Start and completion times of procedures in operating theatres to comply with WHO requirements are wholly insufficient to plan future lists based on average surgical durations. The variability of durations becomes so wide, that it typically leads to significant over-runs (54% of all procedures) under-runs (43% of all procedures). The situation is further compounded because unstructured surgical data, which is typically what most surgical data is, has long impeded the predictability of surgical procedure durations and therefore optimised scheduling. Data cannot be relied upon by surgical decision-makers in European healthcare systems such as the NHS, necessitating the need for transformation.

TCC-CASEMIX® rises to this challenge and for the first time presents structured data according to an ontology validated in-use and through clinical literature, with its data offering a substantial opportunity for companies developing medical technology applications to optimise surgery schedules.

The TCC-CASEMIX® proposition: Better Data to meet Big Clinical Challenges

Demand increasingly exceeds supply in the NHS, with demand growth outpacing *assumed* capacity increases, and making the goal of "short waits" for surgery impossible to meet[1]. The number of patients waiting for surgery in elective care has grown year-on-year since April 2012 and the 18-week referral to treatment standard failing to be met nationally[2]. In the last three months of 2019, over 23,000 elective procedures were cancelled for non-clinical reasons[3]. The COVID-19 pandemic has made this problem even graver, with over 110,000 people waiting more than a year to begin hospital treatment and the patient backlog at a 12-year high[4]. Not only must the NHS do more with less[5] to overcome issues before the pandemic, but dramatically increase surgery throughput to cut through the backlog of patients.

To achieve this, overcoming sub-optimal planning is key, something which already causes 291,327 people to miss out on urgent surgery annually[6], either through late starts, intra-surgery delays and early finishes. For example, a surgery may finish two hours earlier than planned: with the list completed, resources are wasted due to ineffective planning and unknown variability. Alternatively, a surgery overruns due to an unknown risk factor to the team, only because a 'known' risk factor not communicated into the acute care setting, failed to be identified during a 'standard' preoperative assessment. The consequence of that risk is delay to surgery, leading to a list over-run and potential cancellation. Opportunities for those scheduling theatre lists are large, but only if provided with the appropriate data.

This raises the question as to what data is required to optimise surgery schedules and increase predictability? Furthermore, how can we ensure that holistic patient centric data identifies appropriate risks? In other words, how can data be humanised?

TCC-CASEMIX® answers these through its complete data ontology for surgery, with its data able to be consumed by medical technology application companies (through a licencing agreement) enabling them to support better list planning in the NHS.

The TCC-CASEMIX® solution: Data Acquisition and Quality Assurance

TCC-CASEMIX® has been acquiring relevant data along the patient pathway through surgery to meet the needs for predictable list planning. Data quality is assured by design and verified using data quality measures. The data ontology has been extensively validated through a repository of

[1] NHS (2019) NHS Long Term Plan. National Health Service. Available at: http://www.longtermplan.nhs.uk/
[2] Briggs, T. W. R. (2019) Operating theatres: opportunities to reduce waiting lists. London, UK: NHS Improvement.
[3] NHS Digital (2020) 'Cancelled Operations (elective only)'. Available at: www.england.nhs.uk
[4] Braddick, I. (2020) 'Number of people waiting over a year for NHS treatment reaches 12-year high amid coronavirus pandemic. '. Evening Standard. 1. [Online]. Available at: www.standard.co.uk
[5] Carter, P. (2016) Operational productivity and performance in English NHS acute hospitals: Unwarranted variations. London: Department of Health. Available at: www.gov.uk
[6] See footnote 2.

Grateful acknowledgement to the University of Plymouth for their support in the production of this case study.

literature, reviews with surgeons, and through a field ambassadors' network, with the resulting ontology given in Figure 1.

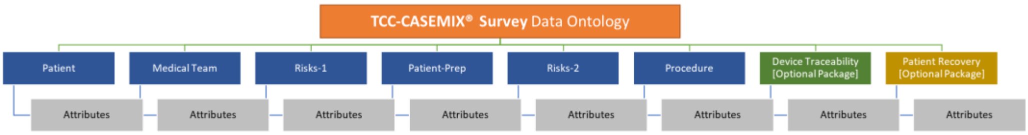

FIGURE 1: TCC-CASEMIX® SURVEY DATA ONTOLOGY

The TCC-CASEMIX® solution: Humanised Data that Captures Variability

FIGURE 2: DATA CAPTURED IN TCC-CASEMIX® SURVEY FOR AN INTERMEDULLARY NAILING PROCEDURE IN HUNGARY

The opportunities for medical technology application companies to acquire new knowledge of surgery are listed in a selection of examples below:

- **Granular Surgery Duration Measurement**. Structuring this data using the SNOMED Clinical Terms definitions, an approved information standard for the NHS[7], TCC-CASEMIX® Survey captures the duration of each sub-procedure at the most granular level (Figure 2), as well as overall theatre time.
    - Sub-procedures within a procedure which contribute to variability are identified.
    - Granular variability is correlated with patient and surgeon attributes (see below).
    - Productive and non-productive time derived from sub-procedures creates a rich evidence set to create policy to reduce downtime, a major issue for the NHS[8].
- **Patient Attribute Capture**. TCC-CASEMIX® Survey captures relevant patient attributes which affect performance in surgery to allow for variability of surgical duration. Regression, statistical analysis or machine learning methods can correlate attributes with procedure and sub-procedure duration, identifying relationships (see below).
- **Comorbidity Coding**. The surgeon records a variety of diagnostic codes, from cardiac disorders to social circumstances to the Charlson Comorbidity Index[9] to structurally capture these for statistical analysis.
- **Surgeon Attribute Capture**. Surgeon years of experience and specialty must be captured, having attributed this variable, it identifies forecast impact on operative time[10].

[7] NHS Digital (2020) SCCI0034: SNOMED CT. England: National Health Service. Available at: digital.nhs.uk

[8] See footnote 2

[9] A summary comorbidity measure (Austin, S. R., Wong, Y.-N., Uzzo, R. G., Beck, J. R. & Egleston, B. L. (2015) 'Why Summary Comorbidity Measures Such As the Charlson Comorbidity Index and Elixhauser Score Work'. Medical Care, 53 (9), pp. e65-e72.)

[10] Maruthappu, M., Duclos, A., Lipsitz, S. R., Orgill, D. & Carty, M. J. (2015) 'Surgical learning curves and operative efficiency: a cross-specialty observational study'. BMJ Open, 5 (3), pp. e006679.

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The TCC-CASEMIX® solution: Humanised Data Analysis to Control Variability

Having captured the relevant data, TCC-CASEMIX® Data Analysis creates profiles of patients according to risk, with statistical methods assessing the impact of different patient demographics on surgery duration. The impact of each profile is described by the change in forecast duration (*d*) and impact on the variability (σ, or standard deviation) to appreciate the full impact of demographic.

Described mathematically, this is $RI_d = \frac{\Delta d}{d} [\%]$ and $RI_\sigma = \frac{\Delta \sigma}{\sigma}$ $[\%]$

The story that could be told by this analysis follows: *<PatientID = value> is <patient age=range> and <patient BMI = value> from <location = postcode> and <ethnicity=value>. They present with the following <comorbidities = categories> and require <specialty= category> surgery, <SNOMED ID = value>, performed with <device = GUDID>.* **Using the procedure and patient profile, the API estimates the procedure to take** *<procedure-duration = time> with variability of <procedure-std-dev = time>.*

Example Scenario Application: Four Patient Journeys

Four different patients are due to undergo a sigmoid colon structure (SNOMED CT ID 84604002).

Josaphine, 76
Patient ID: 68298
10+ years surgeon experience
Patient BMI: 19.3
White British Non-Smoker

Hyun, 56
Patient ID: 71417
Under 5 years experience
Patient BMI: 32.5
Korean Smoker

Jasmin, 74
Patient ID: 76153
10+ years surgeon experience
Patient BMI: 19.2
Black British Non-Smoker

Aran, 58
Patient ID: 29420
Under 5 years experience
Patient BMI: 31.9
British Asian Smoker

Under the current 'state of the art', the list scheduler would not have access to structured patient attributes and only limited information, with data from pre-operative assessment stored in a "silo." The surgeon may be asked to predict the length of surgery, though limited by their own knowledge and unreliable data from previous operations[11]. However, typically standard planning templates are used, and it is assumed that through 'swings and roundabouts' that the over-runs and under-runs cancel each other out, but they do not because significant under-utilisation of theatres is the consequence.

This approach is inclusive of variability from both different, and irrelevant patient attributes. Often, data for many surgeries would be unavailable, further impeding reliability. Humanising data makes this possible: Predictions for Hyun and Aran, middle-aged male smokers operated on by a less experienced surgeon would be identical to that for the two older but healthy women operated on by more experienced surgeons. For all patients and without the ability to filter risk factors, expected duration is 104 minutes with a standard deviation of 33 minutes. Likelihood of large overruns or early finishes are therefore high, with a 68% confidence all procedures take between 71 and 137 minutes. Such overruns are the main cause of cancelled operations and inefficient resource use[12].

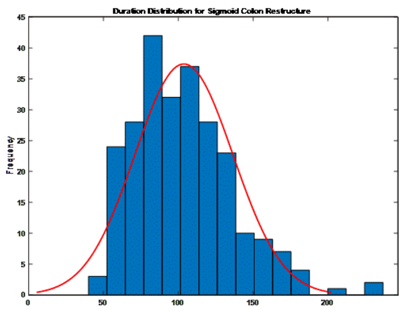

FIGURE 3 - DURATION DISTRIBUTION FOR ALL SIGMOID COLON STRUCTURES FITTED TO A NORMAL DISTRIBUTION

[11] Eijkemans, M. J. C., Van Houdenhoven, M., Nguyen, T., Boersma, E., Steyerberg, E. W. & Kazemier, G. (2010) 'Predicting the Unpredictable'. Anesthesiology, 112 (1), pp. 41-49.

[12] See footnote 2

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Under the novel approach using TCC-CASEMIX® data, the theatre planner is now able to query a subset of this relevant to the specific patient demographic, with the process given in Figure 4.

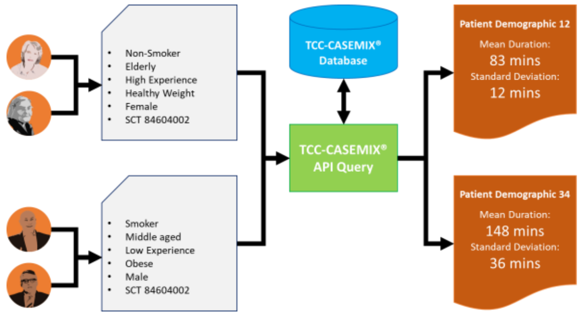

FIGURE 4: TCC-CASEMIX® API QUERY FOR THE DIFFERENT PATIENT DEMOGRAPHICS

Here, despite undergoing the same surgery, patient demographics affect duration distribution. Hyun and Aran's demographic takes much longer and is more variable, aggravated by being overweight, a smoker and the planned operation being undertaken by a relatively inexperienced surgeon. The older women are a healthy weight, non-smokers and will be operated on by a surgeon of greater years of experience, with surgery predicted to finish much earlier than Hyun and Aran's. Smoking, surgeon experience[13] and BMI[14] have been found to significantly impact surgery time.
The benefit for acute care trusts is not the shorter expected duration, but the increased predictability. Standard deviation has been reduced significantly for low-risk patients, representing a decrease in variability owing to basing predictions of relevant demographic and surgeon information. We appreciate demographic impact at a granular level, with those affecting surgery time identified in TCC-CASEMIX®'s literature review. This translates into a more efficient use of theatre time as it becomes more predictable: the previous status quo would have seen an early finish for both Josephine and Jasmin's surgeries, with resources going to waste by an early finish for the entire theatre list. With thousands of surgeries being carried out each year, this wastage would be significant, but the TCC-CASEMIX® approach significantly reduces this, and controls variability leading eventually to greater productivity. Without our analysis, patients presenting Hyun and Aran's risk profile, attracting both increased duration and variability would lead to late finishing lists and/or cancelled procedures.

Our value proposition

Why? *In everything we do, we believe in making transformational change possible.*
How? *Our quality assured surgical procedure data, automatically structured in SNOMED CT, and combined with patient demographics and patient risk factors, enables significant new knowledge to be acquired for the whole surgical pathway leading to much improved predictability of surgical services delivery.*
What? *Through our unique analytics we guide surgical planning and maximise productivity. We humanise data to always ensure a holistic patient focus and optimal patient outcomes from surgery. We also enable much improved revenue recovery from the Commissioners.*

For more information, please contact TCC-CASEMIX® Limited at info@tcc-casemix.co.uk or telephone 01823 423356

[13] See footnote 11
[14] Saiganesh, H., Stein, D. E. & Poggio, J. L. (2015) 'Body mass index predicts operative time in elective colorectal procedures'. Journal of Surgical Research, 197 (1), pp. 45-49.

Grateful acknowledgement to the University of Plymouth for their support in the production of this case study.