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Exploring Argument Mining and Bayesian Networks for Assessing Topics for City Project Proposals

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Abstract

The digital transformation of cities inspired the city administration of Aschaffenburg, Germany, to apply artificial intelligence to reduce the significant amount of manual administrative effort needed to evaluate citizens' ideas for potential future projects. This paper introduces a methodology that combines argument mining with Bayesian networks to evaluate the relative eligibility of city project proposals. The methodology involves two main steps: (1) clustering arguments extracted from public information available on the Internet, and (2) assessing and comparing selected urban issues, planning topics, and citizens' ideas that have been widely discussed to measure public interest in potential candidate projects. The results of the clustering are fed into a Bayesian network, along with scores for several evaluation criteria, to generate a relative eligibility score. The framework was applied to three candidate projects, resulting in the selection of one of them, while the other two were rejected with a given explanation. The latter motivates the decision and provides transparency to all parties involved in the decision process. The methodology is applicable to other cities after adjustments of criteria.

Keywords: Bayesian networks; argument mining; project evaluation; urban planning

1. Introduction. General Project Description and Context

In early 2021, the German "Free State of Bavaria" announced a competition of proposals for innovative digital solutions or services for Bavarian municipal administrations, developing them into "a town hall of tomorrow"[1]. A lot of citizens are willing to help their city transform into a "smart city". Bavarian communities needed a visionary approach to rethink citizen participation by combining digital and dialogue-oriented approaches. One of the 10 winning ideas was "Digitale Manufaktur" (DiMa), proposed by the northwest Bavarian city

1. The website of the competition of proposals "Kommunal? Digital!" can be found here: `https://kommunal-digital.bayern/` [Accessed 22 Aug 2024]

of Aschaffenburg. Its aim is to support the municipalities with smart assistants, utilizing artificial intelligence (AI) in order to reach transparent and trustworthy decisions. These decisions should be acceptable to both city administrators and to citizens who are willing to actively participate in the city design process.

Therefore, a prototype needed to be developed, demonstrating how a large number of citizens could participate in the development of sustainable digital projects and how submitted project ideas could be developed collaboratively. Citizens expect to obtain access to a collaborative digital platform for citizen participation enabling them to contribute new ideas on controversial urban debates. Such a platform should provide access through two main channels: analogue-digital through a local contact point and by a web-based solution. The analogue-digital aspect of this project has been realized by methods of design thinking, which required also direct dialogue-oriented approaches.

This paper describes the developed web-based prototype. The methodology developed in the *Digitale Manufaktur* (DiMa) project[2] is implemented in a new prototype assistant on decision making for the city administration. This assistant is briefly called *Bay-KI* as a merger of *Bay* (Bayes network) and *KI* (a German AI-acronym for *Künstliche Intelligenz*). It is based on evaluating eligibility scores for the supplied project ideas from citizens, together with the public opinion on these ideas. Bay-KI helps where two or more submitted ideas are on similar topics, by analyzing which of the ideas should be implemented as a matter of priority. To do this, Bay-KI combines two concepts: argument mining and Bayesian network for decision modeling (Kjærulff and Madsen, 2013). Argument mining is used to analyze the contributions of citizens who express their opinions on selected ideas on the Internet and thus gives a picture of the mood, sentiment or motivated position (arguments) towards an idea. For the decision modeling and evaluation, Bay-KI is trained on predefined urban decision criteria. These criteria include: the added value of this idea on citizens' requirements, development goals of urban planning, environmental and social acceptance, a city council resolution, available budget, and others.

The assistant allows explanation of decisions, based on criteria, extracted from citizens' arguments and from city planning. Sentiment analysis allows to distinguish positive and negative arguments. The sentiments are quantitatively represented by statistical measures, expressing the strength of each sentiment in relation to others. Argument mining is used to extract the most widely discussed topics in a city, along with the associated arguments. The arguments are utilized for explanations after the decision making. Explanations are provided based on a combination of the most popular citizens' ideas and the evaluation criteria, used for the selection decision as reached by the Bay-KI-assistant. The explanations ensure transparency for all parties involved. By combining the information provided, the AI calculates a recommendation as to which of the ideas should be transferred into the implementation phase for further development.

We will describe the developed Bay-KI assistant on the example of three use cases: 1) charging stations for e-bikes, 2) organizing a short term rental of scooters and 3) renovating and improving the bike path along the river Main promenade. These three use cases have been selected from the mobility and traffic sector.

2. https://digital.aschaffenburg.de/DiMa/ [Accessed 22 Aug 2024]

The remaining parts of the paper are organized as follows. Section 2 lists relevant background literature while Section 3 presents the novel methodology introduced in this paper. Section 4 describes the application of the methodology and our Decision Support System (DSS) to three use cases as different potential projects, considered by the city of Aschaffenburg. Finally, Section 5 completes the paper with a discussion and conclusions.

2. Background Knowledge and Methods

2.1. Argument Mining

Argument mining is a computational technique that involves extracting structured information from unstructured text, specifically focusing on identifying arguments, their components, and relationships within a given text (Lawrence and Reed, 2020). As a reference use case, in customer feedback analysis and social media monitoring, argument mining enables businesses to extract valuable insights from customer reviews, identify emerging trends and topics, and to understand customers' stance towards products and services (Skiera et al., 2022). As opposed to sentiment analysis, argument mining seeks to extract opinionated statements that give reasons as to why the opinion holder is supporting or opposing a topic (which can be a product and/or service), rather than just expressing favor or disfavor. Extracting arguments from different sources (i.e. multiple documents, potentially from different origins) has been labeled as information-seeking argument mining in previous work (Stab et al., 2018; Trautmann et al., 2020). Information-seeking argument mining is typically framed as a text classification task with two inputs (a topic and an argument candidate). A language model can be used to determine whether the *candidate* is either a non-argument, pro-argument, or con-argument, given the *topic*. State-of-the-art language models can solve this task with high accuracy (Schiller et al., 2023).

While information-seeking argument mining helps to identify different perspectives from a diverse document collection, it can be pretty cumbersome to read through the resulting arguments, in particular when they are repetitive. To that end, previous work suggested to use clustering to sort and group arguments by similarity (Reimers et al., 2019; Bar-Haim et al., 2020). While there are different approaches to argument summarization (Van Der Meer et al., 2024), we follow the work described in Daxenberger et al. (2020), which uses a fine-tuned language model to detect argument similarity and agglomerative hierarchical clustering to build groups of recurring arguments (also referred to as *key points* in other work). To give groups a meaningful name, argument aspects are detected subsequently using the approach described in Schiller et al. (2021). Table 1 gives a full example.

For the usage of argument mining as a tool in facilitating citizen participation, Romberg and Conrad (2021) developed a model to identify and classify argumentative discourse units within public participation processes in Germany. They detect argument structures with high accuracy, improving the ability of municipalities to analyze large volumes of textual contributions effectively.

In our context, information-seeking argument mining is used to infer arguments on topics of public relevance from city council protocols and online news. The arguments corresponding to a given search keywords are selected and clustered. The amounts of supporting and opposing arguments contribute to the quantification of the topic.

Cluster label (aspect)	Argument	Stance
Wald erFahren (*Explore Forest*)	If you are out and about with electric assistance, you will be delighted with the 100 or so charging stations that the "Wald erFahren – Einfach E-Biken" (*Explore Forest – Simply e-Biking*) project has made available throughout the Spessart.[a]	pro
	With the award-winning "Wald erFahren" initiative, the Spessart offers the largest charging infrastructure for e-bikers in the whole of Germany.[b]	pro
	The "Wald erFahren" project has therefore grown significantly in recent months and now offers the opportunity to charge free of charge at 98 charging stations in 49 municipalities from Miltenberg to Obersinn and from Alzenau to Marktheidenfeld.[a]	con

Table 1: Clustered and labeled arguments on the topic of "E-Bike charging stations". Sources: [a]https://agil-dasmagazin.de; [b]https://www.tambiente.de.

2.2. Bayesian Networks

A Bayesian network $N = (G = (V, E), \mathcal{P})$ is an efficient representation of a joint probability distribution $P(\mathcal{X})$ over a set of (discrete) random variables $\mathcal{X}$, where G is an acyclic, directed graph over vertices V and directed edges E such that there is a one-to-one correspondence between V and $\mathcal{X}$. In the set $\mathcal{P}$ of conditional probability distributions (CPDs) there is one CPD for each variable $X \in \mathcal{X}$. It is a factorization of the joint $P(X)$ such that:

$$P(\mathcal{X}) = \prod_{X} P(X \mid \mathrm{pa}(X)),$$

where $\mathrm{pa}(X)$ denotes the parents of X in G. A Bayesian network can be used to compute the posterior probability distribution $P(X \mid \epsilon)$ of any non-observed variable X given evidence ϵ. We assume only hard evidence. Probabilistic inference is the process of computing posterior marginals for all non-evidence variables by message passing (a.k.a. propagation of evidence) in a secondary computation structure.

2.3. Related Work for Bayesian Network Modelling of Citizen Participation

Modeling of citizen participation by use of Bayesian Network (BN) has been attempted during the last years. Kopacheva (2021) deals with predicting online the citizens participation through BN analysis, and suggest that there remains a lot to be done in participation research when it comes to identifying and distinguishing factors that stimulate new types of political activities. Liu et al. (2021) pursue research based on a BN to deal with collaborative governance. The results indicate that the cooperation degree of related governments, conflict resolution efficiency, degree of public participation, and normality of public participation may be key factors that lead to collaborative behavior.

The understanding of driving factors of land-use change decisions, which support decision-making to attain the sustainable development goals has been addressed by participatory BN modeling in Andriatsitohaina et al. (2020). Further aspects of citizen participation for sustainability and resilience have been modeled from a generational cohort perspective on community brand identity perceptions and development priorities in a rural community (Paunovic et al., 2023). They suggest new conceptual and methodological approaches for taking inter-generational equity into account in regional planning processes in rural and other areas (Thananithichot, 2012). BN modeling is used to represent the political engagement and participation of Thai citizens.

The ideas of previous works show various challenging aspects associated with the modeling of citizen participation. In our work, the focus has been on the evaluation of urban development projects' eligibility towards a "livable city", so this required to formulate and use some generic project criteria, which is an approach with some similarity to Sierra et al. (2018). Their work proposes a method to optimize infrastructure projects by assessing their social contribution. We focus on mobility, transport and city development ideas.

3. Methodology

3.1. Argument Mining

As laid out in Section 2.1, we use information-seeking argument mining to extract qualitative information from the sources mentioned in Section 4.1. We used the tool provided by summetix GmbH that implements argument extraction and clustering through a web-based dashboard[3]. It allows to search different sources for free-to-chose *topics* and applies agglomerative hierarchical clustering and aspect detection (see Section 2.1) to the extracted arguments. Users can add "queries" which determine the source and topic. Arguments (sorted by stance: pro or con) are then extracted on the given topic from relevant sentences in the source data. Those arguments discussing similar topics are grouped and the groups are named with a short description, cf. Table 1. The result of a query can be downloaded in a tabular format to be further processed on the *DiMa* website.

The summetix tool performs argument mining on city council protocols and regional online news as well as comments from social media. Extraction of the criteria is given below. At this prototype stage, no expert interviews as proposed in the Delphi method (Sierra et al., 2018) were conducted. Therefore, the criteria are not evaluated yet, but will be during the deployment phase of the project. This will enable the automated evaluation of criteria, which is an essential requirement to speed up the process.

3.2. Bayesian Network Model

Bayesian Network (BN) models facilitate decision-making by quantifying the uncertainties associated with different decisions. They can calculate the expected benefit or risk associated with different decision-making paths, thus helping to choose the optimal decision. Whenever similar ideas are submitted, the tool makes a recommendation to the city administration as to which of the ideas should be implemented with priority. In doing so, the tool uses both the opinion of the urban population (determined through argument mining on social media, see above) and the model-integrated urban decision-making criteria. Decision criteria were defined in the project as specified in Table 2. The order 1–12 gives the priority

3. https://dashboard.summetix.com. Access restricted to authorized users.

of criteria. The meaning of the criteria is clarified by the questions. The importance of evidence is weighted by: 0–5.

Table 2: Criterion assessment: criteria, guiding question, evidence for example, weights.

#	Criterion	Question	Status	Evidence	Weight
1	Requirement	Is there a need for the implementation of the idea?	Yes	More tourists visiting the city by e-bike; existing infrastructure	5
2	Justification	Is there an objective justification for implementing it?	Full	Tourist enhancement, image enhancement	5
3	Council decision	Is there a city council resolution on the subject?	Yes	City Council Resolution from 02.04.2019	5
4	Legal basis	Is there a legal basis?	Yes	AO Bavarian Construction Regulations	4
5	Budget approach	Budget funds available?	Yes	Special appropriations	5
6	Location	Is there a suitable location for the idea (if physically implemented)?	Yes	Electricity connection available near a bicycle parking lot	5
7	External support	Is external support needed for the implementation: construction companies?	Yes	Building yard and Municipal Electricity Authority for structural construction and power supply	5
8	Opportunity	Are there higher goals, that justify the idea?	High	Transport transition, climate change	4
9	Explanation	Does the implemented idea lead to added value and for which user groups?	Full	Added value for citizens and visitors to the city	4
10	Strategy Paper	Is there an urban strategy paper that justifies the implementation of the idea?	Yes	Cycling concept (traffic development plan)	3
11	Representative	Is here a representative to promote the idea?	Yes	Cycling Commissioner	1
12	Funding	Are there funding opportunities that simplify financially the implementation?	Yes		0

The BN $N = (G, \mathcal{P})$ developed to support the ranking of project ideas has three main components: (1) a Naive Bayesian Model (NBM) over a set of indicators I_{AM} representing the results of argument mining, (2) a NBM over the decision criteria from Table 2, and (3) a component implementing a scoring system as the city may want to enforce a minimum required score for each criteria. The structure of the model is illustrated in Figure 1 where C is a criteria, A is an argument mining indicator $\in I_{AM}$, T is the score threshold associated with C. Let the three components be denoted G_1, G_2, G_3. The target variable of the BN is the binary variable E with states 0 and 1 where 1 denotes that the idea is eligible.

The root variables of the two components G_1 and G_2 are linked to an intermediate variable EC, while the root variable of G_3 encoding the constraints on the score thresholds has a binary variable PS specifying if any criteria has not received the required score, in which case the proposal is considered not eligible. The vertices PS and EC are parents of

E, where E equals EC unless PS specifies that a criteria is not satisfied. In this case, E is false. In total, G has 96 vertices as all variables appear twice (once for each project idea).

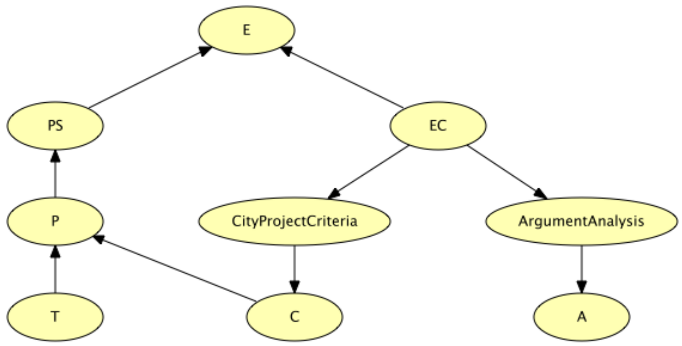

Figure 1: Illustration of the structure of the underlying Bayesian network

The weights of each $A \in I_{AM}$ were assessed using expert knowledge, by first sorting the elements of I_{AM} according to desired relative impact. In the same way, the decision criteria of Table 2 have been weighted by experts according to the order in the table. The most influential design criteria is *Requirement* (and the least is *Funding*). Similarly, the most influential indicator of I_{AM} is the cluster ratio of PRO- and CON-clusters.

The results of the argument mining weights are slightly higher than the decision criteria (with the exception that a decision criteria that does not obtain a score above the threshold will make the project idea ineligible). The BN was tested on a selected set of project ideas and further validation on a larger set of ideas is work in progress.

3.3. Decision Support System (DSS): Web Infrastructure

The developed methodology is combining argument mining and Bayesian networks. It supports the process of decision between competing project ideas. It has been implemented into a prototype web-based DSS, which is available to employees of the city administration as a web interface.[4] Figure 2 shows the underlying system architecture. It consists of a web user frontend and a backend that utilizes the HUGIN Engine and the summetix API.

The summetix API allows to access the functionality described in Section 3.1 in terms of search, clustering and aspect detection through programmatic interfaces. Through the API, the communication between the web user frontend and the argument mining tools can be streamlined without the need to use a separate dashboard.

The HUGIN software is a general-purpose tool for developing and deployment of Bayesian networks. The HUGIN Graphical User Interface has been used to develop the Bayesian network while the HUGIN Engine is a core component of the DiMa web architecture as it is responsible for performing inference in the Bayesian network.

When computing the eligibility of a project idea, the user first performs an argument search, using a set of keywords. Once the search is complete and the user is satisfied with the results, the next step is clustering of arguments. Both steps are performed by the

4. The web site of the prototype can be found here: https://DiMa.hugin.com. Access restricted to authorized users.

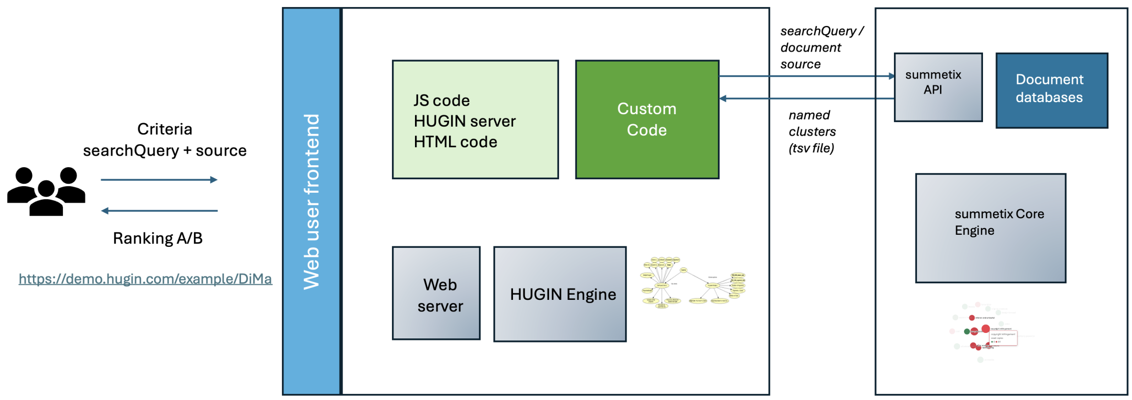

Figure 2: Web Architecture

backend, utilizing the summetix API. Once the argument mining is complete, the values of the argument mining indicators are computed. The user enters the values and score thresholds for the 12 city project criteria. The collected evidence is propagated in the Bayesian network and the results are presented to the user. If any of the criteria does not pass the threshold, it is highlighted by a red circle (see Figure 5) and the entire idea is assigned a score of zero. The parts of the web interface corresponding to argument mining are displayed in Figure 3 and the evaluated city project criteria are shown in Figure 5.

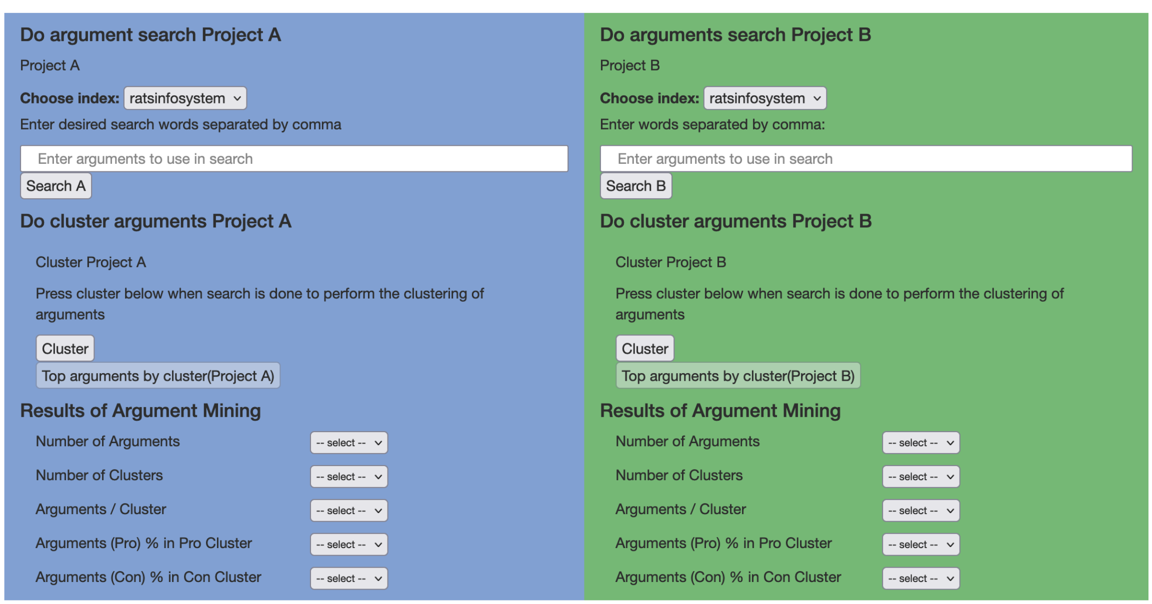

Figure 3: Web Interface for Argument Mining (Figure 5 shows city project criteria).

4. Results

The methodological framework is applied on three project topics that have been considered by the city council of Aschaffenburg. In accordance with the principle of representative democracy, city council members exercise a free mandate. They are only obliged to their conscience and are not bound by instructions. However, they are not parlamentarians and do not hold a general political mandate, as their decision-making powers and responsibilities are limited to local matters and specific tasks that fall within the jurisdiction of the city (Stadt Aschaffenburg, 2021).

4.1. Data Sources

The source of information for our digital prototype are city council protocols and regional online news as well as comments from social media covering the city of Aschaffenburg and its surroundings. We recurred to the city council protocols as a representation of relevant topics for city planning. They are very well redacted and count with a decade long record, which together is representing high quality data. As official and officially edited source, by design, any possible (implicit) citizens' comments were filtered out. To include further perspectives, we also added online news (regional newspapers and websites) as well as public comments from regional Facebook groups.[5]

4.2. Topic Choice

Besides the general assembly, called *plenum*, the City Council deals with specific topics within 20 dedicated committees. The *Planning and Transport Senate* deals with the area from which the projects had been selected: transport and mobility. By an examination of currently discussed topics within urban society in this area, we identified three most relevant topics: (a) E-Scooter, (b) E-Bike charging stations, (c) river Main bike trail. The argument mining procedure is applied on each of these topics, using the main topic as search phrase. Figure 4 shows the clusters of the chosen topics.

In the clusters, size and number of the coloured circles reflect the frequency of arguments. For *E-Bike Charging Stations*, to obtain 4 clusters, the minimal cluster size had to be set manually down from the standard value 5 to the value 3. Table 3 makes the quantification more transparent. The number of input arguments depends on the frequency of the mentioning a certain topic in the source. Evidently the topic of *river Main bike trail* is most prominently discussed, as it is a catchy and transversal topic, particularly within the long-term challenge of a more beautiful design of the palace riverside. The topic of *E-Scooter* is due to the emerging general mobility trend in cities, causing controversial discussions on whether or not to allow rental services. The topic *E-Bike Charging Stations* streamlined the administrative process in order to reach greater tourism attraction.

In the dashboard it is possible to revise each single argument, that is collected in the cluster, with an option to trace back to the source. For each cluster the arguments can be summarized. This is also possible with the help of a a large language model. The

5. Due to license restrictions, online news and social comments cannot be made publicly available, so they were only available to employees of the city administration.

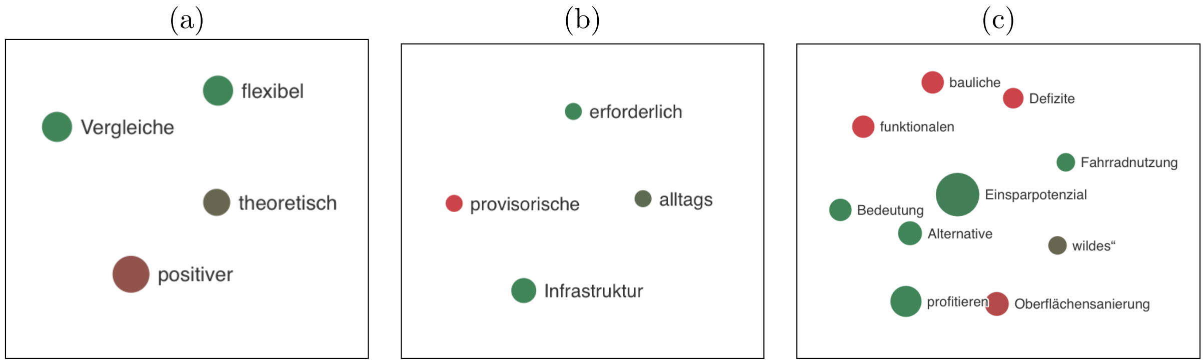

Figure 4: Clusters for considered project topics: (a) E-Scooter, (b) E-bike Charging stations, (c) river Main bike trail; colored circle size is proportional to arguments' frequency; color scale corresponds to sentiment, range from green (pro) to red (contra arguments).

	E-Scooter	E-Bike Charging Stations	River Main Bike Trail
Input arguments	110	38	254
Clustered arguments	26	14	112
Clusters	4	4	10

Table 3: Quantification of clustering for different topics: Number of input arguments, number of clustered arguments, number of clusters.

following quotation summarizes the arguments on the largest cluster, called “Infrastruktur” (*infrastructure*):

> *The charging station system is based on solidarity and benefits both the citizens of Aschaffenburg and day trippers from the surrounding area. The provision of charging stations in the Spessart has led to more cycle tourists exploring the area. Public charging stations are particularly important for multi-day tours and long day tours. The feedback from the municipalities is positive and shows that the uniform infrastructure benefits both national cycle tourism and regional day-trippers. E-bikes are very important in the tourism sector.*

This summary is quite accurate on the opinions, related to the advantages of the project for tourism, serving as a major argument in favor of the installation.

4.3. Evaluation

Within the general methodological framework, the above three topic examples of citizens' ideas are evaluated as candidates of potential project proposals. In the user interface, shown in Figure 3, the argument mining part is filled automatically (by calling the embedded microservices) upon choosing the data source and the search topic. In the demo version, the project criteria can be loaded from a prepared data base. Figure 5 compares the project eligibility criteria for the *E-Bike charging stations* (left blue, Project A) versus *E-scooter* (right green, Project B). The results show that the topic *E-Bike charging stations* obtains higher scores, and thus turns out to be the more eligible project. A user friendly design allows to explain the DiMa evaluation results: green and red circles are showing which criteria are satisfied or not (status: yes/no) and the score achieved. Figure 6 is showing through the lengths of the bars which project idea has obtained a higher score. Project B did not satisfy at least one criteria, so it is not eligible.

Figure 5: User interface: comparison of criteria (with status and scores) for two competing project ideas; the main components of the Bayesian network.

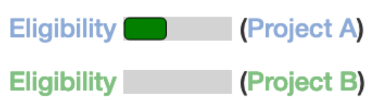

Figure 6: User interface: comparison of eligibility for two projects.

5. Discussion and Conclusions

The DiMa prototype has been presented to the public in April 2024. It represents a framework combining two AI conceps: argument mining (for filtering, quantification of arguments and selection of most popular ideas) and Bayesian networks for evaluation of potential project ideas with respect to eligibility, based on the developed explainable and transparent model.

The DiMa framework rethinks citizen participation by using AI. It uses an AI-assistant for citizen participation, in the form of a website, where citizens can enter their ideas for urban design, submit them to the city administration and obtain assistance through the preparation phase. The ideas are processed using AI tools with information that is useful for implementing the idea. This information will be included in a project folder that will be sent digitally to the responsible person in the city hall for final decision-making and implementation.

The evaluation results are presented in a user friendly manner to allow explanations by comparing the status and achieved scores on criteria. The DiMa AI-assistant prototype Bay-KI allows fast processing of new ideas and reduces the amount of work related to checking all sources of requirements and criteria. The aim is to make the city of Aschaffenburg more livable, since the enormous pool of ideas can be checked thoroughly to identify the best ideas. Two main advantages were highlighted:[6] a) The citizens obtain a transparent[7] explanation on "why some ideas cannot be followed further". As a result, citizens may understand that it is not necessarily the city that is unwilling to follow a certain idea, but there might be legal, technical, environmental or other issues, which make it infeasible. b) Enormous reduction of processing time for the city, allowing to speed up the process, through an AI assistant selecting the most popular ideas, automating criteria check, comparing eligibility and keeping the arguments for explanations. The final decision is still taken by the responsible person in the city hall.

The city administration is inspired by the assistance through the newly developed DiMa prototype. During the upcoming deployment phase, structured test procedures will be used to verify how time gains due to the use of AI can be quantified. Shorter processing time, combined with transparent decision criteria, is intended to lead to high-quality results, which in turn will strengthen trust in administrative decisions. The developed Bay-KI assistant is configurable for the application of the framework in other cities and by other types of organizations.

After the end of the two-year project follows a one-year deployment and exploitation phase. The prototype will now be tested in practice until March 2025, expanded in an agile and iterative manner and further developed into a finished product. It will be used to further optimize DiMa and test it for practical suitability on a number of use cases.[8]

The deployment phase of the project will investigate from a modelling point of view, whether general conceptualization of criteria, priorities and/or weights might be formulated independently of a specific project. Eventually, if there are systematic differences between types of projects, these will be identified, classified and represented at a top level of the model as states of a representative variable. The deployment phase is the basis for transforming Bay-KI into a fully implementable solution that can serve as a model for other municipalities. Its goal is to establish a sustainable mechanism for urban development that enables fast and well-founded decisions and also takes into account economic and ecological criteria.

6. Acknowledgments

The project "Digitale Manufaktur" (DiMa) was funded through the program "Kommunal? Digital!" by the Bavarian State Ministry for Digital Affairs. Therefore this research was partially funded by the Bavarian State Ministry for Digital Affairs.

6. See press coverage in https://www.tvmainfranken.de/mediathek/video/digitale-manufaktur-in-aschaffenburg-buergerbeteiligung-mittels-kuenstlicher-intelligenz/ and https://www.primavera24.de/aktuelles/news/aschaffenburg-digitale-manufaktur-vorgestellt [Accessed 22 Aug 2024].
7. For further reading on the question of whether digital systems can be helpful in making decisions transparent, see Reder and Koska (2024).
8. The result of DiMa is a prototype. For this reason, the website of the citizen participation assistant is still offline and cannot be accessed by the wider municipal community.

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