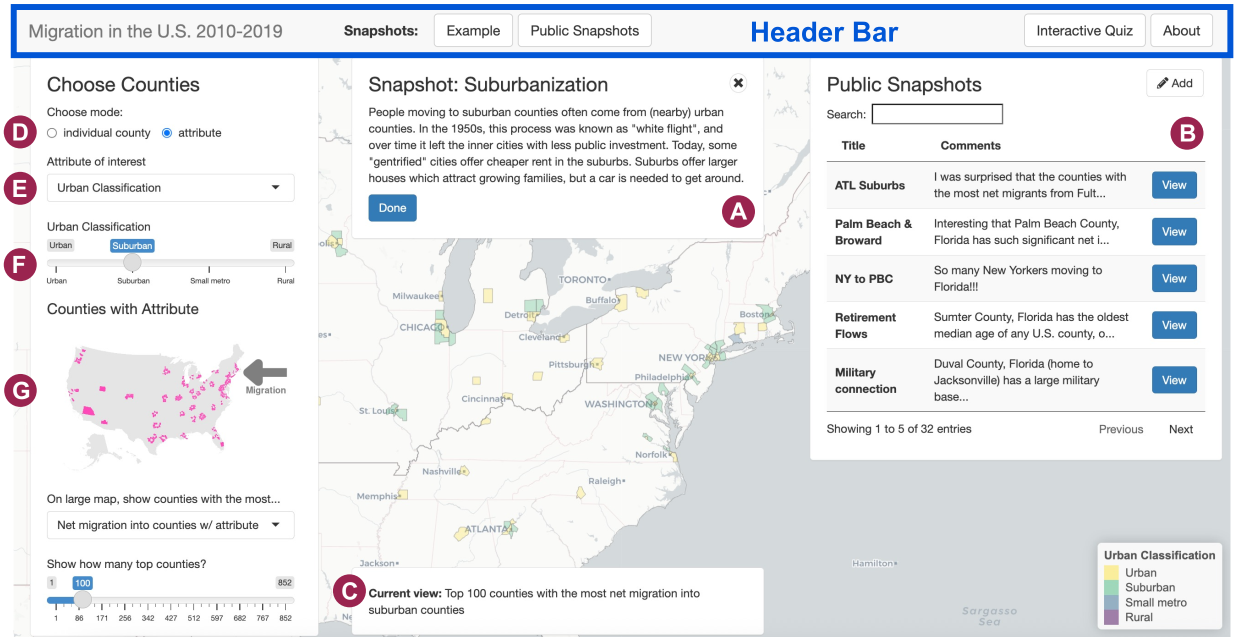

Figure 3: The revised system UI. (A) A pop-up window shows the text snippet for a snapshot selected by the user; (B) the **snapshot panel** shows all the currently saved public snapshots; (C) the **current view** text describes the semantics of the main map. The new **header bar** at the top of the UI enables access to the snapshots and quiz. (Note: The linked scatterplot is hidden when the snapshots panel is shown.) The **sidebar** in attribute mode is populated by the following dynamic query options: (D) the **mode selector**; (E) the **attribute of interest**; (F) the **attribute slider**; and (G) the **sidebar map**. The other options (some omitted from this figure) are the same as in individual county mode.

5.4.1 Approach

For the non-expert user studies, we recruited 17 participants (N1-N17) who were university students enrolled in an introductory data visualization course. We held these study sessions in-person, and each lasted around 45 minutes. Sessions followed a semi-structured protocol with tasks including taking the interactive quiz, browsing the snapshots, and engaging in free exploration. Each session ended with a semi-structured debriefing interview about overall impressions of the system and suggestions for improvement.

For the domain expert studies, we recruited 9 participants (E1-E9) including 8 professors of geography, sociology, or a related field at U.S. universities and 1 U.S. Census Bureau employee. We first reached out to experts using targeted emails and then employed a snowballing process to find more participants. We conducted expert study sessions remotely over Zoom, and each lasted around 30 minutes. The study protocol was similar to that for non-experts, with slight differences due to time constraints, the remote nature of the sessions, and the different questions we had for the expert users. Each of these sessions likewise ended with a debriefing interview.

After the provision of consent, the entirety of each study session was screen- and audio-recorded. The recordings were taken on the researcher's laptop for the non-expert sessions and through the Zoom meeting for the expert sessions. The authors later transcribed the audio recordings (with the help of assistive software) and categorized participant quotes through affinity diagramming.

5.4.2 Findings & Reflections

Here we summarize some of our main interim evaluation findings:

- **Non-expert impressions of the tool were generally, though not universally, positive.** Overall, non-experts liked the tool and found it *"easy enough to use [...] if you're a novice"* (N12). However, a few participants indicated that the many options in the interface felt *"overwhelming"* (N1), especially compared to something like a data-driven online article (N13).

- **Features designed for learning were largely helpful.** Non-experts *"really like"* the interactive quiz (N14) and said it was *"really well done"* (N10). The current view text was helpful (N3, N17), but its placement on the screen led to it often being overlooked. Several participants strongly liked the public snapshots as a sort of shortcut to insights (N10, N13); however, fewer expressed willingness to post their own. On this latter point, we note that unlike in prior work [27], the visualization views in ROBIN lack an existing narrative framing that users can employ as a scaffold for their own posts.

- **Migration data is personal.** Almost all non-experts investigated counties that were personally relevant. The proclivity for viewers to strongly connect with personally relevant data visualizations has also been found previously [37]. Non-experts' focus on familiar counties may be somewhat attributable to a lack of knowledge about other areas. Nevertheless, leveraging personal connections with datasets is a promising direction for promoting student engagement.

- **Experts found the tool potentially useful for both teaching and research.** Overall, expert participants reacted positively to the tool. Experts who were university professors expressed notable interest in utilizing the system as a teaching tool; E2 particularly liked the interactive quiz for this purpose. Multiple experts (E2, E3) also mentioned that they envisioned using the tool for exploring preliminary research hypotheses.

- **Experts requested two new features regarding the data.** Four experts reflected that in addition to raw and net migration, they wanted the system to support a metric called *migration efficiency* – a measure of how one-sided the migration flow is between two areas. Several expert participants also requested the ability to download the data from the tool's current view at any time, either for research or student activities.

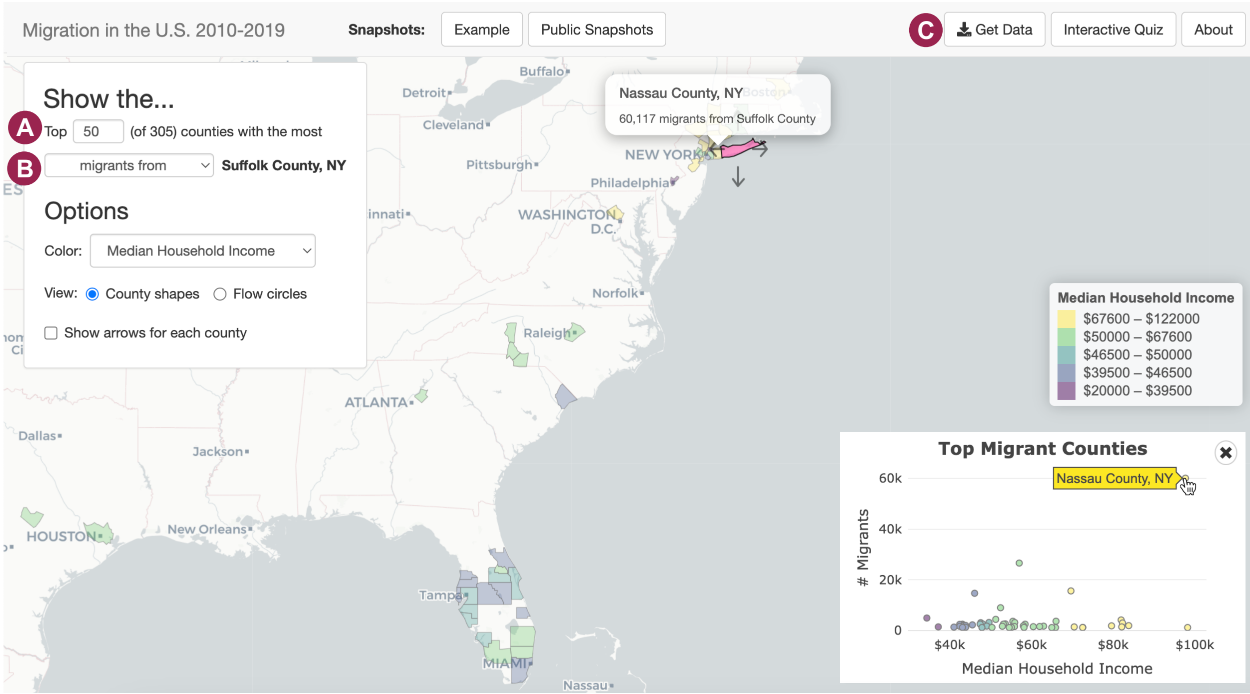

Figure 4: The final system UI in individual county mode after clicking on Suffolk County, New York. Note the main changes: The current view text integrated with (A) the **number of top counties** input and (B) the **migration flow option**; (C) the new data download feature in the header bar.

Following our interim evaluations, we again took a step back to reflect. We were encouraged by the reception of ROBIN by both sets of users, and we were able to collect actionable suggestions for further improvement. However, we did not seem to be progressing in our initial goal of making a tool that would be useful for analysis. During the study sessions, domain experts often used the tool to construct views demonstrating migration phenomena with which they were already familiar. While experts expressed some interest in using the tool for research, this was mostly as a sort of *"hypothesis generator"* (E3) before more advanced analyses could be run.

The mostly simplistic research uses for domain experts initially felt like a disappointment, and we considered adding more advanced statistical analysis features to address this issue. However, upon further consideration, it became apparent to us that the experts were much more enthusiastic about using ROBIN as an educational tool and communication aid than as an analysis tool. While experts already had existing tools and procedures for research, they seemed more eager to adopt our tool as a novel artifact in the classroom. For instance, E2 envisioned having students take the interactive quiz to learn *"what the possibilities are"* with the dataset. For this reason, we decided that the most beneficial path forward would be to lean into the concept of ROBIN as an education aid, as doing so would allow the system to provide utility both to domain experts as educators and to non-experts as students. We found this to be a relatively straightforward way to serve both of our user groups, given the feedback we had received during the interim evaluations.

6 PHASE 3: REFINING THE SYSTEM

6.1 Key Changes & Final Interface

Our interim evaluation and subsequent commitment to designing the tool as an education aid informed three key revisions to create the final ROBIN system (see Figure 4). First, we **merged the query controls with the "Current View" text** as suggested by N13, to help prevent this useful component from being overlooked by users. Second, we **computed the migration efficiency metric** and added a sidebar option to see the most efficient migration into or out of the selected county or counties. Third, we added a new button in the header bar which **enabled users to download the data** for the current query, a feature which we envision supporting classroom activities (based on expert feedback).

6.2 Summative User Study Highlights

6.2.1 Approach

We contacted the same 9 domain expert participants (E1-E9) from the interim evaluation (Section 5.4), but we were only able to secure the commitment of 5 experts for these sessions (E3-E6 and E8 in particular). Like the interim evaluation sessions, these expert sessions were conducted remotely using Zoom and lasted around 30 minutes each. After a brief demo by the researcher, participants then spent 10 minutes exploring the data in individual county mode, followed by 10 minutes in attribute mode, and were encouraged to ask for help when necessary. Each session ended with a debriefing survey and interview for experts to evaluate the tool from an educator's perspective. As in Section 5.4, the sessions were recorded, and the researchers later transcribed participants' quotes and subsequently analyzed them using affinity diagramming. We also analyzed the survey results quantitatively (see the Robin system paper [3]) to serve as additional evidence for the interview findings.

6.2.2 Takeaways & Reflections

The main takeaways from these user studies were as follows: Experts mentioned that they appreciated the new migration efficiency metric (E5, E8) and data download feature (E3, E4), and all experts who clearly remembered the previous version reported that the revised version was a meaningful improvement. More importantly to us, these user studies also confirmed that ROBIN would be well-received as an education and communication aid. Four experts who regularly taught university courses very much recognized the teaching utility of the tool, with E4 noting that he thought it *"could be really, really useful to students"*. E8 particularly mentioned the snapshots as helpful in a classroom setting for students to share findings as an engaging activity (*"Yeah, I like that feature"*). We were also pleased when E5 identified ROBIN's potential to help communicate with other non-expert audiences outside of the classroom: *"I talk to media people a lot, and for them to be able to look at something like this while I was talking to them would be another thing that would be a use of it for me."* We have not yet had the opportunity to partner with domain experts to study their use of ROBIN in the classroom or in other contexts long-term. However, we are optimistic about doing so in the future given the expressed interest of the experts.

7 Discussion

In this section, we holistically reflect on this project and how it can inform future work. Based on our design process and user study findings, we compare our approach to the traditional design study methodology to describe the unique considerations in doing visualization research for education. We then conclude by outlining some potentially fruitful directions for future work in this space.

7.1 Reflections on the Design Study Methodology

We now review and reflect on the differences between our approach and that of a traditional 9-stage design study, going through each stage in turn. We note that our work is only a first step towards designing for education and communication, and we envision that a full-fledged, formal modification to the design study methodology could emerge after more projects in this space.

7.1.1 The *Learn* Stage

The very first stage, *learn*, calls for the researchers to gain a solid understanding of the visualization literature. This stage remained largely unchanged in our approach. All authors are visualization researchers with solid knowledge of the field, and we conducted a literature review at the beginning of this project to assess existing work (see the Related Work section in the main Robin paper [3]).

7.1.2 The *Winnow* Stage

In the standard methodology, the *winnow* stage is where visualization practitioners assess whether potential collaborations are promising to pursue. It typically involves discussions with sets of potential stakeholders to assess the likelihood of a successful research collaboration. However, our initial winnowing was more similar to the version of this stage presented in the data-first design study methodology [36], where the goal is to "assess and prioritize the set of potential stakeholders" with respect to (1) the data and (2) user tasks. While we initially established any interested users (both domain experts and non-experts) as the target audience of an analysis-focused tool, our winnowing in some sense continued throughout our iterative design process. We gradually shifted towards supporting non-expert and student learning (Sections 5.1-5.3), and we later decided to eschew expert analysis altogether to focus concretely on educational use cases (Sections 5.4.2-6.1).

We note that in a future project where the explicit goal of supporting instructors and students is present from the beginning, this recurrent winnowing may not occur. However, other considerations could still arise in the *winnow* stage which would affect the decision of whether the researchers should pursue the project. Namely, when support for both domain expert educators and non-expert students is a priority, the ability to "winnow down" stakeholders to a very narrow and precise level is somewhat limited compared to a usual design study. In our case, the data we worked with was all publicly available from U.S. government agencies or universities and covered topics that are at least understandable to novices at a basic level. The intended user tasks with the system were also relatively high-level and exploratory from the beginning, meaning that these tasks were appropriate for non-experts in the first place. Of course, design studies which focus instead on proprietary data and highly advanced analytic tasks can still be of immense value. However, the different considerations in our *winnow* stage primed us to investigate a broader design space than if we had focused solely on data analysis in domain expert workflows.

7.1.3 The *Cast* Stage

In the *cast* stage, stakeholder roles are established. Sedlmair et al. identify 6 main roles that researchers and collaborators often take in design studies. Generally, these roles are still applicable in our case, with some modifications and differences in relative importance. For instance, *front line analysts* (end users) now not only consist of domain experts, but also non-expert students. This makes the role of *connectors* slightly more important, since these individuals are tasked with connecting the visualization designers with front-line analysts. Having an author with domain expertise and connections helped her to serve as a liaison to expert educators. We also found through our user studies that some expert participants were willing to help connect us with other researchers who may be interested in our tool as an education or communication aid.

On the other hand, we may want to identify individuals outside the immediate research team as connectors to help achieve broader adoption of our system as we move towards public deployment (see the Deploy stage below). *Translators*, who can abstract domain-specific problems and tasks into broader goals, are key when designing for educational use cases. These goals are also different than in a traditional design study, being closer to learning goals than analysis objectives. In our project, the translator role was again taken on by the author with domain knowledge at first and then partially by other experts through the user studies. Note that connectors and translators are described only as "useful, but not crucial" roles by Sedlmair et al., whereas we regard them as much more central. Finally, *gatekeepers* (described as "critical" by Sedlmair et al.) are not as much of a concern for a project like ours, particularly with regards to gaining access to data. As mentioned above, designing for broad sets of users almost necessitates the selection of a dataset with few, if any, usage restrictions.

7.1.4 The *Discover*, *Design*, and *Implement* Stages

The *discover* stage is usually where requirements are elicited by speaking to and observing domain experts. According to Sedlmair et al., the researchers must "learn about [...] the practices, needs, problems, and requirements of the domain experts". Although we initially intended to create a tool focused on data analysis, our initial stage of requirements establishment was less focused on domain expert end-users than in a traditional design study. Instead, we sought to support interested non-experts in conducting data analysis as well. We thus leveraged the expertise of an author of this paper with knowledge in both the migration domain and visualization to formulate our initial design requirements. In doing so, we followed a distinctive approach to design studies known as Designing as Domain Experts (DaDE) [19]. After the *discover* stage, we believe embracing the DaDE approach also helped us progress more efficiently in our first pass through the *design* stage (choosing basic visual encodings and interactions) and *implement* stage (programming an initial prototype).

We later looped back in our design process to gather additional requirements from the perspective of non-expert students (Sections 4.3 and 5.4) as well as external domain expert educators (Section 5.4), and we revised the system accordingly each time. Indeed, each of the three big design phases outlined in this paper is essentially one pass through the three-stage process of *discover*, *design*, and *implement*. While multiple iterations of each stage are permitted by the methodology outlined by Sedlmair et al., we view repeated instances of these three stages as essential – and highly beneficial – for understanding the needs of both instructors and students, who have very different levels of domain expertise.

7.1.5 The *Deploy* Stage

In traditional design studies, the *deployment* of the system is ideally meant to take place as part of an *in situ* evaluation lasting at least several weeks. Traditionally, domain experts use the developed system to conduct whichever data-related task is part of their regular responsibilities. Quantitative metrics such as task completion time are often (though not exclusively) the focus of such evaluations. As mentioned previously, our user studies (Sections 5.4 and 6.2) were highly qualitative in the data collected and were conducted in a lab setting with sessions lasting less than an hour in all cases. Although we were seeking feedback to evaluate our design decisions, some of these user studies (the interim evaluations in particular) were somewhat more aligned with *discovery* of user requirements, and thus a more naturalistic evaluation is warranted in the future. We aim to conduct a longer-term deployment of the final ROBIN system in a classroom setting in partnership with some of the domain experts who have already been involved in this project.

In a longer-term *in situ* evaluation of a system designed for education and communication, we envision several likely differences from a traditional design study system deployment. An obvious difference is that such an evaluation would need to include student users (i.e., domain non-experts). Choosing quantitative evaluation metrics could be very system- or course-specific, and analysis of the collected data would likely necessitate triangulation with qualitative data to truly understand; consider the complexities and subtleties in studying something like "how students utilize the public snapshots feature". In a deployment, we would also seek to evaluate the learnability of the system, to make sure there is little friction in students getting started with ROBIN. This is vital because we would likely not work directly to extensively train users (especially students) as in some design studies. Perhaps most importantly, such a deployment would heavily seek to evaluate the tools' ability to support educators' desired learning outcomes for their students [28], which could be assessed leverage approaches from the education literature [6, 34]. Finally, we note that several of these unique considerations for visualization systems designed for education and communication resemble those for collaborative analysis systems like Many Eyes or SenseUs. We can thus draw from those projects' approaches for deployment and evaluation accordingly.

7.1.6 The *Reflect* and *Write* Stages

Our two manuscripts on the ROBIN system – namely, the main system paper [3] as well as this workshop paper – represent the culmination of the last two stages: *reflect* and *write*. In our experience, design study papers often focus heavily on the system, and detailed reflections are usually the first casualties of word and page limits. Thus, our main point of divergence from the traditional approach in these stages is pursuing two separate publications focusing on the system and methodology, respectively. While separating the papers certainly simplified the writing process, the main benefit of this approach has been receiving feedback from different perspectives. Critically, sharing our work with both systems-focused and education-focused audiences has encouraged us to more deeply consider the contributions that our work makes to each community.

7.1.7 Summary of Key Ideas

The main differences between our approach and that of a traditional design study can be summarized as follows. Rather than solely focusing on the stakeholders being domain experts completing work responsibilities, we focus on domain experts as educators and loop in non-expert students as well (*winnow*). Leveraging connections from the domain expert author, we collaborate with external expert stakeholders as well as non-experts (*cast*). Starting with the expert author's expertise and then looping in educators and students, we design, refine, and preliminarily evaluate our system – with multiple design iterations being critical for serving this varied group of stakeholders (*discover*, *design*, and *implement*). While we conducted lab-based evaluations along the way, having educators use the system in the classroom (*deploy*) remains as a next step. Finally, we *reflect* on our methodology and *write* a dedicated reflection paper for education researchers in addition to a system-focused manuscript. For future projects, we envision that visualization researchers could use the *cast* and *discover* stages to more solidly define learning goals and classroom activities earlier in the system development cycle. This would help chart a clear path towards classroom *deployment* and make it easier for researchers and educators to measure deployment success.

7.2 Opportunities for Visualization Research

Beyond potential benefits to students and educators, we believe designing visualization systems that focus on education and communication offers two main benefits for visualization research. First, such tools demonstrate how visualization can help make analytic processes and insights from experts understandable by students and other non-experts. To this end, prior work has discussed the potential for interactive visualizations to help researchers improve public knowledge and advocacy about their domain [47], as well as the utility of domain expert interaction logs to guide non-expert users in data exploration [29]. Second, designing such systems can also serve to increase the visibility and practical value of visualization research by producing tools that are equipped to achieve more broad and sustained adoption (in this case, in the classroom) – a key challenge in expert-focused design studies [1, 9, 24]. Taken together, we argue that taking a more thoughtful and deliberate approach to design studies for education can expand the possibilities and reach of visualization research, similarly to how the approaches of casual and narrative visualization have already done.

Based on the considerations of public availability of data as well as broad interest, we believe sports data visualization [18, 26, 38] and visualization of COVID data [8, 61] or other public health data [52] provide ripe opportunities to feasibly design systems for education and communication. This is not to discount existing use cases of visualization for education in multiple fields, especially in STEM [20, 35, 57]. Finally, future work can consider visualization or data analysis expertise along with domain expertise when designing systems for audiences with a range of skillsets and knowledge. We distinguished between experts and non-experts/students based mainly on knowledge in the domain of migration, and we designed our tool assuming that users lack experience in visualization or data analysis. However, our non-expert study participants were students enrolled in a data visualization course and were thus likely more experienced with visualization than, for instance, non-expert users as characterized by prior work [60]. In the visualization literature, data domain expertise is sometimes conflated with experience in data analytics when referring to non-expert users [5]. We argue that this distinction is crucial for visualization design and worth investigating in a more explicit manner.

8 Conclusion

Design studies showcase how visualization can help domain experts complete tasks more easily. However, we argue that limiting the user group of visualization systems to domain experts is not always necessary, and that there can be benefits to designing for domain expert educators and their students concurrently. In this work, we recount the development of the ROBIN system for visualizing U.S. migration data which incorporates several narrative and textual design elements to support non-expert student users. We also detail our points of divergence from the traditional design study methodology and reflect on the implications for visualization in education. We hope that our work encourages more visualization research that strives to design visualization tools for education and communication around freely-available data with societal importance.

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