Complexity Metrics for Decision Model and Notation (DMN) Models

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Abstract

Complexity impairs the maintainability and understandability of conceptual models. Complexity metrics have been used in software engineering and business process management (BPM) to capture the degree of complexity of conceptual models. The recent introduction of the Decision Model and Notation (DMN) standard provides opportunities to shift towards the Separation of Concerns paradigm when it comes to modelling processes and decisions. However, unlike for processes, no studies exist that address the representational complexity of DMN decision models. In this paper, we provide an initial set of complexity metrics for DMN models. We gather insights from the process modelling and software engineering fields to propose complexity metrics for DMN decision models. Additionally, we provide an empirical complexity assessment of DMN decision models. For the decision requirements level of the DMN standard 19 metrics were proposed, while 7 metrics were put forward for the decision logic level. For decision requirements, the model size-based metrics, the Durfee Square Metric (DSM) and the Perfect Square Metric (PSM) prove to be the most suitable. For the decision logic level of DMN the Hit Policy Usage (HPU) and the Total Number of Input Variables (TNIV) were evaluated as suitable for measuring DMN decision table

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complexity.

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1. Introduction

Decision modelling has seen a surge in scientific literature, as illustrated by the vast body of recent work on DMN [1–6]. DMN 1.2 [7] is a standard for decision modelling introduced by the Object Management Group. DMN consists of two levels. Firstly, the decision requirement level in the form of a Decision Requirement Diagram (DRD) is used to portray the requirements of decisions and the dependencies between the different constructs in the decision model. Secondly, the decision logic level is used to specify the underlying decision logic, usually in the form of decision tables. The standard also provides an expression language FEEL (Friendly Enough Expression Language), as well as boxed expressions and decision tables for the notation of the decision logic. In DMN rectangles are used to depict decisions, corner-cut rectangles for business knowledge models, and ovals to represent data input. The arrows represent information requirements (from data or decisions). DMN aims at providing a clear and simple representation of decisions in a declarative form and offers no decision resolution mechanism of its own. Rather, the invoking context, e.g. a business process, is responsible for ensuring a correct invocation and enactment of the decision, as well as ensuring data processing and the storage and propagation of data and decision outcomes throughout the process. This makes DMN particularly interesting for a *Service-Oriented Architecture*, as DMN is independent of the applications and the invoking context. This way, DMN is able to capitalise on the benefits that are inherent in service-orientation in terms of maintainability, scalability, understandability, and flexibility, both for modelling and mining decisions.

Complexity metrics have been adopted in the BPM field for process model complexity and applied on for instance the Business Process Model and Notation (BPMN) standard [8]. Despite the adoption of the DMN standard in the BPM field, a discussion of DMN model complexity is still lacking in literature. This paper aims at addressing that research gap and at proposing a set of metrics for the DMN standard, both at the decision requirements level as well as at the decision logic level. Note that all metrics that will be proposed in this paper have a lower value when indicating simpler models and a higher value when indicating more complex models.

The contribution of this paper is threefold:

1. We are the first to provide a set of complexity metrics tailored towards the decision requirements level of DMN decision models.

2. This paper is the first to provide a set of complexity metrics tailored towards the decision logic level of DMN decision models.

3. Finally, we are the first to empirically address DMN decision model complexity.

This paper is structured as follows. In Section 2, relevant works on complexity are provided, as well as running examples that will be used throughout the paper. Section 3 proposes a set of DRD metrics for DMN models, while Section 4 proposes metrics for the decision logic level of DMN, i.e. the decision tables. Section 5 outlines a discussion of the evolution of the proposed metrics in terms of their evolution across models. Section

6 provides an empirical evaluation of the metrics and thus of DMN model complexity. In Section 7 a discussion about integrated decision requirements and decision logic metrics is provided together with an agenda for future research. Finally, Section 8 concludes the paper.

2. Related Work and Running Example

In this section we provide an overview of related work for DMN, complexity metrics in the BPM field, and complexity assessments to the DMN standard in particular. Additionally, we provide running examples which will be used to illustrate the proposed complexity metrics in the subsequent sections.

2.1. Related Work

Recent BPM literature moves towards accommodating decision management into the paradigms of The Separation of Concerns (SoC) [2, 9, 10] and and Service-Oriented Architecture (SOA) [5], by externalising decisions and encapsulating them into separate decision models, hence implementing decisions as externalised services. Literature proposes several conceptual decision service platforms and frameworks [5, 11, 12] and industry has adopted this trend, as several decision service systems have appeared, e.g. SAP Decision Service Management [13]. This externalisation of decisions from processes provides a plethora of advantages regarding maintainability and flexibility of both process and decision models [2, 5, 10, 14–17].

A plethora of works on software complexity metrics exists [18–20]. Additionally, software metrics have been transformed and applied on processes and workflow nets in a vast array of studies [21–27]. Most of these studies focus on the BPMN standard. A systematic literature review of process metrics is provided in [28], where the authors identify and discuss 65 process metrics found in BPM literature.

Unlike for processes and BPMN, few works on complexity metrics for DMN models exist. In [29], the meta model complexity of the DMN modelling method is assessed according to the theory specified by [30]. Additionally, an exploratory study of the notational aspects of DMN was conducted in [31]. In this study the authors focus on the cognitive analysis of the DMN notation in the light of theories on effective visual design. Hence, DMN complexity was assessed on a meta model level, i.e. the theoretical complexity of the modelling method as a whole, and on the cognitive visual level. However, no works on the complexity of DMN decision models exist in literature. In the following sections, we propose an initial set of complexity metrics for DMN decision models.

2.2. Running Examples

Figure 1 provides a running example of a DRD model that will be used in the coming sections to illustrate the decision requirements level complexity metrics. The DRD represents an event selection decision based on the preferred location and the food and drinks that are offered, while taking into consideration the season, the number of guests, whether children are allowed, the sleeping facilities, and the budget. The value of every proposed DRD metric will be calculated for this DRD.

Figure 2 provides a running example of a DMN decision table that will be used in the coming sections to illustrate the decision logic level complexity metrics. The decision table represents the decision logic of choosing an accommodation type for a vacation based on the

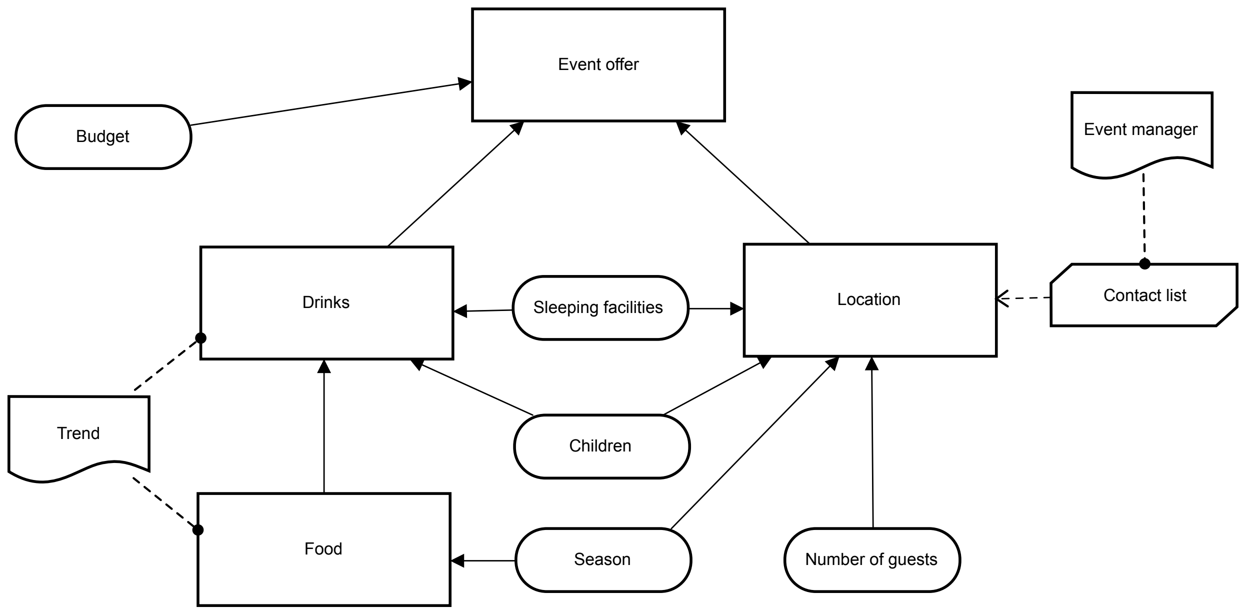

Figure 1: DMN DRD running example.

type of residency, the level of comfort, the number of adults and the number of children. The value of every proposed DMN decision table metric will be calculated for this DMN table.

3. Decision Requirements Diagram Metrics

In this section we provide a set of DRD metrics that are capable of representing graph complexity in analogy with business process or software engineering literature. For every metric, a brief explanation is provided. Additionally, we calculate the value of every proposed metric for the running example provided in Figure 1. An overview of the metrics and the metric values for the running example is given in Table 3. Later on, we will discuss the evolution of the metrics and validate them through an exploratory survey.

3.1. Number of Decisions (NOD)

As proposed by [23], BPMN complexity can be measured by counting the number of activities. They called this metric *number of activities* (NOA), which is a summation of all

Room					
U	*Input*				*Output*
	Residency	**Comfort**	**Adults**	**Children**	**Room**
	String	Boolean	Integer	Integer	String
1	Non-existent	-	-	-	Non-existent
2	Pool Villa	-	-	-	Villa Room
3	Hotel, Pool Hotel, Ranch, Restaurant Hotel, Sushi Hotel	T	1	0	Single Suite
4				1	Double Suite
5				> 1	Family Suite
6			2	0	Double Suite
7				> 0	Family Suite
9		F	1	0	Single Room
10				1	Double Room
11				> 1	Family Room
12			2	0	Double Room
13				> 0	Family Room
15	Igloo	-	-	-	Igloo Room
16	Riad	-	-	-	Souk
17	Student Hostel	-	-	0	Shared Room
18			-	> 0	Non-existent
19	Villa	-	-	-	Villa Room
20	Wine Domain Villa	-	-	-	Villa Room

Figure 2: DMN decision table running example.

activity elements in the model. A similar metric can be worked out for DMN, counting the number of decision nodes in the DRD model instead of counting the activities, thus arriving to the metric of *number of decisions* (NOD). Applied to the running example of Figure 1, the NOD is 4. As the models grow larger, they tend to have more decision elements. Thus, this metric will go up if a decision element is added to the model, indicating that the model has become more complex according to this metric. Given that DMN is a standard for modelling decisions, we assume that the number of decisions that are modelled within one DRD model will be indicative of the complexity of the model. However, note that the granularity of the DRD will play a crucial role as well, as one decision node can possibly be decomposed into a number of decision nodes each containing a portion of the underlying decision logic. Therefore, it will be of paramount importance to develop complexity metrics for the logic layer of DMN as well to capture these changes in granularity of the DRD model.

3.2. Number of Elements (NOE)

The *number of elements* (NOE) is the sum of all building blocks of the DRD. Hence, NOE takes into account all elements of the DRD rather than only the decision nodes, as is the case in the NOD metric. More specifically:

$$\begin{aligned} NOE = {} & \#decisions + \#inputs + \#knowledgesources \\ & + \#businessknowledgemodels + \#informationrequirements \\ & + \#knowledgerequirements + \#authorityrequirements \end{aligned}$$

Applied to the running example model in Figure 1, the NOE is 27. The larger the DRD model, the higher NOE will be. This is self-explanatory, as DRD models are solely made up out of these elements.

3.3. Number of Basic Elements (NOBE)

The most basic elements of a DRD model are decisions nodes, input nodes, and information requirements. They form the spine of a DRD model. Therefore, the *number of basic elements* (NOBE) probably is a good metric. NOBE can be calculated as follows:

$$NOBE = \#decisions + \#inputs + \#informationrequirements$$

Applied to the running example in Figure 1, the NOBE is 20. Clearly, the NOBE metric will be higher as basic elements are added to the DRD model.

3.4. Number of Decisions and Information Requirements (NODIR)

The NOAC metric (Number Of Activities and Control-flows) was suggested in BPM literature, such as in [23], and it requires counting the activities and control flow elements in

BPMN. The NOAC summation consisting of the number of activities and control flows (splits to be precise) can be applied in the DMN context as well by summing up the number of all decisions elements and information requirements in the DRD. We call this metric Number Of Decisions and Information Requirements (NODIR).

$NODIR = \#decsions + \#informationrequirements$

Applied to the running example in Figure 1, the $NODIR = 4 + 11 = 15$.

3.5. Density (Dens)

This Density metric was suggested by [25], and later discussed by [28] and [21]. It aims at measuring the ratio of the actual and the maximum number of arcs in the BPMN model. The metric can be adapted to measure DMN complexity, more precisely by dividing the actual number of arcs by maximum number of arcs possible.

$Dens = \#ActualArcs/\#MaximumArcs$

For counting the maximum number of arcs, only valid connections (according to DMN rules) are considered. This metric can be applied to the running example in Figure 1. In that case, the Density can be calculated as follows:

$Dens = 15/38$

3.6. Total Number of Data Objects (TNDO)

As discussed in [28], the *total number of data objects* (TNDO) represents all data objects in the BPMN diagram. For a DRD, data objects are represented by all input data objects present in the model. The running example in Figure 1 has 5 input data elements, hence the TNDO is 5.

Similar to the explanation of NOD and NODIR, bigger models tend to have more input data elements. By adding a data input element to a model, the TNDO metric will grow.

3.7. Number of Complex Decisions (NCD)

The Number of Complex Decisions (NCD) metric is extracted from [28]. It requires all complex decisions in the BPMN diagram to be counted and is represented by the summation total. In this case, complex decisions represent all decisions that require the output of one or more sub-decisions as input. In other terms, all decisions with another decision as predecessor. Consequently, understanding the complex decisions underlying logic requires unfolding this complex decision into smaller subsets of supporting decisions to expose the full decision path. The NCD of the running example in Figure 1, is 2 since the DRD model contains 2 of these complex decisions, i.e. *Drinks* and *Event Offer*.

3.8. Durfee Square Metric (DSM)

As described in [21], the Durfee Square Metric is obtained by executing the following process: first, list all used elements in the BPMN model. Then count each element type's occurrence. Next, the elements need to be ordered from most used to least used and are given indices i representing the total number of element occurrences in the model. The DSM is represented by the index i of the last element with an occurrence greater than or equal to that index. This metric can be adopted directly for usage with DMN. The elements used is the complete set of existing nodes and arcs. For instance, in the running example in Figure 1, we get the table shown in Table 1. This table shows the DSM for this model is 3.

Index	**Element**	**Occurrence**	**Index ⩽ Occurrence**
1	Information requirement	11	YES
2	Input data	5	YES
3	Decision	4	YES
4	Authority requirement	3	NO
5	Knowledge source	2	NO
6	Business knowledge model	1	NO
7	Knowledge requirement	1	NO

Table 1: Durfee Square Metric for the model in Figure 1.

3.9. Perfect Square Metric (PSM)

This metric can be calculated by listing the set of element types ranked in a decreasing order by the number of their occurrences, as described in [21]. The PSM is the (unique) largest index where the set of element types, starting from index 1 to the current index i, cumulatively occur at least i^2 times. The authors of [21] continue to assert that the metric is easy to interpret and provides basic information about the structural complexity of the model. The metric was based on the g-index [21, 28]. Non-occurring elements are not considered. This metric was adapted to be usable with the DMN standard and its elements as depicted in Table 2, where the PSM metric has a value of 5 for the running example in Figure 1.

Index	Element	Occurrence	Cummulative occ.	Index^2	Index$^2 \leqslant$ Cum. occ.
1	Information requirement	11	11	1	YES
2	Input data	5	16	4	YES
3	Decision	4	20	9	YES
4	Authority requirement	3	23	16	YES
5	Knowledge source	2	25	25	YES
6	Business knowledge model	1	26	36	NO
7	Knowledge requirement	1	27	49	NO

Table 2: Perfect Square Metric for the model in Figure 1.

3.10. Sequentiality (SEQ)

As pointed out by [28], the sequentiality (SEQ) of BPMN is equal to one minus the percentage of nodes with no more than one incoming and outgoing arrow. In other terms: the percentage of nodes that have more than one successor or predecessor. This metric can be used in the same way for the nodes of a DRD. Sequentiality is expressed as a number between one and zero. If the DRD looks more like a sequence rather than a parallell network, the value of the sequentiality metric will be low. This corresponds with a less complex model, and vice versa. Applying this to the running example in Figure 1, we get the formula:

$SEQ = 1 - 4/12 = 0.6667$.

Models with a lot of single-path sequences will have a low complexity value. Also note that sequentiality in DMN will be greatly impacted by leaf elements since DRD models usually have multiple input data elements, thus increasing the SEQ metric.

3.11. Decision Node Sequentiality (DNSEQ)

Similar to SEQ, we propose DNSEQ, which is expressed as one minus the percentage of nodes with no more than one incoming and outgoing arrow. However, DNSEQ only takes decision nodes and their connections into account instead of all model elements. In this way, long *tails* of edge node sequences do not manipulate the metric value. Applying this to the running example in Figure 1, we get the following metric value:

$DNSEQ = 1 - 3/4 = 0.25$

3.12. Diameter (Diam)

The geodesic of two (connected) nodes in a graph is the shortest path between these nodes. The diameter of a graph is the longest geodesic of that graph. In other terms: the diameter is the longest, shortest path [28]. This metric can also be used with DMN. Of course, only valid connections are considered since the arcs have directions. The diameter will be the longest shortest path between the root node and leave nodes. In the running example in Figure 1, a diameter of 4 is found. This is the length of the path going from *Season* to *Food* to *Drinks* to *Event offer*.

3.13. Longest Path (LP)

Unlike BPMN, a DRD model does not allow loops. Therefore, the *longest path* (LP) can be measured unambiguously. Calculating the longest path of a DRD graph, which in essence is a directed acyclic graph (DAG), is done by topologically sorting the graph [32]. In the running example of Figure 1, the LP of 4 is found. This is the length of the path going from *Season* to *Event offer* through *Food* and *Drinks*. It is not possible to find a longer path in the model. Typically, the longest path and the sequentiality metrics of a DRD will oppose in value. When a model is more sequential, it will have a low complexity according to the *sequentiality* metric. However, the model will typically have longer paths and thus higher complexity according to the *longest path* metric. This proves the importance of using multiple complexity metrics to assess DRD model complexity from different perspectives. As DRD models get bigger and more arcs, i.e. requirements in the DRD graph, are introduced, the value of LP will indicate a higher complexity.

3.14. Average Vertex Degree (AVD)

The *average vertex degree* (AVD) [33] is calculated as the average of all incoming and outgoing connections across all nodes of the DRD. This can be applied directly to DRD graphs. The bigger the AVD, the more complex the model. Applying this to the running example in Figure 1, we get the following result:

$$AVD = (1 + 3 + 1 + 5 + 2 + 6 + 2 + 2 + 2 + 3 + 2 + 1)/12 = 2.5$$

The average vertex degree heavily relies on the number of connections between DRD model elements. In other terms, the more the decision requirements diagram resembles a strongly connected network, the more complex it is. Additionally, it might be interesting to look at the modular behaviour of the DRD model trough fan-in and fan-out metrics that are heavily dependent on the average vertex degree.

3.15. Coefficient of Network Complexity (CNC)

The *coefficient of network complexity* (CNC) was proposed to measure the degree of complexity of a critical pass network [34]. It was adapted by [23] to measure the degree of complexity in processes by dividing the number of arcs by the number of the activities, splits and joins in the BPMN diagrams. It is possible to have identical values of the coefficient of network complexity for different models but with different comprehensibility due to a different set of used node types. This metric can be adopted for the DMN standard by focusing on the nodes and arcs in the decision requirements diagram. Applying this to the running example in Figure 1 gives the following result:

$CNC = 15/12 = 1.25$

Clearly, if an arc is added to the DRD graph, the CNC value will increase because of the increasing effect on the numerator.

3.16. Knot Count (KC)

In decision models, some components, more specifically requirement associations, may be forced to cross each other. This is captured in the *knot count* (KC) metric. Each occurrence of a crossing is expressed as a knot and each knot occurrence in a DRD means an increase in the complexity of understanding the model. Unlike the metrics used by [18] which focused on counting the knots created by the crossing of only arrows, counting all requirement relation crossings, regardless of their types, is suggested for DMN adoption. This is due to the fact that DMN has different requirements relations that are frequently used between elements, as opposed to process models where control flow arrows are highly represented. The higher the knot count value, the higher the complexity assumed. The running model in Figure 1 does not have knot occurrences, and hence has a knot count value of 0.

As more arcs and nodes are introduced in the DRD model, the more difficult it becomes to avoid crossing arcs, i.e. knots. This will thus likely result in a higher knot count.

3.17. Decision Nesting Depth (DND)

The existing metric found in [20] measures complexity of business process graphs in terms of hierarchical depth levels. DMN nesting is suggested to be in following levels: low-level decisions (leaf nodes, which only create output from existing input data), mid-level decisions (which take output of sub-decisions as input) and the top-level decision (root decision). Both perspectives are possible: on the one hand, we can inspect the depth of DRDs, where the output of one node can be the input for another; on the other hand, in decision tables, where a table can have output variables of other tables as input variables. The higher the DND, the higher the complexity. This is explained by the high probability of existence of many sub-decisions that are below the main decision which is a container of all lower-level decisions starting from the lowest level (leaf nodes). This metrics value is expected to be similar to the Longest Path value with the difference that LP takes all model elements into account, while DND only looks at decision elements. The running example in Figure 1 has a DND of 3.

3.18. Cyclomatic Complexity (CC)

In [23] the adaptation of McCabes *cyclomatic complexity* (CC) metric [35] for process is proposed. According to [19], this is one of the most widely used complexity metrics. The cyclomatic complexity formula for non-strongly connected graphs, such as a DRD graph, is the number of edges (E) minus the number of nodes (N) plus two times the number of connected components. Since a decision requirements diagram is one connected component, the formula can be reduced to the following calculation for the running example in Figure 1:

$$CC = E - N + 2 = 15 - 12 + 2 = 5$$

Thus, larger models, especially those that contain many arcs, are likely to have a higher CC value.

DRD Metric	Value
Number of decisions (NOD)	4.00
Number of elements (NOE)	27.00
Number of basic elements (NOBE)	20.00
Number of decisions and information requirements (NODIR)	15.00
Density (Dens)	0.39
Total number of Data Objects (TNDO)	5.00
Number of Complex Decisions (NCD)	2.00
Durfee Square Metric (DSM)	3.00
Perfect Square Metric (PSM)	5.00
Sequentiality (Seq)	0.67
Decision node sequentiality (DNS)	0.25
Diameter (Diam)	4.00
Longest Path (LP)	4.00
Average Vertrex Degree (AVD)	2.50
Coefficient of Network Complexity (CNC)	1.25
Knot Count (KC)	3.00
Decision Nesting Depth (DND)	3.00
Cyclomatic Complexity (CC)	5.00
Interface complexity (IC)	130.00

Table 3: DRD metrics as calculated for the running example in Figure 1.

3.19. Interface Complexity (IC)

In [23], the Information Flow Metric of [36] was adapted to BPMN by mapping the fan-in and fan-out of the original formula to the input and output of BPMN activities. This resulted in the following formula to calculate IC:

$$IC_D = Length * (\#inputs * \#outputs)^2$$

The value of the variable length can be obtained by applying the lines of code or alternatively the cyclomatic complexity metric as defined by [35]. IC can be used with DMN as well. Here, the input and output of decision nodes can be used instead of those of activities. Only the input and output originating from input data or decision elements are considered.

In an attempt to adapt IC for the complete DMN model, rather than just a single decision node, the product of number of inputs and outputs is made for all decision nodes individually, squared and then summed. This summation is then multiplied by the length, i.e. McCabe's cyclometic compexity.

$IC = CC * \sum(\#inputs * \#outputs)^2$

Applied to the running example in Figure 1, the interface complexity gives a value of 130.

4. Decision Table Metrics

In this section we provide a set of decision table metrics. For every metric, a brief explanation is provided. Additionally, we calculate the value of every proposed metric for the running example provided in Figure 2. An overview of the metrics and the metric values for the running example is given in Table 4. Later on, we will discuss the evolution of the metrics and validate them through an exploratory survey.

4.1. Average Number of Possible Input Scenarios (ANPI)

The variables of decision tables are divided in categories, or even into distinct integers, expressions, and lists. More categories make the table more complex. For an individual table, the number of possible input scenarios can be found by counting the number of possible input combinations supported by the decision table. In the running example in Figure 2, there are 58. The number of all theoretically possible input scenarios, all not necessarily supported by the decision table, is defined as the product of all possible input values. This metric grows when a table adds more input variables to the equation. The values for individual tables can be seen as a complexity metric. However, to evaluate the entire model, an average of these values could be taken across all decision tables in the DMN model.

4.2. Average Number of Possible Output Scenarios (ANPO)

For an individual table, the number of possible output scenarios can be found by counting the possible unique output values. In the running example in Figure 2, there are 11. In most cases, there will be only one output variable. Then, the ANPO will be equal to the number of distinct output values.

4.3. Average Number of Value Categories (ANVC)

The number of value categories of an input variable can easily be calculated by counting the possible, distinct values of that variable. In variable Children of the running in Figure 2, there are 4 possible value categories (0; > 0; 1; > 1). Note that this metric heavily depends on whether the decision table is contracted and to which degree the contraction was carried out. This metric should be considered for individual variables. Again, to get the overall result of the model, an average can be taken over all table input variables. In the case of our running example a ANVC value of 4 is obtained.

4.4. Hit Policy Usage (HPU)

DMN Decision tables can have one of the following hit policies:

- Unique hit (U)
- First-hit (F)
- Priority hit (P)

- Any hit (A)
- Collect-with-aggregation (C+, $C <$, $C >$, $C\#$)

For the full explanation of DMN decision table hit policies, we refer to the DMN standard [7].

Some hit policies are perceived more complex than others. Thus, some penalties can be allocated to increase the complexity score of a table. For a DMN model, a metric Hit Policy Usage (HPU) can be created. The value of this metric is the summation of all hit policy penalties p_i of the tables.

$\sum_{i=1}^{i=n} p_i$

With n = total number of tables in the model The following values of the penalty p_i of table i are arbitrarily chosen by us. However, these values are subjective and can be changed to the modellers opinion.

- $p_i = 0.1$ when the hit policy is U
- $p_i = 0.3$ when the hit policy is A
- $p_i = 0.4$ when the hit policy is F or P
- $p_i = 0.7$ when the hit policy is $C <$ or $C >$
- $p_i = 0.8$ when the hit policy is C+ or $C\#$

We perceive the Unique hit policy as the simplest kind since all input variants correspond with only one output possibility. The Any hit policy is quite simple as well because an arbitrary choice must be made. Generally speaking, the outcomes of the decision rules are ordered from high to low priority in a Priority hit policy table. In this case, its complexity penalty is equal to those of First hit policy tables. However, one might argue that Priority hit policy tables are slightly more complex since it must be checked that the rules are in fact ordered by priority. Finally, Collect-with-aggregation hit policy tables might be considered the most complex type. In $C<$ and $C>$ hit policy tables, a single rule must be extracted, while in both other forms calculations must be performed. The running example in Figure 2 has a Unique hit policy. Hence, a penalty of 0.1 is assigned to the model that uses this table.

4.5. Total Number of Rules (TNR)

For individual tables, the number of rules can easily be counted. The number of rules in the running example in Figure 2 is 20. This value should not be high for an individual table. Tables with the same number of input variables may have a different number of decision rules. The TNR makes the summation of the number of rules of all tables used in the model to get an overall value. Note that this metric is also heavily dependent on whether the decision table is contracted or not and to which degree the contraction is carried out.

4.6. Total Number of Input Variables (TNIV)

The input variables of an individual table can be found in the first part of the columns. It is good practice to prevent this number from growing too large. In the running example in Figure 2, 4 input variables are found, i.e. *Residency*, *Comfort*, *Adults*, and *Children*. Tables with the same number of decision rules may have a different number of input variables. The total amount of input variables used in all decision tables has an impact on the overall complexity. Logically, the more variables decision tables use as input, the larger the table will grow and the more complex the overall model will be perceived.

4.7. Schema Size (SS)

For an individual table, the schema size is equal to the number of rows multiplied by the number of columns. In the running example in Figure 2, there are 20 rows and 5 columns. This gives us a SS of 100. Thus, the SS of an entire model is the summation of the separate table SS metrics. Table cells are often contracted. Therefore, it is important to note that SS measures the table size, not the number of cells.

Decision Table Metric	Value
Average number of possible input scenarios (ANPI)	42.00
Average number of possible output scenarios (ANPO)	11.00
Average number of value categories (ANVC)	4.00
Hit Policy Usage (HPU)	0.10
Total number of rules (TNR)	20.00
Total number of input variables (TNIV)	4.00
Schema Size (SS)	100.00

Table 4: Decision table metrics as calculated for the running example in Figure 2.

5. Expected Evolution of the Metrics

5.1. DRD Metrics

In this section we concisely discuss the evolution of the metric values when a certain element is added to the DRD model. We limit our discussion to adding arc requirements and decision nodes to the DRD model respectively. When a decision requirements diagram gets larger in terms of number of elements, most metrics will indicate that the representational complexity of the decision model has increased. Model size is what most of the proposed metrics rely on. NOD, NOE, NOBE, NODIR and TNDO are simple count metrics that grow larger as relevant elements are added to the model. Other metrics, e.g. SEQ, LP, AVD, CNC, KC, and CC, are also indirectly dependent on the number of DRD elements. Here too, adding an element to the DRD model is likely to result in an increase in complexity metric values.

5.2. Requirement Arcs

The following metrics all rely on the number of arcs in the model, i.e. information requirements, authority requirements, and knowledge requirements. When a requirement is added to a DRD model:

- Density will increase because of the increasing effect on the numerator in the formula.
- NOE increases since it is the summation of all elements.
- NOBE and NODIR increases if that arc is an information requirement.
- LP may increase, depending on whether the added arc results in a longer, longest path.
- AVD will definitely increase because the new connection will always positively impact exactly two model elements, which in turn increases the overall average vertex degree.
- CNC will increase given the increasing effect on the numerator in the formula.
- DND can never decrease. When a new information requirement forwards the output of an existing decision to a non-complex decision, the receiving decision becomes a complex decision which always increases the overall complexity.
- KC will increase if the new arc crosses existing arcs.

- CC will increase given the increasing effect on the first term in the formula.
- IC will increase if the added arc is an information requirement since there will be more inputs and/or outputs per node.

5.3. Decision Nodes

The following metrics all rely on the number of decision nodes in the model. When a decision node is added to a DRD model:

- NOD increases by definition.
- NODIR increases, since it is the summation of the number of decision elements and information requirements.
- NCD increases when the added node is not a leaf node. NCD remains the same if the added node is a leaf node since it will be attached to a previously existing leaf node that becomes a complex decision. However, NCD will never decrease if a decision node is added.
- NOE increases since it is the summation of all elements.
- NOBE increases since a decision node is a basic element
- LP is either not affected or will increase, depending on whether the added decision node results in a longer, longest path.
- CC stays unchanged or decreases. While the formula suggests that CC would increase, this is not the case in reality. When a decision node is added, at least one edge is added as well to connect the node to the rest of the graph.

5.4. Link with Decision Table Metrics

A growing total decision table size, i.e. an increasing SS, also often implies one or more of the following:

- A larger NOD value. When there are more decision elements, there will be more tables. However, these tables will be much smaller if larger decision tables are decomposed into smaller sub-decisions.
- ANVC and ANPI are larger as well. When certain variables get more value categories, the decision tables that use these variables as input tend to become larger.
- The TNR is larger. When rules are added to a decision tables, the tables by definition will also have more cells and SS will increase as well.
- The TNIV is larger. When additional input variables are introduced in a decision table, the table will also have more cells, and potentially more rules as well.

When more connections are made with the same amount of decision nodes, the tables related to these nodes will likely have more input and/or output variables. This results in larger decision tables. ANPI roughly corresponds to the average number of rows per table. This means that ANPI and Density are expected to correlate in a positive way.

Hence, there exists a trade off between the decision table metrics and the DRD metrics. A complex decision table can represent a whole decision, resulting in high decision table complexity and low DRD complexity. However, that same decision table can be decomposed into multiple smaller sub-decision tables, thus decreasing the complexity of individual decision tables at the cost of an increasing size of the DRD model.

5.5. Overview of expected metric evolution

In this subsection we provide an overview of the evolution of the metrics when certain elements are added to the model. We again distinguish between decision requirements metrics and decision table metrics. The overview for the DRD metrics is given in a tabular form in Tables 5. We look at the additions of the following elements to the model: decision nodes, input data nodes, business knowledge model nodes, knowledge source nodes, information requirement arcs, knowledge requirement arcs, and authority requirement arcs. We use a "+" to indicate an increasing metric value and a "−" to indicate a decreasing metric value. Likewise, a "(+)" is depicted for possibly increasing values and a "(−)" for possibly decreasing values.

DRD Metric	D	ID	BKM	KS	IR	KR	AR
NOD	+						
NOE	+	+	+	+	+	+	+
NOBE	+	+			+		
NODIR	+				+		
Dens					+	+	+
TNDO		+					
NCD	(+)						
DSM	(+)	(+)	(+)	(+)	(+)	(+)	(+)
PSM	(+)	(+)	(+)	(+)	(+)	(+)	(+)
Seq	+	+	+	+	+	+	+
DNS	+				+		
Diam	(+)	(+)	(+)	(+)	(+)	(+)	(+)
LP	(+)	(+)	(+)	(+)	(+)	(+)	(+)
AVD	-	-	-	-	+	+	+
CNC	+	+	+	+	+	+	+
KC	(+)	(+)	(+)	(+)	(+)	(+)	(+)
DND	(+)				(+)		
CC	(-)	(-)	(-)	(-)	+	+	+
IC	+				+		

Table 5: Overview of DRD metric evolution. D = Decision element; ID = Input Data element; BKM = Business Knowledge Model; KS = Knowledge Source; IR = Information Requirement; KR = Knowledge Requirement; AR = Authority Requirement.

Table 6 provides an overview of Decision Table metric evolution. The symbols for (possibly) increasing and decreasing metric values are the same as in Table 5. For decision table metrics we consider the addition of input variables, output variables, decision rules, as well as adding or changing hit policies.

DT Metric	IV	OV	DR	HP
ANPI	(+)		(+)	
ANPO		+	(+)	
ANVC	+		(+)	
HPU				(+)
TNR	(+)	(+)	+	
TNIV	+			
SS	+	+	+	

Table 6: Overview of Decision Table metric evolution. IV = Input Variable; OV = Output Variable; DR = Decision Rule; HP = Hit Policy.

6. Empirical Evaluation

An exploratory survey was held during the master's course of *Knowledge Management and Business Intelligence* at KU Leuven. Students were presented with 11 DRD models and 11 decision tables respectively, ranging from simple to complex in an arbitrary order. The students were asked to indicate on a visual analogue scale how complex they perceived each of the DRD models or tables to be. In total 22 students with previous knowledge about DMN took part in the DRD survey, while 18 students with previous knowledge about DMN took part in the decision tables survey. The tested DRD models are provided in Appendix A, while the tested decision tables are given in Appendix B. The full questionnaire provided to the students is available in Appendix D.

To detect how well the proposed metrics describe the perceived complexity as indicated by the survey, the metric values were compared to the survey results. This was done by calculating the correlation and the sum of squared differences (SSD) of the metric values for respectively all the DRD models and tables, and the survey averages. In order to calculate a valid sum of squared differences, the metric values were first scaled to a range from zero to ten, i.e. reflecting the complexity range of the visual analogue scale of the survey.

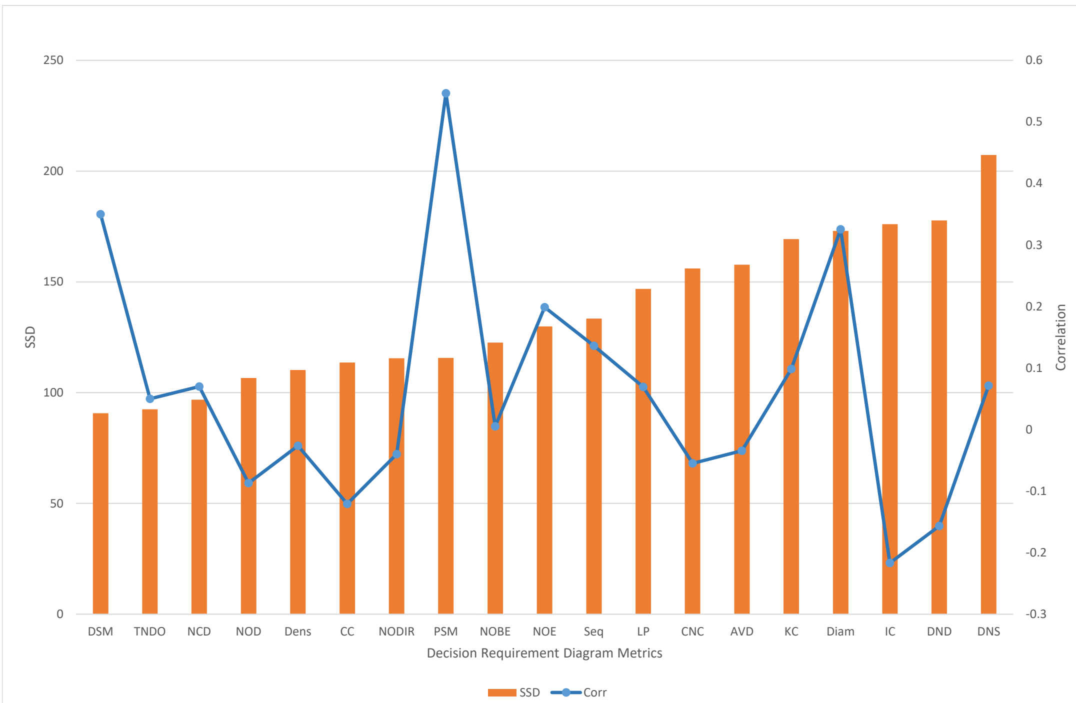

Figure 3: Decision requirement diagram metrics chart.

Results for the DRD metrics are presented in Table 7 and Figure 3, while Table 8 and Figure 4 represent the results for the decision table metrics. For all the 11 tested DRD models and decision tables, the metric value of all the proposed metrics are calculated and included in the respective tables. Higher (lower) values of the metrics represent a higher (lower) degree of complexity. The final two rows of the table give the average degree of complexity as indicated by the students in the survey on the visual analogue scale (on a scale of 10) and the standard deviation of the complexity as indicated in the survey. The final two columns in Table 7 and 8 depict the correlation and the sum of squared differences (SSD) of the metric values and the survey results respectively. For an easier interpretation and comparison, the SSD values and correlations are depicted in the form of charts as well: Figure 3 gives an overview for DRD metrics, while Figure 4 provides a summary for decision table metrics.

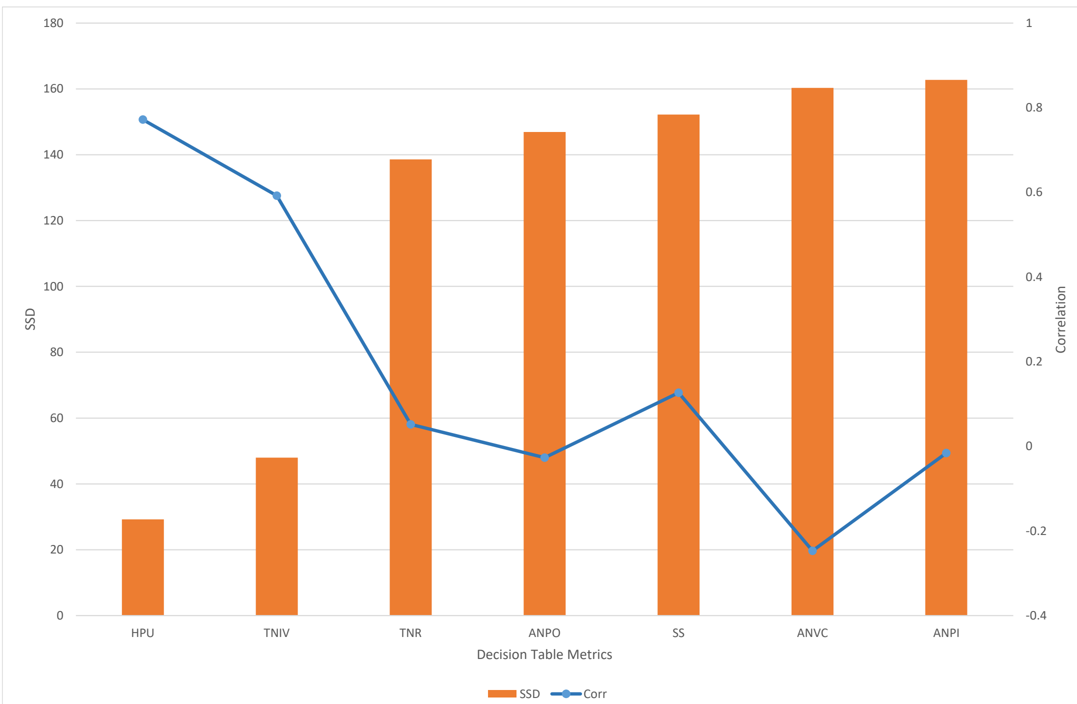

Figure 4: Decision table metrics chart.

By examining the sum of squared differences in Table 7 and Figure 3 we can conclude that basic metrics such as Number of Elements (NOE), Number of Decisions (NOD), Number of Complex Decisions (NCD), and Total Number of Data Objects (TNDO) measure the perceived complexity quite well, indicated by the low values in SSD. Additionally, the

Cyclomatic Complexity (CC) also showcases a low SSD, indicating that the popular CC metric might be a good measure for DRD model complexity as well. Also, Durfee Square and Perfect Square metrics prove to fulfil their purpose, as they display both low SSD values and high correlations between the metric values and the empirical assessment.

For the table metrics, the results in Table 8 and Figure 4 are obvious. Hit Policy Usage (HPU) and Total Number of Input Variables (TNIV) both have high correlations (respectively 0,57 and 0,79) and low sum of squared differences (respectively 29,26 and 48,00) with the survey results. This means that it is advised to consider these metrics while constructing decision tables. Moreover, we conducted the analysis again for the product of HPU and TNIV and the results improved even further with a correlation above 0,9 and a sum of squared differences around 30. Unique table metrics with a relatively low number of input variables prove best practice.

7. Discussion and Future Work

We have proposed complexity metrics for the DMN standard, both at the requirements level and the logic level, under the assumption that complexity is a measure of the cognitive effort of understanding. This perceived complexity was tested in surveys as well and the empirical results were compared to the theoretical values of the proposed complexity metrics. Note that the results are only indicative as the statistical significance was not tested yet and that the conclusion validity is still to be improved with a larger sample of survey participants. Also note that a vast array of metrics was proposed and that some of the metrics showcased intercorrelation, e.g. AVD and CNC are perfectly correlated, indicating that certain metrics measure the same phenomenon, hence making the metrics redundant. The metric correlation

Table 7: DRD metric values for all 11 DRD models compared against the survey results.

DRD Metric	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Correlation	SSD
NOD	2.00	2.00	5.00	4.00	7.00	4.00	8.00	7.00	5.00	5.00	11.00	-0.09	106.65
NOE	9.00	16.00	17.00	27.00	29.00	27.00	46.00	42.00	28.00	37.00	33.00	0.20	129.88
NOBE	9.00	8.00	13.00	20.00	29.00	20.00	43.00	21.00	20.00	29.00	40.00	0.01	122.56
NODIR	6.00	6.00	11.00	15.00	26.00	15.00	30.00	18.00	16.00	20.00	36.00	-0.04	115.49
Dens	0.57	0.37	0.26	0.39	0.40	0.39	0.17	0.19	0.34	0.26	0.17	-0.03	110.19
TNDO	3.00	2.00	2.00	5.00	4.00	5.00	14.00	2.00	3.00	9.00	4.00	0.05	92.49
NCD	1.00	0.00	2.00	2.00	4.00	2.00	4.00	5.00	4.00	4.00	8.00	0.07	96.80
DSM	2.00	2.00	2.00	3.00	3.00	3.00	3.00	4.00	3.00	3.00	5.00	0.35	90.71
PSM	3.00	2.00	3.00	5.00	3.00	5.00	5.00	6.00	5.00	6.00	7.00	0.55	115.72
Seq	0.40	0.50	0.22	0.67	0.82	0.67	0.43	0.58	0.58	0.33	0.55	0.14	133.42
DNS	0.00	0.00	0.20	0.25	0.43	0.25	0.25	0.43	0.40	0.40	0.45	0.07	207.29
Diam	3.00	3.00	3.00	4.00	4.00	4.00	5.00	6.00	5.00	5.00	6.00	0.33	173.01
LP	3.00	3.00	3.00	4.00	6.00	4.00	5.00	6.00	5.00	5.00	7.00	0.07	146.87
AVD	1.60	1.89	1.78	2.50	3.45	2.50	2.09	2.42	2.67	2.11	3.10	-0.03	157.74
CNC	0.80	1.00	0.89	1.25	1.73	1.25	1.04	1.16	1.33	1.06	1.52	-0.06	156.03
KC	0.00	0.00	0.00	0.00	8.00	3.00	1.00	4.00	0.00	0.00	28.00	0.10	169.32
DND	2.00	1.00	3.00	3.00	5.00	3.00	4.00	4.00	3.00	3.00	5.00	-0.16	177.72
CC	1.00	2.00	1.00	4.00	13.00	5.00	3.00	7.00	6.00	3.00	8.00	-0.12	113.63
IC	4.00	0.00	3.00	104.00	780.00	130.00	210.00	161.00	198.00	195.00	688.00	-0.22	176.08
Survey AVG	3.54	3.72	1.62	4.04	1.23	7.19	2.89	4.89	3.41	4.93	4.56		
STDEV	2.23	1.95	1.16	1.79	1.74	2.07	1.79	1.54	1.54	2.32	1.92		

Table 8: DT metric values for all 11 decision tables compared against the survey results.

DT Metric	Table 1	Table 2	Table 3	Table 4	Table 5	Table 6	Table 7	Table 8	Table 9	Table 10	Table 11	Correlation	SSD
ANPI	22.0000	4.0000	16.0000	7.0000	4.0000	5.0000	11.0000	58.0000	2.0000	4.0000	10.0000	-0.02	162.73
ANPO	7.0000	3.0000	2.0000	5.0000	2.0000	3.0000	11.0000	11.0000	2.0000	6.0000	2.0000	-0.03	146.93
ANVC	4.0000	2.6667	2.0000	3.6667	2.0000	2.2500	5.5000	4.0000	2.0000	5.0000	4.0000	-0.25	160.29
HPU	0.1000	0.1000	0.4000	0.1000	0.4000	0.4000	0.8000	0.1000	0.4000	0.3000	0.4000	0.77	29.26
TNR	22.0000	3.0000	16.0000	7.0000	4.0000	5.0000	11.0000	20.0000	2.0000	4.0000	10.0000	0.05	138.57
TNIV	4.0000	2.0000	6.0000	2.0000	3.0000	4.0000	3.0000	4.0000	2.0000	1.0000	2.0000	0.59	48.00
SS	132.0000	9.0000	112.0000	21.0000	16.0000	25.0000	44.0000	100.0000	6.0000	8.0000	30.0000	0.13	152.21
Survey AVG	1.96	1.68	7.14	2.40	5.83	6.03	7.08	3.91	4.21	2.03	3.67		
STDEV	1.60	1.74	2.31	2.06	1.80	1.94	2.29	2.00	2.18	2.18	2.51		

matrix is given in Appendix C. The matrix showcases, for instance, that Density and NOD have a high negative correlation (-0.70). This makes sense, since a bigger model generally means more decision nodes. As a consequence, it can be concluded that Dens is expected to decrease when NOD increases.

Next to the individual metrics for the DRDs and the decision tables, in future work we will look into combining DRD and decision table metrics into aggregated and holisitc complexity metrics, thus denoting the complexity of the entire DMN decision model. To do so, the focus has to mainly be set on negatively correlating table and DRD metrics. This is due to the fact that there is a trade off between DRD complexity and decision table complexity. A decision can be modelled in a single encompassing decision table containing all the logic. This however results in a high decision table complexity and a low DRD complexity, since the DRD only contains one decision node representing the holistic decision table. The holistic decision table can be decomposed into a number of smaller and interconnected tables containing parts of the decision logic. This decreases the complexity of the individual decision tables. However, the complexity of the decision requirements diagram is likely to increase, because the top-level decision is decomposed into multiple sub-decisions, thus introducing additional decision nodes and information requirements into the DRD model. Note that for instance ANPI and Density showcase a negative correlation in the correlation matrix in Table C.9, while Density and TNIV showcase a strong negative correlation (-0.62). Hence, the combination of Density and TNIV could be a very interesting one since one of them is a DRD metric and the other is a table metric and they are negatively correlate.

In addition to this theoretical metric discourse on DMN complexity, in future work we will look into additional empirical validation for the proposed metrics through additional surveys.

Additionally, the challenge of aggregating DRD and decision table metric provides additional opportunities for future research. Finally, inquiries into the complexity of integrated process and decision models will be conducted, by combining and integrating complexity metrics of DMN decision models and BPMN process models. That way, it can be investigated how the separation of process and decision concerns influences the complexity of the process and decision models respectively, as well as the complexity of the integrated process-decision model as a whole.

8. Conclusion

This paper provides a discussion on complexity metrics for individual DMN decision models. For the decision requirements level of the DMN standard, 19 complexity metrics were proposed, while 7 complexity metrics were put forward for the decision logic level. Furthermore, the evolution of the metrics was discussed and a survey was conducted to empirically evaluate the proposed complexity metrics. Results revealed that the simple metrics were suitable for capturing DRD complexity (e.g. Number of Elements (NOE), Number of Decisions (NOD), Number of Complex Decisions (NCD), and Total Number of Data Objects (TNDO)), while the Durfee Square Metric (DSM) and the Perfect Square Metric (PSM) prove to be the most suitable, as they display both low sum of squared differences values and high correlations between the metric values and the empirical assessment in the survey. For DMN decision tables, the Hit Policy Usage (HPU) and the Total Number of Input Variables (TNIV) were evaluated as suitable for measuring DMN decision table complexity. Additionally, an agenda for future inquiry into DMN decision model complexity was suggested. The emphasis was put on combining the metrics of both the logic level and the requirements level into aggregate metrics for the DMN model as a whole. Furthermore, the need for additional empirical validation for all type of metrics was emphasised. Finally, the complexity of integrated process and decision models needs to be assessed, by combining and integrating complexity metrics of DMN decision models and BPMN process models.

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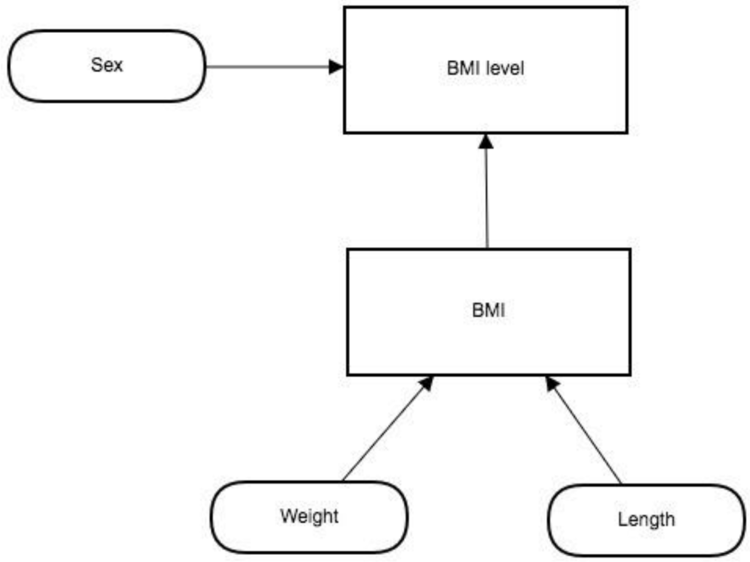

Figure A.5: DMN DRD Model 1.

Appendix A. DMN Decision Requirements Models

Appendix B. DMN Decision Table Models

Appendix C. Correlation Matrix of All Metrics

Appendix D. Survey Questionnaire

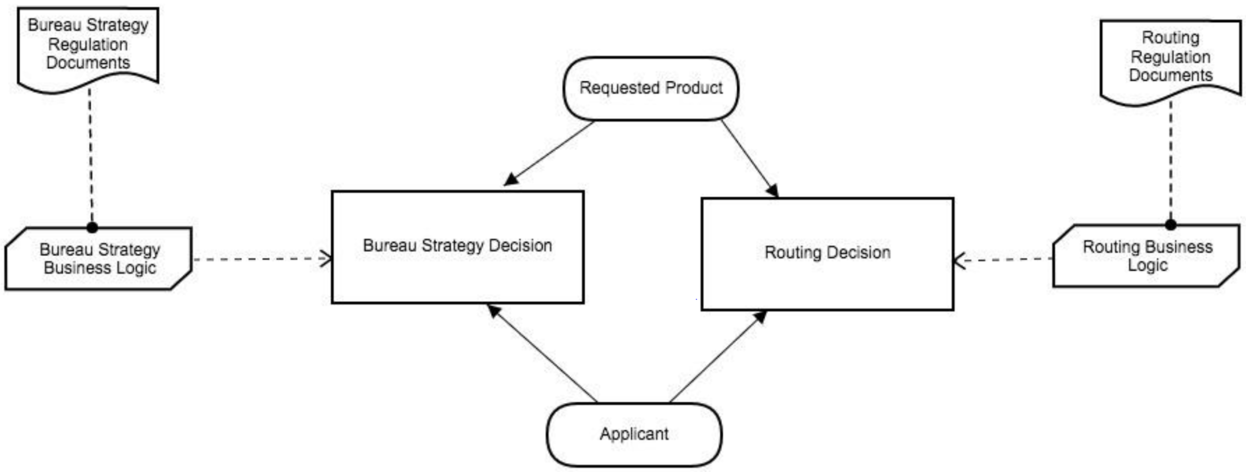

Figure A.6: DMN DRD Model 2.

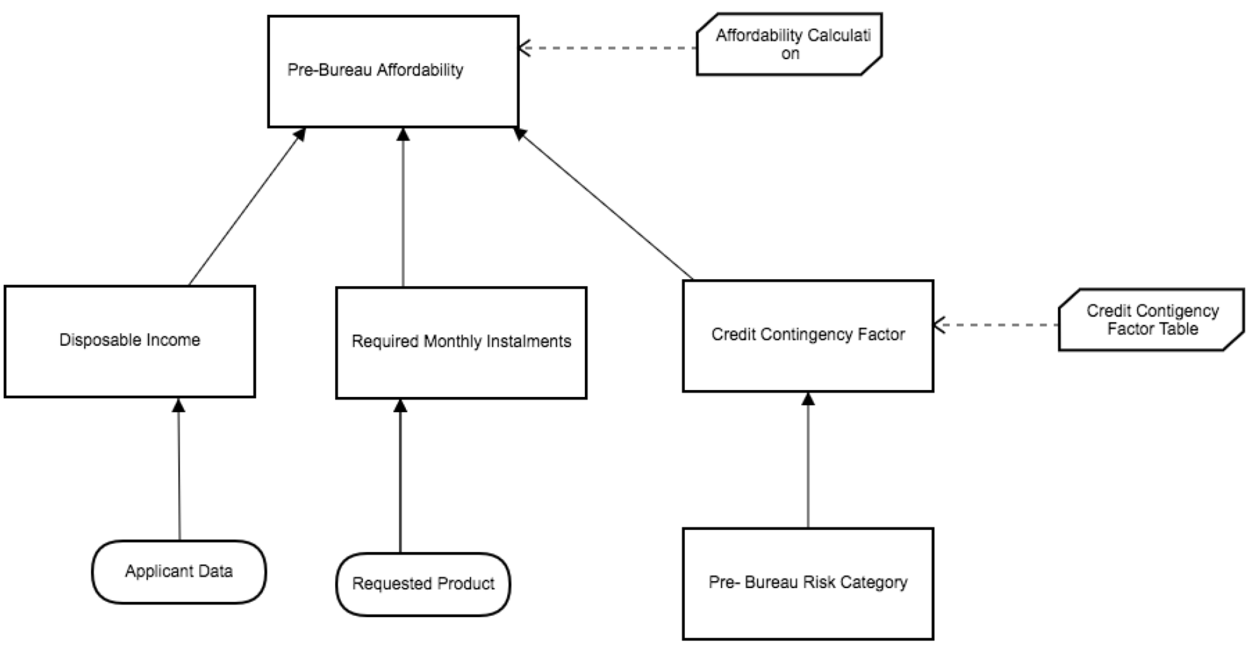

Figure A.7: DMN DRD Model 3.

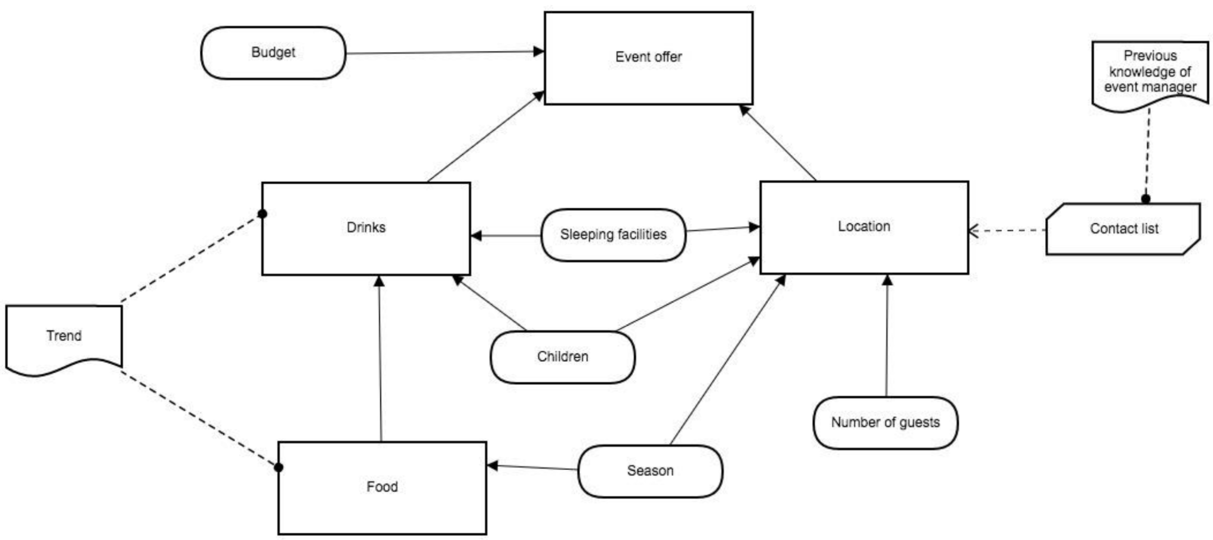

Figure A.8: DMN DRD Model 4.

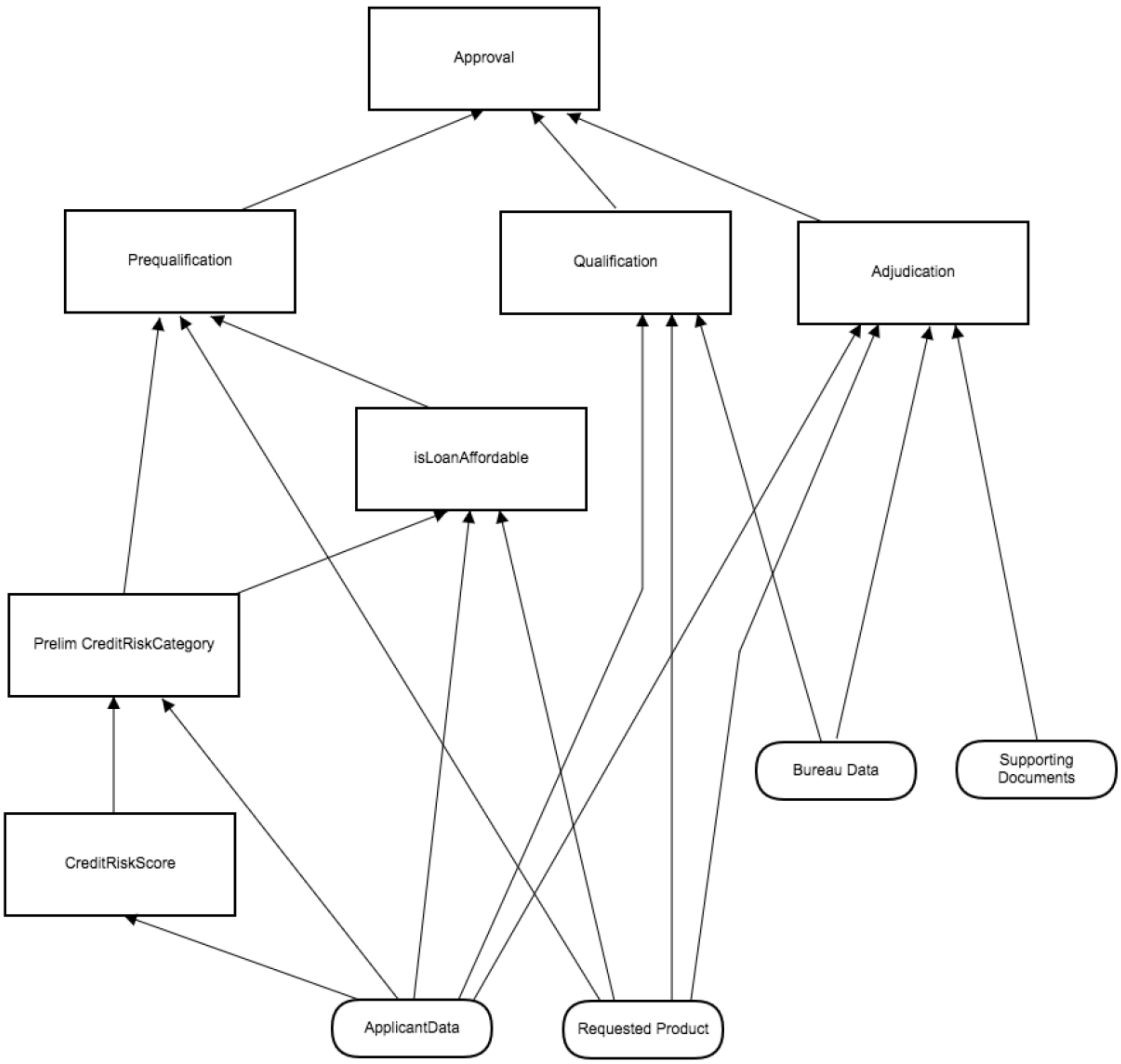

Figure A.9: DMN DRD Model 5.

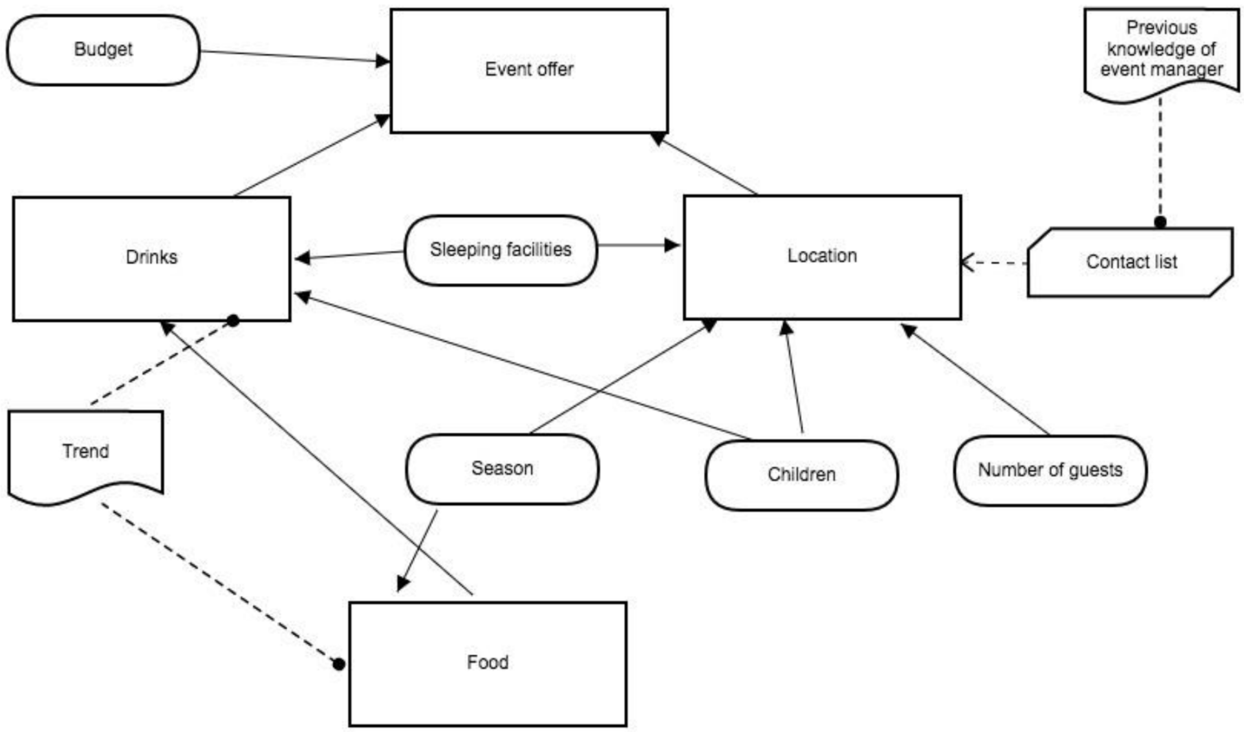

Figure A.10: DMN DRD Model 6.

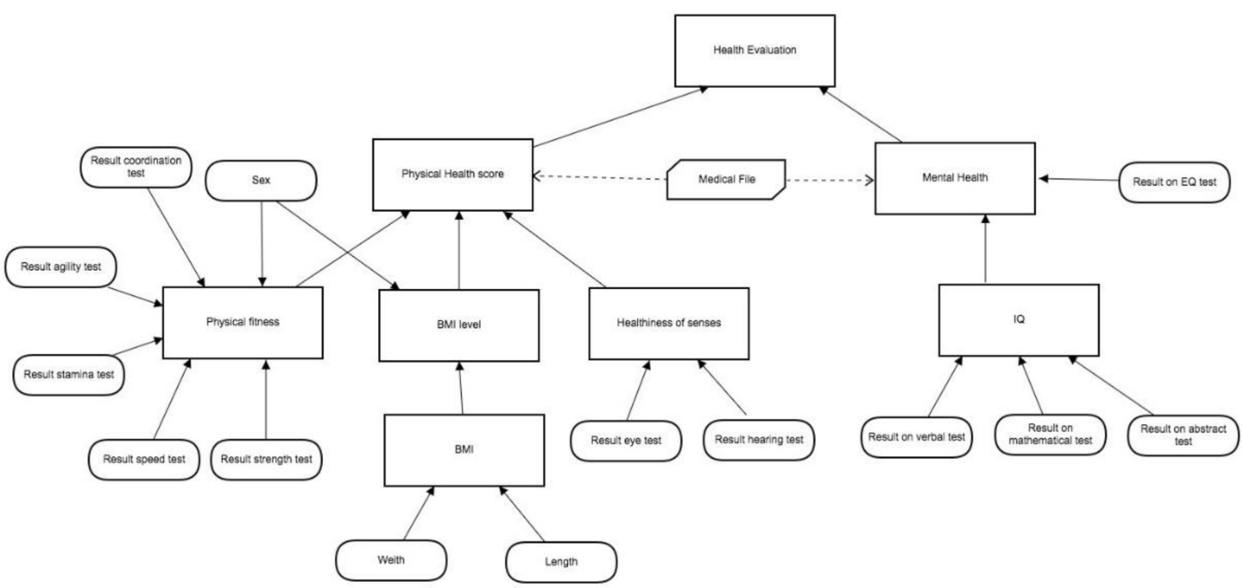

Figure A.11: DMN DRD Model 7.

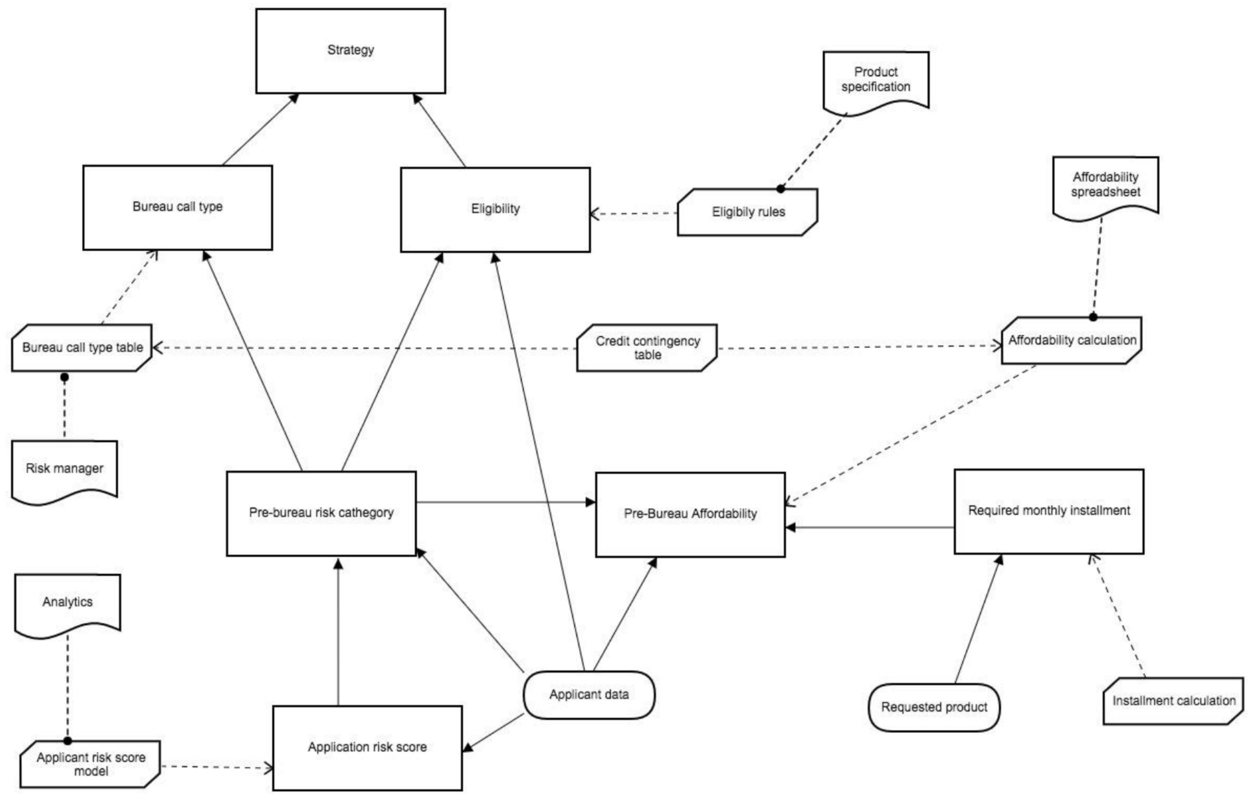

Figure A.12: DMN DRD Model 8.

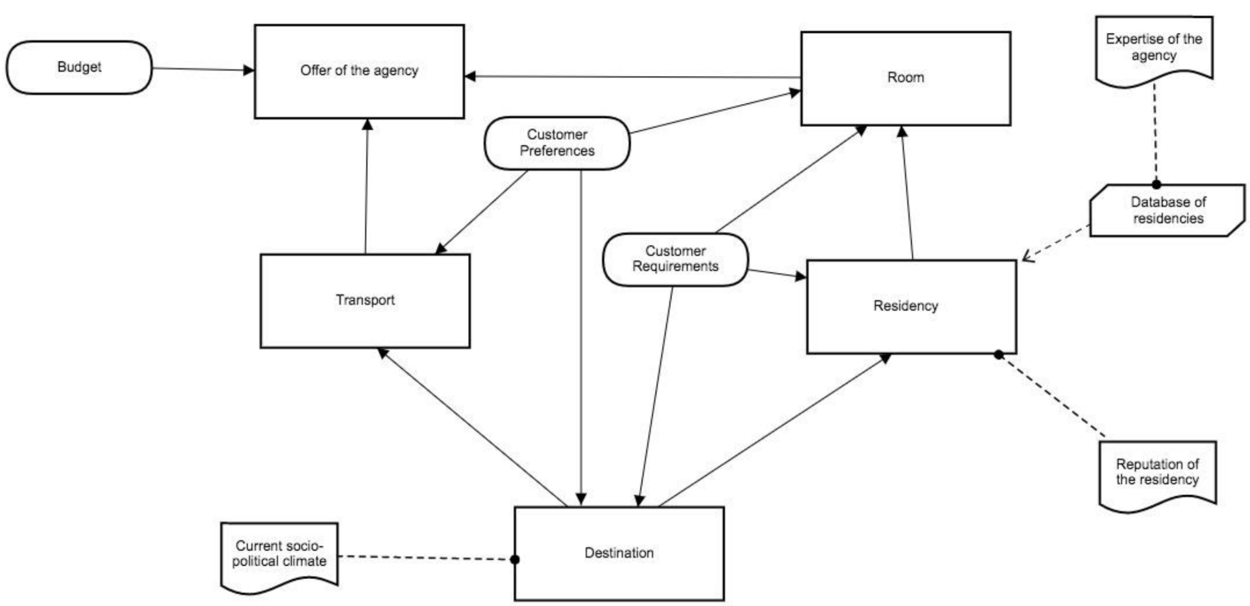

Figure A.13: DMN DRD Model 9.

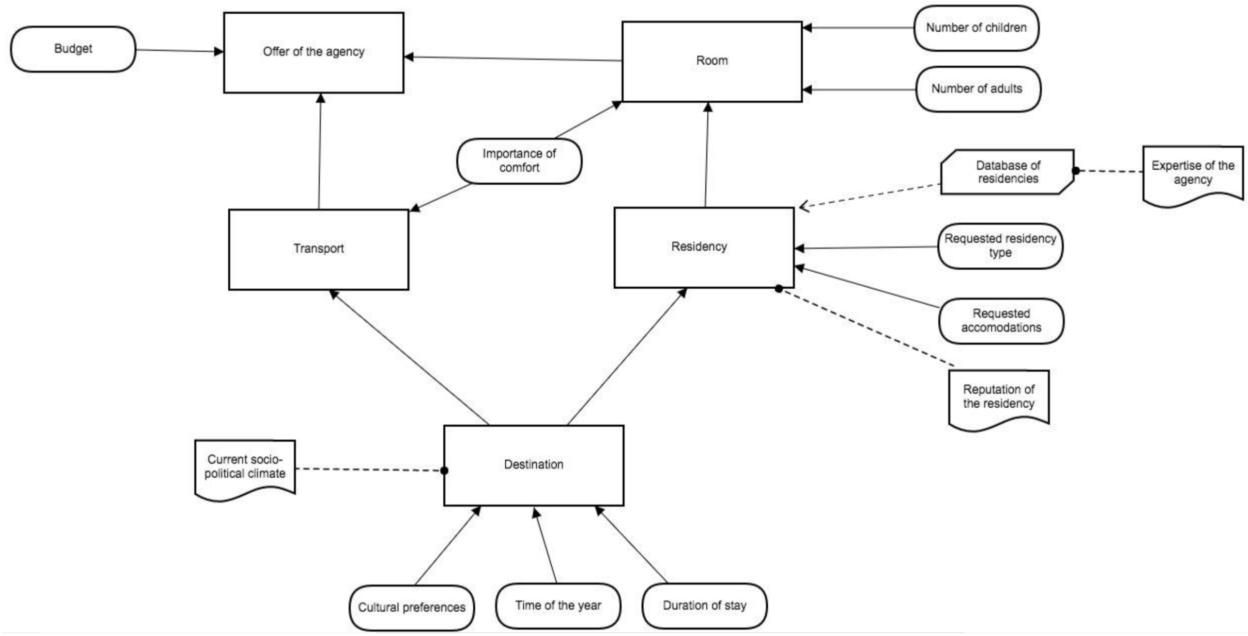

Figure A.14: DMN DRD Model 10.

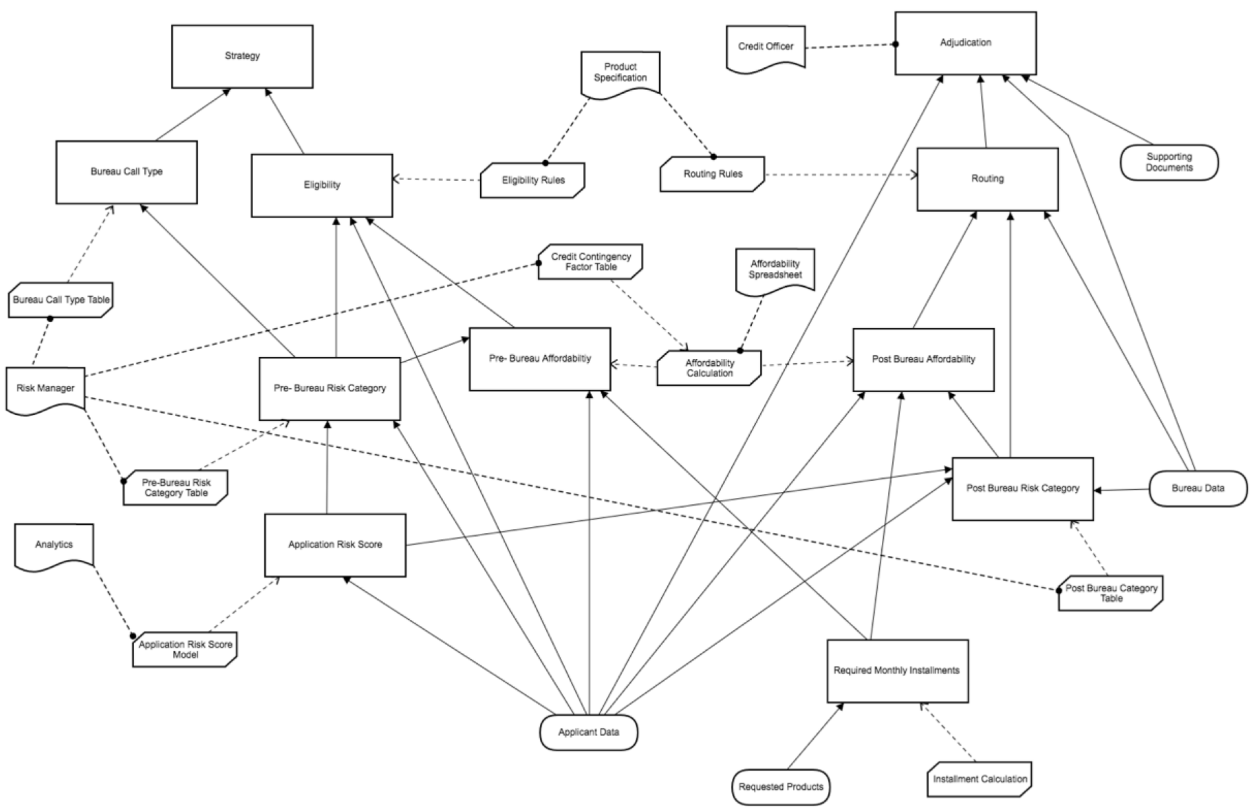

Figure A.15: DMN DRD Model 11.

<table>
<tr><th colspan="7">Location</th></tr>
<tr><th rowspan="3">U</th><th colspan="4">Input</th><th colspan="2">Output</th></tr>
<tr><th>Season</th><th>Guests</th><th>Sleeping facilities</th><th>Children</th><th>Location</th><th>Costs</th></tr>
<tr><td>String</td><td>Integer</td><td>Boolean</td><td>Boolean</td><td>String</td><td>Double</td></tr>
<tr><td>1</td><td rowspan="8">Winter</td><td rowspan="4">< 30</td><td rowspan="4">-</td><td rowspan="2">T</td><td rowspan="2">Cabin in the woods</td><td rowspan="2">100</td></tr>
<tr><td>2</td></tr>
<tr><td>3</td><td rowspan="2">F</td><td rowspan="2">Blue Ocean</td><td rowspan="2">200</td></tr>
<tr><td>4</td></tr>
<tr><td>5</td><td rowspan="4">>= 30</td><td rowspan="2">T</td><td>T</td><td>Cabin in the woods</td><td>100</td></tr>
<tr><td>6</td><td>F</td><td>Snow Igloo</td><td>100</td></tr>
<tr><td>7</td><td rowspan="2">F</td><td rowspan="2">-</td><td rowspan="2">Grandma's restaurant</td><td rowspan="2">300</td></tr>
<tr><td>8</td></tr>
<tr><td>9</td><td rowspan="8">Spring</td><td rowspan="4">< 30</td><td rowspan="2">T</td><td rowspan="2">-</td><td rowspan="2">Surfer's Bay</td><td rowspan="2">400</td></tr>
<tr><td>10</td></tr>
<tr><td>11</td><td rowspan="2">F</td><td>T</td><td>Pirate's Playground</td><td>500</td></tr>
<tr><td>12</td><td>F</td><td>Private Club</td><td>800</td></tr>
<tr><td>13</td><td rowspan="4">>= 30</td><td rowspan="2">T</td><td rowspan="2">-</td><td rowspan="2">Surfer's Bay</td><td rowspan="2">400</td></tr>
<tr><td>14</td></tr>
<tr><td>15</td><td rowspan="2">F</td><td>T</td><td>Surfer's Bay</td><td>400</td></tr>
<tr><td>16</td><td>F</td><td>Private Club</td><td>800</td></tr>
<tr><td>17</td><td rowspan="8">Summer</td><td rowspan="4">< 30</td><td rowspan="2">T</td><td rowspan="2">-</td><td rowspan="2">Surfer's Bay</td><td rowspan="2">400</td></tr>
<tr><td>18</td></tr>
<tr><td>19</td><td rowspan="2">F</td><td>T</td><td>Pirate's Playground</td><td>500</td></tr>
<tr><td>20</td><td>F</td><td>Private Club</td><td>800</td></tr>
<tr><td>21</td><td rowspan="4">>= 30</td><td rowspan="2">T</td><td rowspan="2">-</td><td rowspan="2">Surfer's Bay</td><td rowspan="2">400</td></tr>
<tr><td>22</td></tr>
<tr><td>23</td><td rowspan="2">F</td><td>T</td><td>Surfer's Bay</td><td>400</td></tr>
<tr><td>24</td><td>F</td><td>Private Club</td><td>800</td></tr>
<tr><td>25</td><td rowspan="8">Autumn</td><td rowspan="4">< 30</td><td rowspan="4">-</td><td rowspan="2">T</td><td rowspan="2">Cabin in the woods</td><td rowspan="2">100</td></tr>
<tr><td>26</td></tr>
<tr><td>27</td><td rowspan="2">F</td><td rowspan="2">Blue Ocean</td><td>200</td></tr>
<tr><td>28</td><td>200</td></tr>
<tr><td>29</td><td rowspan="4">>= 30</td><td rowspan="2">T</td><td>T</td><td>Cabin in the woods</td><td>100</td></tr>
<tr><td>30</td><td>F</td><td>Snow Igloo</td><td>100</td></tr>
<tr><td>31</td><td rowspan="2">F</td><td rowspan="2">-</td><td rowspan="2">Grandma's restaurant</td><td rowspan="2">300</td></tr>
<tr><td>32</td></tr>
</table>

Figure B.16: DMN Table 1.

<table>
<tr><th colspan="4">Bureau Strategy</th></tr>
<tr><th rowspan="3">U</th><th colspan="2">Input</th><th>Output</th></tr>
<tr><th>Eligibity</th><th>Bureau Call Type</th><th>Bureau Strategy</th></tr>
<tr><td>Class</td><td>Class</td><td>Class</td></tr>
<tr><td>1</td><td>INELIGIBLE</td><td>-</td><td>DECLINE</td></tr>
<tr><td>2</td><td rowspan="2">ELIGIBLE</td><td>FULL, MINI</td><td>BUREAU</td></tr>
<tr><td>3</td><td>NONE</td><td>THROUGH</td></tr>
</table>

Figure B.17: DMN Table 2.

F	Physical fitness						
	Input						*Output*
	Sex	**Coordination**	**Agility**	**Strength**	**Speed**	**Stamina**	**Physical fitness**
	Class	P/F	P/F	P/F	P/F	P/F	String
1	M	P	P	P	P	-	Fit
2	M	P	P	P	F	P	Fit
3	M	P	P	P	F	F	Not fit
4	M	P	P	F	-	P	Fit
5	M	P	P	F	-	F	Not fit
6	M	P	F	P	P	P	Fit
7	M	P	F	P	F	-	Not fit
8	M	P	F	F	P	P	Fit
9	M	P	F	F	F	-	Not fit
10	M	F	P	P	P	P	Fit
11	M	-	-	-	-	-	Not fit
12	F	P	P	-	-	-	Fit
13	F	P	F	P	F	F	Not fit
14	F	P	F	P	-	-	Fit
15	F	P	F	F	P	P	Fit
16	F	P	F	F	-	-	Not fit
17	F	F	P	P	F	F	Not fit
18	F	F	P	P	-	-	Fit
19	F	F	P	F	P	P	Fit
20	F	F	P	F	-	-	Not fit
21	F	F	F	P	P	P	Fit
22	F	F	F	-	-	-	Not fit

Figure B.18: DMN Table 3.

<table>
<tr><th colspan="4">BMI Level</th></tr>
<tr><td rowspan="3">U</td><td colspan="2">Input</td><td>Output</td></tr>
<tr><td>BMI</td><td>Sex</td><td>BMI Level</td></tr>
<tr><td>double</td><td>class</td><td>class</td></tr>
<tr><td>1</td><td rowspan="2">< 18.5</td><td>Male</td><td>Severely underweight</td></tr>
<tr><td>2</td><td>Female</td><td>Underweight</td></tr>
<tr><td>3</td><td rowspan="2">[18.5, 24.9]</td><td>Male</td><td>Underweight</td></tr>
<tr><td>4</td><td>Female</td><td>Normal</td></tr>
<tr><td>5</td><td rowspan="2">[25, 29.9]</td><td>Male</td><td>Normal</td></tr>
<tr><td>6</td><td>Female</td><td>Overweight</td></tr>
<tr><td>7</td><td rowspan="2">> 30</td><td rowspan="2">-</td><td rowspan="2">Obese</td></tr>
<tr><td>8</td></tr>
</table>

Figure B.19: DMN Table 4.

P	Eligibility			
	Input			*Output*
	Pre-Bureau Risk Category	**Pre-Bureau Affordability**	**Age**	**Eligibility**
	Class	Boolean	Integer	{INELIGIBLE, ELIGIBLE}
1	DECLINE	-	-	INELIGIBLE
2	-	FALSE	-	INELIGIBLE
3	-	-	< 18	INELIGIBLE
4	-	-	-	ELIGIBLE

Figure B.20: DMN Table 5.

Routing					
	Input				*Output*
P	**Post-Bureau Risk Category**	**Post-Bureau Affordability**	**Bankrupt**	**Credit Score**	**Routing**
	Class	Boolean	Boolean	null, [0...999]	{DECLINE, REFER, ACCEPT}
1	-	FALSE	-	-	DECLINE
2	-	-	TRUE	-	DECLINE
3	HIGH	-	-	-	REFER
4	-	-	-	< 580	REFER
5	-	-	-	-	ACCEPT

Figure B.21: DMN Table 6.

Credit Risk Score				
	Input			*Output*
C+	**Age**	**isMarried**	**employmentStatus**	**CreditRiskScore**
	Integer	Boolean	{ Employed.Self-employed...}	Integer
1	<= 21	-	-	32
2	]21...25]	-	-	35
3	]25...35]	-	-	40
4	]35...50[	-	-	43
5	>= 50	-	-	48
6	-	FALSE	-	25
7	-	TRUE	-	45
8	-	-	Unemployed	15
9	-	-	Student	18
10	-	-	Employed	45
11	-	-	Self-employed	36

Figure B.22: DMN Table 7.

<table>
<tr><th colspan="3">Room</th><th colspan="3"></th></tr>
<tr><td rowspan="3">U</td><td colspan="4">Input</td><td>Output</td></tr>
<tr><td>Residency</td><td>Comfort</td><td>Adults</td><td>Children</td><td>Room</td></tr>
<tr><td>String</td><td>Boolean</td><td>Integer</td><td>Integer</td><td>String</td></tr>
<tr><td>1</td><td>Non-existent</td><td>-</td><td>-</td><td>-</td><td>Non-existent</td></tr>
<tr><td>2</td><td>Pool Villa</td><td>-</td><td>-</td><td>-</td><td>Villa Room</td></tr>
<tr><td>3</td><td rowspan="12">Hotel, Pool Hotel, Ranch, Restaurant Hotel, Sushi Hotel</td><td rowspan="6">T</td><td rowspan="3">1</td><td>0</td><td>Single Suite</td></tr>
<tr><td>4</td><td>1</td><td>Double Suite</td></tr>
<tr><td>5</td><td>> 1</td><td>Family Suite</td></tr>
<tr><td>6</td><td rowspan="3">2</td><td>0</td><td>Double Suite</td></tr>
<tr><td>7</td><td rowspan="2">> 0</td><td rowspan="2">Family Suite</td></tr>
<tr><td>8</td></tr>
<tr><td>9</td><td rowspan="6">F</td><td rowspan="3">1</td><td>0</td><td>Single Room</td></tr>
<tr><td>10</td><td>1</td><td>Double Room</td></tr>
<tr><td>11</td><td>> 1</td><td>Family Room</td></tr>
<tr><td>12</td><td rowspan="3">2</td><td>0</td><td>Double Room</td></tr>
<tr><td>13</td><td rowspan="2">> 0</td><td rowspan="2">Family Room</td></tr>
<tr><td>14</td></tr>
<tr><td>15</td><td>Igloo</td><td>-</td><td>-</td><td>-</td><td>Igloo Room</td></tr>
<tr><td>16</td><td>Riad</td><td>-</td><td>-</td><td>-</td><td>Souk</td></tr>
<tr><td>17</td><td rowspan="2">Student Hostel</td><td rowspan="2">-</td><td>-</td><td>0</td><td>Shared Room</td></tr>
<tr><td>18</td><td>-</td><td>> 0</td><td>Non-existent</td></tr>
<tr><td>19</td><td>Villa</td><td>-</td><td>-</td><td>-</td><td>Villa Room</td></tr>
<tr><td>20</td><td>Wine Domain Villa</td><td>-</td><td>-</td><td>-</td><td>Villa Room</td></tr>
</table>

Figure B.23: DMN Table 8.

<table>
<tr><th colspan="2">Healthiness of senses</th><th colspan="2"></th></tr>
<tr><td rowspan="3">F</td><td colspan="2">Input</td><td>Output</td></tr>
<tr><td>Eye</td><td>Hearing</td><td>Senses</td></tr>
<tr><td>Pass/fail</td><td>Pass/fail</td><td>String</td></tr>
<tr><td>1</td><td>P</td><td>P</td><td>Healthy</td></tr>
<tr><td>2</td><td>F</td><td>-</td><td>Unhealthy</td></tr>
</table>

Figure B.24: DMN Table 9.

<table>
<tr><th colspan="2">Food</th><th></th></tr>
<tr><td rowspan="3">U</td><td>Input</td><td>Output</td></tr>
<tr><td>Season</td><td>Food</td></tr>
<tr><td>String</td><td>String</td></tr>
<tr><td>1</td><td>Winter</td><td>Deer stew, Fondue</td></tr>
<tr><td>2</td><td>Spring</td><td>BBQ, Chicken salad</td></tr>
<tr><td>3</td><td>Summer</td><td>BBQ, Shrimp salad</td></tr>
<tr><td>4</td><td>Autumn</td><td>Deer stew, Vol au vent</td></tr>
</table>

Figure B.25: DMN Table 10.

Event offer			
	Input		*Output*
F	**Total costs**	**Budget**	**Event offer**
	Double	double	Boolean
1	<= 200	>= 200	T
2	<= 200	< 200	F
3	<= 400	>= 400	T
4	<= 400	< 400	F
5	<= 600	>= 600	T
6	<= 600	< 600	F
7	<= 800	>= 800	T
8	<= 800	< 800	F
9	<= 1000	>= 1000	T
10	<= 1000	< 1000	F

Figure B.26: DMN Table 11.

Table C.9: Metric Correlation Matrix

CORRELATION MATRIX	NOD	NOE	NOBE	NODIR	Dens	TNDO	NCD	DSM	PSM
NOD	1								
NOE	0.87566	1							
NOBE	0.95272	0.95132	1						
NODIR	0.99068	0.90142	0.97296	1					
Dens	-0.70419	-0.91023	-0.79514	-0.71733	1				
TNDO	0.70123	0.85919	0.87725	0.74661	-0.78597	1			
NCD	0.87454	**0.80079**	0.82666	0.86187	-0.60143	0.55625	1		
DSM	0.75926	**0.80529**	0.74209	0.77772	-0.57219	0.48247	0.82077	1	
PSM	0.42181	0.69701	0.56219	0.46422	-0.53346	0.58539	0.62765	0.77778	1
Seq	0.22969	-0.04135	0.00439	0.2023	0.20905	-0.39298	0.10287	0.38057	-0.19011
DNS	0.72904	0.68369	0.64409	0.72992	-0.478	0.29141	0.90583	0.89898	0.622
Diam	0.89153	0.73097	0.78025	0.88013	-0.53568	0.4085	0.93767	0.80013	0.41219
LP	0.89153	0.73097	0.78025	0.88013	-0.53568	0.4085	0.93767	0.80013	0.41219
AVD	0.55959	0.30187	0.3404	0.53593	-0.09919	-0.13705	0.55076	0.65794	0.07982
CNC	0.53627	0.27979	0.31206	0.51128	-0.09981	-0.1657	0.51551	0.62556	0.03535
KC	0.48522	0.13512	0.30032	0.48545	0.07475	-0.08212	0.33187	0.32733	-0.25459
DND	0.89618	0.66046	0.7943	0.89662	-0.35716	0.44846	0.82275	0.7746	0.34427
CC	0.55277	0.21823	0.31653	0.52506	-0.01959	-0.16365	0.52298	0.51582	-0.08941
IC	0.64026	0.32902	0.43572	0.62335	-0.11132	-0.02683	0.66329	0.5696	0.02358
ANPI	0.185	0.38207	0.21988	0.17139	-0.39866	0.17104	0.59009	0.43224	0.67202
ANPO	-0.06569	0.10614	-0.00482	-0.04617	0.09127	-0.01358	0.34137	0.46409	0.75723
ANVC	-0.05067	0.05704	-0.018	-0.03719	0.16077	-0.06602	0.38232	0.42881	0.6867
HPU	-0.00913	0.00171	-0.03068	0.04113	0.21857	-0.1609	-0.10978	0.42108	0.1965
TNR	0.28238	0.48525	0.32133	0.27209	-0.48042	0.2566	0.65451	0.53351	0.73899
TNIV	0.8378	0.81753	0.81137	0.85004	-0.61753	0.56572	0.75638	0.88141	0.57813
SS	0.64135	0.84141	0.75264	0.66262	-0.70541	0.75763	0.58828	0.79731	0.84099

CORRELATION MATRIX	Seq	DNS	Diam	LP	AVD	CNC	KC	DND	CC	IC	ANPI	ANPO	ANVC	HPU	TNR	TNIV	SS
Seq	1																
DNS	0.36381	1															
Diam	0.36129	0.92423	1														
LP	0.36129	0.92423	1	1													
AVD	0.8627	0.75658	0.76496	0.76496	1												
CNC	0.87191	0.73093	0.74406	0.74406	0.99778	1											
KC	0.73718	0.43453	0.59524	0.59524	0.7998	0.80146	1										
DND	0.4928	0.77933	0.9015	0.9015	0.75999	0.72826	0.71838	1									
CC	0.81603	0.67964	0.76091	0.76091	0.96633	0.96656	0.89824	0.76714	1								
IC	0.66655	0.77206	0.86078	0.86078	0.9227	0.91522	0.86171	0.83001	0.97089	1							
ANPI	-0.35513	0.59547	0.39529	0.39529	0.03849	0.01759	-0.35374	0.05934	-0.04731	0.09573	1						
ANPO	-0.10108	0.44966	0.13456	0.13456	0.05309	0.00741	-0.29584	0.06972	-0.08427	-0.00922	0.6877	1					
ANVC	-0.08635	0.47933	0.19126	0.19126	0.10114	0.05426	-0.21305	0.11947	-0.00189	0.08791	0.69568	0.9849968	1				
HPU	0.70225	0.17629	0.01838	0.01838	0.46569	0.456	0.35836	0.26093	0.32841	0.20083	-0.36213	0.2330275	0.1651887	1			
TNR	-0.30497	0.6576	0.4628	0.4628	0.09578	0.07245	-0.28077	0.14676	0.00175	0.13863	0.98504	0.6853727	0.6818188	-0.29482	1		
TNIV	0.38688	0.761	0.7797	0.7797	0.62223	0.59808	0.52428	0.80754	0.5532	0.58183	0.1994	0.1605421	0.1303153	0.3424062	0.348886	1	
SS	-0.00872	0.50584	0.43272	0.43272	0.14856	0.11369	-0.11363	0.47885	-0.01939	0.02567	0.31488	0.3678509	0.2638929	0.2807297	0.4260935	0.7429554	1

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Figure D.27: Survey.

In this survey, we will ask you to assess the complexity of 11 DRD models and decision tables. Please ***mark an 'X'*** *on the visual* ***scale line****, indicating* ***how complex you think each model is****, ranging from* ***not complex at all*** *to* ***very complex****. Also,* ***answer the accompanying questions*** *(to make sure you properly understand the models and do not answer randomly).* ***<u>When you want to change your answer, make sure to circle your final 'X'</u>****. Thank you.*

Please also fill in/circle your answer to following questions:
R-number: ....
Highest achieved diploma: Bachelor / Master / MaNaMa / Other: ....
Study field of highest achieved diploma (e.g. Business Engineering, Statistics,...): ....
Current study program: ....
I have followed a course that covered/discussed DMN in the past: Yes / No

Model 1: *How many inputs does "IsLoanAffordable" require?* ....

Not complex at all |——————| Very complex

Model 2: *Is the budget taken into account by "Room"* ....

Not complex at all |——————| Very complex

Model 3: *Which decisions (if any) are affected by "Requested Product"?* ....

Not complex at all |——————| Very complex

Model 4: *How many input data elements does "Physical Health Score" use in total?* ....

Not complex at all |——————| Very complex

Model 5: *What input data is directly necessary to make the decision "BMI Level"?* ....

Not complex at all |——————| Very complex

Model 6: *How many input data elements affect "Routing"?* ....

Not complex at all |——————| Very complex

Model 7: *Can we make the "Routing Decision" with "Bureau Strategy Business Logic"?* ....

Not complex at all |——————| Very complex

Model 8: *Which decisions are not affected by applicant data?* ....

Not complex at all |——————| Very complex

Model 9: *Can we make the "Drinks" decision if we don't know the season?* ....

Not complex at all |——————| Very complex

Model 10: *How many input data elements affect "Residency"?* ....

Not complex at all |——————| Very complex

Model 11: *Is "Location" in any way affected by "Food"?* ....

Not complex at all |——————| Very complex

Table 1: *What output is generated by following data?* ....
Season = Summer; Guests = 20; Sleeping facilities = F; Children = T

Not complex at all |——————| Very complex

Table 2: *What output is generated by following data?* ....
Eligibility = Eligible; Bureau Call Type = MINI

Not complex at all |——————| Very complex

Table 3: *What output is generated by following data?* ....
Sex = F; Coordination = P; Agility = P; Strength = F; Speed = P; Stamina = F

Not complex at all |——————| Very complex

Table 4: *What output is generated by following data?* ....
BMI = 20; Sex = Female

Not complex at all |——————| Very complex

Table 5: *What output is generated by following data?* ....
Pre-bureau Risk Category = - ; Pre-bureau Affordability = FALSE; Age = 16

Not complex at all |——————| Very complex

Table 6: *What output is generated by following data?* ....
Affordability = TRUE; Bankrupt = FALSE; Risk Category = HIGH; Credit Score = 650

Not complex at all |——————| Very complex

Table 7: *What output is generated by following data?* ....
Age = 22; isMarried = TRUE; employmentStatus = Student

Not complex at all |——————| Very complex

Table 8: *What output is generated by following data?* ....
Residency = Iglo; Comfort = F; Adults = 2; Children = 2

Not complex at all |——————| Very complex

Table 9: *What output is generated by following data?* ....
Eye = F; Hearing = P

Not complex at all |——————| Very complex

Table 10: *What output is generated by following data?* ....
Season = Summer

Not complex at all |——————| Very complex

Table 11: *What output is generated by following data?* ....
Total costs = 700; Budget = 250

Not complex at all |——————| Very complex