D3.1 Prototype versions of Inform & Enlight

inSight & enLIGHT Project

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Introduction

When planning new buildings, neighborhoods, or the restoration of current ones, it seems reasonable for the municipality to align the expected outcomes with the needs and wishes of the affected citizens and other relevant groups of stakeholders. In the following, a brief overview of a process, based on both qualitative and quantitative data, which can inform public decision making is presented. The process bridges two already established methods, namely Allies' *Association Wheel* (AW) and Preference's decision analysis framework, commonly referred to the *Delta Multiple Criteria Framework* (DMC) from one of its earliest decision evaluation methods. This deliverable reports upon how to enable for how to bridge these two methodologies for an initial pilot case of the project.

Prior to the design outlined in this document, a couple of co-creation workshops have been carried out, hosted by eGovLab. These are reported upon on D1.1 of this project.

Allies' Association Wheel

This section aims to formally outline the underlying structure of the Association Wheel. The Association Wheel is a survey method for capturing beliefs and preferences in a flexible yet structured way from a set of stakeholder respondents. Importantly, an Association Wheel survey is done relative to a *context*, such as "Climate Goals" in an international policy context or "Neighbourhood Service Level" in a local urban development context. In general, when using Association Wheel, given the context, each respondent is free to initially propose a limited number of proposed *value drivers* or *expectations*, deemed by the respondent to be of importance in order to achieve an overall goal. The overall goal is related to the context, such as reaching a climate goal or providing a required service level for a neighbourhood to be attractive.
Example below:

Association Wheel Question 1. Value drivers.
"The development of urban district A will be ready by 2025, and one important part of this development is an increased service level. What are your expectations on the services offered in district A? (Businesses, restaurants, mail offices, banks, pharmacies etc.)"

In the following, we denote the set of value drivers proposed by respondent q with $R_q = \{r_{q1}, r_{q2}, \ldots\}$ and let $\mathbf{R}$ be the set of all proposed value drivers such that $\mathbf{R} = \cup R_q$. The respondents are then asked for assessing the value drivers based upon two dimensions, "Rank" and "Rate" with meanings according to the below.

Rank - expresses the believed importance of the value driver or expectation in order to achieve the overall goal(s) and is given in the form of a ranking by the respondent.

Rate - expresses how well prepared the context is to accommodate for the effectiveness of the value driver/expectation. In general terms, it can be interpreted as the *feasibility of* r_{qk} *given the context*. The *Rate* assessment is specified by the respondent on an ordinal scale, where a lower value means that the context is poorly prepared and the value driver might create problems in other areas or be expensive. See Association Wheel Question 2 and 3 below for examples.

Association Wheel Question 2. Ranking.
Of the value drivers r_{q1}, r_{q2}, *... provided, which are most important for you? Rank the x most important ones.*

Association Wheel Question 3. Rating.
For each ranked value driver r_{qi}, *to what extent do you consider this to be fulfilled today in District A?*
or
For each ranked value driver r_{qi}, *to what extent do you consider District A:s readiness for fulfilling this value driver?*

Optionally, follow up questions can be posed in an Association Wheel instance, enabling for increased understanding of the rationales and the context. See Wheel Question 4 and 5.

Association Wheel Question 4. Rank follow up question.
You mentioned Y as the most important expectation, can you please elaborate?

Association Wheel Question 5. Rate follow up question.
You mentioned that the level of fulfilment of value driver r_{q1} *was very high, can you please elaborate?*

Figure 1. Screen shot of an Association Wheel rank question.

Selection of Value Drivers for Analysis

In a survey setting, there is a need of a method for selecting the value drivers subject to inclusion in the decision analysis model and those who are to be discarded from further analysis. Here, we may initially adopt a c*lustering and cardinality* approach to the selection of value drivers. Clustering refers to form clusters of similar value driver proposals, which are proposed by different respondents.

Formally, let $r_{qi} \sim r_{kj}$ mean that the value driver r_{qi} proposed by respondent q is "similar" to r_{kj} proposed by respondent k, then a value driver cluster C is a set of value drivers $\{r_{kj}, \ldots, r_{qj}\}$ all deemed to be similar but proposed by different respondents. Following this we can define $\boldsymbol{R_C} = \{r_1, r_2, \ldots\}$ as the set of value drivers proposed in the Association Wheel process that are kept for decision analytical modelling after clustering, so that for each value driver $r_i \in \boldsymbol{R_C}$ there is a corresponding cluster.

Of importance for further modelling is then to define the cluster remaining respondent proposal. In other words, for each respondent, its proposed value drivers that has a cluster and remains in the model for decision analytical treatment. Value drivers proposed that are not associated with a cluster will be considered as being discarded from further analysis.

Definition 1: Cluster Remaining Respondent Proposal

Denote the set of value drivers initially proposed by respondent q with $R_q = \{r_{q1}, r_{q2}, \ldots\}$. Given a set of identified value drivers $\boldsymbol{R_C} = \{r_1, r_2, \ldots\}$ then the cluster remaining respondent proposal $R_{q|C}$ is given by $r_{qi} \in R_q$ such that $r_{qi} \sim r_j$ holds for some $r_j \in \boldsymbol{R_C}$. From this it follows that $R_{q|C} \subseteq R_q$.

Preference's Delta Multiple Criteria Framework

This section aims to describe some of the properties and features of Preference's decision analysis methodology, implemented in a set of different decision tools subject to be tested within this project. The Preference methodology conforms to multi-attribute value theory (MAVT) generally assuming the existence of a so-called value function $v(a)$ such that if $v(a_k) > v(a_l)$ then alternative a_k is preferred to alternative a_l. Under many criteria, the value of an alternative a_k is given by aggregating according to the additive value function

$$v(a_k) = \sum_{j=1}^{M} w_j v_{kj} \quad (1)$$

where M is the total number of criteria, w_j is the weight (or scaling constant) of criterion j and v_{kj} is the value of alternative a_k under criterion j, where v_{kj} is defined as the value of a measurable value function, see, e.g., (Eisenführ et al, 2010) for a comprehensive introduction to this preference model. The same model can be used for group decision making, having N stakeholders or decision makers, the model is

$$V(a_k) = \sum_{j=1}^{M} k_q v_k^q \quad (2)$$

where k_q is the scaling constant (similar to weight) of each stakeholder and v_k^q is is the q:th stakeholders' value of alternative k. In a group setting, then the group would prefer a_k to a_l if and only if $V(a_k) > V(a_l)$. When each alternative is evaluated on more than one criterion, it extends into

$$W(a_k) = \sum_{q=1}^{N} k_q \sum_{j=1}^{M} w_j^q v_{kj}^q \quad (3)$$

where w_j^q is respondents q's weight for the j:th criterion, v_{kj}^q is the q:th stakeholders' value of alternative k under the j:th criterion, see, e.g., (Dyer & Sarin, 1979). All value functions share the same range, typically [0,1] and the weights and scaling constants lies in the [0,1] interval and adds up to one.

Thus, the information required in order to utilise this decision model consists of stakeholders' assessments of the value of each alternative, the importance of each stakeholder, and the relative importance of each criterion in cases of multiple criteria. The ambition of Preference and Allies within this project is to provide means for how stakeholders can provide this information in a flexible, intuitive, and fast way.

The Preference methodology conforms to the above approach, but treats the values, weights, and scaling constants as variables subject to constraints delivered by interpreting different forms of user statements such as rankings instead of numerical values. The variables are collected in constraint sets; a value base **V** holding constraints on value variables $v_.$ and a weight base **K** holding constraints on weight and scaling variables[1]. A member constraint in a base is either a range

[1] Criteria weights and stakeholder scaling constants have computationally identical properties.

constraint or a comparative statement. A comparative statement is of the form "alternative a_k is preferred to alternative a_l", represented in the value base **V** as the inequality $v_{ik} > v_{il}$. For weights, a comparative statement "criterion *i* is more important than criterion *j*" is represented in the weight base **K** as the inequality $w_i \geq w_j$. Similarly, for scaling constants, the expression "all stakeholders are equally powerful" leads to $k_i = k_j$. Range statements, such as "the value of alternative a_k under criterion *i* is between 0.4 and 0.6" is represented as $v_{ik} \geq 0.4$ and $v_{ik} \leq 0.6$. The bases **V** and **K** span polytopes, or feasible regions, and act as formal the representation of a decision problem.

An important feature of the Preference DMC framework is the representation of so called "surrogate values". A surrogate value is a point value $\overline{k_j}$ of a weight/scaling constant or a point value $\overline{v_j}$ representing the most reliable point within the variable bounds. The Preference DMC are able to suggest these surrogate values regardless of the amount of input statements provided by a user, and then exploiting these surrogate values for advanced multi-dimensional sensitivity analysis which are embedded in decision evaluation algorithms conforming to the decision rule stipulated above. See, e.g., see (Danielson 2004; Danielson et al. 2019) for a more comprehensive treatment.

Recent developments on the DMC framework have focussed on the ability to work with purely rank-based input instead of providing pairwise comparisons such as the above examples, and enabling for the use of computational decision analysis with embedded sensitivity analysis when a user has provided rankings. It is of interest for this project to design a method utilising this, exploiting the flexibility of the Association Wheel when reaching out to stakeholders are thereby improving the possibilities for gathering meaningful stakeholder data online.

Decision Analysis Interpretation

Both the *Rank* and the *Rate* statements can be subject to interpretation in the Preference approach through the use of a criteria model employing comparative statements, cardinal rankings or interval statements in different ways. For instance, a value driver could be viewed as a fundamental criterion, where the rank statement indicates the relative importance of the criterion. This implicates both some ambiguity with respect to its decision analytic interpretation, but also leaves room for some flexibility both for survey design and for data interpretation.

Given a set of $\boldsymbol{R_C}$ **=** $\{r_1, r_2, \ldots\}$ of value drivers selected for analysis, in this approach we are now interested in which statistics to exploit for aggregation of the *Rank* and *Rate* statements done by the respondents. Here, we face the issue that due to the inherent flexibility of the Association Wheel, the respondents do not necessarily rank the same set of value drivers but only the ones proposed by themselves, i.e. for two respondents p and q, we have that $R_p = R_q$ does not hold. This means that two rankings from two different respondents cannot be directly compared, which leads to a non-trivial task of defining a meaningful approach towards aggregation of decision data. Below we outline an interpretation and an approach which draws upon cardinal ranking. We will denote the *Rank* statement as an ordinal function $\alpha(r_{qi}) \longrightarrow \{1,2,3,\ldots, Q\}$ and the *Rate* statement as an ordinal function $\beta(r_{qi}) \longrightarrow \{1,2,3,\ldots, P\}$.

Cardinal Ranking

When considering information regarding how much more or less value a value driver provide, we have a so-called *cardinal ranking* even though this information itself is provided in an ordinal manner. We may use $>_{s(i)}$ to denote the strength of the rankings between criteria or alternatives, where $>_0$ means that they are ranked equally. Then $r_i >_1 r_j$ means that value driver r_i is provides more value to the overall goal than value driver r_j, and $r_j >_2 r_k$ means that that value driver r_j provides "much" more important than value driver r_k and so forth. These statements have a corresponding representation in the value constraint set **V** of DMC, however a treatment of this is beyond the scope of this report, we refer to (Danielson and Ekenberg 2016) for details.

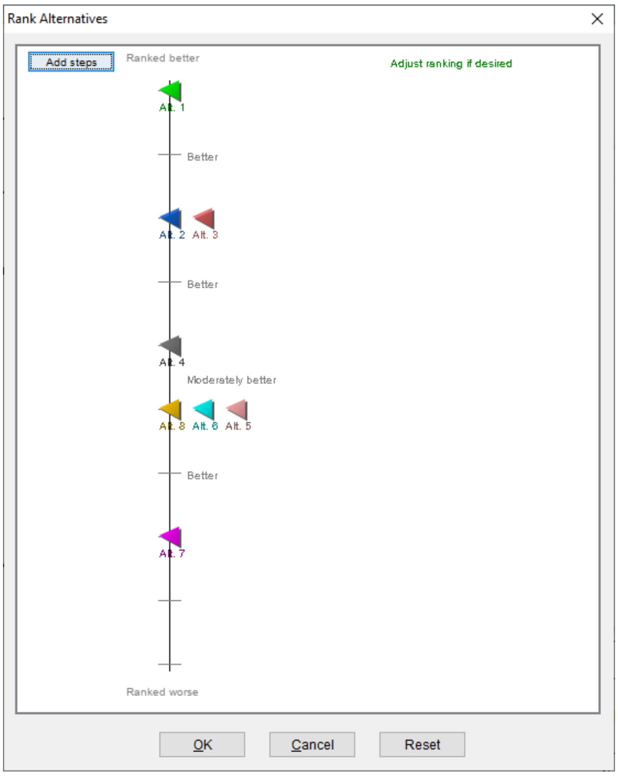

Figure 2. Cardinal ranking of eight alternatives in the *Decide*IT tool.

However, in order to proceed, we need to stipulate some basic assumptions on what a respondent actually mean with the ranking. An Association Wheel *Rank* or *Rate* ranking is done on positions 1, 2, …, Q or 1, 2, …, P in decreasing order. A value driver r_{qj} is ranked on a position $\alpha(r_{qi})$ and $\beta(r_{qi})$ on this scale for *Rank* and *Rate* respectively. The following basic assumptions rely upon the existence of an ordinal value function $O[\alpha(r_{qi}), \beta(r_{qi})]$ representing the ordinal value of the value driver for a respondent q, such that if $O(\alpha(r_{qi}), \beta(r_{qi})) > O(\alpha(r_{qj}), \beta(r_{qj}))$ for respondent q, value driver r_{qi} would deliver more value to the overall goal compared to value driver r_{qj}.

Assumption 1: $O[1, P] \leq O[\alpha, \beta]$ for all $\alpha \neq 1$ and $\beta \neq P$. Everything has a higher value than the least important value driver for which there is no readiness (or everything has a higher value than the least important value driver which already is fulfilled).

Assumption 2: $O[Q, 1] \geq O[\alpha, \beta]$ for all $\alpha \neq Q$ and $\beta \neq 1$. Nothing has a higher value than the most important value driver for which there are the greatest readiness (or nothing has a higher value than the most important value driver not being fulfilled).

Assumption 3: $O[\alpha, \beta] \leq O[\alpha, z]$ for all $z < \beta$ and $O[\alpha, \beta] \leq O[z, \beta]$ for all $\alpha < z$. This is a weak form of independence assumption. It says that given an importance $\alpha(r_{qi})$, more readiness will provide more value, and given a readiness $\beta(r_{qi})$, more importance will provide more value.

Table 1. Rank-Rate ordering matrix.

$\beta(r_{qi})$/ $\alpha(r_{qi})$	**1**	**2**	**3**	**4**	**5**
1	3	5	7	9	12
2	3	5	7	9	11
3	2	4	6	8	10
4	1	3	5	7	9
5	0	3	5	7	9

These basic assumptions now allow for the stipulation of an ordering matrix herein called the "rank-rate ordering matrix", see Table 1 for an example where $Q = P = 5$. This matrix indicates for each pair ($\alpha(r_{qi})$, $\beta(r_{qi})$) an ordinal function value $O(\alpha(r_{qi}), \beta(r_{qi}))$. The MAVT interpretation and the corresponding cardinal ranking representation in the Preference DMC can then be done. A conservative interpretation would be to only interpret $O(\alpha(r_{qi}), \beta(r_{qi}))$ is an ordinal function, leading to Rank-Rate Interpretation 1 below.

Definition 2: Conservative Rank-Rate Interpretation

$O(\alpha(r_{qi}), \beta(r_{qi})) = O(\alpha(r_{qj}), \beta(r_{qj})) \implies r_i^q >_0 r_j^q$

$O(\alpha(r_{qi}), \beta(r_{qi})) > O(\alpha(r_{qj}), \beta(r_{qj})) \implies r_i^q >_1 r_j^q$

A less conservative interpretation would be to interpret $O(\alpha(r_{qi}), \beta(r_{qi}))$ as having some non-explicit representation of cardinality, leading to a second interpretation.

Definition 3: Less Conservative Rank-Rate Interpretation 2

$O(\alpha(r_{qi}), \beta(r_{qi})) = O(\alpha(r_{qj}), \beta(r_{qj})) \implies r_i^q >_0 r_j^q$

Given that $O(\alpha(r_{qi}), \beta(r_{qi})) > O(\alpha(r_{qj}), \beta(r_{qj}))$, let
$d = O(\alpha(r_{qi}), \beta(r_{qi})) - O(\alpha(r_{qj}), \beta(r_{qj}))$
then
$O(\alpha(r_{qi}), \beta(r_{qi})) > O(\alpha(r_{qj}), \beta(r_{qj})) \implies r_i^q >_d r_j^q$

We however need to provide DMC with a rule for how to put a value on value drivers selected for analysis, but which a respondent q has not proposed, meaning that q does not have a statement for it. The reasonable choice is to set the value of this to zero so that given a set of identified value drivers $\boldsymbol{R_C} = \{r_1, r_2, \ldots\}$ and a cluster remaining respondent proposals $R_{q|C}$ where it does not exists a $r_{qi} \in R_{q|C}$ such that $r_{qi} \sim r_j$ for some $r_j \in \boldsymbol{R_C}$, then by definition $v_i^q = 0$.

Further to complete the model the scaling constants k_q remains to be investigated. A common approach when dealing with the public is to award all respondents or stakeholders with equal values of k_q, reflecting that they share the same importance. However regardless of such choices, since the respondents may not share the same set of value drivers, the stakeholder scaling constants needs to scale the respondents value according to how many each respondent actually do rank, as otherwise respondents with a larger set of value drivers ranked will be penalised with respect to their marginal value contribution[2]. This leads us to Definition 4.

Definition 4: Stakeholder Rescaling
Given a set of respondents with associated cluster remaining respondent proposals $R_{q|C}$ and a stakeholder constant k_q, the stakeholder rescaling factor f_q for marginal value contribution equality is given by:

$$f_q = \frac{|R_{q|C}|}{\max\left\{|R_{k|C}|\right\}_{k=1}^{N}}$$

where N is the number of respondents.

Given this, the Preference DMC will be able to provide a corresponding value constraint set **V** and a weight base **K**. The total value of a value driver r_j, taking all respondents Association Wheel *Rank* and *Rate* statements into account is defined according to Definition 5 below.

Definition 5: Total Value
Given a value driver r_j for which each respondent has corresponding value driver r_{qj} with associated Association Wheel rate and rank statements $\alpha(r_{qi})$ and $\beta(r_{qi})$ respectively, the total value of r_j is given by

$$\boldsymbol{V}(r_j) = \sum_q f_q k_q v_j^q$$

Where f_q is the stakeholder rescaling factor, k_q is the stakeholder scaling constant and v_j^q is the value of r_{qj}.

Process Outline

This section outlines the process foreseen when integrating Association Wheel and DMC in a pilot case. We primarily consider the situation where city planners need to be informed about the public opinion regarding the development or re-development of an area. In the urban planning context, Association Wheel basically captures the basic attitude towards a proposed change in the urban environment, or a basic attitude to a clearly defined change.

Furthermore, one could consider the process to cover at least two cases. In the first one, there are no alternatives available to the respondents, and thus the purpose of the survey will be to in a sense calibrate the opinions of the respondents relative to areas already well known to them. In second case one could imagine more or less developed alternatives, such as the result from a

[2] This is a consequence of the cardinal ranking methodology and the properties of the value function where the value differences between objects are of main interest.

competition among architects. However, the latter would require a different sort of preparatory work on the behalf of the respondents and thus be more suited for a workshop format. A rather abstract description of each process step is outlined below.

1. If there are no present alternatives, ask which ones, of a set of areas that are well known to the respondent. This question is for comparison purposes in case there are no clear alternatives. The selection of areas for comparison is chosen by the city.

2. Ask what the respondent considers important aspects given the overarching question; these would be top-of-mind aspects.

3. The value drivers collected in (2) are ranked using, for example, the CAR method or a scale of 0 to 1. This step certainly requires a different granularity than the current scale used in Association Wheel.

4. Each well-known area (or alternative) is then evaluated relative to each of the aspects using, for example, the CAR method or a scale of 0 and 1. We need to discuss whether the level of fulfillment is relative to the other well-known areas (or alternatives) or if it is relative to some maximum value as imagined by the respondent in question. This is an important methodological question.

5. The respondents will be asked to provide motivations for: (1) the aspect with the highest ranking (how would this turn out if several aspects are ranked the highest?), and (2) one of the alternatives (or well-known areas) that has the lowest value on a highest ranking aspect. The latter one should be seen as a suggestion for improvement.

6. A second poll for qualitative data specific to the clusters obtained in the previous steps could generate data which could strengthen the decisions to be made and further inform the result generated by Preference DMC. In particular, one should look for motivations pertaining to clusters with a greater leverage potential (for example, a potential of large improvements coupled with a small cost).

7. The clusters from Association Wheel could be imported into Preference DMC together with the underlying data. Some form of middleware would have to make the necessary data transformations.

8. The result from Preference Methodology together with the qualitative results from Association Wheel and a second poll should provide part of a basis for a decision by the city. It could also be used together with additional data such as cost or time to reason about various trade-offs.

A Note on Well-Known Areas and Alternatives

There are known alternatives

If the alternatives already have been constructed, then step 4 above will pertain to the level of fulfillment of an alternative for each criterion. Since it requires quite some time to read up on a set of alternatives, this might be better suited for a workshop than for an online survey.

There are no alternatives

When there are no alternatives available for the respondents, the question about valuation in step 4 can be used for obtaining a better idea of how the rest of the answers can be interpreted. For example: Assume that two groups of respondents, A and B, both respond that greenness is important for a neighborhood. Group A lives in an area with predominantly green areas while group B lives in a neighborhood of concrete with only patches of green. If both groups respond that the current area fulfills their need for greenness, then either they have very different views of what greenness is, or they are very insensitive to large differences in greenness. Hence, a single patch of green might be as fulfilling as ten patches of green.

Concluding Remarks

This report defines the process for interpretation of Association Wheel data for decision analysis purposes. A main challenge was to enable for a method that acknowledge that different respondents are allowed to propose different value drivers and thus provide preferential statements on differing entities. This was addressed through a clustering approach, together with a conservative quantitative interpretation of the data, but still enabling for capabilities of discriminating between the value drivers proposed by the respondents. The abovementioned approach will be tested in the first and second pilots of the project.

Based upon the learnings and discoveries done in the co-creation workshops, as well as from analyzing the current process at the City of Stockholm, we stipulate here that a process being able to exploit an integration of Association Wheel and Preference DMC for urban planning decision making requires at least.

1. An increase in the granularity of the scales used in Association Wheel, and possibly of how the survey is visually presented.

2. An additional survey based on the aspect clusters generated from the first one.

3. A middleware process in which the data from Association Wheel is transformed into data that can be fed into DMC.

4. A way of presenting the results to city planners such that they will find it meaningful and useful.

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