Low-cost Digitalisation Opportunities in Healthcare: A Histopathology Department Case Study

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Abstract: Healthcare facilities are critical social infrastructures that need timely intervention and careful management for seamless operations. Digital technologies offer significant advantages to healthcare infrastructures, especially in the post-COVID era. They improve access to care, facilitate communication and collaboration among healthcare professionals, and enable data-driven decision-making, ultimately leading to more efficient and effective healthcare delivery. This paper identifies the different aspects that can be digitalised in a hospital department, focusing on clinical laboratory settings. This work aims at defining the operational criticality of each stage of the process to support the evaluation of the their digitalisation opportunities. This enables the possibility of re-using low-cost, off-the-shelf technologies for industrial digitalisation, thus bridging the gap between industry and hospitals. We propose a set of methods to identify the digital technologies opportunities and prioritise their adoption in an histopathology department. The main variables controlling each space/function of the laboratory are modelled, the process phases are prioritised, and a set of existing and potential new digital technologies are identified within each chosen histopathology process phase. The benefits to deploying and adopting these digital technologies are identified, while adopting a low-cost digitalisation approach. The results of a pilot case, involving the Operations Managers of the Histopathology department in a regional hospital in the UK, show two main benefits that can be achieved; namely increasing the laboratory efficiency, in terms of throughput and turnaround Time (TAT), and increasing the granularity of information gathering.

1 Introduction

Digital Twins (DTs) are now being increasingly used in industrial systems modelling and management. More recently, the concept has gained momentum in the infrastructure sector [1]. A DT is widely conceptualised as:

> *'A set of virtual information constructs that mimics the structure, context and behaviour of an individual/unique physical asset, or a group of physical assets, is dynamically updated with data from its physical twin throughout its life cycle and informs decisions that realize value'* [2].

Many other definitions and examples can be found in literature, for example in the manufacturing [3], Aerospace [2], Built Environment [4] and Smart Cities [5] sectors. All these definitions agree on the fact that DTs require access to and process a wide variety of data within the broad Asset Management (AM) domain. However, data availability can be a blocker in most applications; when information is not available, organised and accessible, the capabilities of the DT applications are limited and their impact is reduced. Therefore, the digitalisation of information, processes and assets is a pre-requisite for DT development.

Digitalisation involves the conversion of information into a digital format, where data is organised into bits. In a broader context, it refers to integrating digital technologies into everyday life, business operations, and industries. This transformation allows for more efficient processes, personalised experiences, and data-driven decisions. In industries, adopting low-cost digital solutions for digitalisation has opened up many opportunities for innovation and efficiency. By leveraging affordable technologies such as Internet of Things (IoT) devices, cloud computing, and open-source software, small and medium-sized enterprises (SMEs) can now access tools once reserved for large corporations. These digital solutions enable real-time machinery monitoring, predictive maintenance, and data-driven decision-making, reducing operational costs and increasing productivity [6]. Furthermore, integrating digital platforms enables collaboration across different departments and even with external partners, fostering a more agile and responsive industrial ecosystem [7].

In the healthcare sector, low-cost digitalisation solutions have revolutionised delivering and managing care. Telemedicine platforms, electronic health records (EHRs), and mobile health apps make healthcare more accessible and personalised, especially in remote or underserved areas [8]. These technologies allow healthcare providers to monitor patients' vital signs, manage chronic conditions, and offer virtual consultations at a fraction of the traditional cost [9]. Additionally, data analytics and AI-driven tools enable healthcare professionals to predict health trends, identify at-risk populations, and implement preventive measures [7]. This enhances patient outcomes and optimises resource allocation, making healthcare more sustainable and patient-centric.

In hospital management operations, the advantages of low-cost digitalisation are many-fold, extending across facilities, laboratories, systems, supply chains, and logistics. Hospital infrastructures can be broadly clustered into four groups [10]:

1. Fabric - includes infrastructure and systems around building structural components. HVAC systems, and others.;
2. Processes - include operations handling administration, patient flows, support services, diagnostics, maintenance, etc.;
3. Resources - these primarily include equipment, IT and OT infrastructure;
4. Supply chain – deals with the inflow and outflow of materials, medicines, supplies, etc.

The integration of digital tools such as EHRs, Laboratory Information Management Systems (LIMS), and Supply Chain Management (SCM) systems enables seamless coordination and real-time tracking. For instance, EHRs facilitate the centralised storage and retrieval of patient information, enhancing the efficiency of care delivery [6]. In laboratories, digital solutions enable the automation of testing procedures, reducing errors and turnaround time. Moreover, digitalisation ensures accurate inventory tracking, demand forecasting, and optimised resource allocation in the supply chain and logistics, leading to cost savings and improved patient satisfaction [7]. These advancements collectively contribute to a more streamlined, responsive, and patient-centric healthcare ecosystem.

The concept of 'Digital Manufacturing on a Shoestring' presents a novel approach to enabling low-cost digitalisation for hospital management. It emphasises the utilisation of affordable, off-the-shelf technologies to create customised solutions tailored to specific operational

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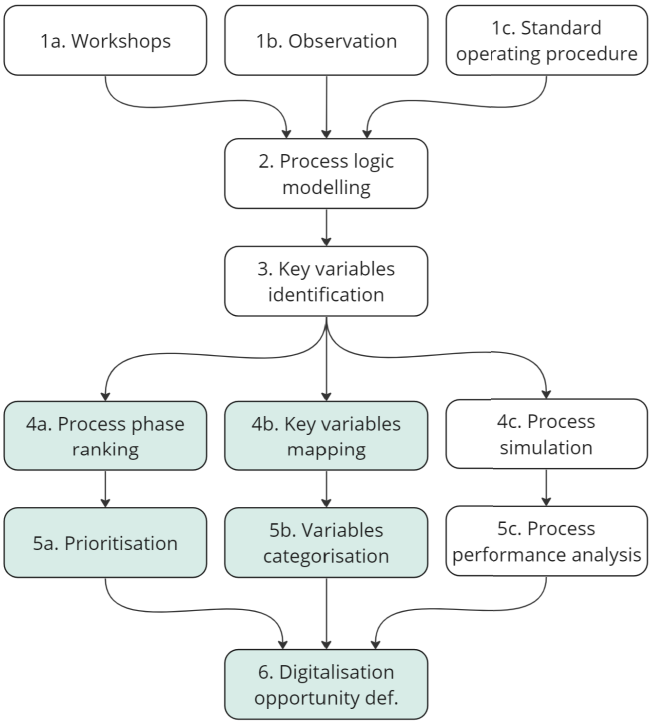


Fig. 1: Research process steps. Steps described in the paper are highlighted in green.

needs [11]. This approach can be applied to equipment monitoring, patient flow optimisation, and waste reduction in hospital management. 'Shoestring' approaches are primarily peripheral and non-patient-centric, enabling them to mitigate the risks and challenges associated with patient-centric digital solutions – decision inaccuracies, real-timeliness, stringent regulations, and often costly and time-consuming certification processes. By leveraging existing hardware and open-source software, hospitals can incrementally develop and trial digital solutions without significant capital investment. This approach democratises access to digital tools, allowing even smaller healthcare facilities to harness the benefits of digitalisation. The 'Digital Manufacturing on a Shoestring' approach thus holds significant promise in transforming hospital operations, making them more efficient, agile, and operations-focused [12].

1.1 Research Questions

This work aims to identify low-cost, non-safety-critical, peripheral, and non-patient-centric digitalisation opportunities that may be present in a healthcare environment by using a Histopathology department as a case study. This work holistically looks into the following research questions and attempts to answer them in the subsequent sections:

1. How to evaluate the operational criticality of stages within a process, to identify digitalisation priorities?
2. How to choose a low-cost digitalisation solution area from the multiple digitalisation opportunities present in the stages of the process?

1.2 Paper Organisation

The rest of this paper is organised as follows. Section 2 provides a brief outline of the case study at a chosen hospital department, followed by Section 3, which outlines the methodology we adopted for this work. Section 4 describes the ranking and prioritisation process we developed for identifying the various stages within the department based on their calculated criticality. Subsequently, Section 5 analyses the various variables across the stages of the chosen case study and identifies the possible low-cost (Shoestring) digital solutions. This is followed by a discussion on how the proposed approach can be used in Section 6. Finally, Section 7 concludes this work by identifying future scope of research that this work opens up.

2 Case Study Background

We applied our research process to the histopathology Department of Addenbrooke's Hospital, a large regional hospital in the East of England and a 'centre of excellence' for services such as transplantation, neuroscience, genetics and paediatrics. The department is a critical hub and the timely availability of reports on biological samples (for testing and diagnosis) is paramount for the delivery of high quality healthcare services in the region. Post-Covid, this department has been under significant stress to meet the strict TAT requirements set by the Royal College of Pathologists (RCPath), due to the large number of tissues received every day for testing. Various challenges have been identified, including external challenges as the supply chain lags as well as internal challenges concerning how to optimise staff allocation, equipment utilisation, and inventory management. DT-based approaches can help address these issues; for example, live measurement of the process performance, the development of process simulations, and scenario analyses allow managers to produce additional insights for better operation of the histopathology department. However, DT applications require access to process and quality data, which is not always available/accessible from the existing legacy systems already in use within the department. Variable identification, process ranking, and prioritisation allow us to identify where the digital technology deployment can have the biggest impact on improving the laboratory productivity and efficiency. The subsequent section discusses the methodology, process ranking, and prioritisation process we applied for this work.

3 Methodology

A process mapping and modelling approach has been used to acquire knowledge on the target assets and processes within the histopathology department. Each step has been empirically observed in the laboratories and modelled using the Business Process Modelling (BPM) approach [13]. The process mapping and modelling requires the identification of the inputs, transformations and outputs of each phase of the process. *Inputs* are the information resources and parts/consumables requires to carry out a job and can be identified though the direct observation, the analysis of the Standard Operating Procedures (SOPs), the user manuals etc. The *transformations* are the state changes of the information, assets, and parts (including part assembly/disassembly). A transformation generates a process event and happens at a specific moment in time. The *outputs* are the results of the transformation (namely each phase of a process) and can be parts/components, information, status of parts and assets.

In this work, an empirical and evidence based approach has been used to map the target processes. The knowledge acquired through observation has been enriched by the analysis of the SOPs and the direct engagement with the Operations Management team.

Table 1 Histopathology Laboratory Process Phases

N	Phase	Sample Processing	Category
1	Reception	-	Information / Management
2	Cut-up	Single	Clinical
3	Processing	Batch	Clinical / Information
4	Embedding	Single	Clinical
5	Microtomy / Slide printing	Single	Clinical
6	H&E staining	Batch	Clinical
7	Slide cover-slipping	Batch	Clinical
8	Digital scanning	Batch	Information
9	Case/slide collation	Single	Clinical / Information
10	Block check and Quality checks	Single	Clinical / Information / Management
11	Case allocation	Batch	Clinical / Information
12	Reporting	Single	Clinical / Information

Fig. 1 represents the main methodological steps of the research. The steps highlighted in green are those described in this paper. Steps 1 to

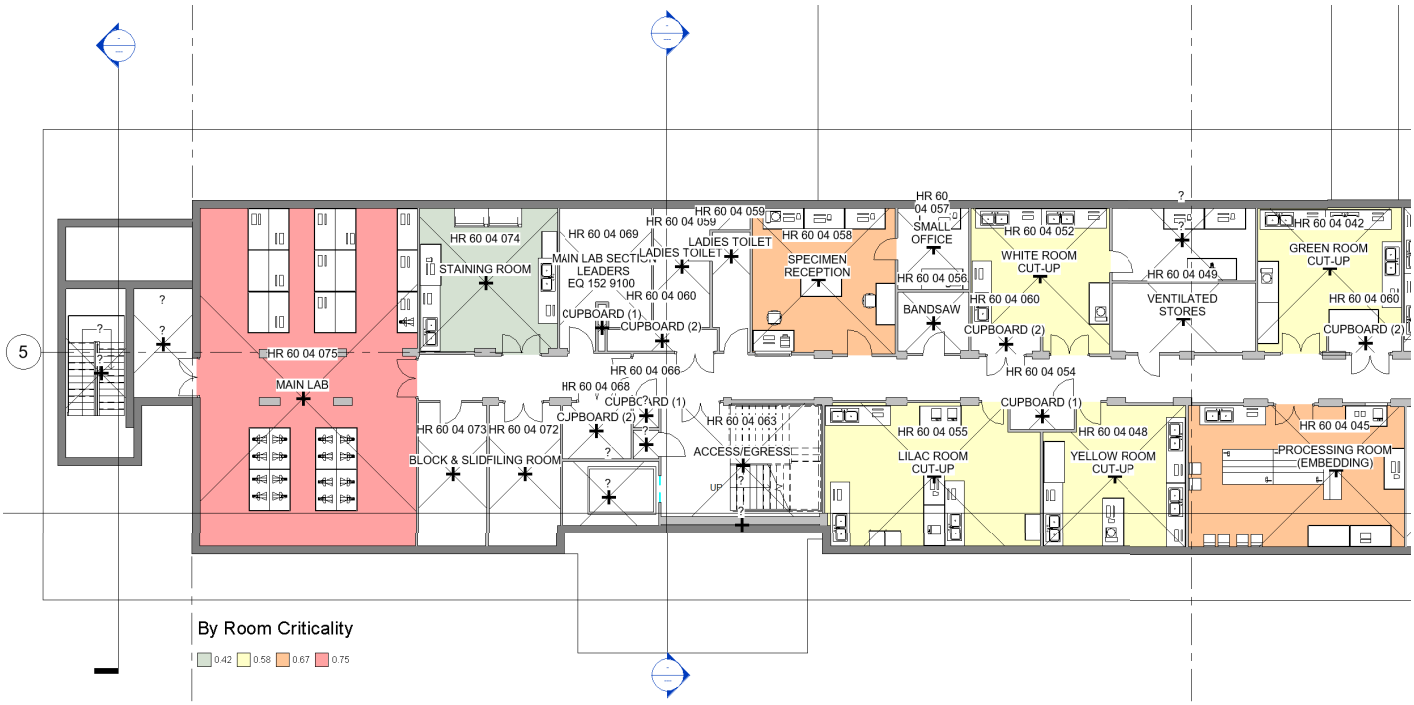


Fig. 2: Colour-coding of the Histopathology laboratory's criticality, representing the most critical process phase for each room.

2 are newly introduced in this paper and are fundamental for variable identification, a crucial part of the process modelling. Step 3 allows us to develop a template for analysing the key variables of the hospital processes, and is described in [10]. The parameters (i.e., groups of variables) are then used to rank the process phase according to the impact they have on the overall success of the process (Step 4a), thus the digital innovation of the most critical process phases can be prioritised (Step 5a). Recurring variables, such as equipment and supplies, are mapped to each process phase (Step 4b) and are subsequently categorised according to the connected or standalone solutions (Step 5b). Steps (5a) and (5b) are jointly used to identify the process digitalisation opportunities. Step (5c) is being developed to verify the process performance uptake, but lies beyond the scope of this paper. Finally, Step (6) identifies the viable low-cost digital solution areas (Shoestring solutions) that can be used to address the identified digitalisation opportunities.

4 Process Ranking & Prioritisation

We have modelled the main phases of the laboratory process via observation of the histopathology process phases, dialogue with the operations team at the Histopathology department, and analysis of SOP documents. The critical Key Performance Indicator (KPI) in this study is the laboratory turnaround time (TAT). The variables affecting the processing time have been identified and grouped into eight parameters as described in [10], namely inputs, outputs, equipment, supplies, information, constraints, disposal, and human efforts. Each of these parameters consists of several variables, which may be shared across all the stages of the histopathology department or may be unique to a particular stage only. Table 1 represents the main process phases analysed. For each stage of the process, the variables have been analysed and the corresponding parameters have been rated on a 1–5 scale (Table 2) according to the impact they have on the processing time.

Table 2 Severity of the Impact on the Laboratory Turnaround Time

Impact	Description
1	Very little impact
2	Minor
3	Average
4	High
5	Very high

We observed that there are three parameters that can have a significant impact on the laboratory TAT:

- **Equipment** – equipment and their properties (e.g., computers, barcode scanners, AFOS workbenches, etc.);
- **Human effort** – human efforts/actions required to complete the primary operation of the phase (e.g., cut-up time, loading/unloading machines, etc.);
- **Constraints** – limits on the capabilities of a phase in the process in terms of time, cost, space, security, etc.

It is possible to describe both the natural and forced delays in the process in terms of these parameters. Natural delays depend on the inherent duration of each activity and depend, for instance, on the equipment operating time (e.g., decalcification time or sample processing time). The latter depending on the activity waiting for something else to happen in the preceding phase (batching time, loading/unloading the machine, etc.).

For each of the three key parameters above, the normalised criticality score X of the parameter is derived from the 1–5 scale using the expression $X = (X^* - 1)/4$, where X^* is the unnormalised score, thus producing a scale between 0 and 1. The normalised scored for the equipment (E), human effort (H), and constraint (C) parameters are then combined into a weighted score, with each parameter receiving equal weight, i.e.,

$$R = \frac{E + W + C}{3}. \quad (1)$$

Table 3 and Fig. 3 represent the criticality results of each Histopathology process phase. The graph shows also the normalised breakdown of each parameter, which is used in a later stage for the identification of digital innovation opportunities. Moreover, Fig. 2 allows one to visualise the results on a colour-coded floor plan of the laboratory space, where red represents the most critical phases and green the least critical ones (as shown in the legend at the bottom of the figure). When two phases are physically carried out in the same laboratory space, the colour-coded floor plan represents the criticality of the process phase with the higher criticality rating.

4.1 Observations

From this analysis, we identified that the Reporting phase is the most critical in terms of its potential impact on the overall TAT. However, this is not considered in the laboratory TAT, as it is mostly governed by external factors not specific to the laboratory process. The time for the reporting phase depends on the specialists' availability, their time to report, complexity of cases and any further testing requirements. From the remaining phases, we identify Microtomy/Slide printing as the most critical (0.75), followed closely by Specimen reception (0.67) and Processing (0.67). This gives us an indication of where the deployment of low-effort and low-cost digital solutions can have an immediate

Table 3 Criticality Rating of Each Histopathology Process Phase

Phase	Score (R)	Raw score E^*	Raw score H^*	Raw score C^*	Normalised score E	Normalised score H	Normalised score C
Reporting	0.75	2	5	5	0.25	1.00	1.00
Microtomy/Slide printing	0.75	3	5	4	0.50	1.00	0.75
Specimen reception	0.67	2	4	5	0.25	0.75	1.00
Processing	0.67	5	2	4	1.00	0.25	0.75
Cut-up	0.58	3	4	3	0.50	0.75	0.50
Embedding	0.58	2	5	3	0.25	1.00	0.50
Case allocation	0.58	1	5	4	0.00	1.00	0.75
Block check & Quality check	0.50	2	5	2	0.25	1.00	0.25
Coverslipping	0.42	2	4	2	0.25	0.75	0.25
H&E staining	0.33	3	2	2	0.50	0.25	0.25
Digital scanning	0.33	5	1	1	1.00	0.00	0.00
Case / Slide collation	0.25	1	3	2	0.00	0.50	0.25

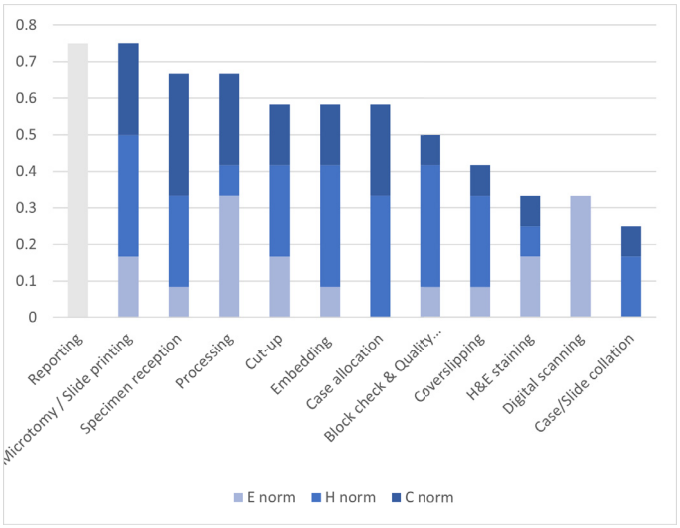


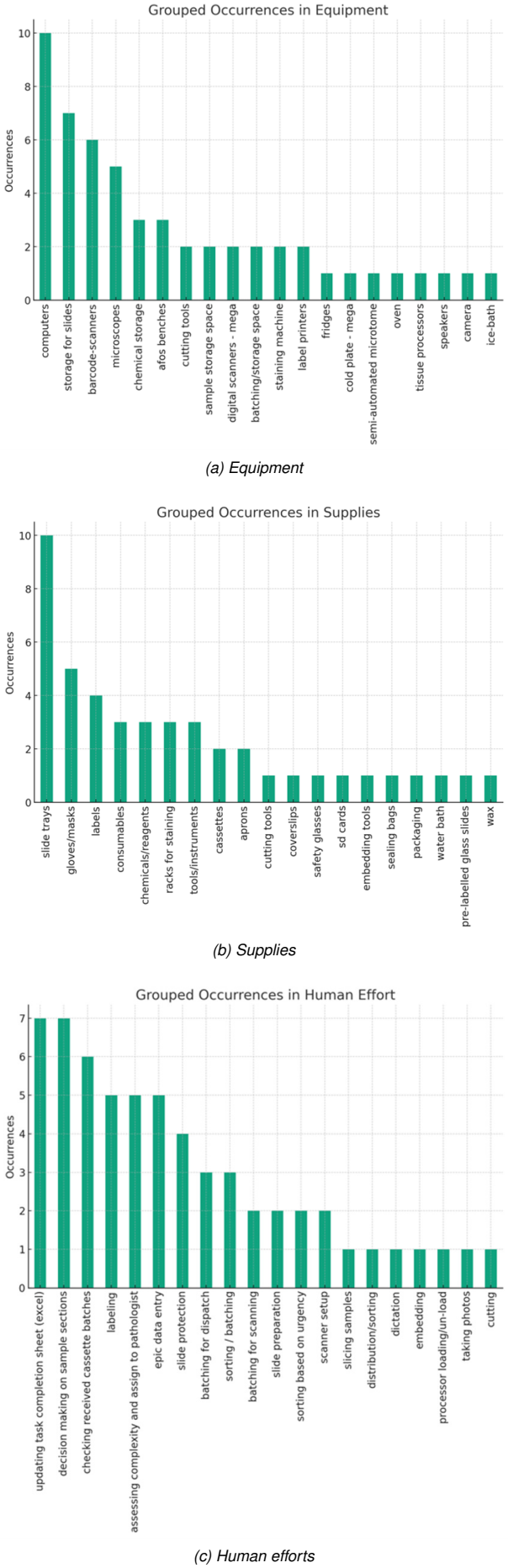
Fig. 3: Ranking of the Histopathology phases based on their criticality. The coloured segments represent each parameter's contribution to the weighted score.

impact. Fig. 2 provides a useful guide for the operations managers of the department, allowing them to spatially visualise the criticality rankings of the process phases and plan their work accordingly. For this case study, the space variable has been identified as one of the most impactful constraints on the laboratory TAT and this tool offers the possibility to analyse it visually.

5 Low-cost Digitalisation (Shoestring) Opportunities in Histopathology

In continuation of the above section, as described in Fig. 1, we identify opportunities for low-cost digitalisation within the Histopathology department. As this work focuses on low-cost digitalisation opportunities, we consider only those parameters that can be non-intrusively digitalised, (i.e., no access to mainframe systems nor changes to physical infrastructure), especially those we believe lead to peripheral yet impactful solutions. We cross-referenced these solutions with the criticality rankings described in Section 4. In addition to the three key parameters used in Table 3, we also added the 'supplies' parameter to our identification process of digitalisation opportunities.

Figure 5 shows the graph of how all these variables are connected with the various process stages. It can be seen that some of the stages of this process are highly linked with each other as they share several variables; conversely, some variables are common across two or more process stages. In contrast, there are many variables that are unique to individual stages (represented by the leaf nodes in Fig. 5). Figure 6



(a) Equipment

(b) Supplies

(c) Human efforts

Fig. 4: Frequency of occurrence of variables for the specific parameters across all stages (top 20 selected)

shows a view of the same graph as before but only considers common variables across two or more stages, helping us easily identify the dependencies within the stages.

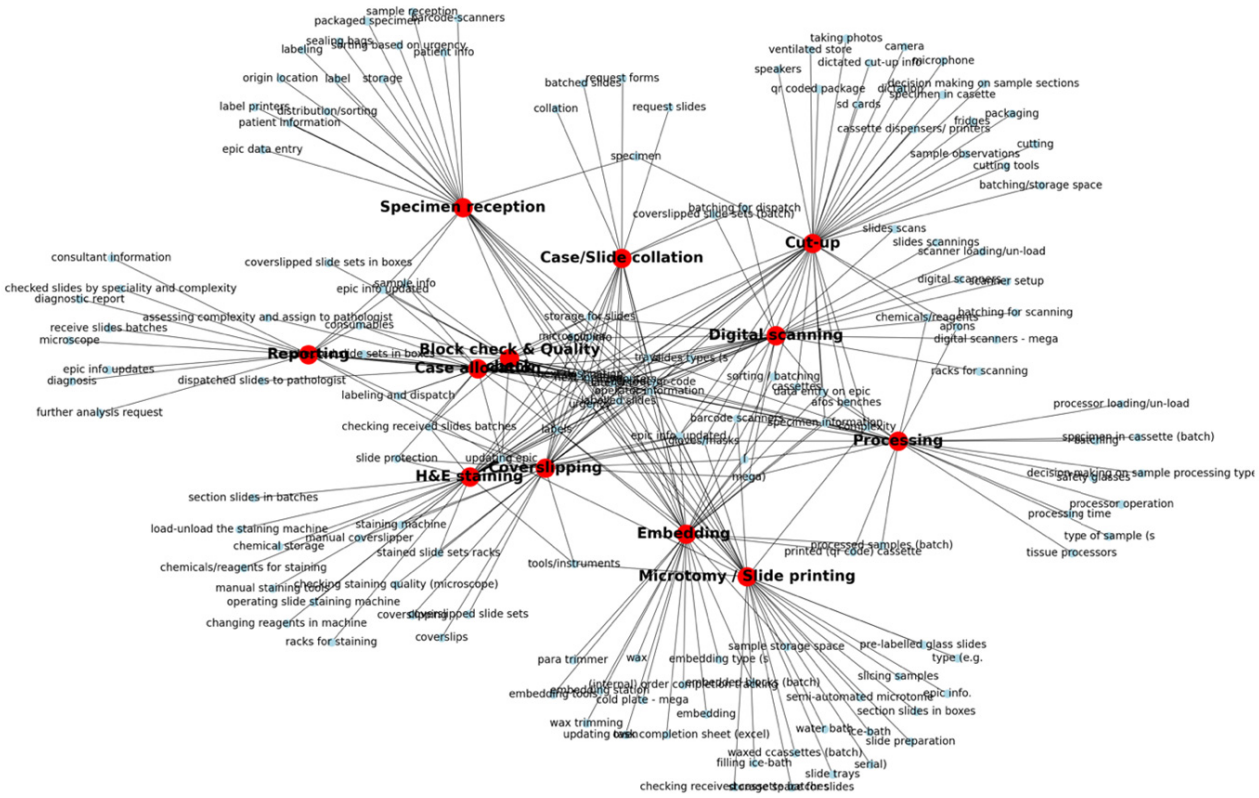


Fig. 5: A graph representation of the Histopathology department stages and the identified variables in each stage.

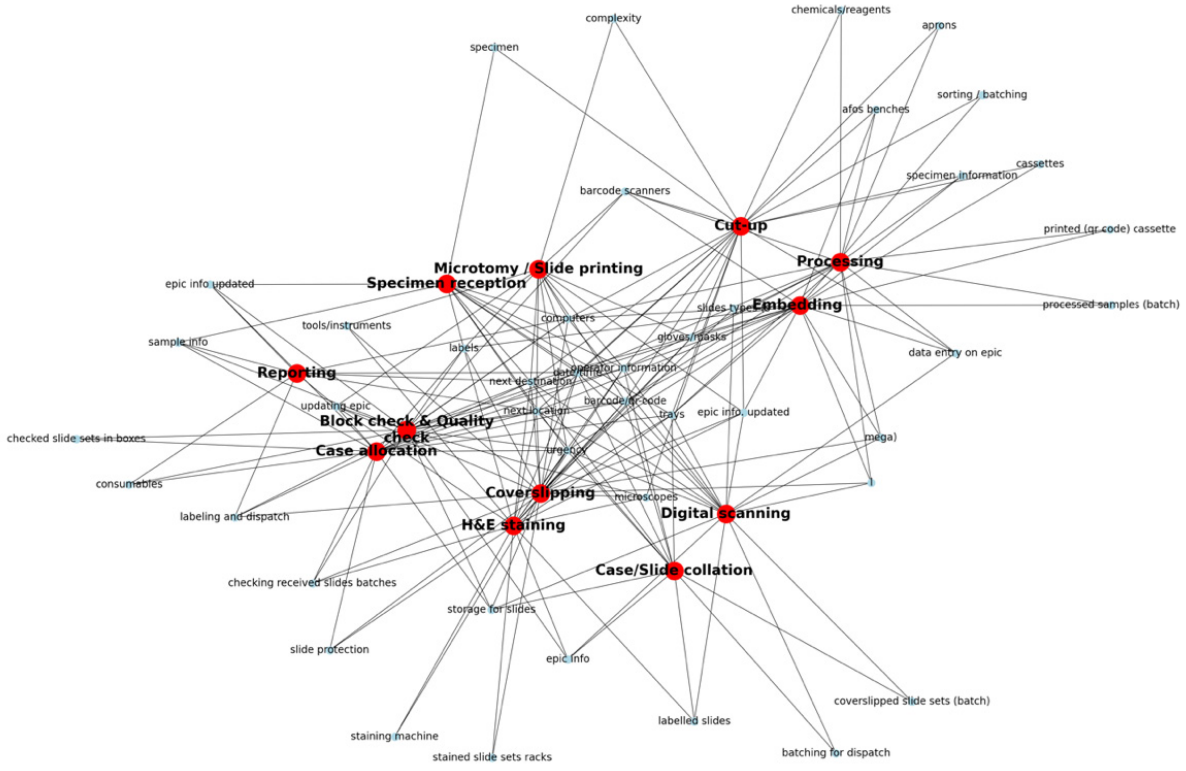


Fig. 6: A graph representation of the histopathology department's stages, showing only those variables which are shared between stages (commonalities).

Table 4 Opportunities for Low-Cost Shoestring Digital Solution Areas (Connected)

Shoestring Digital Solution Areas	Related Parameters	Top 5 Variables
Job tracking (location & status)	Input, Output, Human Effort	Assessing complexity and assign to pathologist, Batched slides, Batching, Batching for dispatch
Digitised work instructions and assembly procedures	Equipment, Human Effort	AFOS workbenches, Assessing complexity and assign to pathologist, Barcode scanners, Microscopes
Internal lead time monitoring	Output, Human Effort	Assessing complexity and assign to pathologist, Batched slides, Batching, Batching for dispatch
Digital job cards	Input, Human Effort	Assessing complexity and assign to pathologist, Batching, Batching for dispatch, Batching for scanning
Process monitoring	All categories	AFOS workbenches, Aprons, Assessing complexity and assign to pathologist, Barcode scanners, Microscopes
Product lifecycle management (for patient treatment, equipment, medicine)	All categories	AFOS workbenches, Aprons, Assessing complexity and assign to pathologist, Barcode scanners, Microscopes
Library of typical errors/faults with corrective instructions	All categories	AFOS workbenches, Aprons, Assessing complexity and assign to pathologist, Barcode scanners, Microscopes
Automated quality inspection	Output, Human Effort	Assessing complexity and assign to pathologist, Batched slides, Batching, Batching for dispatch
Waste monitoring	Supplies, Equipment	AFOS workbenches, Aprons, Barcode scanners, Microscopes
Environment monitoring	All categories	AFOS workbenches, Aprons, Assessing complexity and assign to pathologist, Barcode scanners, Microscopes
Disruption monitoring	All categories	AFOS workbenches, Aprons, Assessing complexity and assign to pathologist, Barcode scanners, Microscopes

Further, for each of the three key parameters listed in Section 4, we count the number of stages in the histopathology process in which each variable is associated with that parameter. The results are shown in Fig. 4, showing the top twenty variables for each parameter. This exercise further highlights the most critical variables from a digitalisation point of view, helping us plan and prioritise low-cost digital solutions. Fig. 4a shows that computers, storage for slides, barcode scanners, microscopes, chemical storage, and AFOS workbenches are the equipment types involved in the most process stages. Similarly, Fig. 4b shows that slide trays, gloves/masks, and labels are the supply types involved in the most process stages. Finally, Fig. 4c highlights 'task updating', 'decision-making on sample sections', and 'checking received cassette batches' as the most frequently-appearing tasks (human effort variables) across all process stages.

Based on the above factors, we generate Tables 4 and 5, which shows the various possible Shoestring low-cost digital solution areas [11] based on the three chosen parameters – 'equipment', 'supplies', and 'human efforts' in the hospital's Histopathology department. We identify the appropriate parameter and the top five variables against each possible Shoestring solution area. We also label if that solution area can be connected or act as a standalone solution based on the variables against them.

The connected solutions in Table 4 indicate integrated systems operating across various stages or components of a stage or across stages. Connected solutions are designed to interact with multiple elements, sharing data, functionality, or resources. In the context of Table 4, we analysed connected solutions, which relate to multiple (possibly all) parameters within the stages. These potential solutions aim to enable seamless communication, collaboration, and efficiency by linking different parts of the stages, allowing for real-time updates and holistic management.

In contrast, the standalone solutions in Table 5 are self-contained and operate independently without relying on other parts of the stages. They are designed to fulfil a specific task or function within a single parameter's purview. These solutions are typically simpler to implement and manage but may need more comprehensive integration than connected solutions.

The joint use of process phase ranking and digital technologies identification for low-cost digital technology innovation is described in the Discussion section.

6 Discussion

Section 4 addressed the first research question in Section 1.1 by providing a process ranking and stage prioritisation approach. This approach enables the sorting of process stages based on three chosen parameters of 'equipment', 'human efforts', and 'constraints', which were selected from a larger set of eight parameters as outlined in [10]. Subsequently, Section 5 collectively analyses the identified variables across all the stages in the process to derive insights into their behaviour. This helped us map the various parameters to the low-cost Shoestring digital solution areas. Given the prioritisation of the process phases and cross-referencing these results with the Low-cost digitalisation opportunities, we can identify the most impactful standalone and connected technologies for each high priority stage. This helps us address the second research question for this work.

As an example, the Microtomy/Slide printing phase (see Table 3) shows a higher criticality for the 'Workforce (or Human efforts)' parameter than the other two parameters. In this area, the available low-cost digital connected technologies include internal lead time monitoring and job tracking, whereas standalone solutions for this area include task scheduling and digitised training. As a further example, we consider the processing stage (see Table 3). In this case, the ranking shows a higher criticality for the 'Equipment' parameter. Low-cost digital solutions for this case under the connected category include process monitoring, digitised work instructions and assembling procedures; whereas the standalone solutions include condition monitoring and capacity monitoring.

This approach can be used for all the process phases for which a variety of connected and standalone solutions can be implemented. The proposed approach for selecting appropriate digital solutions (for any stage in the process) is robust enough so that any changes in the priorities expressed by the Operations Managers is easily reflected. The combination of the prioritisation and low-cost digital technologies identification parts addresses the fundamental objective of this work.

7 Concluding Remarks

The analysis and prioritisation of the histopathology process innovation is not an easy task. Many variables need to be controlled simultaneously and a variety of external factors add high variability. In this paper, we focused on impacting the most critical KPI for the laboratory, namely the TAT. To do so, we ranked each phase in the histopathology process based on the impact of time-dependent variables on the TAT. These variables are classified based on their association with the Equipment, Human effort, and Constraints parameters. Additionally, the process variables have been analysed to identify those for which low-cost off-the-shelf digital technologies have the highest potential benefits, based on the number of stages impacted by each variable for each of the three key parameters. Cross-referencing these results, it is

Table 5 Opportunities for Low-Cost Shoestring Digital Solution Areas (Standalone)

Shoestring Digital Solution Areas	Related Parameters	Top 5 Variables
Capacity monitoring (of resources such as devices, equipment, rooms)	Equipment	AFOS workbenches, Barcode scanners, Microscopes, Batching/storage space
Predictive maintenance (forecasting when devices/products need servicing)	Equipment	AFOS workbenches, Barcode scanners, Microscopes, Batching/storage space
Task scheduling	Human Effort	Assessing complexity and assign to pathologist, Batching, Batching for dispatch, Batching for scanning
Inventory tracking	Supplies	Aprons, Cassettes, Chemicals/reagents, Chemicals/reagents for staining
Energy usage monitoring and reporting	Equipment	AFOS workbenches, Barcode scanners, Microscopes, Batching/storage space
Tracking and assignment of equipment	Equipment	AFOS workbenches, Barcode scanners, Microscopes, Batching/storage space
Digitised training	Human Effort	Assessing complexity and assign to pathologist, Batching, Batching for dispatch, Batching for scanning
Maintenance management	Equipment	AFOS workbenches, Barcode scanners, Microscopes, Batching/storage space
Condition monitoring of equipment	Equipment	AFOS workbenches, Barcode scanners, Microscopes, Batching/storage space

possible to prioritise the digital innovation of the most critical phases, through high-impact, low-cost, off-the-shelf digital technologies.

In the future development of this research, the prioritisation approach can be improved and the weight of each term in the ranking equation (1) can be adjusted. To achieve this, the Analytical Hierarchy Process (AHP) coupled with the Delphi method can be used [14]. This would allow us to more accurately capture the opinion of the Histopathology team, in terms of the impact that each parameter has on the laboratory TAT. Note that the selection of the three key parameters for equation (1) was conducted based on the analysis of the related variables and considering the impact that these can have on the natural and forced delays. On the other hand, more variables could potentially be included in equation (1), thus incorporating a wider spectrum of exogenous factors as the supply chain, dependencies on other departments, working patterns, etc.

Fig. 2 was developed using a Building Information Modelling (BIM) approach which is not explained in this paper. BIM is the main information management technique in the built environment domain [15]; however it has been used in this paper for visualisation purposes only. BIM is a technology which can increase the quality of data related to built assets, equipment and spaces, thus directly impacting on the space-dependent variables. Further opportunities in integrating laboratory process management and space/assets management are currently being explored. An example is how to use BIM data to support the process simulation (a phase represented in Fig. 1, though outside the scope of this paper).

In conclusion, in this paper we demonstrated how to prioritise low-cost digital technology-based innovation of a clinical laboratory. Additional work is planned to deploy the most impactful digital technologies and to measure uptake compared to the current low-digitised situation.

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