# Assuming Consensus: How Socio-technical Assumptions are Influencing Decision-Making in the Age of Machine Learning

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This paper explores the evolving landscape of collective decision-making facilitated by the integration of Artificial Intelligence (AI). It focuses on the integration of Machine Learning (ML) in Group Decision Making Support Systems (GDSSs)– software systems helping groups optimize decision-making. We conduct a qualitative discourse analysis and discuss five socio-technical assumptions that underlie the integration of ML in GDSSs. While prior literature discusses integrating AI in decision sciences, less research has focused on integrating ML in GDSS software services available in the market. Our findings and discussion question the belief that ML-driven GDSSs inherently lead to improved decision-making by illustrating how assumptions are translated into technical design. We argue that translating collective decision-making into technical design is a complex, non-linear process that requires careful consideration of the social and organizational contexts in which these systems are deployed. Finally, we identify areas for further research for technologists, facilitators, product developers, and academics to address the limitations and potential biases inherent in ML-driven GDSSs.

Additional Key Words and Phrases: Human-centered computing → Computer-Supported Cooperative Work, Group Decision Making Support Systems, Machine Learning, Artificial Intelligence, Civic Technology, Discourse Analysis

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## 1 INTRODUCTION

The manner of group decision-making is undergoing a transformation due to the rapid advancements in Artificial Intelligence (AI). This technological evolution is driving the creation of diverse software systems specifically engineered to enhance collective participation, optimize information dissemination, and streamline efficient decision-making processes across companies, communities, and democratic institutions alike.

This change is already taking place on the global stage. The Taiwanese government is experimenting with Polis[17], a platform that leverages inclusive discussion and decision-making to inform policy [87][73]. Japan is using Decidim [4] to foster civic participation [30]. Fora, a deep listening software system [9], is used in smaller communities like Maine's public schools to "strengthen student voice" as well as in NYC's Department of Health and Mental Hygiene to make high-risk populations "feel like they are part of the solution". Metagov and Murmur focus on improving collaborative decision-making in dispersed online communities and teams [13][15].

Despite their diverse applications, these tools can all be classified as Group Decision Making Support Systems (GDSSs). GDSSs are interactive software platforms that facilitate and support collaborative group decision-making [44]. Their aim is to help groups that are struggling with the challenges of online decision-making: group divisiveness, information access, communication, and sentiment analysis. They typically offer a range of features

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like decision modeling, voting mechanisms, and other digital tools to help groups make better decisions in a more efficient manner.

In pursuit of efficiency and “optimizing” decision-making processes, these tools increasingly integrate Machine Learning (ML) into their systems. By integrating ML, GDSSs aim to foster collaboration, increase diverse opinions, gain visibility to public sentiment, and make the decision-making process easier, faster, and simpler. While integrating ML into GDSSs creates new potential for collective decision-making, we analyze the underlying assumptions embedded in the design of these technologies and prompt future research to explore their potential short and long-term implications.

Through qualitative discourse analysis [51], we find five socio-technical assumptions in ML-driven GDSSs that build on one another. We begin with (1) the assumption that social, human processes can be replaced (or removed) by technology to optimize for efficient decision-making. From there, we focus on the assumption that (2) tools can optimize the process of decision-making by presuming what information, method of deliberation (or conversation), and kind of vote will result in the best and most efficient decision. This presumption, in turn, creates the assumption that (3) decision-making is linear. From there, a series of more technical-level assumptions emerge about the (4) reliability of the algorithmically derived insights–specifically, (5) analyzing information based on sameness will authentically reflect the opinions of a group.

## 2 GROUP DECISION-MAKING SOFTWARE SYSTEMS

GDSSs are software systems that help groups optimize decision-making [44] [50]. They aim to support groups of varying sizes – from corporate teams to national democracies – and contexts, including digital democracy, organizational management, and community organizing [45]. GDSSs vary in their approach (computer-based, in-person, or hybrid), the expected decision outcomes (final vote, decision options, information gathered, idea generation), and the target group size and level [53]. GDSSs offer a range of in-person and online approaches, mechanisms, and tools that help groups arrive at a decision. For example, these often include online forums, surveys, pools where participants share their opinions to inform decision-making processes, recording software that maps key topics and groups' sentiments in interactive displays, structured online debate interfaces that build and visualize arguments to support consensus-building, and opinion prioritization and voting mechanisms based on historical data or sentiment analysis).

Given GDSSs' interdisciplinary nature, existing academic literature intersects with Information Management, Computer Science, Human-Computer Interaction, and Computer-Supported Cooperative Work [82][78]. Literature in information management defines a GDSS as an interactive computer-based system that aims to augment the effectiveness of decision groups through the interactive sharing of information between the group members and the computer" [45][50]. The academic term “GDSS” is a subset of Decision Support Systems (DSS) [79]. DSS are an umbrella term for a range of informational computer systems that aim to improve a company, organization, government, and/or community's decision-making capabilities. However, unlike general decision support systems, which often make decisions autonomously, GDSSs are specifically designed to *help groups of individuals* make decisions collaboratively.

As GDSSs increasingly use digital technologies to foster collaboration, Machine Learning (ML) offers new integration capabilities in decision-making processes. Machine Learning (ML) is a subset of artificial intelligence that empowers computers to learn from data– identify patterns, relationships, and trends within datasets–without explicit programming. ML expands across various domains as technology advances, and the specific ML algorithm chosen depends on the industry, challenge, and the type of data available for training and testing. Since the early 1990s, prior works have discussed GDSS's capabilities of integrating Intelligent mechanisms to assist, enhance, and expedite decision-making processes. Studies throughout the 90s focused on the impact and effects of GDSSs– such as evaluating automated versus human facilitation [66][58][31], possibilities for idea generation

[26], testing success in achieving group consensus [93][40], effects on leadership styles [65][91][50], developing open frameworks [63], and outlining various technical issues [25]. Recent literature on the integration of AI in GDSS, focuses on technical implementations to improve flexible and modular GDSS systems (namely, multi-criterion decision-making techniques, augmenting dialogues [39], generating ideas[90], negotiating solutions [39], improving communication through NLPs [91], and building consensus models in multi-granular linguistic context[70]) as well as predictive insights, such as using ML to predict judicial decisions [49]. A few studies have evaluated the application of GDSS in the fields of healthcare, education, and crisis management [28] [56][79]. However, no prior research–to our knowledge– takes a qualitative approach to understanding the *integration of machine learning* in group decision support software systems in the market.

As GDSSs integrate ML, their inherently interdisciplinary nature expands, taking on "new" and overlapping classifications. For instance, in computer-supported cooperative work, GDSS are sometimes referred to as Groupware [78] or Collaborative Decision-Making Tools [54]; in Human-Computer Interaction (HCI), they are referred to as Interactive Decision Support Systems [79]; Science and Technology Studies (STS) uses civic technology and/or crowdsourcing initiatives [80]; and within the field of information management, GDSS systems using AI can be classified as a subset of Intelligent Decision Support Systems (IDSS) [88][52]. For brevity and specificity, we refer to these systems as "ML-driven GDSS": *software systems that use machine learning to help groups of individuals make decisions.*

## 3 METHODS

Our research investigates the utilization of machine learning (ML) in Group Decision Support Systems (GDSSs) to understand how technology aggregates information and facilitates decision-making processes. The research questions (RQs) guiding this study are: (RQ1) *How do GDSSs use ML to support decision-making processes?* (RQ2) *What assumptions underlie the implementation of MLAs in GDSS?*

### 3.1 Data Collection

We employed a mix of keyword searches and industry reports to evaluate over 100 GDSSs based on specific criteria (shared below). We searched for specific phrases such as "collective decision-making software" and "digital voting tools" to find various software companies. By filtering for "similar companies," we identified and included a diverse range of emerging GDSSs that were not easily accessible or identifiable through traditional sampling methods. This approach allowed us to gather a comprehensive dataset that represents the wide (and expanding) landscape of GDSSs. Additionally, it allowed our data set to reflect the nascent nature of software systems leveraging machine learning to support group decisions. Notably, many of the GDSSs that met our criteria do not "self-identify" as GDSS. To identify relevant GDSSs, we evaluated software systems that met the following criteria:

- **The entity [1] must offer or use a software service.**
- **The entity must support groups of people** of varying sizes, ranging from small groups (e.g., 5-6 members) to larger groups (e.g., hundreds or even thousands).
- **The entity must be aimed at supporting the decision-making process**- such as identifying group challenges or pain points, aggregating data to support decisions, deciding on a direction, implementing a group decision, reviewing a decision's impact, and/or predicting future decisions.
- **The entity must use a form of automation** to assist decision-making processes, such as k-means clustering, textual analysis, algorithmic sorting, chatbot assistants, etc.

[1]We use the term entity to refer to established organizations or systems, regardless of their sector. Including, for-profit companies, organizations, non-profits, not-for-profits, collectives, governments, institutions.

### 3.2 Data Analysis

Our data analysis consisted of two phases intended to further our understanding of the GDSS product landscape. Our findings and discussion focus only on Phase II; however, we share our data analysis to provide transparency into our process.

**Phase I.** In Phase I, we conducted a general landscape mapping of the 103 software systems that met our aforementioned criteria of GDSSs. We identified each GDSS's (1) core aims, (2) challenges, (3) approach to addressing the challenge, (4) data source, and (5) data analysis system. We sorted the software systems based on their core aims for internal clarity. We developed a codebook [71] to classify each "type" of software into Civic Engagement, Community Tools, Data Analytics, Direct Decision Support, and Information Management. From there, we identified each GDSS's (6) intended audience, (7) target area of support in group decisions, and (8) role of automation in their respective systems. We categorized each GDSS based on the various stages of the decision-making process (e.g., identifying objectives, gathering information, analyzing data, making decisions, implementing actions, reviewing outcomes, and predicting future trends). Finally, we evaluated the role of human interaction in automation across various stages, such as data collection, processing, and analysis, distinguishing between fully and partially automated processes.

**Phase II.** After reviewing the data from Phase I, we noticed significant trends regarding GDSSs' use of Machine Learning. Consequently, we opted to transition towards a discourse analysis approach [51]. Discourse analysis is a valuable research method for studying the socio-technical assumptions in ML-driven software systems because it allows us to examine how language constructs design [51]. We leverage discourse analysis to evaluate GDSSs' use of language, content, and UX design and understand how these elements further assumptions about group decision-making. At times, we examined how user interfaces, such as voting mechanisms, buttons, and marketing messages, guide users' interactions with technology, thus reinforcing ideologies. This method provides a nuanced understanding of the complex interplay between technology, language, and society, helping future researchers to identify and address potential ethical and social implications of ML-driven software systems[51]. We contextualize and analyze these insights in academic literature to highlight how these software systems reinforce specific ideologies and assumptions.

While our findings and discussion are undoubtedly grounded in Phase I, we felt that a discourse analysis approach was ultimately more accessible and within the scope of our limitations. That said, we abstain from reporting numerical findings from the dataset because they do not directly inform our discussion of socio-technical assumptions in machine learning.

### 3.3 Limitations

Firstly, the evolving nature of ML integration in GDSS technology industry posed a challenge to our complete comprehension of the landscape. Software companies frequently launched and integrated new AI GDSS tools throughout our data analysis, requiring frequent adaptations and amendments to our understanding of these systems. At times, the information was scarce, restricted to customers, or non-existent. Additionally, we acknowledge inherent limitations due new updates post-data collection and unavailable information about machine learning tools.

Secondly, the term GDSS – as an academic concept – is limited and does not fully encompass the diverse and rapidly growing range of software systems and products we examined. The scale, focus, and applicability of GDSSs are also evolving as intelligent technologies emerge. The nascent nature of the space, however, pushed the limits of what constitutes "a defined group?" or what classifies "collaboration"? To address this challenge, we developed a broad criteria of inclusion. The two researchers co-coded the data, discussing the inclusion of each software system. While the range of GDSSs we include may extend beyond traditional existing interpretations of GDSS in Information Sciences and Management, we believe are able to understand a breadth of emerging technologies and discuss wide-reaching implications.

Thirdly, our technical analysis of these software systems is grounded in the disciplines of STS, Digital Humanities, and qualitative HCI research. The lead researcher's background in digital humanities and HCI offers a critical perspective on software systems– namely, focusing on the social and cultural implications rather than just technical application. The second author's background in governance, and group facilitation provided insights into the nuanced social processes. While the lack of technical interoperability can be viewed as a limitation, we believe that a healthy distance from the technical development is a strength. We approach this research knowing that "expertise" takes many forms. In short, this research functions complementary to future technical studies.

## 4 FINDINGS AND DISCUSSION

This section outlines the landscape of ML integration in GDSSs and examines five underlying socio-technical assumptions. Our findings and discussion challenge the notion that ML-powered GDSSs automatically enhance decision-making by demonstrating how these assumptions influence technical design.

### 4.1 Landscape of GDSS integration of Machine Learning

As ML is improving at processing large unstructured datasets, GDSSs aim to leverage these technologies to aggregate information from many participants while improving group communication, deliberation, and decision forecasting. GDSSs, specifically, seek to leverage ML to make decision-making "easier," "faster," and "simpler" by addressing a range of specific challenges:

- **Online divisiveness**: Existing research highlights how divisive conversations and echo chambers on social media fuel polarization [81] [59] rather than create generative debate or mutual understanding– thus, hindering communication and collective decision-making. To address this, GDSSs use ML to aggregate and analyze conversations and identify areas of overlap in people's opinions, which is then used to guide discussions based on shared perspectives to optimize for consensus.
- **A lack of diversity of opinions**: Ensuring that individuals impacted by decisions have the opportunity to participate in the decision-making process is crucial to "good governance"[77]. However, achieving widespread inclusion can be resource-intensive, and individuals, especially socially, economically, and politically marginalized individuals, may be inadvertently excluded. This exclusion results in the absence of valuable local insights in decision-making. To increase the diversity of opinions and integrate participatory processes, GDSSs [1][14]aim to automate data analysis [84] from large-scale participatory surveys [95] – using crowdsourced analytics, they aim to identify valuable perspectives, feedback, and ideas that are often overlooked.
- **Difficulty gauging the sentiment of large groups**: Prior work highlights the challenge of understanding and interpreting group sentiments at scale[92]. As a result, governments, organizations, and institutions apply ML-driven GDSSs to interpret group sentiment, track emerging issues, and identify areas of concern or opportunity [89].
- **Group decision-making processes can be slow.**: Many organizations struggle to aggregate information across multiple stakeholders and experience apathy in contributing [53]. ML-driven GDSSs aim to enhance the speed, "accuracy," and "overall effectiveness" of group decision-making within a group [5][16].

To address these challenges, GDSSs rely on ML specifically to (1) interpret the sentiment of group conversations, (2) identify underlying themes, and (3) cluster similar topics and/or opinions within conversations. Data is typically derived from recording group discussions, participatory surveys, and internal documents/databases. Notably, GDSS use of ML occurs at various stages of the decision-making process (e.g., identifying core challenges, gathering relevant data, analyzing information, deciding on decisions, and modeling future predictions), and currently involves various levels of human involvement. The specific ML systems GDSSs use include K-means clustering, natural language processing, and recommender systems. We present these high-level definitions to provide context for our discussion below.

- **K-Means (or KMeans++)** clustering algorithms are algorithms that attempt to create clusters in a dataset [46][67]. In GDSSs, these algorithms are used to convert words into numerical representations (using programs like SBERT) [19], and group words that are similar in meaning. GDSSs often employ K-means clustering algorithms in addition to NLPs to group people based on preferences, opinions, and personas. For instance, Polis uses K-means clustering algorithms to generate a map of participants' opinions, clustering participants using K-means assigned opinion groups[85].
- **Natural language processing (NLP)** systems specialize in interpreting and analyzing textual data. They offer text classification, sentiment analysis, information extraction, speech recognition, and topic modeling. NLP systems are often used to sort data into categories such as positive, negative, or neutral and/or identify underlying topics or themes [75]. Processes such as keyword extraction play a role in summarizing content and tagging words with sentiment score gauge sentiment, which is then used to model general sentiments across a dataset [91]. For instance, CitizenLab [2] uses topic modeling algorithms to identify key topics based on the co-occurrence of words in feedback submitted by citizens. It then uses visualizations (such as word clouds, bar charts, etc.) to display the most prominent words associated with each topic and their prevalence in the dataset.
- **Recommender systems** aggregate and analyze historical data that can be used to predict future outcomes. They can assist in aggregating individual preferences or votes into a collective decision [68]. Within GDSSs, for instance, a recommender system can analyze historical data related to a group member's voting patterns on N statements. Based on this analysis, it can then predict whether the member is likely to agree or disagree with an unseen statement. Platforms such as Konveio [12] and Imagina [11] gather data from users' past behavior and recommend future actions that reflect existing patterns in participant data.

## 4.2 Socio-technical assumptions underpin the implementation of ML-driven GDSSs

The assumptions outlined in this paper build on one another, starting at the most foundational, systems-level assumptions about decision-making, from which a set of more technical-level assumptions are made on an algorithmic level.

*4.2.1 Assumption 1: Consensus is an output.* At their core, GDSSs aim to improve decision-making. By aggregating, analyzing, and synthesizing large sets of diverse information, ML-driven GDSSs aim to help groups make decisions faster. To do this, these systems focus on broadening participant input, identifying patterns across different data sets, and simplifying the method and manner of choice. ML-driven GDSSs optimize for a decision (i.e., a majority vote, commonly referred to in this context as "consensus") as the final output of the system [47][94]. For example, The Collective Intelligence Project (CIP), an incubator for new governance models for transformative technology, is experimenting with using blockchain to create programmable governance that can "achieve consensus at scale" [23]. For CIP, "consensus" is used as a synonym for a majority, such as a tallied vote. They elaborate on their website, "Consensus is signaled through a user interface that displays the vote tallies for each option, and the value created is represented by the financial value of the governance token" [36].

Definitionally, this assumption reduces consensus to the output of decision-making, substituting the participant-driven process elements of consensus building with software. As a process, consensus decision-making aims to facilitate open dialogue, active participation, and a commitment to finding solutions that everyone in the group can accept [34][24]. In this process, it is not about having everyone "agree," but, rather, it is about allowing a group to achieve a shared understanding and move forward together. These processes are inherently iterative and non-linear in nature. Such approaches to decision-making can be found across cultures and time, from Indigenous communities [60] and Quakers [21] to social movements [6] and pirates [86].

The current approach to ML-driven GDSSs treats consensus as an output for which the system is optimizing. For instance, Polis organizes individual opinions by tallying votes to pinpoint areas of group cohesion [85], a concept known as group-informed consensus[22]. Consensus statements are identified as the desirable outcome of roundings of voting. Here, they operate under the assumption that deliberation can be deduced to three outcomes – a "yes," "no," or "neutral" vote. A newer GDSS, called Common Ground [7], iterates on this approach. Instead of voting on consensus statements in isolation, they “match participants into small groups of three people where they are encouraged to deliberate over the Statements they vote on, and where an AI moderator powered by GPT4 synthesizes new Statements from the content of their discussion”[7]. Building consensus is often costly

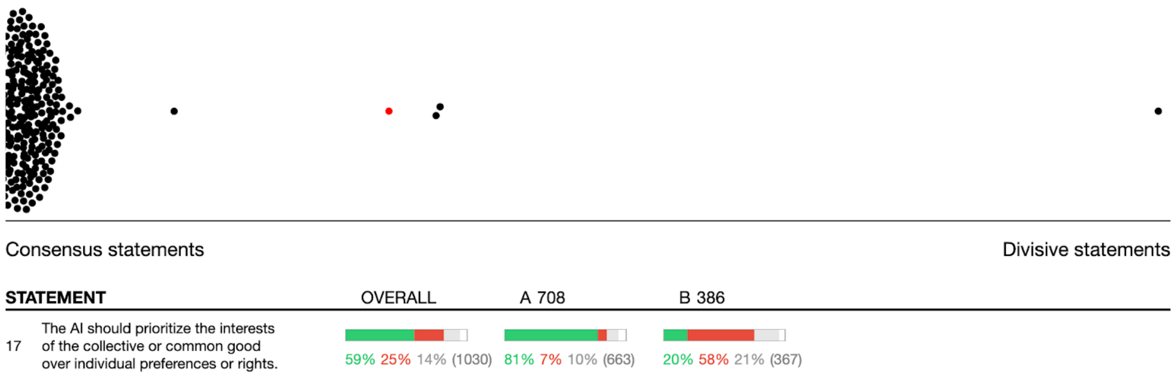


Fig. 1. Polis’ Data Visualization of Consensus Statements, 2021, [85]

and efficient — variables these systems seek to optimize against. For instance, Murmur writes, “Waiting around for consensus leaves your team… waiting around” [15]. In many ways, the cost and the complexity associated with it at scale are the exact problems these systems seek to solve through tech solutions.

This seems like an obvious assumption. Logically, software systems designed to support decision-making would seek to product a decision. However, this assumption prompts the question: What is lost when we remove or greatly condense open and inclusive deliberation, discussion, and negotiation from decision-making?

No single response exists to this question, as not all organizational or institutional constellations or group problems require the same combination of process and outcome. And yet, by assuming consensus is an output of the system, not a process undertaken by its participants, ML-driven GDSSs do exactly that: assume what information and process can be condensed or removed to arrive at good outcomes for a given set of organizations and decisions (i.e., their users). We will further explore these assumptions later on.

This optimization process also risks the loss of something at the root of the Latin word consensus — *consentire* or “feel together.” How groups not only make decisions together, but coordinate and collaborate on the implementation and impact of those decisions requires group cooperation, cohesion, and trust. Group cultures that possess these elements are often based on mutual respect and understanding — qualities so commonly cultivated and tested in moments of overcoming conflict and disagreement [47]. Put differently: assuming that the process ends with the output of a decision made may overlook what is needed to make the implementation of decisions successful in practice [34]. It also may undervalue the messy alchemy of how people achieve understanding as a group — or “feeling together”.

*4.2.2 Assumption 2: The manner and method of group decision-making can be presumed.* GDSSs presume the path a group will take in making a decision — from the information needed to inform a decision to the type of deliberation and the method of voting. Given ML's proficiency in analyzing information, ML-driven GDSSs assume what information and method of deliberation is needed for group decision-making.

For example, ThoughtExchange[20] is a GDSS that gathers diverse perspectives, ideas, and feedback from large groups to solve complex problems. One of their products [23] allows participants to share their thoughts anonymously, view, and rate their peers' thoughts. ThoughtExchange uses ML to analyze ratings and process data to identify trends, patterns, and insights. The platform allows organizers to view real-time visualizations of sentiments, priorities, and emerging consensus during the ongoing exchange. ThoughtExchange is an example of a GDSS assuming that group participants will benefit from summarized insights about their peers' preferences devoid of detailed discussion. Similar assumptions manifest in GDSSs that use recommender systems that presume suggestions based on historical data or individual preferences to expedite decision-making.

To prevent or hinder polarization, some GDSSs leverage argument-based systems that allow users to explain or justify their vote/opinion [39]. This approach is furthered by aspect-based sentiment analysis (ABSA) technologies that classify opinions and cluster them based on similar perspectives. Other GDSSs, like Polis, limit or remove back-and-forth comments to minimize trolling and reduce divisiveness [18]. For example, Murmur, a platform for collective decision-making, promotes the idea of faster decision-making by simplifying choices into binary options — consent or object. Decisions are made with three rounds of voting to either "consent or object." Each decision has an expiration date and opportunities to collect feedback. Their approach assumes that (1) deliberation hinders progress and (2) automated systems can optimize team alignment. Similar to CIP, Mumur's approach to consensus building is viewed as a product of aggregated preferences, in this case, tallied votes. [15]. Similarly,

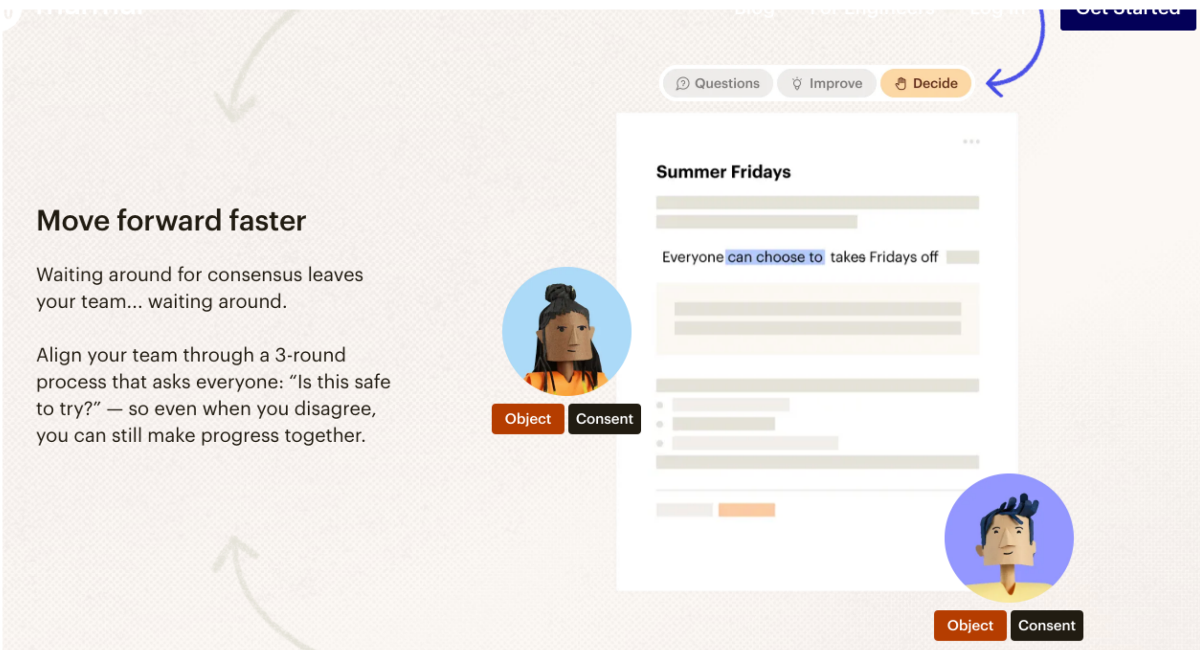


Fig. 2. Murmur's Landing Page

Polis' consensus statement dashboard assumes a singular vote or metric may accurately capture someone's stance or context [Figure 1] [85]. They believe that if participants can visualize where their opinions lie relevant to others, consensus can be achieved faster. It's crucial to note, however, that deliberation yields information beyond this binary framework. Others, like Inclusive.AI [84], are experimenting with distributed voting (instead of a single vote) to gauge how strongly people feel about consensus statements by allowing them to distribute voting tokens across many statements.

GDSSs use ML to streamline decision-making by reducing arguments and predicting options algorithmically. Aiming to optimize group decision-making for consensus results in predictions about how a group will arrive at a consensus [33]. One example presumes that data-driven recommendations can enhance the decision-making process, while the other believes reducing argumentation and simplifying user choices will expedite group decisions. Despite the different approaches, both presume that ML can effectively optimize the information required for group decisions, thus reinforcing a linear process that overlooks creativity, conflict, iteration, and flexibility in the name of optimization.

*4.2.3 Assumption 3: Decision-making processes build linearly.* ML-driven GDSSs simplify dynamic group facilitation into digital processes to facilitate consensus. GDSSs use a range of techniques (i.e., Majority Rules, Unanimity, Plurality, the Condorcet Method, Borda Count, the Delphi Method, and Nominal Group Techniques) to support groups in reaching consensus. However, automating these processes comes with a trade-off, as it tends to simplify the decision-making procedures, often adhering to linear approaches [55]. Despite efforts to build customizable

**Figure 1**
**Polis Process Overview**

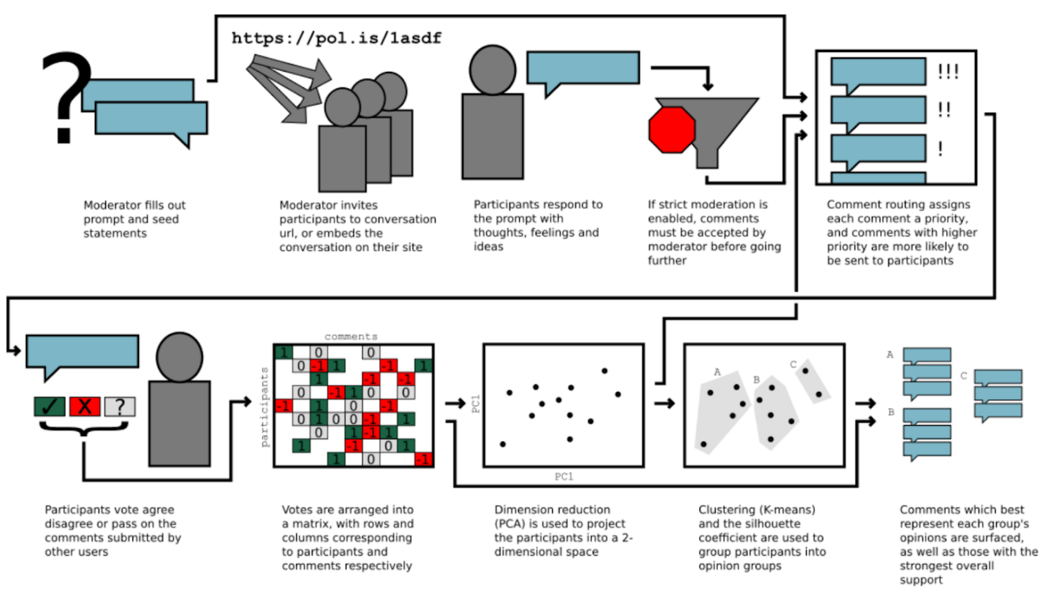


Fig. 3. An example of Polis' process using algorithms to order and scale democratic participation [85]

[94] or modular [70] ML-driven GDSSs systems, the baseline assumption is one of linearity — that the system itself ultimately drives towards a decision being made (see aforementioned sections 1 and 2).

Assuming a linear approach to decision-making risks overlooking the richness of diverse perspectives, creative solutions, and complex interactions that arise during group deliberations. When the outcome is prioritized over the process, ML-driven GDSSs may inadvertently limit the exploration of unconventional ideas and hinder the emergence of innovative solutions that could arise from more open-ended, non-linear approaches to decision-making.

*4.2.4 Assumption 4: Clustering information based on similarity leads to deeper insights about group sentiment.* GDSSs commonly use NLPs for sentiment analysis and topic modeling[40], with the goals of creating "trustworthy dialogue" [9], "removing bias" [2], "amplifying real voices" [9], "developing collective intelligence" [10], and "providing proof of listening." In other words, they aim to leverage intelligent technologies to make sure everyone is heard and opinions are overlooked. However, using NLPs to profile people, ideas, and themes based on algorithmic correlation assumes that clustering information based on similarity will lead to deeper community insights and, therefore, optimize decision-making. This assumption runs the risk of oversimplifying contextual nuance in datasets, overlooking individual differences, debate, and perspective as core tenets of collective decision-making processes.

Consider Citizen Lab, a software platform used for capturing and prioritizing public opinions and ideas to inform policy-making and group decision-making [2]. Citizen Lab uses an NLP model to analyze the most popular keywords or concepts discussed within a community. The platform claims that by using AI and NLP, it can understand the meaning behind each post, categorize them, and provide recommendations [29]. Specifically, they use NLP to cluster important keywords, making frequently mentioned ones more prominent for community managers to easily identify key topics. Similarly, Coritco's Fora AI platform also uses social listening technologies

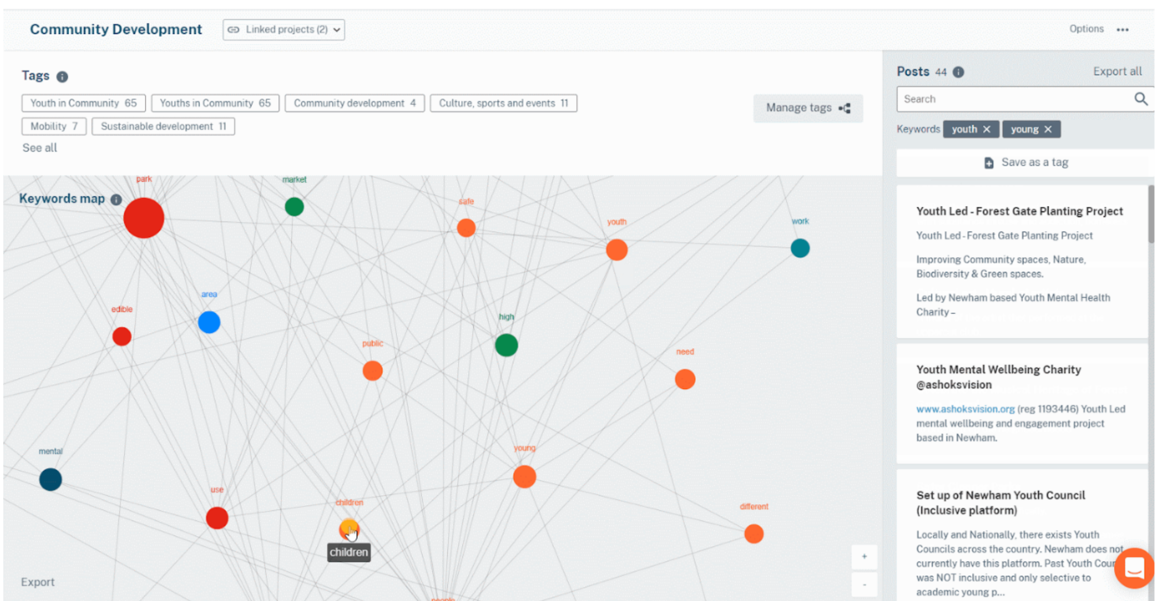


Fig. 4. Citizen Lab's Keyword Map of "Community Development"[29]

to organize sentiment amongst small group dialogue based on perceived group "sameness" [9]. They focus on "creating trust," "promoting openness," and "intimacy" within communities by offering software for customers to memorialize conversations and provide "proof of listening." While it is unclear exactly how Fora operates, their parent company, the Local Voices Network, uses NLP systems to extract topics from larger texts based on the word and/or phrase frequency [3].

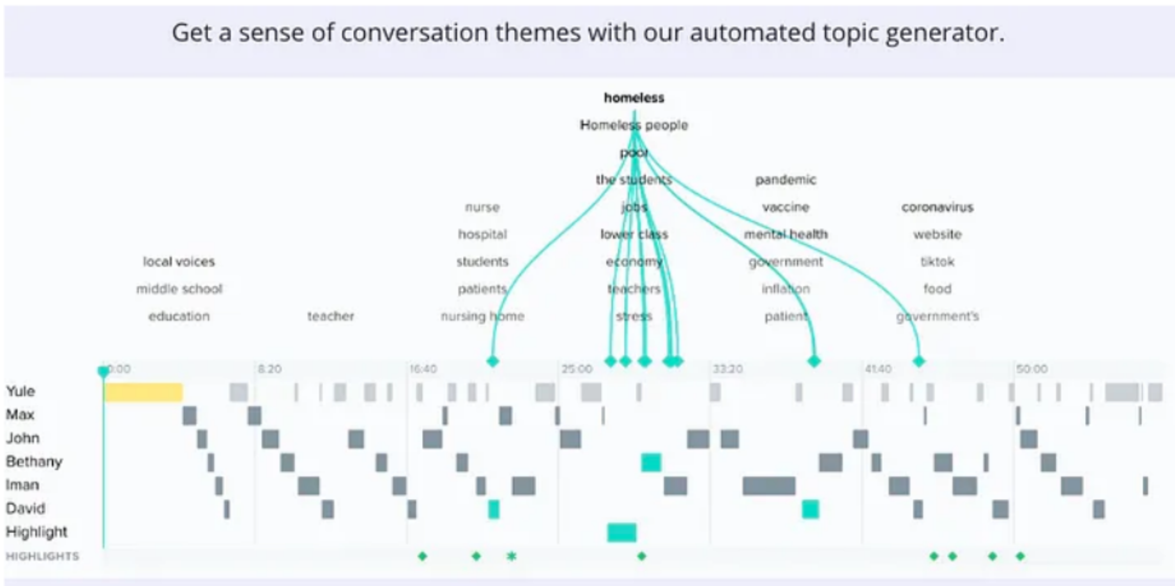


Fig. 5. Local Voice's Automated Topic Generator [3]

These two examples reflect a fundamental assumption of homogeneity — that groups of sameness (in this case, based on the frequency of specific words and or extracting emotional nuances from textual data) will contribute to a more profound understanding of a community. While topic modeling and sentiment analysis clustering may prove useful in some cases, this assumption will continue to (mis) interpret information, especially as these technologies increase data interoperability [57][61][27].

Existing literature highlights the contextual issues of NLPs for sentiment analysis and topic models– specifically, challenges in accurately understanding the context or cultural nuances of a conversation to deem the relevance or meaning of information [61][64]. While some GDSS tools, such as Fluicity [8], are attempting to work collaboratively with local moderators to ensure outputs reflect their specific context, this assumption goes beyond the known challenges of lexicon differences, understanding context or cultural nuances [64], registering tonal detection[27], and ensuring quality datasets to interrogate how these systems cluster information based on sameness[38].

*4.2.5 Assumption 5: Correlation between data points is meaningful or significant.* On a foundational level, the method of clustering information assumes that connections between data points are significant. By significant, we mean that patterns in a dataset are not statistically random nor due to chance. GDSSs using ML analyze datasets to identify meaningful patterns and relationships [83]. As previously discussed, they often use K-means clustering algorithms to group similar data points based on perceived "sameness" or NLPs to categorize sentiment and identify topics in the text [38]. Regardless of the method, identifying sameness (or correlation) is how ML algorithms determine agreement (or consensus), and expedite collective decision-making [38].

As individual experience is bucketed into clusters of sameness, based on correlation, GDSSs assume that there is a "ground truth" of information that is "relevant," "authentic," "meaningful," or "significant" [38]. If any correlation could be found, what information can be considered authentic?

Wendy Chun's book *Discriminating Data* explains how correlation is a co-relation and is not always significant [38]. As technological systems reduce the number of variables to make data searchable, Chun explains how correlation "…is a complicated technical process and is not simply a one-to-one relationship" [38, p.52] Rather, correlation "measures how two or more variables vary together" [38, p.52].

However, such statistical models are often reduced to numbers, devoid of context. Safiya Noble comments on this point, "reducing the conversation about algorithms and AI to saying it's just math really strips away the social context within which the math is deployed, which has all kinds of politics and meaning attached to it" [74]. For example, correlation is directly associated with the concept of homophily, the idea that people seek out those who are similar to themselves [69][43]. Specifically, "homophily structures networks by creating clusters; by doing so, it also makes networks searchable" [69][62]. Moreover, "it [homophily] presumes consensus and similarity within local clusters, making segregation a default characteristic of network neighborhoods" [38, p.78][37]. For instance, grouping individuals based on shared attitudes, values, or opinions on specific issues–like topic modeling– is an example of homophily in data science[72]. However, academics and technologists in the disciplines of Critical AI

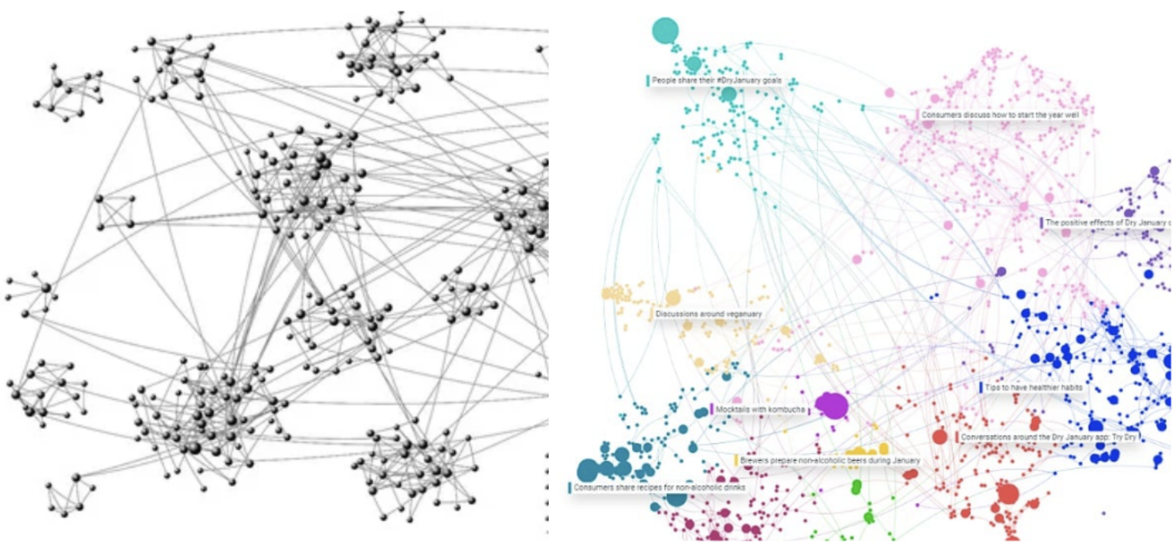


Fig. 6. (Left) Illustration of homophily in network science, (Right) TalkWalker's Keyword Map

and Information Sciences [38][32][42][74][76][48] demonstrate how grouping data (or people) based on "their being 'like' one another amplifies the effects of historical inequalities"[38, p.58]. Existing literature on credit scoring, healthcare, and social media has already explored this assumption, revealing how organizing information based on "clusters of sameness" assumes the outcomes are significant when, in reality, they overlook differences and result in bias and discrimination[76]. As GDSSs use technologies founded upon a privileging of "sameness," the understanding of collective decision-making fundamentally changes. Social processes are conflated with algorithmic outputs that imitate flawed systems. Human experience, relationship-building, and healthy discourse become reduced to proximity between data points.

### 4.3 Discussion

ML-driven GDSSs analyze preferences, cluster people based on "similarity," and simulate dialogues to reach consensus faster, easier, and simpler. However, as optimization is prioritized, we find ourselves at a crossroads where the very tools designed to unify human understanding through data-driven decisions may inadvertently sow the discord they seek to mitigate.

A self-fulfilling prophecy occurs when an expectation or belief influences behavior, thus causing the belief to "come true." Simply put, ML-driven GDSS may be building "intelligent" positive feedback loops. Assumptions inform the system's inputs and, through correlation, confirm the outputs — creating self-fulfilling prophecies. As Wendy Chun explains, technology organizations seek to disrupt the future by making disruption impossible[38]. ML-driven group decision support systems illustrate how technological systems arespun into the feedback loops they aim to disrupt.

At the heart of this argument is the emerging reality that "consensus" as a collaborative social process is collapsed into a technological system based on data science. *Consentire*– the ability to "feel together"– is removed. Adrienne Maree Brown's conversation with Autumn Brown captures this best, "Recognizing that consensus does not mean or require equal status. It rather requires equal voice. But truly, it is also hard because our society functions less and less along the lines of what we need, as humans, to make good decisions" [34, p.170].

When software systems conflate aggregated preferences (such as a majority vote or data points based on proximity) as a signal of consensus, they run a risk of (1) assuming that a group that has researched collective understanding, (2) expecting the group to feel a sense of group ownership of their decision, to recommit and build on those decisions with future choices, and, finally, (3) obscuring accountability when future decisions have unintended consequences.

## 5 FUTURE CONTRIBUTIONS

The aforementioned sociotechnical assumptions reveal numerous areas for future research in HCI, Computer-Supported Cooperative Work (CSCW), and Decision Sciences, as well as technology product development. We highlight opportunities for experimentation on localized implementation of ML-driven GDSS, longitudinal studies on the impact of ML-driven GDSSs, the effects of group decision ownership, and the role of trust in augmented vs human moderation. Future research in these areas will further a better understanding of the impact of ML on decision-making processes and its implications for individuals and communities.

- **Localized GDSS Implementation:** The challenges of scaling collective decision-making processes while maintaining context are evolving. Some GDSS tools, like Fluicity[8], aim to address this challenge by collaborating with local moderators to ensure outputs reflect specific contexts. However, research on localized approaches to ML-driven GDSSs is lacking. Future studies could explore how these systems preserve, correct, or include context and colloquial lexicon, as well as the role of human moderators in different ML-driven GDSSs and how their involvement affects group dynamics.
- **Longitudinal Studies on ML Use in Group Decision-Making:** While there are some studies on the long-term impacts of GDSSs in communities studies[35], research on the evolving role of ML in GDSSs is limited. Given that ML is still in its early stages of implementation, current research and technology organizations should invest in monitoring the ongoing and long-term impact of ML-driven GDSSs. Such projects could evaluate how ML-supported decisions age over time, how ML-driven GDSSs with human moderators differ from those with AI moderation, and how communities leveraging ML-driven GDSSs approach the attribution of decision ownership.
- **Human-Computer Interaction and Collective Identity Formation:** As users are increasingly exposed to ML-driven recommendations, questions about algorithmic identity formation and its influence on individuals' and communities' perceptions of self arise [66]. Future research in HCI should explore how

these systems influence collective identity formation. One area for potential exploration is “Black box gaslighting” [41]. Black Box gaslighting describes the phenomena where platforms “leverage perceptions of their epistemic authority on their algorithms to undermine users’ confidence in what they know about algorithms and destabilize credible criticism” [41]. In other words, when users assume technology is more intelligent then one’s intuition, individuals begin to question themselves. In the context of ML-driven GDSSs, studies should explore how decisions made through GDSSs affect in-person working dynamics, group cohesion, and relationship building.

- **Community Implementation and Algorithmic Trust:** Research has shown inconsistent results when applying group decision-making technology in different settings [58], suggesting a need to consider the context [25]. Future research might explore the extent to which users trust in ML influences their participation, and how context can be implied in the various stages of automation. Additionally, studies could examine situations where GDSSs might fail to capture nuance and how these systems can be altered to reflect difference without streamlining and reducing nuance.

## 6 CONCLUSION

The development of Artificial Intelligence (AI), specifically Machine Learning (ML), is changing the way groups make decisions. In this study, we discussed a range of ML-driven GDSSs across industries–from democratic institutions to corporations– to help groups increase collective participation, improve information flows, and optimize decision-making. Through discourse analysis, we argue that emerging ML-driven software systems assume that social processes of decision-making can optimized through technology. In doing so, these tools build systems that: privilege “consensus” vis-á-vis systems of preference aggregation that overlook the intricate dynamics of how people achieve shared understanding; presume linearity by building systems that pre-determine the manner and method (e.g., information needed, method of deliberation, and style of voting) a group needs to make a decision; and, finally, leverage ML systems that algorithmically validate the idea that clusters of sameness will authentically reflect a group’s opinions. The high-level assumptions are not absolute; rather, they offer an intervention into the current method of GDSS development and prompt further researchers, technologists, and facilitators to explore their unfolding impact.

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