Proposing a Holistic Framework for the Assessment and Management of Manufacturing Complexity through Data-centric and Human-centric Approaches

Dominik Kohr[1], Mussawar Ahmad[2], Bugra Alkan[2], Malarvizhi Kaniappan Chinnathai[2], Lukas Budde[1], Daniel Vera[2], Thomas Friedli[1] and Robert Harrison[2]

[1]*University of St. Gallen, Institute of Technology Management, Dufourstrasse 40a, 9000 St. Gallen, Switzerland*

[2]*Automation Systems Group, WMG, University of Warwick, CV4 7AL, Coventry, West Midlands, U.K.*

Keywords: Complexity Management, Manufacturing Complexity, Production, Complexity Drivers.

Abstract: A multiplicity of factors including technological innovations, dynamic operating environments, and globalisation are all believed to contribute towards the ever-increasing complexity of manufacturing systems. Although complexity is necessary to meet functional needs, it is important to assess and monitor it to reduce life-cycle costs by simplifying designs and minimising failure modes. This research paper identifies and describes two key industrially relevant methods for assessing complexity, namely a data-centric approach using the information theoretic method and a human-centric approach based on surveys and questionnaires. The paper goes on to describe the benefits and shortcomings of each and contributes to the body of knowledge by proposing a holistic framework that combines both assessment methods.

1 INTRODUCTION

Complexity is induced through a multiplicity of factors such as technological innovations, dynamic operating environments, and globalisation, and is believed to be one of the main causes of the current challenges in manufacturing, which are lengthy and costly system design processes, high life cycle costs, and the existence of numerous failure modes (Alkan et al., 2016a). According to (Schuh and Schwenk, 2001), complexity in the context of manufacturing, can be grouped into two categories: *i*) internal and *ii*) external. Internal complexity mainly occurs as a result of high product variety due to the need to meet market demands (Chinnathai et al., 2017; Alkan et al., 2016b), whereas external complexity results from market dynamics, political and institutional complexities (Götzfried, 2013). There are three main dimensions of internal complexity: *i*) structural (static) complexity, *ii*) operational (dynamic) complexity and *iii*) organisational complexity (Lindemann et al., 2008). Structural complexity is related to the notion of the architecture of the manufacturing system, which is a network that is composed of a set of interacting components/parts. Operational complexity is driven by the manufacturing systems operational characteristics (Alkan et al., 2016a). Accordingly, a manufacturing system can be deemed complex, if its behaviours are difficult to describe or predict effectively (Calinescu et al., 1998). It should be noted that, system behaviours are often connected to the underlying system architecture, hence dynamic complexity has a strong positive correlation with structural manufacturing system complexity (Sinha et al., 2017). Organisational complexity, on the other hand, is manifested in organisational structures, systems, processes and in communication flows (Kohr et al., 2017).

An increase in complexity results in various problems including: production bottlenecks, reliability issues and a lack of stability (Efthymiou et al., 2016). Therefore the management of complexity is a non-negligible aspect of an organisation's operation and thus, a strategy should be in place in order to remain competitive (Budde et al., 2015). One of the key elements in effective management of complexity is its assessment, which should provide a clear picture of the underlying problems (Alkan et al., 2017). However, the diverse causes and effects of complexity are hard to evaluate. Furthermore, the methods chosen to manage them should be chosen based on the indivi-

Kohr, D., Ahmad, M., Alkan, B., Chinnathai, M., Budde, L., Vera, D., Friedli, T. and Harrison, R.
Proposing a Holistic Framework for the Assessment and Management of Manufacturing Complexity through Data-centric and Human-centric Approaches.
In *Proceedings of the 3rd International Conference on Complexity, Future Information Systems and Risk (COMPLEXIS 2018)*, pages 86-93
ISBN: 978-989-758-297-4

dual complexity drivers of the company.

In this research, two complementary methods for assessing manufacturing complexity have been described in detail. The first method is an information theoretic measure developed by (Frizelle and Woodcock, 1995) defining complexity as the uncertainty in identifying the required information to define the overall state of a manufacturing system. The second method is a survey based approach identifying manufacturing/organisation complexity based on elicitation and aggregation/pooling of expert opinions. The advantages and disadvantages of the selected methods have been identified based on a number of criteria, and the authors provide insight for future researchers of this topic. The combined use of a human-centric and a data-centric approach is further discussed and a framework exploiting the advantages of both methods is proposed.

2 INFORMATION THEORETIC APPROACH

A practical approach to quantify complexity based on an entropic model of a factory was developed by (Frizelle and Woodcock, 1995). In this method, the following assumptions are made: "each sub-system is an immigration-emigration process, reliability is inversely proportional to complexity, cycle time is directly dependant on complexity and complex processes have more probability to become bottlenecks" (Calinescu et al., 1998). Accordingly, two types of complexity are identified, *i.e.* static and dynamic.

2.1 Static Complexity Assessment

Static complexity emerges as a result of the impact of the product on the resource domain. It is defined as the amount of information required to define the state of the production system (S) and is formulated as follows:

$$H^S_{static} = -\sum_{i=1}^{M}\sum_{j=1}^{N} p_{ij}\log_2 p_{ij} \qquad (1)$$

where, M is the quantity of resource existing in system S, N is the number of possible states for the i^{th} resource and p_{ij} is the probability of state j occurring in resource i. In this context, states of resources can be defined subjectively (e.g. busy, idle and breakdown etc.). Static complexity is essentially a measure of the inherent complexity of a production process within a specified time-frame, usually a year. According to (Calinescu, 2002), static complexity reduces when redundant resources are removed and product design is simplified.

2.2 Dynamic Complexity Assessment

In contrast to static complexity, dynamic complexity is a measure of a system's operational behaviour, especially corresponding to queues. The sources of dynamic complexity can vary from internal to external sources, and identifying the underlying reason for queueing helps determine the issues in a process. The dynamic complexity of a facility is obtained using an expression similar to that for structural complexity, except that instead of calculating probabilities for the states as scheduled, the probabilities are estimated from actual observations.

$$H^S_{dynamic} = -\sum_{i=1}^{M}\sum_{j=1}^{N_a} p'_{ij}\log_2 p'_{ij} \qquad (2)$$

where, the p'_{ij} indicates probability estimates based on observed states and N_a is the number of observed (actual) states.

Depending on whether the state of an operation was planned or unprecedented, they can be classified as programmable (e.g. run, set-up, idle, etc.) and non-programmable (e.g. rework, breakdown, etc.) respectively. It should be noted that non-value adding activities such as rework, can potentially create bottlenecks in a system. Dynamic complexity assessment in the information theoretic approach necessitates process observations at regular time intervals for all variants available. Therefore, the information from process should be used to determine the various parameters of assessment, such as frequency and time-frame of the measurements.

2.3 The Application of Information Theoretic Approach

In order to assist with the understanding of the information theoretic approach, a discrete-event simulation study is performed by routing two different product variants through a battery assembly system. The assembly system in Figure 1 produces two battery variants, of which the variant A is designed to provide high power, whereas the variant B provides more energy, therefore, the number and type of cells, bus-bars, cooling system vary widely. The assembly line in consideration, however, is designed to accommodate both variants. The components for both variants are available at each of the stations and the operator is instructed to fit the parts according to the

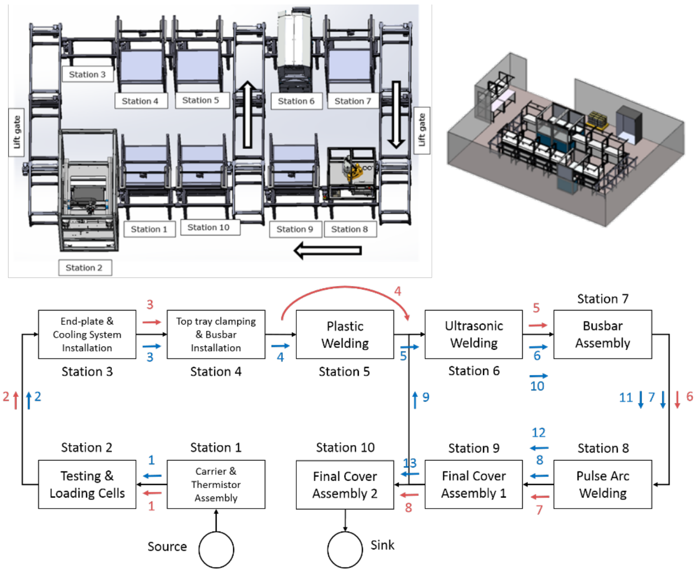

Figure 1: Battery assembly line layout.

work instructions. There are 7 manual stations which are operated by 4 people. There are 3 automatic stations, which are for cell loading, ultrasonic welding and pulse arc welding. As the variants are conveyed through the line, an RFID reader reads the recipe present on the pallet to determine the necessary operations that need to be performed at any station. Therefore, the automatic stations change their configuration depending on the variant in consideration. Some of the stations do not perform any operation for the considered variant. In this situation, the pallet is bypassed through the station. The stations are reasonable balanced to avoid potential queueing. The significant tasks that are performed manually across the seven stations are as follows: carrier assembly, cooling system install, fastening the carrier plates, plastic welding, bus-bar installation, visual inspection of welds, assembly of insulator cover. To understand the challenges in mixed model assembly of a battery assembly line with the above-mentioned characteristics, discrete-event simulations of the system was modelled. Various parameters were introduced and tweaked around to visualise the flow of the products in the system.

The annual net demand for product variants are defined as 500 for each, and the available time per year is 1920 time unit (48 time unit per week). Product and resource information are given in Table 1 and 2, respectively. It should be noted that, variant A is run a week, followed by running variant B for two weeks, thus, the set-up time is calculated depending on the next product to run. The generic states for static complexity is determined as: set-up, make and idle and each state is defined by specifying the product associated to it (Table 2). Then, the probability of each state is calculated (Table 3) and corresponding information content is calculated in Table 4. Accordingly, the static complexity of the assembly system is found as 14.00325 bits.

Table 1: Product information.

	Variant A	Variant B
Operations	CA × (OP1A+ OP2A+OP3A+OP4A +OP6A+OP7A+OP8A+ OP9A+OP10A)	+OP3B+OP4B+OP5B OP3B+OP4B+OP5B +2×OP6B+2×OP7B+ 2×OP8B+2×OP9B+OP10B)
Annual net demand	500	500

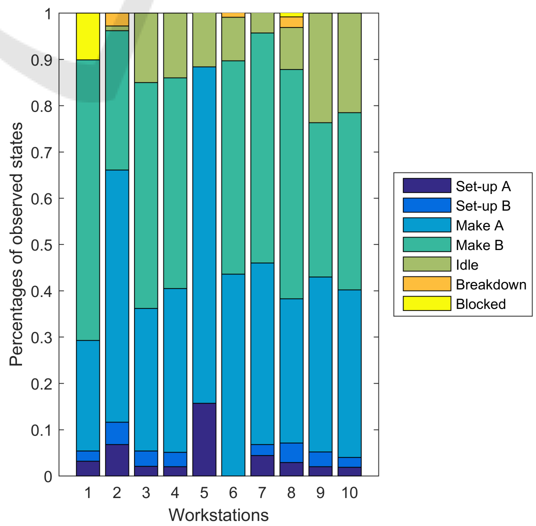

Figure 2: The percentage distribution of observed states for each workstation.

The operational complexity is analysed using dis-

Table 2: Resource information (All values are given in time unit).

	Stations																			
	1		2		3		4		5	6		7		8		9		10		
Operations	OP1A	OP1B	OP2A	OP2B	OP3A	OP3B	OP4A	OP4B	OP5A	OP6A	OP6B	OP7A	OP7B	OP8A	OP8B	OP9A	OP9B	OP10A	OP10B
Set-up	0.3	0.2	0.6	0.4	0.2	0.3	0.2	0.3	0.6	0.0	0.0	0.4	0.2	0.3	0.4	0.2	0.3	0.2	0.2
Total set-up	4.0	5.4	9.6	12.8	2.4	9.6	3.2	8.0	8.8	0.0	0.0	6.4	6.4	4.8	12.8	3.2	9.6	2.4	6.4
Make	1.0	2.4	4.2	2.2	2.0	3.0	2.3	2.8	3.0	4.0	4.0	2.5	3.0	3.0	4.5	3.0	2.5	2.5	2.5
Total make	500	1200	2075	1075	1000	1500	1150	1400	1500	2000	4000.0	1250	3000	1500	4500	1500	2500	1250	2500
Capacity	1.0		2.0		2.0		2.0		1.0	4.0		3.0		4.0		3.0		2.0	
Idle	210.6		322.6		658.0		633.8		411.2	420.0		490.5		402.4		573.9		36.2	

Table 3: Resource/state probabilities.

	Stations									
	1	2	3	4	5	6	7	8	9	10
Set-up A	0.002	0.005	0.001	0.002	0.005	0.000	0.003	0.003	0.002	0.001
Set-up B	0.003	0.007	0.005	0.004	0.000	0.000	0.003	0.007	0.005	0.003
Make A	0.260	0.540	0.260	0.299	0.781	0.260	0.217	0.195	0.260	0.326
Make B	0.625	0.280	0.391	0.365	0.000	0.521	0.521	0.586	0.434	0.651
Idle	0.110	0.168	0.343	0.330	0.214	0.219	0.255	0.210	0.299	0.019

Table 4: Static complexity calculation.

	Stations									
	1	2	3	4	5	6	7	8	9	10
Set-up A	0.019	0.038	0.012	0.015	0.036	-	0.027	0.022	0.015	0.012
Set-up B	0.024	0.048	0.038	0.033	-	-	0.027	0.048	0.038	0.027
Make A	0.505	0.480	0.505	0.521	0.278	0.505	0.478	0.460	0.505	0.527
Make B	0.424	0.514	0.530	0.531	-	0.490	0.490	0.452	0.523	0.403
Idle	0.350	0.432	0.529	0.528	0.476	0.480	0.503	0.472	0.521	0.108
Total (Resource)	1.322	1.513	1.615	1.628	0.790	1.475	1.526	1.454	1.602	1.078
Total (System)	**14.003 bits**									

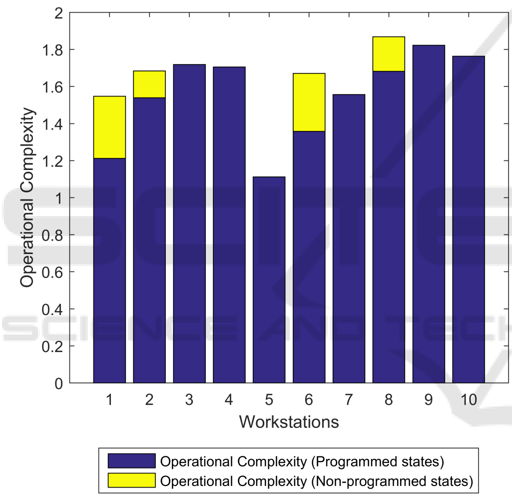

Figure 3: Operational complexity results of individual stations.

crete event simulation model due to the absence of actual production system data. A statistical model, e.g normal distribution, is used to represent the demand profile of both the variants and this introduces complexity which can be compared to that introduced due to market fluctuations. This significantly increases the time spent for set-up for each variant on processors. Moreover, the machine breakdown parameters (a negative exponential distribution is used for mean time between failure (MTBF) and mean time to repair (MTTR) behaviours) are also introduced in the automatic stations, namely 2, 6 and 8. Therefore, two additional non-programmable states, which are blocked, breakdown (including repair) are also tracked during the model run, for which the warm up time is 200 time units and run time is 1920 time units. Please note that, process-flow interruptions due to decision-making are not modelled. Figure 2 shows the percentage of the observed states per resource. The operational complexity results in Figure 3 are obtained by analysing the data gathered from the discrete event simulation model. Accordingly, operational complexity of the system is recorded as 16.224 bits, indicating that the complexity occurring due to the programmable states significantly contributes the overall operational complexity.

3 SURVEY BASED APPROACH

In this section, based on an iterative cycle consisting of literature research and discussions with practitioners, a human-centric complexity assessment methodology is developed to systematically identify the root causes of complexity within an organizational structure.

3.1 Methodology

The actual methodology of the human-centric complexity assessment is divided into three main steps.

3.1.1 Step 0: Identification of Complexity Drivers

In order to develop the human-centric complexity assessment methodology, a representative set of complexity drivers were identified. Therefore, we conducted an interview study and a literature review. The survey draft was peer reviewed by experienced academics. A final review was carried out by industry experts of a reduced sample of nine manufacturing companies to improve the survey validity. Based on the feedback the items and the format of the questionnaire were refined. As a result, a set of 20 complexity drivers were defined in order to evaluate the individual complexity situation of manufacturing companies. In the end it served as a complexity measurement tool in a benchmarking, with 137 participating companies from different sectors of the manufacturing industry.

3.1.2 Step 1: Complexity Driver Analysis

The methodology of the survey based measurement of complexity begins with the evaluation of the complexity drivers regarding their influence on the company's complexity. The survey encompasses complexity drivers which affect the whole company. In order to estimate the perceived complexity of the specific complexity drivers within the company, the participants are asked to rate their influence based on a self-assessment.

3.1.3 Step 2: Calculation of Complexity Index of Complexity Driver k

In the second step, based on the rating of the participants a normalized complexity index is calculated. The complexity index of each driver k is the result of the relation of the rating of the individual complexity driver (CD_k) and the sum of the rating over all complexity drivers ($\sum_1^n CD_i$).

$$CI_k = \frac{CD_k}{\sum_1^n CD_i} \tag{3}$$

where:

- CI_k: the relative rating of the complexity driver k,
- n: total number of complexity drivers,
- CD_i: the rating of complexity driver i.

The normalization allows an evaluation which complexity driver has the strongest influence on the complexity within the company. Furthermore, for evaluation purposes the complexity drivers are clustered in product complexity, production complexity, supply complexity, organizational complexity and market complexity. Hence, an evaluation for each complexity cluster can be conducted in order to derive suitable methods for management.

3.1.4 Step 3: Validation of the Method

For validation purposes, the results of the assessment tool's complexity evaluation are discussed in a semi-structured interview with the industry experts of the international companies. In these interviews, an understanding is built up (based on participant perception) of the causes of complexity. Detailed discussions and explanations regarding the static and dynamic factors reveal the challenges of the company to handle the complexity. The results of the questionnaire and the interview facilitate the assessment of the perceived complexity of the company.

3.2 The Application of the Approach: Precision Manufacturing (PM) Inc.

In the following, the survey based methodology is applied to the Precision Manufacturing Inc. to measure their perceived complexity.

- Rating of the complexity drivers at PM Inc.: First, the company rated the 19 complexity drivers on a Likert scale (1-5). The result is shown in Table 5. These numbers served as input for the next step in order to normalize the complexity drivers.
- Calculation of complexity index of PM Inc.: In this phase, each complexity driver is normalised, as depicted in Table 5. The drivers with the biggest influence are product variety and program dynamics as well as number of customers and the variety of customer demands.
- Validation of the complexity in a semi-structured interview study: In a short semi-structured interview, we build up an understanding of the main complexity drivers of PM Inc. The focus of PM Inc.'s complexity management approach is divided in product related and process related targets. The company aims at reducing the product complexity while at the same time extend their product portfolio. Furthermore, lower production costs and as well as a lower process variation needs to be achieved.

Due to the high variety of customer demands and the number of customers, PM Inc. needed to choose suitable methods to lower the resulted high product complexity. The activities aim at reducing the number of parts for specific existing products. By means of modularization, the company achieved higher rates of carry over parts and standardization within their existing product portfolio. Upcoming new products are designed based on existing components and therefore contribute to sustain a low number of parts.

Product variety, one of the complexity drivers with the strongest impact on the company, also required some changes within the assembly process. Through modularization of the assembly process, PM Inc. managed to reduce their process variety and to establish standardized processes. Employees designated to assembly are now qualified to perform four to five products instead of being specialized to only one product. Furthermore, employees from the production department are involved in the design and approval process of new products in order to lower the effort in the assembly process.

Table 5: Evaluation of complexity driver of Precision Engineering Inc.

Cluster	Class	Driver	Rating	Normalisation
1	Product complexity	Product variety	5	0.8
		(Product) Program dynamics	5	0.8
		Product structure	3	0.05
		Product technology dynamics	3	0.05
		Total	16	0.06
2	Production complexity	Number of value added steps	4	0.06
		Production technology dynamics	3	0.05
		Total	7	0.05
3	Supply chain complexity	Number of suppliers	4	0.06
		Uncertainty regarding delivery dates	3	0.05
		Uncertainty regarding delivery quality	2	0.03
		Number of distribution levels	3	0.05
		Total	12	0.05
4	Organisational complexity	Crosslingking degree of company processes	5	0.08
		Organisational structure	4	0.06
		Cooperate culture	2	0.03
		Total	11	0.06
5	Market complexity	Legal factors	1	0.02
		Political conditions	2	0.03
		Number of customers and customer groups	5	0.08
		Variety of customer requirements	5	0.08
		Volatility of customer demands	4	0.06
		Competitive dynamics	3	0.05
		Total	20	0.06
	Total sum of complexity drivers		66	

4 DISCUSSION

4.1 The Comparison of Two Methods

Up to this point, the authors have demonstrated the two key sources of data for assessing complexity i.e. objective sources such as data models/machine data and subjective sources such as surveys and questionnaires. Furthermore, there has also been a description as to how such sources can be transformed into tools for assessing complexity. The data-centric approach has been described through an example.

The data-centric complexity assessment approach is defined in this research as a means to derive complexity solely through objective means. In truth, this is not entirely possible as any manufacturing complexity assessment model is ultimately designed by humans, and the factors that would be chosen for assessment are at the whim of the assessor. Nevertheless, the sources of the data are inherently objective. This means that for a given assessment model, provided the relevant factors have been included, a systems complexity can be assessed and then monitored as changes are made to control or manage it. Furthermore, data-centric approaches for complexity assessment can be automated, whether by extracting data from models e.g. CAD, virtual engineering models, or from shop-floor machines e.g. through operational equipment effectives (OEE) calculations. This reduces the effort of assessing complexity and therefore reduces the barriers associated with managing it. In addition, such objective approaches offer comparisons between designs (product, process or machine), becoming an additional metric to aid selection.

On the other hand, data-centric approaches, by decoupling somewhat from the human, suffer from an inability to provide an insight into the humans perception of complexity. In fact, in some cases, the data-centric approach offers a skewed human perception of complexity as it can be expression of what the complexity data-model designer perceives should be included within the assessment of complexity. This very issue can result, perhaps most critically, in a system being deemed to be un-complex from an objective point of view but highly complex from a user or operational point of view. One way to extract this information is to directly ask the user. This results in a human-centric assessment of complexity. Complexity assessment through this lens allows one to understand what people deem to be the sources of complexity. This is not only a useful source of information to begin the management process, but also empowers those people asked as they are able to see how concerns raised are being addressed. Furthermore, many of the nuances that can be picked up from an interview or a survey are difficult to obtain from data-centric approaches as the latter is a model and therefore, by definition, a simplification of reality. Despite these benefits, surveys and questionnaires can be time-consuming and therefore complex exercises and there is often more work that needs to be done to derive an assessment.

4.2 A Framework for the Combined Use of Human and Data Centric Complexity Assessment

The authors have examined the literature and to date they have been unable to identify works that appreciate the need to assess and manage complexity. The authors therefore believe there is a significant gap in the literature that needs to be addressed to i) extend the use of data models to assess complexity in industrial settings and ii) combine the use of data models and questionnaires/surveys to assess and therefore manage complexity through multiple levels of an organisation. To address this gap, a framework is proposed (Figure 4) that combines human-centric and data-centric complexity assessment in combination with complexity management.

The framework consists of three layers, with a single research pillar spanning all layers. The lowest layer of the framework is the Data Layer. This layer represents the core data that exists in both the minds of humans as well as that which exists in engineering data models. This data could exist either internal or external to the organisation as well as at almost any level i.e. from management down to operators. As a result of the myriad of data sources, it is necessary to determine what data models and which people should be interviewed in order to get the right data. For this reason, the research pillar exists to help identify the relevant sources or drivers of complexity. At the data layer there exists the information necessary to assess complexity, but at its most raw, unprocessed form. It is necessary for some perspective to be added to the data in order for it to be used to assess complexity. Note that given a different perspective, a different criteria concerning an enterprise could be synthesised.

Above the Data Layer there is the Assessment Layer. At this layer the data sources are processed so that complexity can be assessed. If the complexity data source is a data model, then a complexity model is used. On the other hand, if the perceptions of humans need to be used as a complexity assessor, then the surveys or questionnaires are used on the relevant stakeholders. At this layer again the research pillar is fundamental in either applying or developing the right complexity model for the relevant data source or asking the right questions of the given stakeholder.

Based on the results of the assessment it is necessary to apply the right management strategy. This is carried out in the Management Layer. Note that at the Data and Assessment Layers there is a distinction between the data sources and the assessment methods. However, at the Management Layer the framework aims to combine the complexity assessment to understand i) how they interact, and ii) to therefore implement a management strategy that complements the assessment. The research pillar is essential in determining what management strategies exist and which are most relevant to the results derived from the complexity assessment. Once the management strategy has been identified it is implemented which closes the loop and allows further data to be taken from the Data Layer to understand the impact of the management strategy. This impact is carried out through the evaluation link from the Assessment layer to the Management layer.

The framework brings together only the elements necessary to begin to combine data-centric and human-centric complexity assessment methods. However, considerable work needs to be done to determine how the data should be combined i.e. the triangle spanning the left and right columns in Figure 4 representing the two complexity assessment methods. The authors' are still investigating a robust method to address this problem

5 CONCLUSION

This paper has described two of the key methods associated with deriving an assessment of complexity, namely data-centric and human centric approaches. These two classifications have not, to the best of the knowledge of the authors, been used to categorise complexity assessment methods previously. The respective approaches are discussed and compared with the strengths and weaknesses being identified. This evaluation leads to the formation of an entirely novel framework that combines the two assessment methods into one. As well as assessing complexity, the framework is holistic in that it appreciates the need to manage complexity, close the loop between assessment and management, and for continuously researching to identifying new complexity sources, assessment methods, and management methods. The authors strongly believe that the combination of the two assessment methods are complementary and fundamental to complexity management. This idea is to be tested as part of the case study with the industrial partner and is on-going work.

ACKNOWLEDGEMENT

The authors gratefully acknowledge the supports of the Commission for Technology and Innovation in Switzerland (CTI) through the project Complexity 4.0 (ref: 18993.1), the UK EPSRC through the KDCM

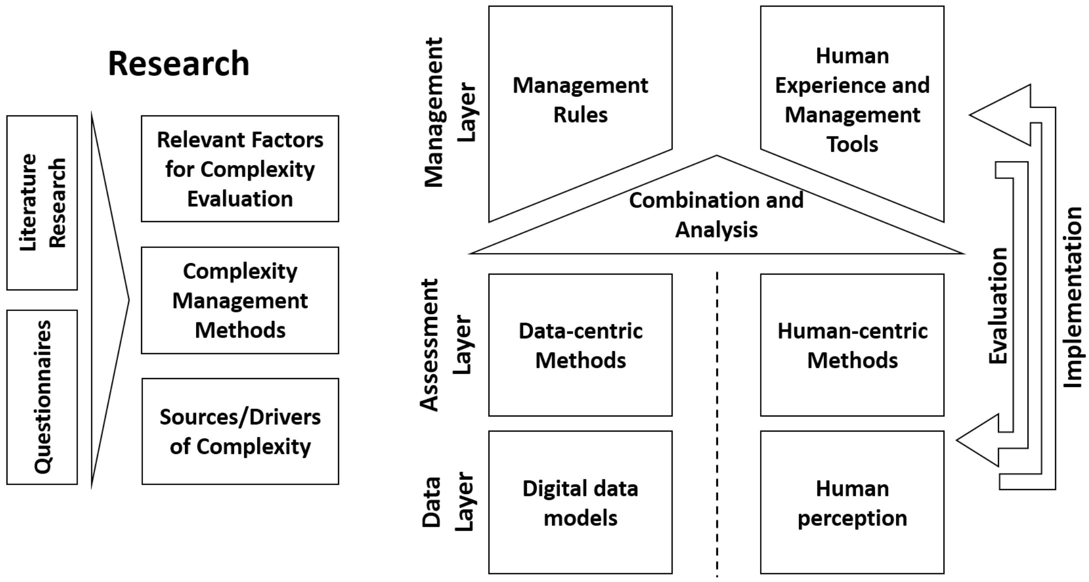

Figure 4: Holistic Framework for combining human-centric and data-centric complexity assessment for management.

research project, and the Innovate UK through the AMPLiFII project (ref: 102490).

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