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Gathering Public Opinion about an Architectural Project: A Text Mining Approach

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Abstract

Public opinion is growing in importance due to the widespread use of social media and the fact that people freely express their opinions on any subject on social media. It is important to include the public in the built environment because it may provide valuable feedback and enable people to share their skills, contribute to the creation of a solution and a choice, and raise awareness of the value of their neighborhood. The article aims to propose a framework for evaluating how an architectural project is perceived by the general public via the use of a machine learning model. The Tulip Tower in London has been selected as a case study to demonstrate how this framework can be applied in practice. Tweets about the Tulip Tower in London from 2018 to 2021 were collected and then have been reviewed and scored. According to the findings, this approach enables the project's current public opinion to be tracked, public concerns to be identified and addressed in real-time in the early design stage, and the project to be re-evaluated in light of the data collected.

Key Words: *Public Opinion, Text Mining, Architectural Design.*

Öz

Sosyal medyanın yaygınlaşması ve insanların sosyal medya üzerinde herhangi bir konuda görüşlerini özgürce ifade edebilmeleri nedeniyle kamuoyu görüşünün önemi artmaktadır. Değerli geri bildirimler sağlayabilecekleri ve insanların becerilerini paylaşmalarına, bir çözüm ve seçim oluşturulmasına katkıda bulunabilecekleri ve yaşadıkları yerin değeri konusunda farkındalık edinebilmeleri amacıyla, kamoyunu yapılı çevreye dahil etmek önemlidir. Makale, bir mimari eserin genel halk tarafından nasıl algılandığını bir makine öğrenimi modeli kullanarak değerlendirmek için bir çerçeve önermeyi amaçlamaktadır. Londra'daki Tulip Tower, bu çerçevenin pratikte nasıl uygulanabileceğini göstermek için bir vaka çalışması olarak seçilmiştir. 2018'dan 2021'e kadar Lale Kulesi (The Tulip Tower) ile ilgili tweetler toplandı ve ardından analiz edilip ve puanlanmıştır. Elde edilen bulgulara göre bu yaklaşım, projenin mevcut kamuoyunun takip edilmesini, kamuoyunun endişelerinin erken tasarım aşamasında gerçek zamanlı olarak tespit edilmesini ve ele alınmasını ve toplanan veriler ışığında projenin yeniden değerlendirilmesini sağlamaktadır.

Anahtar Kelimeler: *Kamoyu Görüşü, Metin Madenciliği, Mimari Tasarım.*

Introduction

Architecture is often thought of in terms of elevations and architectural aspects, omitting to evaluate of its true essence in the process. Using the example of the Chinese philosopher Lao Tzu, Cresswell (2005) explains that Frank Lloyd Wright used to enjoy using the example of the Chinese philosopher Lao Tzu to illustrate this point. Centuries ago, poet Lao Tzu pondered, "What is the substance of the cup?" he inquired in a lyrical manner. "It is the space contained inside the cup that makes it functional." That which provides significance to a cup is the space it holds; this is the core of what the cup is all about. Wright used to say, in a similar vein to Lao Tzu, that the essence of architecture is the three-dimensional space(s) created for human habitation. According to Wright, all excellent architectural qualities are human values, else they are not worthwhile (Creswell, 2005). Throughout the ages, the true essence of architecture has been human. The result is that architectural movement has taken its cues from human perception and ideation. For example, while architects and architectural critics were slow to warm up to the Baroque style, the general people welcomed it (Bianco, 2016). Modernism, on the other hand, was detested by the general population, who thought it was monotonous since it lacked ornamentation, then Post-Modernism was well-received while being despised by architects (Celiker & Cavusoglu, 2005).

Public opinion in architectural processes is supported by a large body of literature (Bakri et al., 2015). Effective involvement will enable the opportunity for long-term sustainability to be accomplished. Moreover, it contributes to the development of community commitment and ongoing participation in the program, so promoting the notion of shared responsibility. It is crucial to have public involvement in the built environment because it may give useful input and allow people to share their expertise, aid in the development of a solution and a choice, and increase awareness of the significance of the place where they live (English Heritage, 2008). Because according to the findings of the research, despite the fact that specialists in the built environment (such as architects, planners, landscape designers, surveyors, and engineers) and the general public have vastly different expertise and objectives, they are still complementary (Mullins, 2006; Wyatt, 2004). Until the last decade, it has been gathered using traditional methods, through deliberative polling, focus groups, public hearings, or surveys. But, with the growth of Internet usage over the last decade, public opinion research has undergone a transformation. The Internet is used by 93% of Americans to connect and seek information (Perrin & Atske, 2021). As a result of this change in behavior, there has been a shift in the way public views are collected and analyzed, as people's motivation to engage in surveys has decreased (Newport, 2011). There is an increasing push for researchers to look into new data sources, particularly social media, in order to keep up with this paradigm change (Japec et al., 2015). While this is going on, computational social scientists are inventing and implementing new tools to better analyze people's behavior in digital settings(Stroud & McGregor, 2018), which is paving the way for multimethod confirmation of conventional social science surveys and experiments (Shah et al., 2015).

To establish the public's perception of the worth of architectural projects, the paper uses a groundbreaking technique to analyze social media comments. The aim of this study is to present a framework for the evaluation of the perception of an architectural project in the public eye by using a machine learning model. This approach can also facilitate the delivery of real-time monitoring of public opinion in order to make revisions to architectural projects and advance in an interactive manner with the public.

Design and Perception

Despite the widespread recognition that monitoring and comprehending the design process is a difficult task, only a small number of research have taken into account the perceptual reactions of participants in the design decision-making process (Bates-Brkljac, 2013; Cross, 2003). In the literature, studies have shown that there are considerable perceptional discrepancies between architects and the general public (Coeterier, 2002), a communication gap between architects and their customers(Watts & Hirst, 1982), and a large perceptional difference between the general public and designers (Mullins, 2006). These distinctions are the most compelling evidence of how people's perceptions of art and architecture alter as a result of their backgrounds.

Historically, the subject of perception of art and architectural projects can be attributed to Palladio and Giovanni Battista Piranesi, who depicted great buildings in a variety of rich paintings(Bates-Brkljac, 2013). Many artists have generally accepted the perception of the work as "art" and attach importance to this issue (Fraser & Henmi, 1994). Several researchers believe that presentation has a substantial influence on perception (Evans, 1997; Hägen, 1986). Their argument is that the presentation functions as a filter for a style of seeing and generates its own recollection, predating, and prefiguring perceptions in the process (Fraser & Henmi, 1994). Using the presentation, it is possible to produce the desired impression while simultaneously changing the current perception. The dynamics of the presentation should also be tailored to the audience's perception of the content. Consequently, if the value of an architectural project is related to its presentation, and the manner in which the presentation will be made is closely related to the perception of the public opinion, the measurement of public opinion becomes increasingly important in determining the value of the architecture work.

Furthermore, there is a significant relationship between perception and participatory design. Due to the fact that there is still a very limited level of cooperation between designers and users, some individuals are even critical of how architects deal with local contexts and environmental challenges while developing constructed environments (Sanoff, 2000). Recently, several designers and planners have advocated for the inclusion of the community in the design of public places. It is becoming more fashionable to include community interaction in effective urban design, and it has also become a common focus in design education. Engaging all stakeholders, including experts, business partners, and end-users in the design process is a key component of Participatory Design. The goal of Participatory Design is to produce a final product that fits the requirements of all stakeholders(Robertson & Simonsen, 2012). Interest in public engagement in the building of public spaces has risen due to the awareness that individuals have the ability to influence design choices based on their own cultural values (Moomaw, 2016). Using bottom-up methodologies, participatory designers look into, comprehend, and encourage the mutual learning processes that emerge among participants throughout the design process. The involvement of users and other stakeholders in the design process is unavoidable (Kensing & Greenbaum, 2013). For the best creativity and to include users as design partners, a designer should have an understanding of what it takes to support a communal design process within academic and practical methods (Sanders & Stappers, 2008). A participatory design technique may enhance public space design and community knowledge of their surroundings by allowing designers to learn about their target audience's real-world situations(Howarth et al., 2017). To have a thorough grasp of the design process, it is critical to understand how it should be structured and who should be participating in the design effort.

Traditional methodologies: A Perspective on Surveys as Public Opinion Measurement Tools

Attempting to capture all important viewpoints on a subject via any technique of public opinion collection is impossible. This is true whether the approach is deliberative polling, focus groups, public hearings, or standard surveys (Chen & Tomblin, 2021). Experts are unable to grasp the whole complexity of these problems or to know all of the appropriate questions to ask, nor are they able to reflect the cultural values and interests of ordinary individuals (Sarewitz, 2015). As a result, it is required to evaluate a diverse range of concerns pertaining to difficult themes. Traditional approaches have flaws since they include a small number of individuals, pose the risk of being provoked by questions, and result in a group of participants in conversations who are more likely to adopt the ideas of the dominant group than the opposing group (Powell et al., 2011). Therefore, a disinterested public can be included in consultation strategies such as public hearings, polls, and debates, according to Fiorino (1990) which could assist to offset biases resulting from selective participation in consultation methods. A common practice among survey analysts is to aggregate the data they collect and analyze; although this has the benefit of summarizing the distribution of public impressions, it has the disadvantage of possibly marginalizing less often heard viewpoints. In other words, it has the potential to result in the consideration of Pervasive views. When it comes to specific issues that are directed towards minorities rather than the majority, minorities may provide valuable insights that are otherwise overlooked (Fishkin, 1992). Furthermore, data gathering for high-quality surveys is time-consuming and expensive, necessitating the expenditure of large financial resources to recruit and encourage participants (Klašnja et al., 2015).

Using social media with Text Mining Approach

In order to get a better understanding of public opinion, public opinion researchers have begun to compare the nature of survey data with data from social media sites. In contrast, to survey data, which is manufactured or produced, it is considered that social media data is organic in nature and hence reliable (Groves, 2011). Furthermore, it can offer an opportunity to gather opinions from members of marginalized groups that may be difficult to recruit for surveys. Social media has been identified as a space where members of counter-publics may express their concerns and rights, according to communication researchers (Chen & Tomblin, 2021). In addition, depending on the platform, gathering public comments through social media could be less expensive than traditional methods.

Furthermore, when compared to survey datasets, social media databases can be enormous (Shah et al., 2015). This makes it feasible to reach out to the views of the general public without being influenced by bias. Additionally, it distinguishes itself from surveys by providing access to real-time data and being simple to repeat.

To effectively monitor social media, it is necessary to have the capacity to automatically analyze and comprehend vast amounts of text-based data. Text mining is the term used to describe this activity. Text mining is the practice of automatically extracting relevant information and knowledge from unstructured natural language text using machine learning techniques (Talib et al., 2016). Opinion mining, to put it another way, is a unique sub-field of text mining that is concerned with automatically deducing the polarity of an individual's opinion (positive, neutral, or negative, agree or disagree, and so on) linked with natural language writings (Liu, 2015).

Methodology

To provide that, sentence-level sentiment analysis on social media is used to understand the effects of the architectural projects. The sentiment analysis is a method for predicting the emotional state of a text by determining how positive, neutral, or negative the content is. The approach given categorizes sentiment polarity as positive, negative, or neutral. The sentiment analysis workflow is depicted in Figure 1.

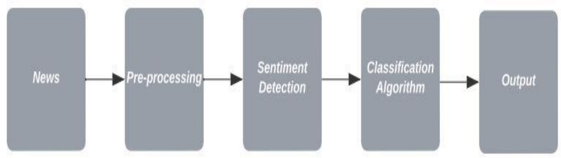

Figure 1. The workflow for sentiment analysis

The system is comprised of five major modules: data gathering, data pre-processing, data processing, classification, and output analysis.

(a) Data gathering: It begins by selecting a topic, and then data containing that term is gathered. This dataset was created for this study. Using keywords and hashtags connected to the architectural project, a dataset of tweets taken from the United Kingdom Twitter stream from November 2018 to December 2021 was found and collected. Tweets were gathered with the help of the scraping tool. The tool was used to extract large amounts of data from websites.

(b) Data pre-processing: During the stage, the data is filtered to remove missing noisy and inconsistent data. Pre-processing tasks include the following: (1)Removing URLs, special characters, punctuations, numbers, etc. (2) Removing stop words (3)Stemming (4) Tokenization. The retrieved tweets were then pre-processed in order to prepare them for automated categorization using machine-learning methods, which were then performed. This procedure included the removal of unnecessary information from tweets and the translation of tweets into numeric vectors that could be handled by a machine-learning algorithm once they were preprocessed. The initial stage in preprocessing is designed to extract just the most useful content from each tweet; for example, links and mentions are removed from the final output. It is temporarily abandoned for reasons of text mining elaboration, but it is revisited for the sake of temporal trend analysis when a tweet is sent. Hashtags were converted to single words by removing the "hash (#)" symbol from the beginning. At the end of the process, a case-folding operation is performed on the texts to transform all characters to lower case form. In specifically, each tweet was initially transformed into the collection of words that it contained before being analyzed further (tokenization). Then, tokens that provided little or no valuable information to the text analysis, such as articles, conjunctions, prepositions, and pronouns, were removed from consideration (Stop-word filtering). Following the removal of suffixes from the remaining tokens, their stems, or basic forms, were determined in order to group words that had semantically similar meanings (Stemming). Then, stems that were not related to the investigation were removed (Stem filtering). During the supervised learning step, a collection of relevant stems was selected and documented.

(c) Data Processing (Sentiment Detection): The primary objective of Sentiment Analysis is to determine the polarity of particular news. "Positive", "Negative", and "Neutral" polarity are the three types of polarity. Polarity identification is accomplished by the use of several lexicons, which aid in the calculation of sentiment strength, and sentiment score.

(d) Classification Algorithm: In sentiment analysis, there are two main approaches: supervised learning and unsupervised learning. Sentiment classification of news data is performed using supervised machine learning techniques such as Nave-Bayes, SVM, and Maximum-Entropy. The efficiency of a classifier is determined by which datasets are utilized for which categorization techniques. In the case of Supervised machine learning techniques, training datasets are utilized to train the classification model, which subsequently aids in the categorization of test data.

(e) Output analysis: The basic idea behind sentiment analysis is to transform unstructured data into important or meaningful data. Following the completion of the analysis, the findings show which tweet is in which category.

Case Study

Using a machine learning model, the article proposes a framework for evaluating how the public perceives an architectural project in order to improve future architectural project evaluations. The Tulip has been selected as a case study to demonstrate how this framework can be applied in practice. Since this article aims to show the importance of public opinion in the design process, this architectural project, which is still in the planning stage, has been chosen.

Figure 2. The Tulip in London (BBC, 2019)

Designed by British architects Foster + Partners, Tulip would be the City of London's tallest skyscraper and one of its most controversial buildings, standing at 1,000 ft (305 m) (BBC, 2021). Tweets taken from the United Kingdom Twitter stream about Tulip from 2018 to 2021 were collected, and the steps stated in the "3.2 methodologies" were followed throughout the collecting as well as throughout the application phase. As a result, the following findings have been reached.

According to the data collected, there were a total of 3,652 tweets on the architectural project between November 2018 when it first appeared on the public agenda, and December 2021. Table 1 shows a selection of the tweets that have been reviewed and scored.

Table 1. Examples of tweets included in the training set.

Text of tweet	Classification label
"Let's face it, it's very optimistic!"	Positive
"City planners give green light to Foster + Partners "The Tulip" tower. It will have a total height of 305.3 meters – making it the second tallest building in Western Europe after the Shard."	Positive
"The Tulip: Plans unveiled for 1,000ft skyscraper in London"	Neutral
"I don't understand why humans are so stupid. This is not a 'Tulip'. How many sodding viewing towers does London need? Why do architect humans have to do whatever rich people tell them to?"	Negative
"Foster + Partners' Tulip tower was rejected by the UK government and dismissed planning proposals for a 305-meter-tall tourist attraction in the City of London over concerns about embodied carbon and the quality of its design"	Negative
"The iconic tulip-shaped tower, already an icon of the city before it was even built, will not be erected because it is "highly unsustainable."	Negative
"Construction of the TheTulip could be completed by 2025"	Neutral

The evaluation of tweets at the sentence level can provide us with valuable information about how the general public perceives the architectural project in question. According to the qualitative analysis, 2,322 out of 3,652 tweets were negatively framed, 798 were positively framed, and 532 were neutral as shown in Table 2.

Table 1. Sentence-Level Sentiment analysis of the tweets

date	# of tweets	# of positive tweets	# of negative tweets	# of neutral tweets
2018-2021	3652	798	2322	532

Tweets classified as positive, negative, or neutral are shown in percentages in the following figure 3.

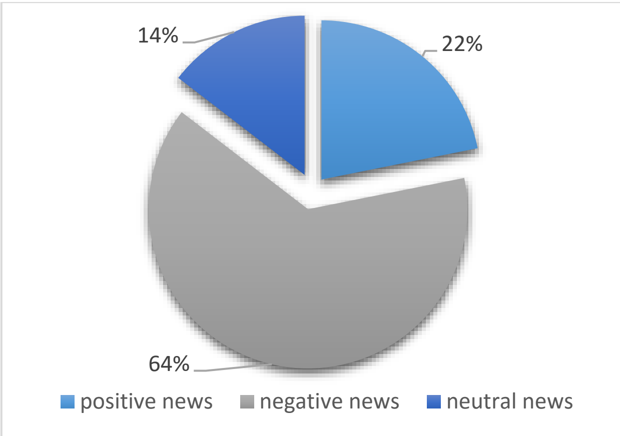

Figure 2. Percentages of the tweets

In the training dataset, the following is a list of word clouds representing both negative and positive tweets.

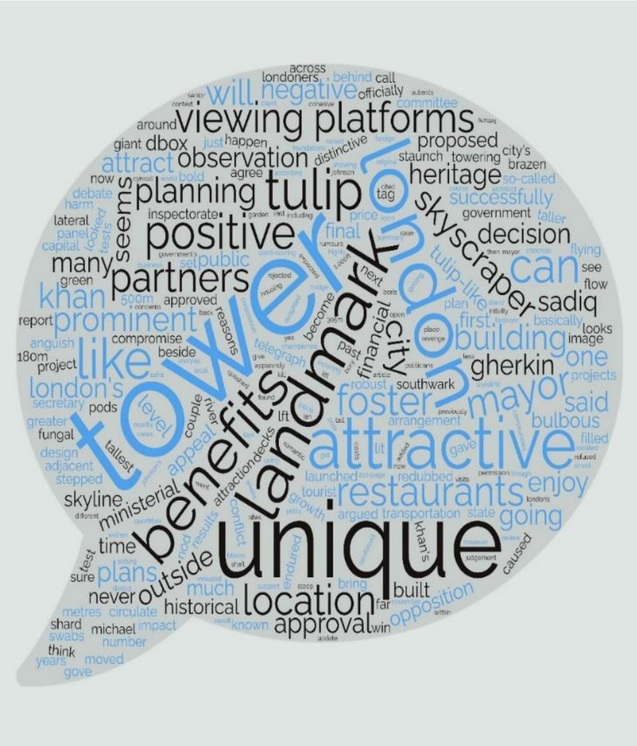

Figure 3. Word cloud representation of positively tagged tweets in the training dataset

A qualitative inspection of Word cloud representations of the positively tagged tweets in the training datasets revealed a greater prevalence of landmark, attractive and unique.

Figure 4. Word cloud representation of negatively tagged tweets in the training dataset

Instead, it is discovered that the number of criticisms directed towards building the Tulip tower is larger in the tweets. They are "cost", "carbon" and "unsustainable". It was "viewing" that was the most often mentioned word in both datasets.

Conclusion and implications

The goal of this paper is to present a framework for assessing the perception of an architectural project in the public eye, which is accomplished via the use of a machine learning model. This approach can also aid in the provision of real-time monitoring of public opinion in order to make modifications to architectural projects and progress in an interactive manner with the general public, among other things. To show how this framework can be implemented in reality, The Tulip tower in London has been chosen as a case study to be studied. Important findings and ramifications have been established as a consequence of the qualitative and quantitative examination of social media. The following are the conclusions and ramifications.

- The fact that the number of negative tweets outnumbers the number of positive tweets makes it possible to conclude that the general public's view is negatively disposed of.
- Analysis of the content of tweets shows that individuals who express negative ideas are concerned about carbon emissions and financial troubles, but those who express positive opinions support that it becomes a center of attraction and a landmark. In this way, it is possible to find the aspects that people worry about and support in the early design process.
- The following are the outcomes of the framework that has been given.
- Analysis of Twitter data provides insight into popular perceptions of an architectural project.
- With this approach, it is possible to keep track of the current public opinion of the

project, identify and address public issues in real-time, and re-evaluate the project in light of the data obtained at the commencement of the project. It provides all the information you need to optimize your design choices.

- The achievement of the possibility of long-term sustainability will be made possible by public participation in the built environment. It also helps the development of community commitment and engagement in the program on a long-term basis, so encouraging the idea of shared responsibility.
- It instantly identifies the most often encountered themes and concerns among the general public.
- It can provide valuable feedback and enable individuals to share their experiences, aid in the development of a solution and a decision, and promote awareness of the necessity of having enough living space for everyone.
- It allows for the detection of not only emerging trends but also previously unknown pain spots by recognizing cross-topics. In this way, problems can be prioritized promptly and effectively.
- It materialized public opinions and proposals to deliver optimum public management.

Extracting public opinion from the texts of social media can become an important technique since responses to the built environment from the public can be revealed, and also one can re-evaluate design and spot the problems in light of this information in the early design stage.

References

Bakri, A. F., Ibrahim, N., Ahmad, S. S., & Zaman, N. Q. (2015). Public Perception on the Cultural Significance of Heritage Buildings in Kuala Lumpur. *ASLI QoL2014 (Annual Serial Landmark International Conference on Quality of Life) / AQoL 2014 Istanbul (ABRA International Conference on Quality of Life), Istanbul Technical University, Istanbul, Turkey, 26 - 28 December 2014, 202,* 294–302. https://doi.org/10.1016/j.sbspro.2015.08.233

Bates-Brkljac, N. (2013). Differences and similarities in perceptions of architectural representations: expert and non-expert observers. *Journal of Architectural and Planning Research*, *30*(2), 91–107.

Bianco, L. (2016). In defence of baroque: The wölfflin-frankl-giedion tradition. *The Journal of Baroque Studies*, *1*(4), 5–20.

Celiker, A., & Cavusoglu, B. (2005). Requestioning architectural design regarding the role of far-eastern philosophies on human-well-being. In *Proceedings of the 5th International Postgraduate Research Conference in the Built Environment* (p.305–311). Manchester: University of Salford.

Chen, K., & Tomblin, D. (2021). Using data from reddit, public deliberation, and surveys to measure public opinion about autonomous vehicles. *Public Opinion Quarterly*, *85*(S1), 289–322. https://doi.org/10.1093/poq/nfab021

Coeterier, J. F. (2002). Lay people's evaluation of historic sites. *Landscape and Urban Planning*, *59*(2), 111–123. https://doi.org/10.1016/S0169-2046(02)00007-5

Creswell, P. (2005). What is architecture? Retrieved December 21, 2021, from *http://rebirthofreason.com/Articles/Cresswell/What_Is_Architecture.shtm*l

Cross, N. (2003). *Expertise in design : Design thinking research symposium*. (e Edmonds, Ed.). Sydney: UTS Printing.

English Heritage. (2008). *Conservation Principles, Policies and Guidance for the Sustainable Management of the Historic Environment*. London: English Heritage.

Evans, R. (1997). *Translation from drawing to building. London: Architectural Association*. London: Architectural Association.

Fiorino, D. J. (1990). Citizen Participation and Environmental Risk: A Survey of Institutional Mechanisms. *Science, Technology, & Human Values*, *15*(2), 226–243.

Fishkin, J. S. (1992). Democracy and Deliberation: New Directions for Democratic Reform. *The Journal of Politics*, *55*, 547. https://doi.org/10.2307/2132298

Fraser, I., & Henmi, R. (1994). *Envisioning architecture: An analysis of drawing*. New York: Van Nostrand Reinhold.
Groves, R. M. (2011). Three eras of survey research. *Public Opinion Quarterly*, *75*(5), 861–871. https://doi.org/10.1093/poq/nfr057
Hägen, M. (1986). *Varieties of realism*. New York: Cambridge University Press.
Howarth, J., Currie, M. A., Morrell, E., Sorensen, J., & Bengle, T. (2017). Challenges of building community-university partnerships in new poverty landscapes. *Community Development*, *48*(1), 48–66. https://doi.org/10.1080/15575330.2016.1244696
Japec, L., Kreuter, F., Berg, M., Biemer, P., Decker, P., Lampe, C., … Usher, A. (2015). Big Data in Survey Research: AAPOR Task Force Report. *Public Opinion Quarterly*, *79*(4), 839–880. https://doi.org/10.1093/poq/nfv039
Kensing, F., & Greenbaum, J. (2013). Heritage: having a say. In J. Simonsen & T. Robertson, *international handbook of participatory design* (p.21–36). Routledge.
Klašnja, M., Barberá, P., Beauchamp, N., Nagler, J., & Tucker, J. (2015). Measuring public opinion with social media data. In *The Oxford Handbook of Polling and Polling Methods* (p.555–582). https://doi.org/10.1093/oxfordhb/9780190213299.013.3
Liu, B. (2015). *Sentiment Analysis: Mining Opinions, Sentiments, and Emotions*. Cambridge: Cambridge University Press. https://doi.org/10.1017/CBO9781139084789
Moomaw, S. M. (2016). Improving local results: Fusing community design and community development. *Community Development*, *47*(5), 670–682. https://doi.org/10.1080/15575330.2016.1228688
Mullins, M. (2006). Interpretation of simulations in interactive vr environments: depth perception in cave and panorama. *Journal of Architectural and Planning Research*, *23*(4), 328–340.
Newport, F. (2011). Presidential Adress: Taking Aapor's Mission to Heart. *The Public Opinion Quarterly*, *75*(3), 593–604.
Perrin, R., & Atske, S. (2021). 7% of Americans don't use the internet. Who are they? Retrieved December 21, 2021, from *https://www.pewresearch.org/fact-tank/2021/04/02/7-of-americans-dont-use-the-internet-who-are-they/*
Powell, M., Colin, M., Lee Kleinman, D., Delborne, J., & Anderson, A. (2011). Imagining ordinary citizens? Conceptualized and actual participants for deliberations on emerging technologies. *Science as Culture*, *20*(1), 37–70. https://doi.org/10.1080/09505430903567741
Robertson, T., & Simonsen, J. (2012). Challenges and Opportunities in Contemporary Participatory Design. *Design Issues*, *28*(3), 3–9. https://doi.org/10.1162/DESI_a_00157
Sanders, E. B.-N., & Stappers, P. J. (2008). Co-creation and the new landscapes of design. *CoDesign*, *4*(1), 5–18. https://doi.org/10.1080/15710880701875068
Sanoff, H. (2000). *Community Participation Methods in Design and Planning*. New York, NY: John Wiley & Sons Inc.
Sarewitz, D. R. (2015). CRISPR: Science can't solve it. *Nature*, *522*, 413–414.
Shah, D. V., Cappella, J. N., & Neuman, W. R. (2015). Big Data, Digital Media, and Computational Social Science: Possibilities and Perils. *The ANNALS of the American Academy of Political and Social Science*, *659*(1), 6–13. https://doi.org/10.1177/0002716215572084
Stroud, N. J., & McGregor, S. C. (2018). *Digital Discussions: How Big Data Informs Political Communication*. New York, NY, US: Routledge.
Talib, R., Kashif, M., Ayesha, S., & Fatima, F. (2016). Text Mining: Techniques, Applications and Issues. *International Journal of Advanced Computer Science and Applications*, *7*(11), 414-411. https://doi.org/10.14569/IJACSA.2016.071153
Tandel, S. S., Jamadar, A., & Dudugu, S. (2019). A Survey on Text Mining Techniques. In *2019 5th International Conference on Advanced Computing & Communication Systems (ICACCS)* (p.1022–1026). https://doi.org/10.1109/ICACCS.2019.8728547
Watts, J., & Hirst, M. (1982). User participation in the early stages of building design. *Design Studies*, *3*(1), 11–18. https://doi.org/10.1016/0142-694X(82)90074-6

Wyatt, R. (2004). The great divide: differences in design style between architects and urban planners. *Journal of Architectural and Planning Research*, *21*, 38–54.