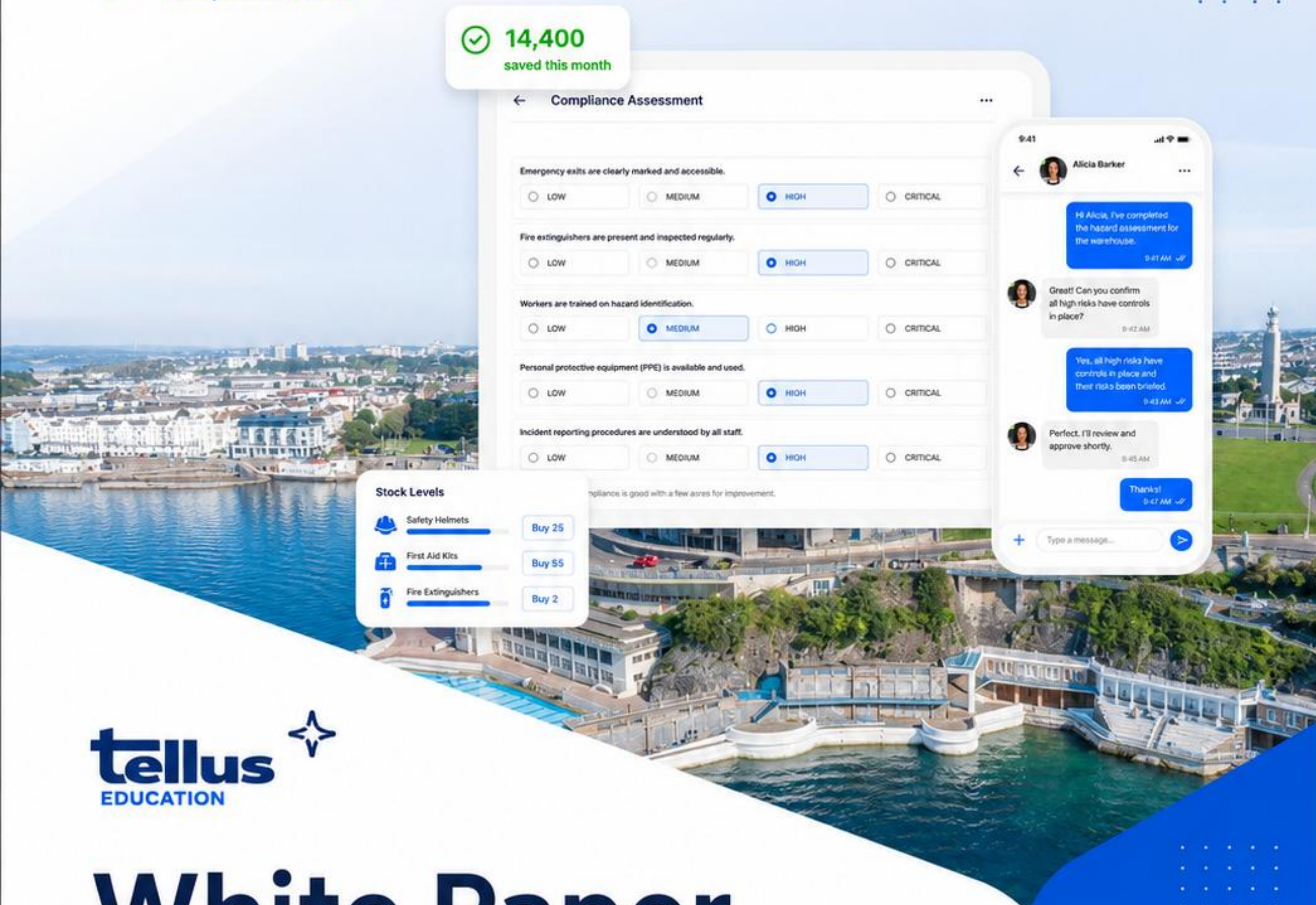
OnePal
Compliance Tablet



tellus
EDUCATION

White Paper

Investigating Learning Outcomes in a Digital Training Environment

A functional non-commercial study conducted with University of Salford Business School in conjunction with Tellus Education Limited, Plymouth, UK

How research into digital training, visual cognition and structured task completion informed the thinking behind **OnePal**

University of Salford
MANCHESTER

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Case Study Profile

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CEO, Tellus Group Limited

Leader of Tellus Group Limited, a Plymouth-based education organisation supporting remote and distributed learning delivery.

- **Participated** in the functional MSc research study as the collaborating organisation representative
- **Context:** education, digital training, remote teams and structured compliance workflows
- **Helped demonstrate** how digital instructions, file navigation and assessment steps can support measurable task completion
- **Tellus provided** a practical real-world setting for testing the study's workflow concept.

1.0. Introduction

When it comes to the training of information workers, both the business systems within an organisation and the cognitive influences of its training methods contribute to the organisation's effectiveness in achieving compliance. On the one hand, contemporary systems-based approaches include the designing of key performance indicators to track user activity suspected to be a proxy for compliant behaviour (Alén, 2019): this lays the foundation for predictive models used to forecast compliance in response to operational scenarios and is expanded by Stöber et al (2018) using a file-location referencing system to track compliance in certain departments.

However, although this referencing-based approach improves how compliance is tracked across a wider variety of tasks inside a single department: the lack of a consistent referencing system for files and functions across all departments prevents current models from measuring task completion and compliance universally (Li et al, 2022), therefore limiting the data available for current predictive models. In addition, although current key performance indicators track compliance using behaviours related to the navigation of digital files: other cognitive indicators that could be used to infer comprehension of a compliance-related task, such as memory and focus (Bellamy et al, 2007), are not yet addressed by contemporary predictive modelling approaches.

This study explores this phenomenon of workplace compliance by addressing the above limitations of both approaches and proposes a new predictive model that combines systems-based task data and cognition-based task data together. In proposing this predictive model for training optimisation, this study tests the impact of a cloud-based training system on compliance outcomes and that be measured within an organisation.

'' When it comes to the training of information workers, the cognitive influences of its training methods contribute to the organisation's effectiveness in achieving compliance''

1.1. Research rationale

To support the development of the OnePal cloud management system, the aim of this research is to enable organisations to make decisions that are more democratic, and that empower employees to contest decisions using a more objective framework for measuring task performance and compliance. The successful completion of an administrative procedure is always followed by a trail of electronic logs and file uploads to designated project folders (Doelle, 2019): such steps can be used to predict model digital behaviour when investigating how reliably routine procedures are being completed. In addition, the successful comprehension of digital training content is always followed by a set of behaviours such as enhanced concentration, memory of past topics and inter-worker collaboration (Olszewski et al, 2019): such signals can be used to predict the model behaviours that would arise when a procedure is being comprehended fully but can also be compared against the above behaviours of digital activity.

Furthermore, due to the relationship between the cognitive processes of comprehension and visual cues within the physical environment of the learner (Bellamy et al, 2007): this study proposes to investigate whether the above digital behaviours linked to performance change in response to changes perceived by the learner in visual attributes for the same piece of digital training material, and whether the proposed predictive model can identify visual attributes that are most cognitively-compatible with the ontology of the learning topic.

1.1.1. Research questions

Q1. *Can varying the visual attributes within a digital learning interface impact learning performance?*

Q2. *Can a predictive modelling framework developed to iterate towards optimum visual attributes be used simultaneously as an information management system for tracking compliance among employees?*

Q3. *To what extent does the visual component of the training experience impact the overall compliance rate of the employee when completing a digital task?*

1.2. Literature review: contributions prior to the post-digital era

In order to understand this role of systems theory and cognitive learning theory in influencing past attempts to increase compliance, this preliminary literature review explores the early stages of the contributions in systems theory, cognitive theory and predictive modelling that set a precedent for the critical analysis of the contemporary literature in Chapter 2 that reveal gaps for this study to investigate; identifies the three research questions for this study; and sets the conceptual architecture for the study as a whole.

1.2.1. The pre-digital era: 1996-2002

In considering the pre-digital applications of systems theory to systematically promote compliance: Maj (1991) proposes a laboratory information management system for the physical healthcare environment, whereby posters containing diagrams are used to prompt workers on laboratory routines that would otherwise be difficult to memorise. In this era, the pre-planning of the workplace layout and use of visual diagrams is used to avoid subjective interpretation of routine procedures as a means of increasing the rate of task compliance within an organisation (Cohen, 1994). However, in addition to the informational role of physical assets in this system, Hemingway (1999) proposes the acknowledgment of inter-worker interactions as social assets that should also be structured to reinforce the information contained within said visual interfaces. Furthermore, building on this psychological component of this systems-based approach: Squire et al (1996) propose the cognition-based model of the procedural memory system that impacts learning within the physical environment, which gives way to later research (see Chapter 2) into how a variety of learning concepts are in-fact influenced by this procedure-based cognition. In addition, Pedell (1994) explores how manipulating visual as well as logic-based features in the design of a multi-media video course may impact learner outcomes, which in-turn leads to further research (see Chapter 2) into how attributes such as colour and element layout act as visual cues that negatively or positively influence the cognition of the learner.

Together, these respective approaches to systems theory and cognitive theory form the conceptual foundation for how an organisation attempts to maintain compliance in the emerging digital era; where the rise of digital work interfaces opens further possibilities for predictive modelling to explore the relationship between these components.

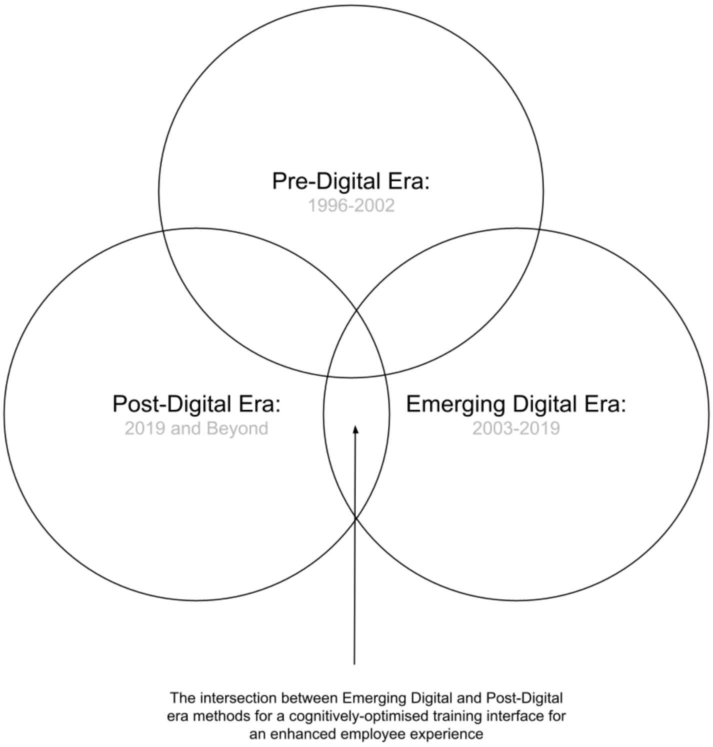
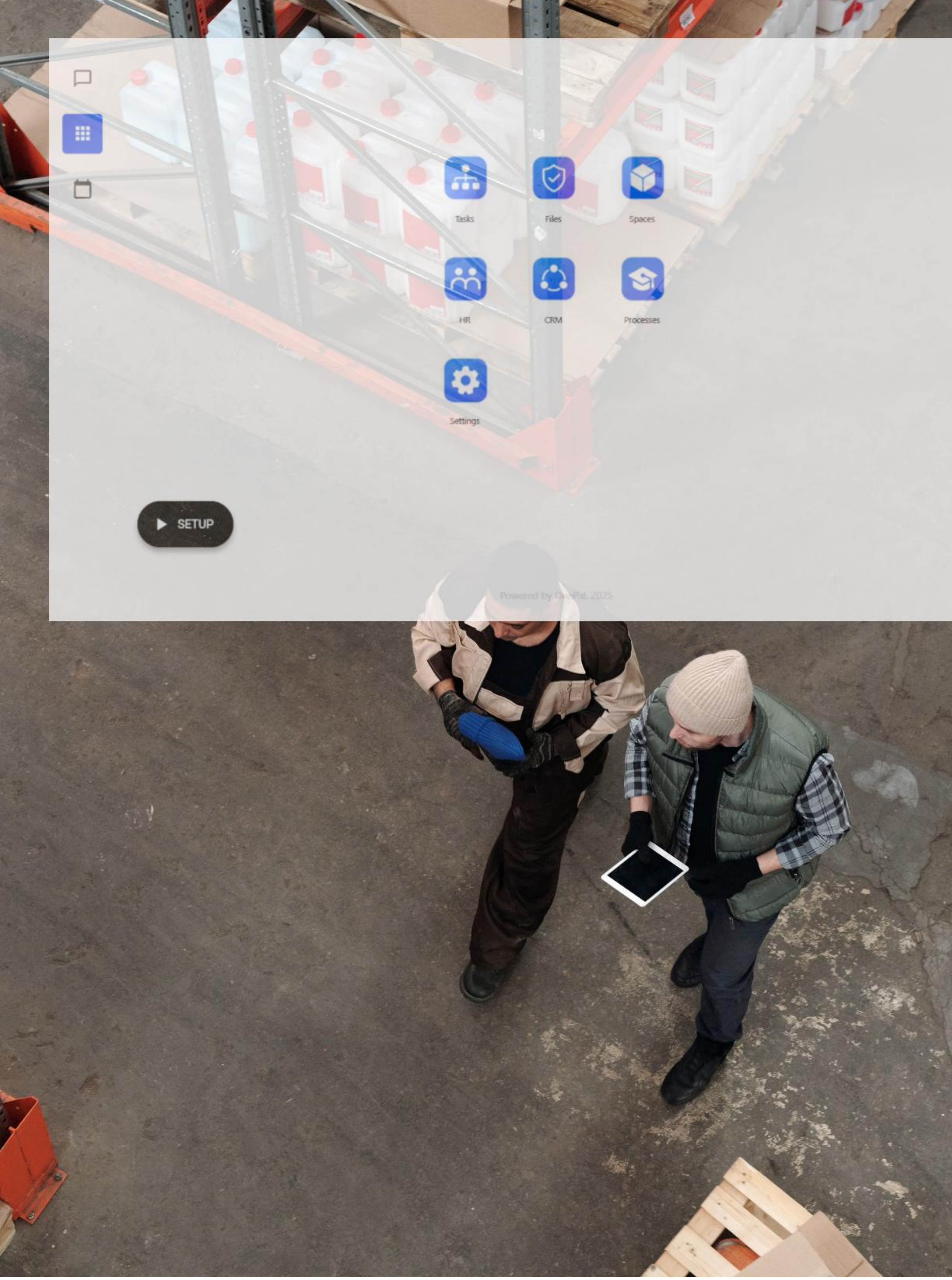


Figure 1: The proposed intersection between the pre-digital, emerging and post-digital e


Tasks
Files
Spaces
HR
CRM
Processes
Settings
SETUP

Building on the possible cognitive role of a visual management system: Bellamy et al (2007) argue that this cognitive role of visual design may create opportunities for collaboration that positively benefit the social interactions previously argued by Hemingway (1999) in the same environment. On the one hand, this introduces the approach of combining systems design originally intended for an informational role with visual design intended to play a psychological role in promoting a constructive learning environment. However, this also leads to further research (see Chapter 2) into how the visual attributes of a learning interface may have deeper cognitive roles beyond social encouragement, including focus, working memory and task congruence.

Furthermore, in considering the increased opportunity for business systems to follow these same behaviours in learning interfaces that are increasingly digital during this era: Alén, (2019) proposes an information management matrix to consolidate metrics of user behaviour: and in-turn automate the weighting of the data categories such as ‘counter measures’ and ‘technical safeguards’. Unlike in the previous era, this approach enables an organisation to connect real-time behavioural inferences and the changes in priority towards distinct cybersecurity protocols. In turn, this dynamic relationship between the behavioural inferences likely impacted by cognitive theory and the previously-separate decision sources from systems theory leads to further research (See Chapter 2) into methodologies of predictive modelling: this not only explores how the design of key performance indicators can incorporate digital touch-points from the users that are more behaviourally associated to compliance, but also how the design of digital file systems and visual design choices in learning material can be optimised systematically using this data.

'' Unlike the pre-digital era, this dynamic relationship between digital worker activity and decision making within the organisation marks a significant step towards designing responsive interfaces that impact workplace compliance''

On the one hand, unlike the pre-digital era, this dynamic relationship between digital worker activity and decision making within the organisation marks a significant step towards designing responsive interfaces that impact workplace compliance. However, this era is still dependent on the physical workplace environment, with predictive modelling methodologies still limited to a statistical approach when associating user behaviour to compliance outcomes. However, in the following era, this is later challenged by the COVID-19 pandemic, pressuring organisations to adopt a virtualized working environment; and with the rise of artificial-intelligence leading to further interest into the cognitive processes behind the learning interface attributes statistically most-associated to higher compliance.

1.2.3. The post-digital era: 2019- Present

In addressing the limitations of statistical probability in the predictive models of the emerging digital era: Olszewski et al (2019) investigates the cognitive properties of the learning environment, arguing that attributes associated with procedural memory may enhance the productivity of repetition-oriented tasks in a production environment; and that the systems-based operational advantage of visual management could be combined with cognitive advantage of diagram-based imagery suspected to trigger the procedural cognition related to the task being trained. In turn, this leads to further research into how the cognitive properties of the physical environment, their relationships to procedural and memory and other forms of mammal-level cognition (see Chapter 2) may be able to be replicated in the visual properties of a digital training interface that Squire et al (1996) were not able to test in the pre-digital period.

On the other hand, building on the advances in system design of the emerging digital, which enabled the statistical tracking of user behaviour to automate the priority weights of compliance task *categories*: Doelle (2019) goes further to argue that an information management system seeking to increase compliance should define the file-upload and communication events as references inside the logic of the procedure itself. Moreover, Stöber et al (2018) propose that categories for digital locations, documents and system software referenced by the logic of cybersecurity procedures should be designed as part of an organisation's operative infrastructure; arguing that this makes the accessing of digital locations by references across procedure steps guaranteed as opposed to simply increased in likelihood as a by-product of compliance-motivated behaviour.

'' Categories for digital locations, documents and system software referenced by the logic of cybersecurity procedures should be designed as part of an organisation's operative infrastructure''

However, though arguing for the conceptual benefit to compliance in making procedures accountable to trackable digital folder locations: Li et al (2022) argue that the capacity for behavioural KPIs to monitor this trail of digital touchpoints is undermined by the inability to retain the consistent file-access logic that would be required for this referencing approach to be applied to different layouts in IT infrastructure in the organisation over time. Conversely, further research into predictive modelling methodologies (see Chapter 2) suggests that resolving this limitation by designing a file-system language that can work with a variety of procedures may enable this trail of behavioural data to be tested against an equally-rich set of variations in visual management, in-turn enabling an organisation to observe how differences in training interface design are followed by changes in learner focus and memory of steps within a task being trained.

1.3. Methodology

In contrast to the empiricist epistemology used in contemporary approaches to developing predictive models, whereby quantitative data of a KPI framework is used to inform a separate process of manual decision-making (Ganesan et al, 2009): this methodology adopts rationalism to derive its interpretations, whereby the seemingly qualitative process of learning is itself treated as a quantitative information management system. However, as the rationale of this study is also inductionist in identifying hypothetical relationships between qualitative behaviours and quantitative measurement, preventing a positivist paradigm; but also that a constructivist paradigm would limit the interpretation of findings to qualitative methods (Corderio et al, 2020): this methodology adopts a pragmatist paradigm, maintaining the focus on a quantitative model for visual or presentational elements, whilst acknowledging the perceived qualitative nature of human behaviour.

Building on this paradigm, this methodology uses literary analysis combining systems theory and cognitive theory to build a predictive model named the Visual Interface Iteration System (VIIS) designed at the conceptual pre-code level: this includes decision-tree logic, systems engineering and data clustering methods of past predictive modelling approaches to inform the rationale of each stage of its design. Furthermore, in addition to this primary theoretical contribution of the study, this methodology uses the results collected by a Plymouth-based education company used to test part of the predictive modelling procedure: this includes a quantitative analysis of the scatter-chart generated by the selections made in the questionnaire, a qualitative analysis of written feedback provided during participation; and a quantitative systems analysis by comparing the results against the original predictions to propose a formula for the Inferred Training Interface Rating (TIR) whereby a group of digital behaviour metrics can be chosen according to the task scenario.

1.4.1. Foreseen limitations

The first limitation to consider in this study is the presupposition that the visual attributes within a digital training interface presented to the learner and their perceived association with the surrounding environment constitute the primary source of cognitive stimuli when interacting with the training module. Conversely, it may be discovered that interactional, social and historical influences are more significant; whereby visual characteristics selected by the participants are in-fact analogs for these non-visual sources of cognition, which would

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Study design

Research Questions & Method

The MSc study was designed to explore whether the visual and interactional qualities of digital training could influence learning outcomes and compliance-oriented task performance. The work combined systems theory, cognitive learning theory and predictive modelling concepts.

Research questions

1. Can varying the visual attributes within a digital learning interface impact learning performance?
2. Can a predictive modelling framework also function as an information-management mechanism for tracking compliance?
3. To what extent do visual and interactional elements influence compliance-oriented digital task completion?

Method overview

1. **Literature-informed KPI design**
   The research identified measurable indicators from systems theory and cognitive learning theory.
2. **Workflow capture**
   A structured cloud-folder environment was designed to capture task-completion events.
3. **Visual feedback capture**
   A questionnaire and image-grid method were designed to collect perceived visual-priority data.
4. **Functional testing**
   The designed process was tested with a participating education organisation in Plymouth.

10 task-completion variables informed the Task Completion Rating (TCR), while 6 visual-preference variables informed perceived visual-priority values used in the conceptual model.

Study process flow

1. **Training material**
   Participants engage with structured digital training content.
2. **Participant task activity**
   Participants complete digital tasks within the training environment.
3. **Questionnaire / image-grid inputs**
   Participants provide perceived visual-priority inputs via a questionnaire and image grid.
4. **TCR + visual-priority analysis**
   Task events and visual-preference data are analysed within the conceptual predictive model.

Σ **TCR** = weighted score derived from 10 observed task events

Visual-priority values = derived from 6 questionnaire variables

The study proposed the Visual Interface Iteration System (VIIS) as a conceptual predictive framework.

nonetheless achieve the study objective. In addition, the second limitation to consider is the extent to which the participating education organisation can test the accuracy of the designed predictive model, requiring the researcher to balance the implications from the quantitative analyses against the context implied by the qualitative analysis of written feedback; implying that obtaining truly repeatable principles from the data collection may require a large minimum number of participants in a future study.

1.4. Case study structure

This thesis is divided into four main chapters following this introduction:

- The **literature review**, expanding the same conceptual architecture of the above literature review of this chapter, which explores how previous approaches to systems theory, cognitive theory and predictive modelling contribute towards improving compliance; their limitations in achieving this objective; and the resulting gap within the literature this study is able to address.

- The **methodology**, which builds on this identified opportunity; provides the epistemological rationale for the predictive model proposed by this study; outlines the research methods used to both inform the design choices for the system and test its implementation; outlines the rationale for selecting the participating organisation; and outlines the ethical considerations when testing the designed Visual Interface Iteration System (VIIS) with the participating education company;

- The **analysis**, which presents the rationale and stages of designing the quantitative components of the Visual Interface Iteration System (VIIS); analyses the quantitative scatter graph data and qualitative text data collected from the participating education company required to fulfil the stages defined in the methodology; and the systems analysis, deriving the proposed Inferred Training Interface Rating (TIR) formula;

- The **discussion**, which will explore the implications of this study and how future studies may apply this predictive model developed at the concept design stage in this study to other applications.

2.0. Literature review

2.1. Advancements in systems theory: attempts to improve compliance

2.1.1. The emergence of behavioural KPIs for the compliance among workers

In considering compliance as a behavioural phenomenon: Khan et al (2011) argue that the capacity for an organisation to achieve compliance to its information management system depends on its effectiveness in promoting cultural values that increase the likelihood that workers will interpret ISO 9001 and ISO 27001 requirements correctly. In using this strategy, the organisation will develop KPIs designed to capture the following perceptions known to impact information security: a) the knowledge of compliance; b) the attitude towards compliance; c) the normative belief towards compliance; d) the intentionality towards compliance; and e) information security behaviours that may impact compliance. On the one hand, this approach to designing compliance KPIs achieves the objective of enabling the organisation to predict the likelihood that its workers will devote the attention required for steps within a compliance procedure to not be missed; but remains limited to measuring reported perceptions collected through HR questionnaires, rather than observing that these behaviours are taking place.

In responding to this limitation, Ghanavati et al (2011) suggest that KPIs built using a number of chosen worker perceptions should instead be measured using active observation and logging of these behaviours over the course of a defined period in conjunction with survey data. However, in addition to increasing the reliability of the compliance KPI: this approach also suggests defining a larger number of more detailed digital behaviours that are indirectly associated with compliance, including: the tendency to provide disclaimers to a stakeholder when sharing sensitive information; the tendency to independently back up files over the course of a work project; and the tendency of project managers to embed compliance protocols into project management briefs. However, in addition to the importance of detecting the likelihood of compliance steps within a digital activity: Alahmari et al (2022) go further to argue that the frequency with which workers can complete the above digital behaviours is in-turn dependent on behaviours that lead to an increased likelihood of scheduled meetings and increased categorisation of project file. Therefore, this approach suggests that HR departments should also track: the frequency of follow-up email clarifications post-action; the frequency of scheduled meetings according to a project theme, suggesting a mental compartmentalisation between projects; and how frequently staff may independently complete admin checks, suggesting a consciousness of data security.

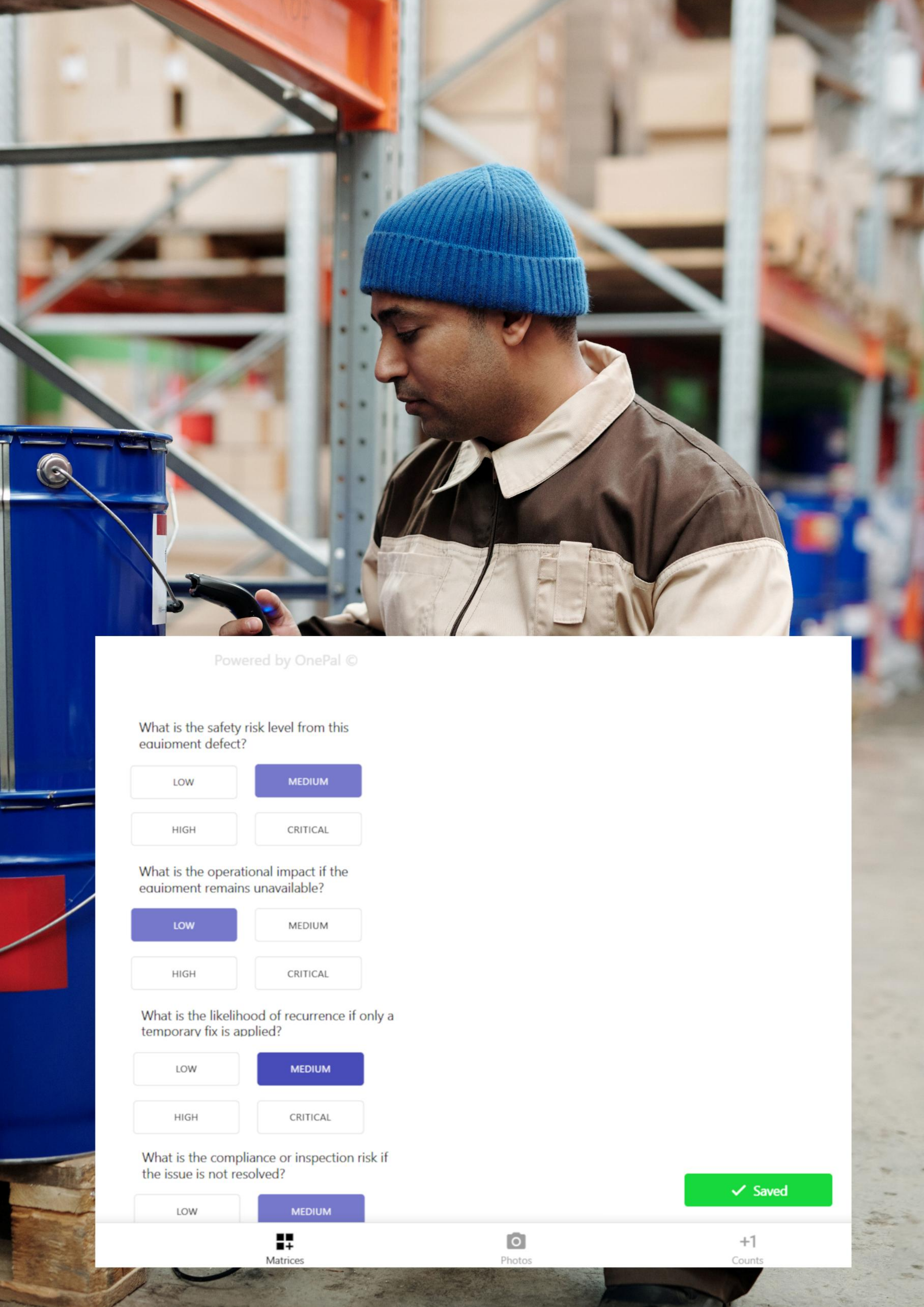
However, although the above approaches for compliance KPI design argued by Ghanavati et al (2011) and Alahmari et al (2022) propose a more reliable method of tracking and confirming the behavioural signals suggested by Khan et al (2011): this approach is still limited to predicting the likelihood with which workers pay attention to steps within a compliance procedure; and does not track the extent to which workers are then navigating the correct digital folders and files within the information management system itself.

" Current systems do not track the extent to which workers are then navigating the correct digital folders and files within the information management system itself"

2.1.2. Applying information management KPIs to inform the design of a HRIS

In response to the limitations of the previous behaviour-based approach to designing compliance KPIs: Staats et al (2012) argue that the observations of the above behaviours should be combined with historical user interaction data to investigate whether the effort of workers to achieve compliance is translating to expected rates of interaction with areas within the information management system associated with compliance. In turn, this approach is applied to monitor compliance training in the financial services sector, and use levels of digital interaction to contribute to the final KPI; but also identify patterns of digital interaction that may infer limitations of the design of the compliance procedure, such as the number of digital locations a worker can be asked to refer to. Furthermore, Bonney et al (2017) argues that this introduction of historical digital interaction data can not only establish limitations for SOP design that relate to how workers intuitively navigate areas within an information security file system; but also how emergent categories of digital behaviours may infer the differences in how users naturally compartmentalise different task themes, thus enabling the final KPI to acknowledge groups of tasks that may be more productive when combined together due to their possible sharing of an underlying cognitive process. However, although this approach enables the organisation to develop compliance KPIs that are more reliable that the method of Ghanavati et al (2011) and takes the further measure of suggesting changes to the design of the procedure: the suggested changes to the final compliance SOP design remain limited to matching digital behaviours, rather than suggesting specific areas within the system a worker should access in a compliance scenario.

Therefore, to respond to this limitation, De Treville et al (2010) suggest that designing a compliance procedure should not only match the natural digital behaviours suggested by Staats et al (2012); but also integrate previous behavioural key performance indicators of Ghanavati et al (2011), such as initiating group meetings, as tasks to request within the logic of the procedure. Moreover, Dottorato (2010) goes further to argue that these set of requested steps should direct the workers towards defined categories of a human resource management system (HRIS), further ensuring that workers interpret the action required for each step correctly, and access the correct digital area that contains further training on how this step should be carried out. In addition, Majeed et al (2016) further expands this concept by arguing that the design of the compliance procedure should not only automate the process of reminding workers to access broad categories with the HRIS; but also to detailed categories that refer to parts of an organisation's IT infrastructure, further ensuring that the worker accesses the correct tools to fulfil the compliance tasks required by the topic area.


Powered by OnePal ©
What is the safety risk level from this equipment defect?
LOW
MEDIUM
HIGH
CRITICAL
What is the operational impact if the equipment remains unavailable?
LOW
MEDIUM
HIGH
CRITICAL
What is the likelihood of recurrence if only a temporary fix is applied?
LOW
MEDIUM
HIGH
CRITICAL
What is the compliance or inspection risk if the issue is not resolved?
LOW
MEDIUM
Saved
Matrices
Photos
+1
Counts

However, although this approach to procedure design further increases the likelihood that the worker will access the correct general area of an information management system: Amare (2022) argues that this approach still requires the learner to subjectively interpret how these steps should translate into more specific actions such as making logs in specific databases for ISO 27001. In addition, as Redner et al (2014) go further to argue that the ability for a worker to access the databases and files needed for these specific actions is dependent on specific references to the specific digital folders that contain these tools; arguing that designing a compliance procedure to refer to general HRIS categories is still less effective than if the procedure contained references directly linked to these tools.

As a solution to this problem, Doelle (2019) suggests that – in addition to reminding the worker to access general areas of a HRIS – the logic of the compliance procedure should contain specific references to specific folder categories within the file structure of the information management system. However, in further developing this approach: Stöber et al (2018) propose that these references should go further to include digital folder locations, documents and system software; enabling the design of the procedure to guarantee that the worker will access these specific tools as opposed to only making this more likely by using reminder to access a broader system category. Furthermore, in considering the potential for increased productivity from this design approach: He (2019) suggests that processes across a range of compliance scenarios could be structured according to the sequence of digital logs, file uploads and in-person meetings that would be expected for the compliance task to be completed successfully; which could then be used to choose the references within the information management system each procedure should contain. However, though this approach presents the opportunity to more objectively quantify the success rate of a compliance task by defining these digital touch-points: Li et al (2022) argue that the ability to track said touch-points for behavioural KPIs in compliance applications is undermined by inconsistencies across the IT infrastructure; and subsequently makes it impossible for procedures to retain the consistent referencing system that would be needed for the digital locations of each step to be measured over time to create a compliance KPIs.

'' This makes it impossible for procedures to retain the consistent referencing system that would be needed for the digital locations of each step to be measured over time''

2.1.3. Identifying information management KPIs to track compliance outcomes

In addressing the above limitation when the referenced locations of an information management system used to form KPIs do not remain consistent: Puhakainen et al (2010) suggest that a matrix of areas should be used to design an information management system, with each area given a permanent name according to its source of compliance data; but also a *health status* based on the compliance procedure behavioural data feeding into this category should trigger in response to a specific scenario. On the one hand, this predictive model resolves the previous limitation of a non-permanent system of referencing, and enables the link between incoming behavioural KPI data and the health of an information security category to stay connected. However, although this predictive model is able to capture data based on patterns of digital behaviour, and continually update the health level of each category within an enterprise risk management (ERM) system: Dhakal (2018) argues that this model should be used to generate more complex inferences, such as a weighting of different suggested actions to apply when interpreting the status of each category; but suggests that the ability to build these KPIs is dependent on how the incoming data for each ERM category can be contrasted against analogous variables collected in other departments within the organisation. Therefore, in order to ensure that compliance KPIs developed for an ERM system are able to capture the variables of separate behavioural metrics needed to achieve this accuracy in the predictive model: Tschakert et al (2019) argue that choosing this sequence of behavioural indicators should be the first step before deciding the structure with which they should interact, and – as contrasting analogous but separate variables of compliance behaviour is intrinsic to the accuracy of the model predicting a suggested protocol – this choice of variables should not be limited to data from one isolated ERM system.

In addition, by building on this approach of defining *action values* as well as status values – but also the advantage of allowing the predictive model to compare variables across multiple ERM systems: Alén, (2019) proposes an information management matrix that utilises data categories ‘bad statistics’ and ‘data breach notification’, which then allow the operator to import metrics of user behaviour manually from separate data sources as part of its in-built predictive model algorithm. As a result, this enables the model to automate the weighting of the respective action categories ‘counter measures’ and ‘technical safeguards’, enabling an organisation to select the correct procedure of compliance in response to a threat or scenario related to an outcome in cybersecurity. However, despite the advantage of this approach in facilitating multiple sources of manually-imported data on behaviour to work in conjunction with a predictive model designing to analyse the structure of a single ERM system: Chaudhary et al (2022) argue that this comparison of data from separate ERM systems lacks the further advantage of contrasting sources of KPI data on digital behaviour intended for different applications, but which have been collected using the same information management methodology; and therefore are able to control influences shared between both ERM systems.

However, as Khameneh et al (2016) argue that the structure with which compliance KPIs across the organisation share common characteristics of digital behaviour, such as logging a completed task in a database for ISO 27001: this suggests that the suggested actions from future predictive models could be developed to not only suggest a priority weight value of a suggested action in response to historical data; but also use a consistent file referencing system across the organisation that would then enable the operator to choose a universal sequence of digital event categories to measure all compliance KPIs, and therefore enable the predictive model to contrast metrics from multiple ERM systems to control for the same target variable.

2.1.4. Applying digital file navigation KPIs to inform the design of SOPs

In responding to the added advantage of standardising the digital touchpoints against which the completion level of a procedure can be measured in a digital environment: Murata (2018) suggests the use of project scenario 'templates' in the physical workplace environment, enabling laboratory procedures to share the same naming system for storage locations, tools and workspace areas. However, as this approach still requires the continual updating of references as the layout and devices within the work environment change; Tull (2018) instead proposes a system of ISO codes for laboratory asset categories, whereby operating procedures are able to continue to refer to the same locations and functions even as the tools and devices used to fulfil those roles are changed over time.

Furthermore, in considering how this analogy of the physical workplace operating system could apply to the digital work environment: Miri et al (2014) suggest that this same advantage of creating meta categories for task principes would enable an organisation to maintain a permanent LMS design for workers to navigate; even as the choices for software and cited areas of the HRIS change over time. However, as this approach still remains limited to referencing permanent procedure *categories* and requires more specific references such as direct database locations to be updated following every update to the file structure of the information management system: Hashmi et al (2012) argue that this limits that ability of compliance e-learning programmes to maintain consistent training on how workers should navigate digital folders and files within the information management system. Moroever, Roza et al (2019) further argue that this lack of a universal referencing system for the folder structure undermines the effectiveness of compliance training, and opportunities to build historical KPI data that is dependent on this consistency; but also that this limits the effectiveness of standard operating procedures among workers for live digital tasks, whereas developing a universal digital folder referencing system would enable the process of directing workers to exact digital locations to be automated.

Furthermore, in considering this advantage of a permanent naming system for digital folders and files, which can then be connected to references within the SOP: Dai (2022) proposes the design of an information management system to increase the rate of compliance among accounting workers, whereby the naming system of folders containing GDPR logs, back-ups of client data and locations for ISO 27001 databases are used to reduce the risk of locating assets in the incorrect locations; and therefore reduce the risk of not passing an audit needed to meet regulatory requirements. However, despite this advantage of enabling a specific department to maintain consistency in its referencing system for compliance, whilst retaining the flexibility of changing the choice of server location for hosting the folder structure and software tools used to interact with its assets: Seyffarth et al (2020) argue that this approach still remains limited to an isolated department; whereas a file structure naming system shared between departments would facilitate more complex KPIs for improving compliance throughout the organisation, but also to compare these metrics of digital behaviour against interaction data related to the staff training interface.

2.2. Advancements in cognitive theory: attempts to enhance learning performance

2.2.1. Applications of cognitive theory to visual management interfaces

Unlike the above approach of Dai (2022), where achieving compliance is considered a problem of information management logic: Bellamy et al (2007) argue that compliance in is a problem of visual management, whereby optimising visual attributes of a training interface can enhance learning cognition. Under this theoretical model, an optimum combination of visual and interactional characteristics exists for every learning topic based on its unique ontology, whereby finding said characteristics would enable a visual training interface for said task to enhance learning cognition. Therefore, in exploring the possible memory systems that may be prioritised differently depending on this variation in ontology: Olszewski et al (2019) argue that this cognitive benefit may be uniquely beneficial to the productivity of repetition-oriented tasks in a production environment; arguing that the operational advantage of procedure referencing proposed by Murata (2018) could be combined with diagrams within a production environment that are biassed towards imagery suspected to trigger procedural cognition in addition to their informational role.

''Achieving compliance is considered a problem of information management logic''

Furthermore, in order to test this role of procedural cognition in second-language acquisition among a group of adult participants: Reppa et al (2020) demonstrate that the performance in declarative memory is correlated with performance in procedural memory; whereby the Alternating Serial Reaction Time Task (ASRT) reveals the strongest convergence with procedural memory, suggesting that procedural cognition may be axiomatic to topics perceived as more abstract and unrelated to repetition-oriented concepts. In addition, in applying the old-new recognition task – whereby two groups of participants were asked to view and memorise fourteen separate novel objects, each varied according to shape morphology but controlled for colour to test the differences in memory recall performance: this experiment reveals that the attribute of colour is not an abstracted quality post-binding process; but rather an axiomatic stimulus in procedural cognition. In-turn, just as this represents an opportunity to enhance learning performance outside of the organisational context: this implies that both colour and shape morphology could play a role in the design choices of a compliance training interface that seeks to optimise this same attention mechanism. However, although this represents a move towards understanding visual management as a source of visual stimuli associated with cognition as well as its informational function: this approach remains limited to acknowledging the two functions of procedural and declarative memory; and does not investigate how optimising colour and morphology characteristics of a visual training interface could trigger *planned* forms of procedural memory, which would in-turn impact the final abstraction of the concept that the learner perceives as conscious mental imagery.

''A move towards understanding visual management as a source of visual stimuli associated with cognition as well as its informational function''

2.2.3. Predicting perceived mental properties during the binding process

In considering the processes that would enable a model to predict the final properties of mental imagery based on the original visual and environmental stimuli that trigger the learning at the first stage of procedural memory: Feldman (2012) argues that the initial conditions during the process of colour-shape binding proposed by Reppa et al (2020) during the attention mechanism phase may be able to infer the colour and abstract shape properties of the related qualia that emerges as mental imagery in the learner. Furthermore, in order to investigate how the properties of initial conditions in procedural memory impact how these morphological characteristics are perceived by the learner: Loorits (2014) expands this approach by arguing that the morphology of mental imagery could in-turn be inferred by the visual features of the original image that are suspected to have bound during the procedural memory phase. However, as this approach still lacks a model of testing optimum combinations of these visual characteristics: this indicates an opportunity to test variations in how features such as colour and other visual qualities appear together in imagery used for a training module; and which of these combinations emerge among participants with the highest performance in a compliance task related to that same module.

Furthermore, in expanding this approach to category theory as a method of organising these combinations of visual characteristics across a set of test images: Tsuchiya et al (2016) argue that repeating this cycle of variation testing is able to build groups of visual characteristics associated with the highest learning performance; enabling the researcher to build an ontological model for how new images could be re-created in response to the contents of the learning topic, and therefore enhance learning performance. However, as this application of category theory remains limited to building groups of design characteristics that are most likely to be associated to a higher level of training performance based on historical data: Arrabales et al (2010) suggests applying these iterated categories not only to the design language of the training image; but also to use the data from the image iteration system to then re-evaluate ten sub-systems of cognition that are most likely to emerge into declarative cognition, enabling a continual improvement of the theorised cognitive model in tandem with an improving system for training image design. Moreover, Victoria et al (2019) approach this relationship between the improvement of the cognitive model and the image design model by investigating the axiomatic role of motor-spatial categories that underly the eventual formation of perceived novel categories that may be captured characteristics contained within an image sketched by the participant. Under this approach, this suggests that the application of category theory to image variation testing not only enables the iteration of the cognitive model and image design model to be updated in-tandem in response to participant performance data; but also that an analysis of sketched depictions may infer characteristics of visual characteristics perceived by the learner in declarative memory, which in-turn could infer the downstream stimuli that originated the eventual mental representation originated. In turn, this suggests the advantage of category theory in contrasting reported perception data from among participants with their performance on a task related to the same training module being tested; but also the unique role of the participant in being able to provide representations that further explain the properties of declarative cognition that are responsible for a higher performance score.

2.2.2. Developments in predictive models for cognitive learning systems

On the one hand, Cegarra et al (2017) continue the previous approach of investigating how unconscious signals are abstracted into declarative memory, and how this manifests as a network of conscious semantic categories perceived in mental imagery by the learner. Under this approach, a possible relationship is suggested between the perceived morphology of said categories – which may change in response to a different task scenario – and the optimum characteristics of the final visual representation, either in the form of the training imagery presented to the learner; but also in the form of a mental representation sketched by learner based on how the topic is mentally perceived. On the one hand, this suggests an advantage of considering reported perceptions using live participants – either in the form of a sketched depiction of a perceived learning topic, or in the form of selected preferences of a presented image variation; which could then be compared against their task performance data tied to the


[OSHA]- Fire Evacuation Log
Add
[OSHA]- Incident Report
Add

same training exercise. However, despite suggesting the role of participant involvement: this approach still does not offer a method of identifying behavioural KPIs directly related to compliance training that could be compared against KPI values related to groups of visual characteristics in the test images.

On the one hand, in responding to this limitation in predicting the mental properties that are perceived by the learning during the binding process: as Ramaraju et al (2020) argue that disrupting this procedural-to-declarative transition of the focus mechanism can distort the perceived ontology in the example of abstract shapes and alphabetical symbols; this suggests that testing correlations between task performance among a participant group and the congruence of these perceptions could enable future predictive models to infer the inverse of this process, and therefore develop KPIs that identify the original colour and morphology stimuli that would have led to optimum performance. Moreover, as Asyraff et al (2021) also argue that an interruption to this focus mechanism can disrupt the perceived ontology of temporal and motor-spatial associations: this suggests that the comparison between optimum and disrupted performance could enable a future model to control for environmental influences as well as colour and morphology, suggesting a wider range of variables that could be used to infer these optimum visual characteristics; but also behavioural KPIs that would be used to signal the optimum procedural-to-declarative memory transition for a learner exposed to the correct combination of visual stimuli. Furthermore, in responding to this possibility of establishing hypothesised stages of procedural through to declarative learning – and then to be able to test these assumptions against a source of data: Kang et al (2021) propose the Sparse-Distributed-Representation algorithm, whereby the predictive model attempts to approximate the hypothesised focus and memory mechanisms in biological systems, but then iterate towards more accurate values within each of the KPIs in response to error data. On the one hand, although this methodology of the iterative testing cycle could be applied in a predictive model designed to contrast learning performance against variations in visual characteristics – enabling the system to iterate towards a design language for imagery for compliance training: this approach is still limited by the internal source of data used to iterate its KPIs.

''Performance data that provides a more accurate measurement of task performance according to the priorities specific to compliance scenarios''

On the one hand, this suggests an opportunity for a future predictive model to introduce the above applications of category theory to build an ontological framework that builds a visual design language for training image design, matching patterns of training image design with increases in task performance. In addition, this also indicates an opportunity to address the above limitations in predictive modelling by introducing task performance data that provides a more accurate measurement of task performance according to the priorities specific to compliance scenarios; and that a new information management system developed for this predictive model is able to resolve the criticism of Dai (2020) by standardising the method with which this data is managed.

3.0. Methodology

The contributions explored in the previous chapter highlight the current limitations and potential of systems theory applied in an information management context to digitally track and measure tasks related to compliance (Dai, 2020); but also how predictive modelling is applied outside the context of the organisation to model the cognitive processes of content learning (Kang et al, 2021). However, as the current information management systems for compliance procedures are restricted to specific departments rather than shared across functions within the organisation (Li et al, 2022): this limits the ability of a human resources department to measure performance across a range of task scenarios, and to then contrast this data with behavioural KPIs that capture the cognitive properties of visual stimuli and procedural memory theorised by Bellamy et al (2007).

In order to address this dilemma, this methodology outlines the methods of literary analysis and systems engineering used to design a new data model that can capture changes in performance during a digital compliance task; and then compare these changes to perceived visual preferences selected by the learner. In addition, this chapter outlines how part of this data model will be tested with a participating education provider using the developed calculator tools built using principles of information management theory, category theory, cluster analysis from past data models.

3.1. Epistemology and paradigm

In responding to Research Question 1 of this study: this methodology should investigate the relationship between a quantitatively measured completion level of a task, and how this changes in response to changes in attributes of a visual management interface; enabling the combination of both data sources to act as a correlate of short-term memory and focus in the learner. In turn, this suggests that this methodology should adopt an inductionist rationale to identify hypothetical relationships between qualitative behaviours and quantitative measurement; therefore preventing this study from adopting a positivist paradigm. However, as a constructivist paradigm would limit the interpretation of findings to qualitative methods and therfore limit the recognition of this quantitative component (Corderio et al, 2020): this study adopts a pragmatist paradigm, maintaining the focus on a quantitative model for visual or presentational elements, whilst acknowledging the perceived qualitative nature of human behaviour. Furthermore, in considering Research Question 2: tracking how task performance changes in tandem with changes in perceptions that represent motor-spatial and visual attributes presents an opportunity to single out visual or presentational elements that may each promote different cognitive processes that benefit learning performance. Consequently, this study departs from the empiricist epistemology of previous data models, where the quantitative data of a KPI framework (See Figure 2 below) is used to inform manual decisions in the organisation (Ganesan et al, 2009); and instead adopts rationalism to derive its interpretations, whereby the seemingly qualitative process of learning is treated as a quantitative information management system. In addition, in considering Research Question 3: this potential to correlate differences in the perceived visual preferences of the learner with changes in task performance and task ontology represents an opportunity to develop distinct visual management design languages that are sensitive to the cognitive differences between different task categories.

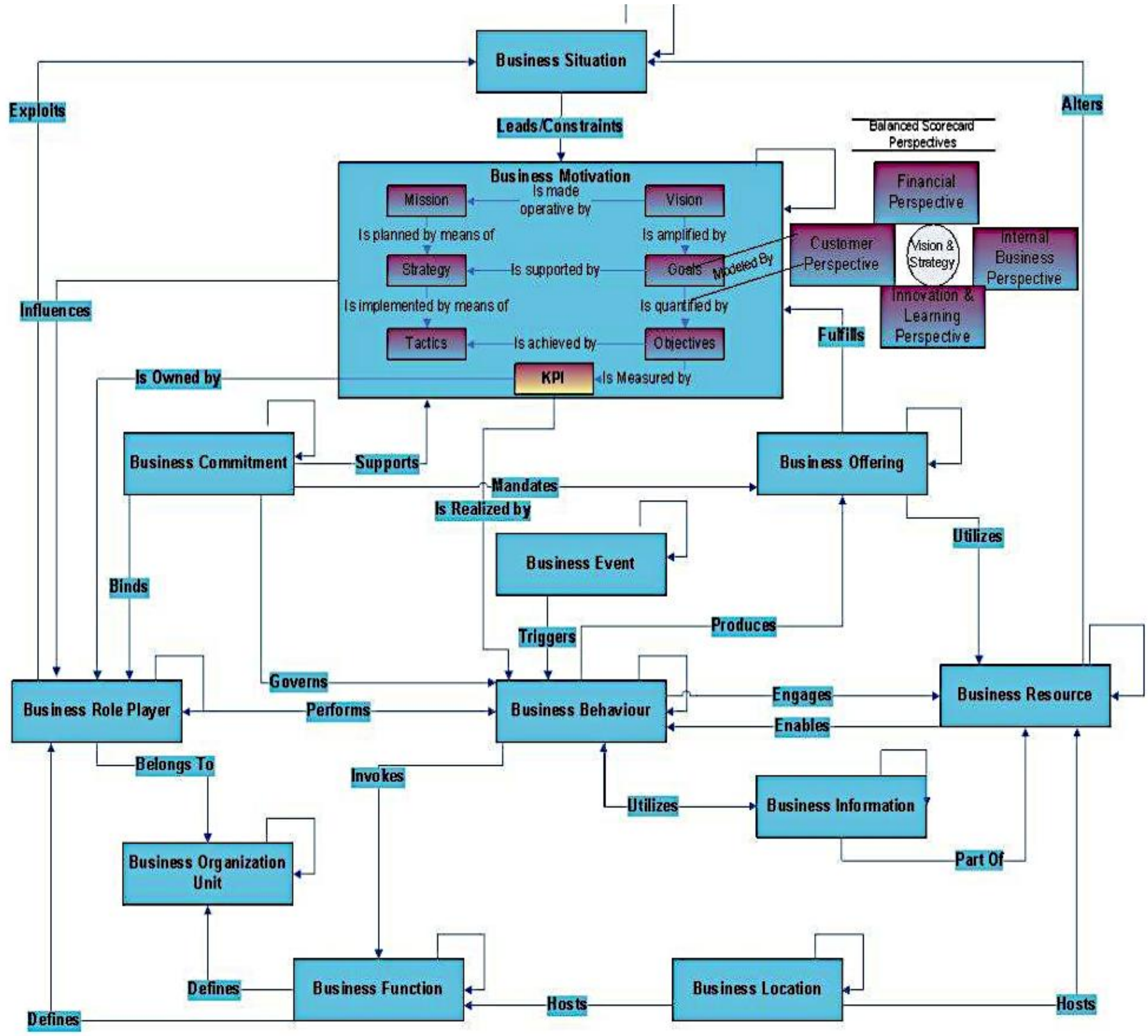
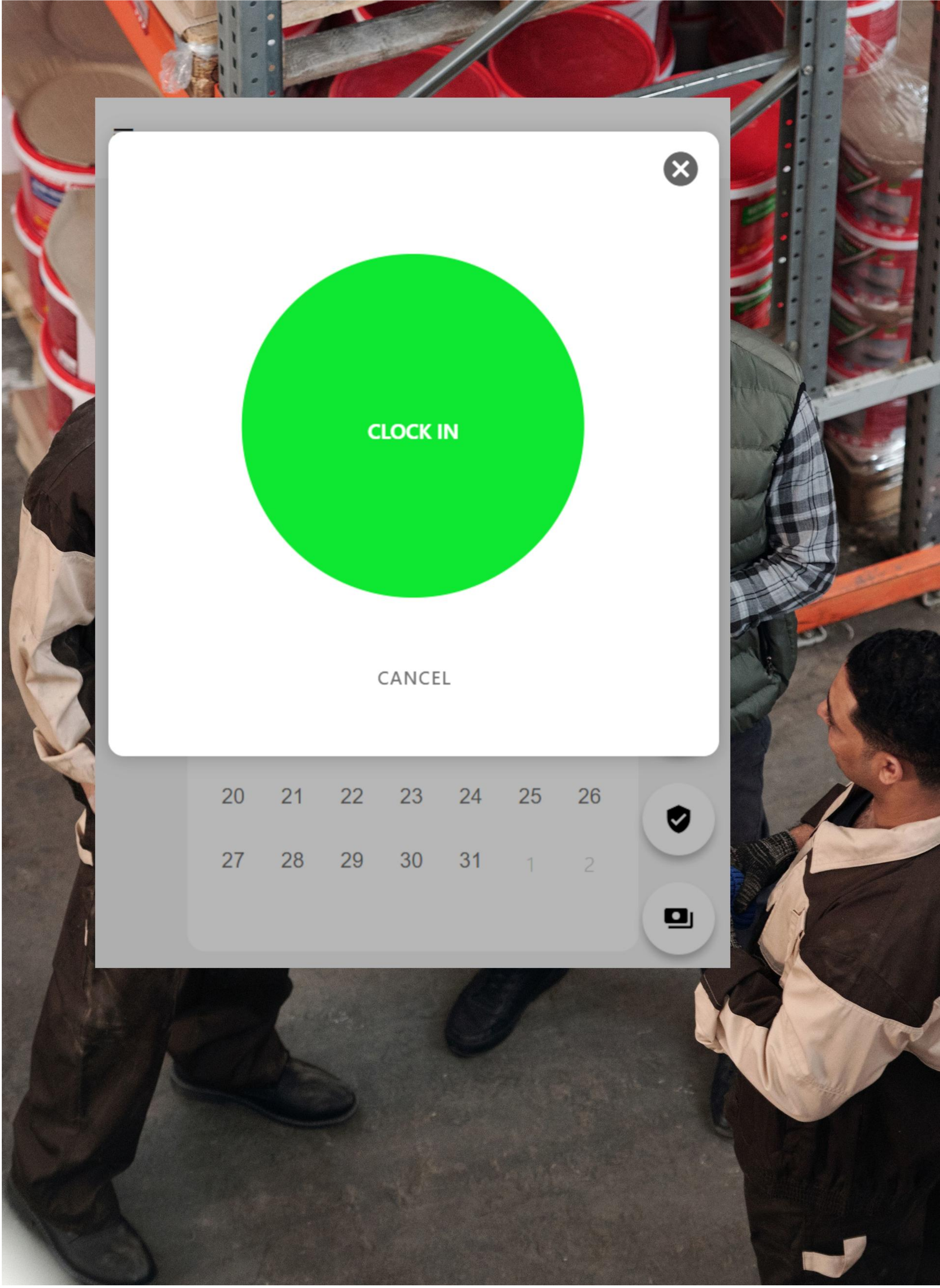


Figure 2: An example data model for behaviour-informed KPIs (Ganesan et al, 2009)


CLOCK IN
CANCEL
20 21 22 23 24 25 26
27 28 29 30 31 1 2

3.2. Systems engineering methods: designing the predictive model

In order to address the limited ability of previous models to track and measure digital behaviours that are specific to compliance (Dai, 2020), but also retain the characteristics (see Figure 1 above) of scenario selection developed by Ganesan et al (2009): the top section of the data model developed for this study (see Figure 3 below) will contain distinct groups of behavioural KPIs, divided according to digital file navigation, selected visual preferences and inferences on learner cognition. In turn, after applying causal inference to derive said theoretical KPIs, the KPIs related to digital file navigation will be used to design an information management referencing system that addresses the limitation argued previously by (Li et al, 2022), enabling any procedure containing this referencing system to work with the same cryptic folder system, enabling digital behaviours to be captured for the above KPIs across a wider range of compliance scenarios.

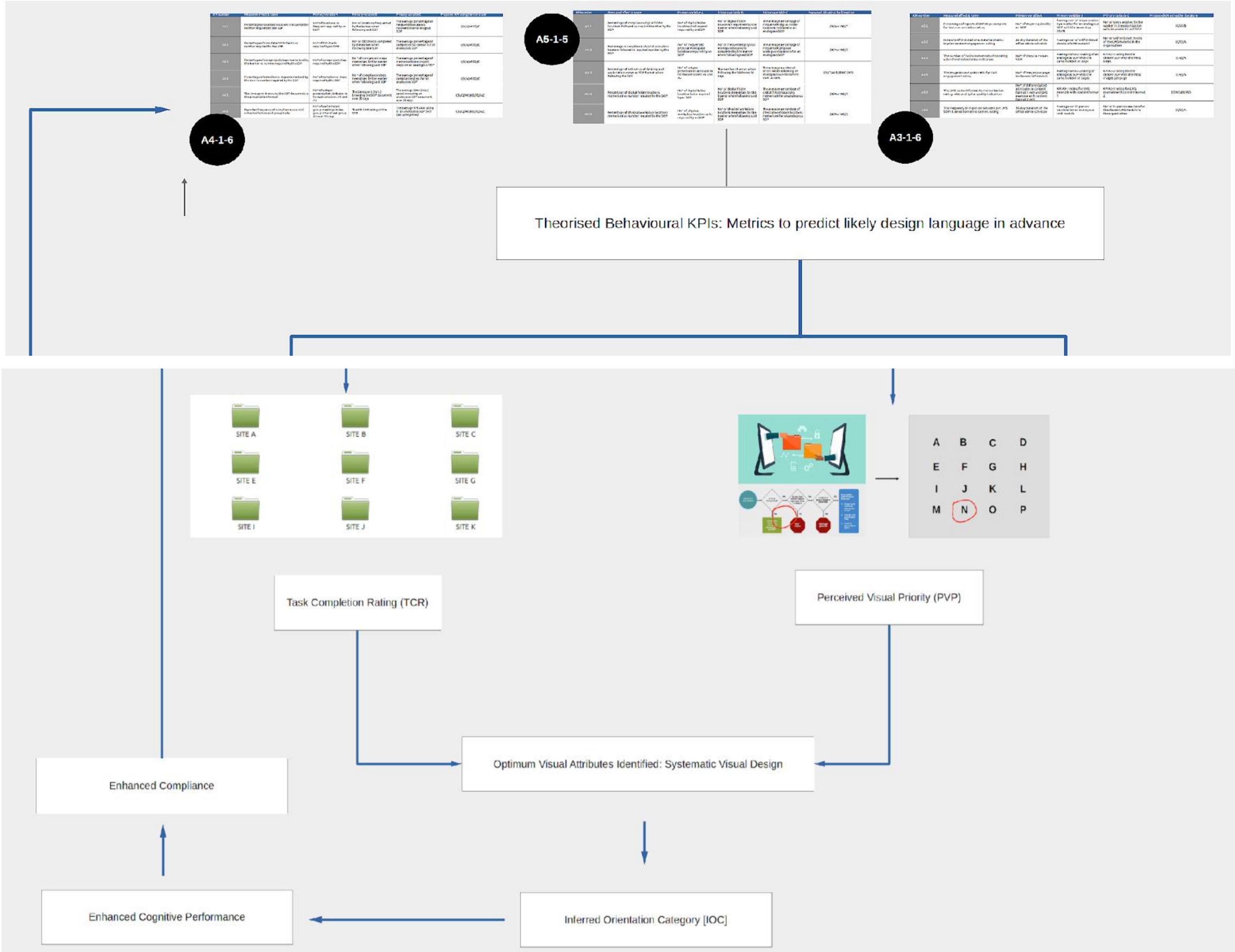


Figure 3: A concept design for the predictive model of this study

3.2.1. Designing the OnePal information management system

First, in order for the folder structure (see Figure 3 above) to be able to capture a rating to objectively measure the completion level of a digital compliance task: the researcher will need to identify the patterns data logging behaviour universal to all digital tasks which are capable of demonstrating that the priority steps such as retrieving the correct files and logging data have been completed: this stage of identifying these universal task patterns will be completed using the literary analysis method of causal inference, enabling the researcher to produce behavioural KPIs that both capture the qualitative influences on the worker whilst making each contributing phenomenon measurable within an information management system context (Nogueira et al, 2022). In identifying these universal task stages, this will enable the researcher to review participant activity within the folder structure, and use each KPI to contribute 'points' towards a Task Completion Rating (TCR).

In addition, as the folder structure will need to address the criticism of limited generalisability argued by Li et al (2022): the referencing system used to design the folder structure will need to utilise the same decision-tree method of event sequencing used in the design of production systems. Just as this referencing method ensures that a procedure designed for a physical workplace environment ensures that tools are accessed consistently – even as the exact devices fulfilling the role of each tool change over time (Persi, 2008): this will ensure that the participant accesses the correct digital folder locations and log spreadsheets over the course of the test compliance task. Furthermore, in order to enable the capability for generalisation argued by Li et al (2022), designing this system will require that this same referencing system is able to be applied to other test procedures (such as a GDPR procedure instead of a backup procedure) that may be assigned to a team member of a different level of workplace permissions. In turn, this will require every possible interaction between the folders (i.e. 'first access folder C1 and then upload your file to folder G) to be tested for potential conflicts in permission level: this will be achieved using the stress-test engineering technique, enabling such conflicts to be identified conceptually in advance before building the final structure and its items in advance (Krishnan Nallaperumal, 2003).

''Users of the structure will be familiar with a cloud-based navigation interface of existing platforms''

Lastly, as participants interacting with the folder structure will be familiar with a cloud-based navigation interface such as Microsoft Sharepoint or Gsuite of their organisation (Aretemi et al, 2023): the cryptic folders and log spreadsheets will be accessed by the participants via a google drive folder, ensuring that interactions by the participant used to build their TCR rating are not distracted by an unfamiliar interface.

3.2.2. Designing the quantitative tools for cluster analysis

In considering the advantage of addressing human behaviour as a quantitative phenomenon in conjunction with additional qualitative instruments, that can together be compared against another source of quantitative data (Campell et al 2014): this suggests that the accuracy with which visual characteristics of training material can be correlated to changes in TCR requires a universal method of categorising selected image sections. Consequently, for the visual preferences of the participant to be captured as quantitative discreet values that can be compared against their TCR value collected from their activity in the cloud folder – but also for this same system of categorising said values to work across multiple image variations: this will require the application of category theory used in AI research, enabling multiple variations of an asset to be tested by users against the same framework of location or function codes; therefore enabling algorithms to rank discrete sections of an image according to user preference (Maass et al, 2022).

Therefore, as the participant completes the test procedure, visual preferences will be shared via a quantitative questionnaire based on the imagery they see in the procedure training PDF, or other visual elements of their experience while completing the task. In turn, the questionnaire will ask the participant to share said preferences using an image grid system (see Figure 3 above), whereby the participant selects the exact spatial area of the above image they perceive as responding to the question: this will enable the most frequently-selected areas among participants viewing the same image to generate a Perceived Visual Priority (PVP) that can be represented (see Figure 3 above) as a scatter chart, and therefore enable the visual features across different images that fall under the same spatial area to be compared in the final analysis stage. In addition, this will enable the data model to compare the participants with the highest task performance value (TCR) with the visual characteristics of the images exposed to this higher performing group, therefore identifying visual features that may be playing the theorised cognitive roles of Bellamy et al (2007) in increasing concentration and memory of these higher-performing participants.

Lastly, this will enable the developed data model to establish groups of visual characteristics according to their cognitive role in enhancing the procedural or declarative memory functions of Reppa et al (2020). Furthermore, this will enable the researcher to update the original behavioural KPI groups with metrics able to capture behaviour suggesting one of these two modes of memory: this stage will build on the iterative cycle of Kang et al (2021), and enable an analysis of future historical data to predict in advance which visual design language would be best suited to a given compliance task.

3.3. Data collection methods and sampling considerations

In considering the design of the conceptual Visual Interface Iteration System (VIIS) as the primary objective of this study: the ability to apply the stress-testing engineering method of Krishnan Nallaperuma (2003) will require the researcher to conceptualise how each component of the final data model would be distributed to a minimum number of participants; and how the designed tools would be applied to group of participants according when controlling for how TCR varies in response to image variations. On the one hand, as ensuring validity of the final results would require that participants be familiar with the context of the test task presented, but also that there be sufficient participants to create reliable averages across the number of controlled variations (Roman et al 2017): this suggests that the minimum number of participants needed to accurately demonstrate the functionality of the data model is infeasible for this study. On the other hand, due to the advantage of comparing results collected from both qualitative and quantitative methods (Campell et al 2014): testing at least part of the data model with a participant will have the advantage of revealing unforeseen factors that influence both TCR and PVP values.

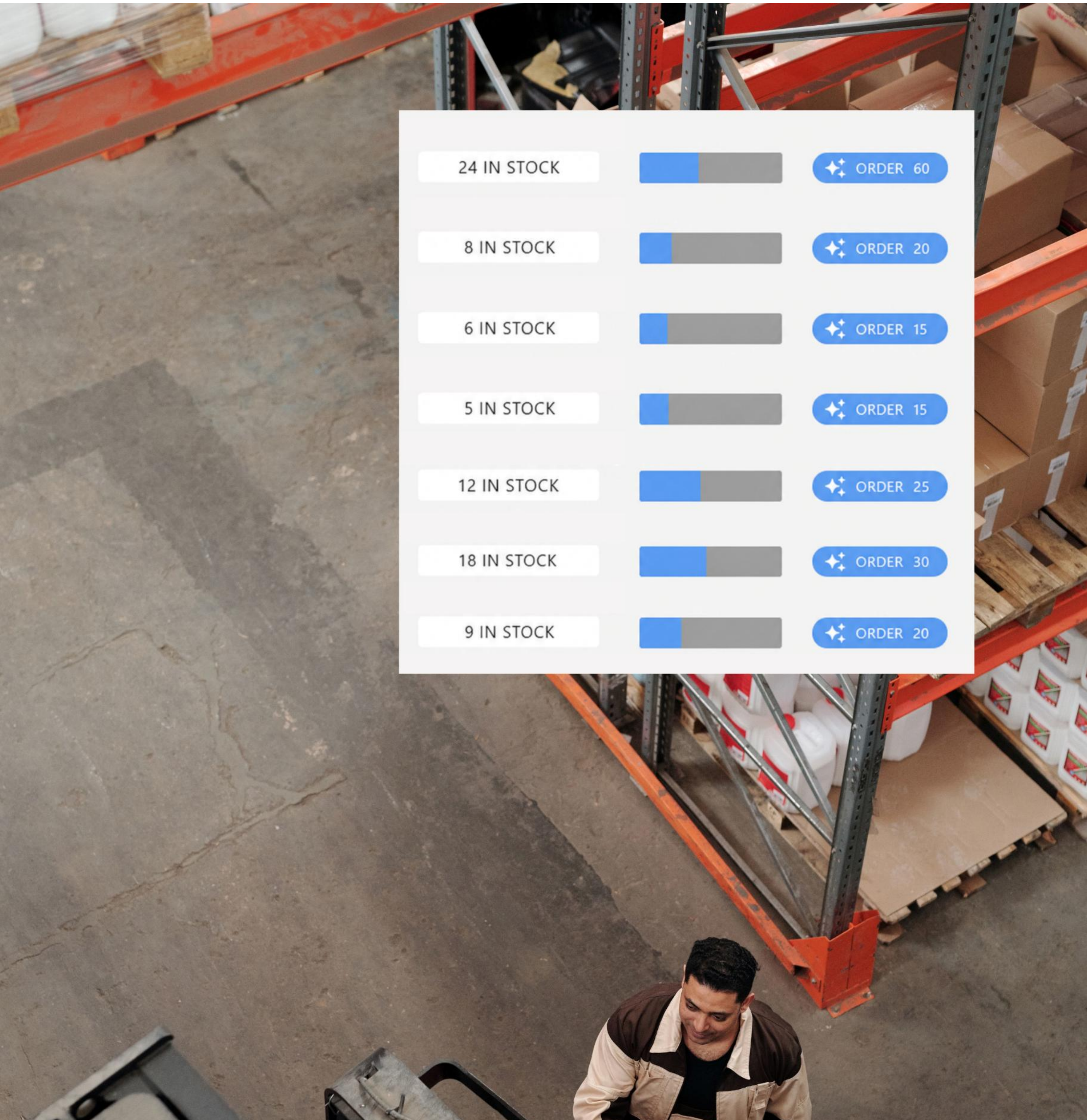
Therefore, in choosing the participant for this study: the researcher has chosen Plymouth-based education company Tellus Group, whereby the CEO has agreed to act as a participant to produce TCR and PVP values (see Appendix C) by interacting with the cloud folder; but also provide verbal feedback using their experience as an education expert. This will ensure that the data collection reveals unforeseen factors as argued by Campell et al (2014); but also that the core functionality of automating the training process functions as intended.

3.4. Research validity and reliability

Due to the importance of maintaining validity and reliability of each stage of the design and data collection process, the research will apply the following two stages; both when applying the literary analysis method of causal inference at each stage of the system design, and when analysing the results collected from the participating organisation:

Stage 1- Validating for variations in environment: To ensure that the KPIs derived through causal inference accurately represent metrics behaviour that are indicative of compliance: this study will validate the derived KPIs for: 1) the anticipation of social factors that may distort collected metrics (Hristov et al, 2019), which may require the final the Inferred Orientation Category (IOC) value revisited in the analysis to consider additional factors such as time-of-week, and a change in the original metrics for observable behaviours to those that are not limited to variations in the culture and professional background. Second, due to the variation with which colleagues within the participating organisation may interact depending on the layout of their workplace environment, and the potential for this varying context to distort the interpretation of the results (Choudhary et al, 2021): the rationale for the derived KPIs will be validated against additional data from time-motion studies and other factors that may influence the experience of the digital worker.

Stage 2- Validating for social factors and incentives: As obtaining accurate Perceived Visual Priority (PVP) and Perceived Orientation Category (POC) values will in-turn be dependent on obtaining results from the questionnaire that avoid misinterpretation: all



responses will be validated against: 1) the role of incentives that may lead a participant to provide a knowingly inaccurate result to avoid being perceived to favour a component of a task seen to conflict with the organisation; 2) the influence of over-preparation as a means of achieving an exaggerated positive Task Completion Rating (TCR) to avoid being perceived as poorly performing by the organisation; and 3) the role of reported social factors, whereby all mitigating circumstances expressed by the participant must be considered in evaluating his or her Task Completion Rating (TCR), and whether the visual selections for Perceived Visual Priority (PVP) and Perceived Orientation Category (POC) values accurately represent their cognitive experience during the exercise (Gray et al, 2021).

3.6. Ethical considerations

In addition to proposing measures for ensuring validity of the collected data, this study also proposes measures to ensure compliance to all regulatory and ethical requirements using two categories: Measures for ensuring anonymity, consent and other regulatory requirements using the participant ID method; measures for ensuring ethical conduct in the literary analysis; and measures for ensuring ethical conduct when applying the predictive model involving the participants.

3.6.1. Measures for ensuring anonymity and consent: the Participant ID system

First, in order to ensure voluntary participation, each participant will be asked to sign a research participant consent form (See Appendix C) in accordance to the research ethics policy of Salford University. Second, in order to ensure informed consent, this will also be ensured by the signing of the participant consent form in accordance to the research ethics policy of Salford University; but will also be supported by the design of the participant log sheet (See Appendix), whereby consent will be logged as a separate step prior to any participants being sent the cloud folder to begin their activity. Third, as the use of a 6-digit Participant ID number increases the effectiveness of accessing the data collected via the questionnaire and project cloud folder not only ensures anonymity, but also enables results between participants to be represented in the analysis without disclosing participant identity (Fusar-Poli et al, 2022): this same method will be applied in both the design of the predictive model and when analysing the data collected from the participating organisation. Moreover, this same ID number system will be used to ensure participant confidentiality; but will also be combined with an additional measure of ensuring that no image representations or questionnaire responses of the participating organisation are shared to a third party outside of the context of this study unless permitted by the Salford University research ethics policy.

3.6.2. Ethical considerations for causal inference in the literary analysis

On the one hand, due to the potential risk of inaccurate evaluations in the literary analysis when deriving KPIs from studies originating from different cultures, regions and socio-economic backgrounds (Reijers et al, 2018): factors specific to isolated cultures and environmental contexts will be weighed against factors considered universal. Moreover, due to the risk of unconscious bias in in the interpretation of derived categories within the KPI framework that contain social and behavioural components, and the potential risk of disregarding signals of productivity that may emerge differently across cultural environments (Abdi et al, 2022): the categories of behavioural KPIs will remove metrics that are limited to manifestations of productivity limited to a single environment.

3.6.3. Ethical considerations for the participating organisation

In considering the researcher-participant relationship, and how a misunderstanding of incentives may lead to an unintentional coercion of the participating organisation (Fusar-Poli et al, 2022): no participant will be asked to re-enter responses or re-create image representations if the participant is uncomfortable or perceives an intrusive nature in the methodology related to learning psychology explored by this study. Furthermore, as the ability to uphold the obligation of making the collected data available to the participant at a later date and enabling ease-of-access throughout the data collection is dependent on the structure with which the data collection files are organised (Cohen et al, 2014): all collected data will be organised and made available in a cloud folder to ensure a transparent communication and access of the results. Furthermore, all parties responsible for examining this dissertation and the University of Salford will be provided top-level access to the cloud based folder, whereby access will be provided to all questionnaires and their response data; spreadsheets and their formulas; participant logs and their results; and the image representations uploaded into each folder (See Figure 4 below).

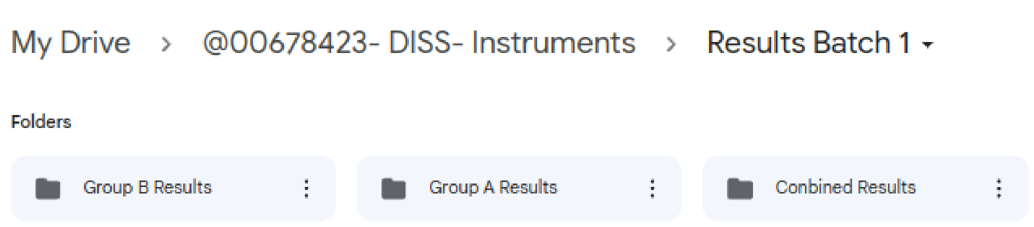


Figure 4: Accessing the results via the cloud folder

3.7. Foreseen limitations and measures

On the one hand, due to the limitations in a predictive model in its ability to accurately model the phenomenon of qualitative human behaviour, and the expectation that the assumptions derived in causal inference for its quantitative metrics will be later modified by identifying unexpected influences reported by the participant (Mottus et al, 2020): this methodology may be limited by the possible constrained role the visual dimension of the training interface may play in influencing visual stimuli in the learner. Moreover, it may be discovered that – though playing an axiomatic role in mentally visualising the ontology of the task during the first interactions with the activity – the visual interactions with the cloud folder itself may play a superior role.

4.0. Analysis

4.1. Design stage 1: Designing the cryptic information management system

4.1.1. Literary analysis: identifying system parameters for task completion

At this stage, the researcher applied literary analysis method of causal inference to derive each of the theorised behavioural KPIs using a three-stage process: 1) identify a qualitative phenomenon that, if tracked, could be universal across workplaces irrespective to socio-economic or cultural influences on working patterns; and 2) identify a metric that, if tracked by an information management system, would directly infer the presence of this behaviour in direct relation to a compliance outcome (Nogueira et al, 2022). As as result of this analysis, the researcher identified the 11 behavioural KPIs below. Over the course of this literary analysis, 12 earlier behavioural KPIs were identified (see Appendix D), which were in-turn modified to create the KPIs below that informed the design of the information management system:

Furthermore, in responding to the criticism of past predictive models – in that attempts to measure compliance rely on reported behaviours, rather than tracking digital tasks within databases that directly indicate compliance (Alén, 2019) – 6 KPIs were developed that could track digital behaviours, including: using logs within an ISO 9001 database to test the frequency with which workers provide disclaimers when interacting with external stakeholders; the frequency of self-initiated backups of data during a compliance task; and the ratio of compliance to non-compliance tasks within a project brief over a controlled period of 30 days (see inferred KPIs A2-1, A2-3 and A2-5 in Figure 5 below).

However, as the frequency of logged events that would indicate group collaboration is also an indicator of compliance (Villazón et al, 2020): the researcher added KPIs for measuring the frequence of email clarifications and the scheduling of group events (see inferred KPIs A2-4, A2-2 and A2-6 in Figure 5 below); but also validated the choices of the KPIs in considering the possible workplace environments in which the participant may complete the exercise when testing the predictive model to avoid misinterpretation of the instructions (Choudhary et al, 2021).

KPI number	Measured effect & name	Primary variable A	Primary variable B	Primary variable C	Proposed KPI using the literature
A2-1	Rate of reported disclaimers: check-box filled	30-day duration of the office admin schedule	Average no* of confirmed items	No* of confirmed items in the subject organisation	(C/B)/A)
A2-2	Rate of reported email clarifications post action: check-box filled	30-day duration of the office admin schedule	Average no* of confirmed items	No* of confirmed items in the subject organisation	(C/B)/A)
A2-3	Rate of self-initiated back-ups post action: back-up notification logged	30-day duration of the office admin schedule	Average no* of confirmed items	No* of confirmed items in the subject organisation	(C/B)/A)
A2-4	Rate of self-initiated meeting scheduling: ISO project code rate per meeting logged	30-day duration of the office admin schedule	Average no* of confirmed items	No* of confirmed items in the subject organisation	(C/B)/A)
A2-5	Core project-to non related compliance task ratio in project brief	30-day duration of the office admin schedule	Average no* of confirmed items	No* of confirmed items in the subject organisation	(C/B)/A)
A2-6	Rate of checked admin to-do-list tasks per month	30-day duration of the office admin schedule	Average no* of confirmed items	No* of confirmed items in the subject organisation	(C/B)/A)

In addition, due to the added benefit to compliance of extending the referencing system concept to the digital as well as physical work environment (Seyffarth et al, 2020): an additional 5 KPIs were developed to test the percentage accessed digital locations known in advance to infer a comprehension of a compliance protocol, and that the training medium was successfully guiding the worker to those correct locations (see inferred KPIs A5-2 in Figure 6 below).

KPI number	Measured effect & name	Primary variable A	Primary variable B	Primary variable C	Proposed KPI using the literature
A5-1	Percentage of compliance digital folder locations followed vs required number by the SOP	No* of digital folder locations to frequent required by an SOP	No* of digital folder locations frequented by the learner when following said SOP	The average percentage of frequented digital folder locations followed in an analogous SOP	((B/A)x100)/C
A5-2	Percentage of compliance physical workplace locations followed vs required number by the SOP	No* of frequented physical workspace locations required by an SOP	No* of frequented physical workspace locations completed by the learner when following said SOP	The average percentage of frequented physical workspace locations for an analogous SOP	((B/A)x100)/C
A5-3	Percentage of self-setup of desktop and workstation errors vs SOP format when following the SOP	No* of unique presentation atributes in format variations A1 and A2	The number of errors when following the SOP over 30 days	The average number of errors when following an analogous SOP document over 30 days	((B/C)/A1)/((B/C)/A2)
A5-4	Percentage of digital folder locations memorised vs number required by the SOP	No* of digital folder location tasks required by an SOP	No* of digital folder locations memorised by the learner when following said SOP	The average percentage of digital folder locations memorised for an analogous SOP	((B/A)x100)/C
A5-5	Percentage of physical workplace locations memorised vs number required by the SOP	No* of physical workplace location tasks required by an SOP	No* of physical workplace locations memorised by the learner when following said SOP	The average percentage of physical workplace locations memorised for an analogous SOP	((B/A)x100)/C

Figure 6: Proposed key performance indicators for procedure design: capacity to aid memory of digital locations

4.1.2. Deriving the Task Completion Value (TCR)

Building on the above behavioural KPIs related to self-initiated clarifications and data backup (see inferred KPIs A2-2 and A2-3 in Figure 5 above); and the percentage of digital locations accessed versus required (see inferred KPI A5-2 in Figure 6 above): this implied that the Task Completion Rating (TCR) needed to be able to measure:

1. How the user navigates the folder structure, inferring an understanding of the stages specific to compliance within the task;
2. How the user adds the logs related to checks for ISO 9001, inferring a comprehension that successful logs constitute a major part of the protocol's outcomes;
3. How the user interprets events related to communication, such as message confirmations before proceeding to the next stage.

Building on the former Gini index and method of defining information technology compliance as a set of weighted digital check-points (Hayble-Gomes, 2022): the researcher applied the decision tree method to conceptualise the universal digital behaviours that would be tracked across all compliance procedures; breaking down the protocol into a series of events, where each event will be given a value of 1 or 0; individually multiplied by a separate 'priority weight value' based on the priority of each step towards the outcome of the procedure; and lastly, the combined sum of these adjusted values would be combined to create the '*Task Completion Rating (TCR)*' for the participant (see Figure 7 below).

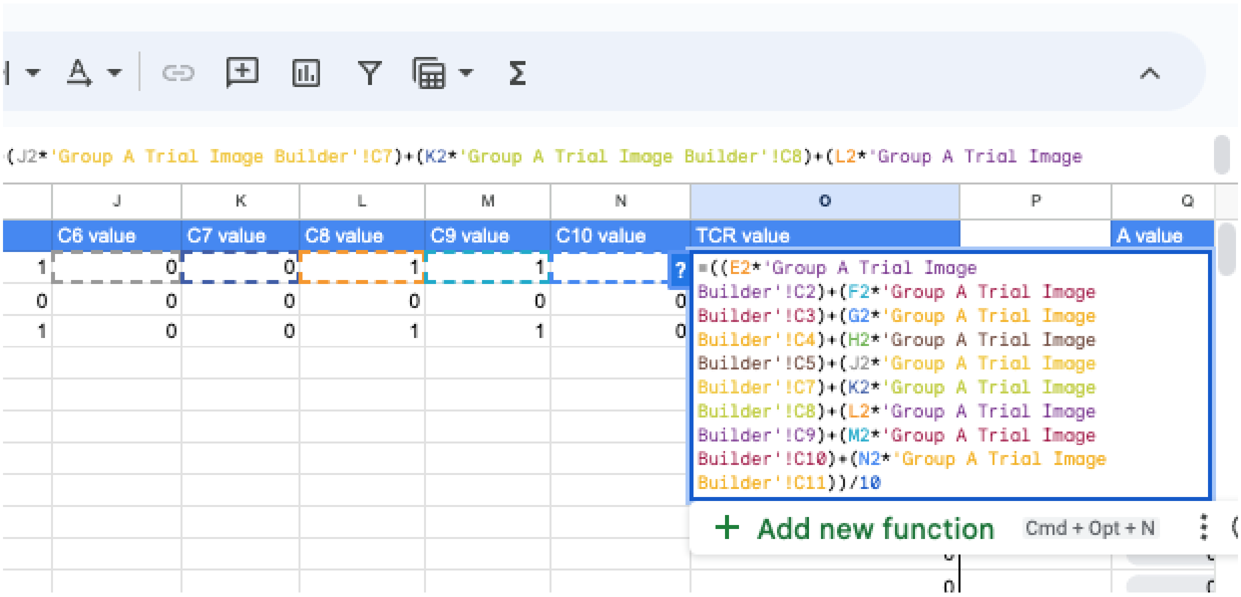


Figure 7: The formula for Task Completion Rating (TCR) for each participant based on their activity in the folder structure and example weight values

4.1.3. Designing the folder structure and information management system

In identifying the above system parameters, and for the final design of the information management system to capture the above TCR value, the researcher designed the information management system according to the below two stages:

'' The platform was measured against a Task Completion Rating (TCR) to ensure consistency across results''

Stage 1- Designing the referencing system language: Due to the importance of the referencing system being able to direct the employee to the software categories and file locations needed for a compliance of a task to be achieved in a range of possible environments (Storber et al, 2019), the following reference categories were added: 1) compliance documentation; 2) spaces within the physical environment named A-L, which could be checked by the user on a separate workspace map, providing the possibility of changing the map structure at a later date whilst being able to retain the same referencing system; and 3) digital folder locations, which would ask the user to navigate to specific folders named A-L in their cloud folder, and – due to the importance of ensuring that references could remain consistent in response to changes in IT infrastructure (Persi, 2008) – also enable the location of each folder to be changed whilst being able to retain the same referencing logic (see Figure 8 below).

Stage 1: Registering new paper files as document assets

- Print the PDF AA1H- Checklist and Declaration Sheet

- Take a selfie and send to your unit manager via WhatsApp with code AA1H-S1

1. If in home office mode, check all desk surfaces at Desk Sites M, L and N
2. If in home office mode, skip to step 8
3. Check for any paper files at desk surfaces at Desk Sites D1, C2, C2, C3, E1 and B1
4. Mark each file in the top-left corner with: Desk Site code, project number, and relationship number
5. Confirm permission with each staff member and all collect paper files

- Take a photo of each surface and send via WhatsApp to your Unit Manager as 'AA1H'

6. Check for any paper files at desk surfaces at Desk Sites A1, A2, A3 and A4.
7. Check any paper files at desk surfaces at Desk Sites A7, A5 and A6.
8. Mark each file in the top-left corner with: Desk Site code, project number, and relationship number
9. Confirm permission with each staff member and all collect paper files

- Take a photo of each surface and send via WhatsApp to your Unit Manager as 'AA1H'

Stage 2- Designing the ISO 27001 folder structure: First, due to the importance of enabling the user to navigate the file strucure in a minimum number of stages to maintain its role of increasing compliance to the procedure (Rezaei. 2022): the researcher repeated the decision tree method to identify the structure of how top-level and sub-level folders would be connected, and in-turn how the text references of said locations could be interpreted intuitively by the user. Second, in order for the above referencing system to work across a variety of compliance tasks, due to the role of the stress-test technique in testing contradictions within the design at the concept design stage prior to designing the final structure (Krishnan Nallaperumal, 2003): every possible interaction between folders and files were tested for potential conflicts according to the permission level of the staff member (see Figure 9 below).

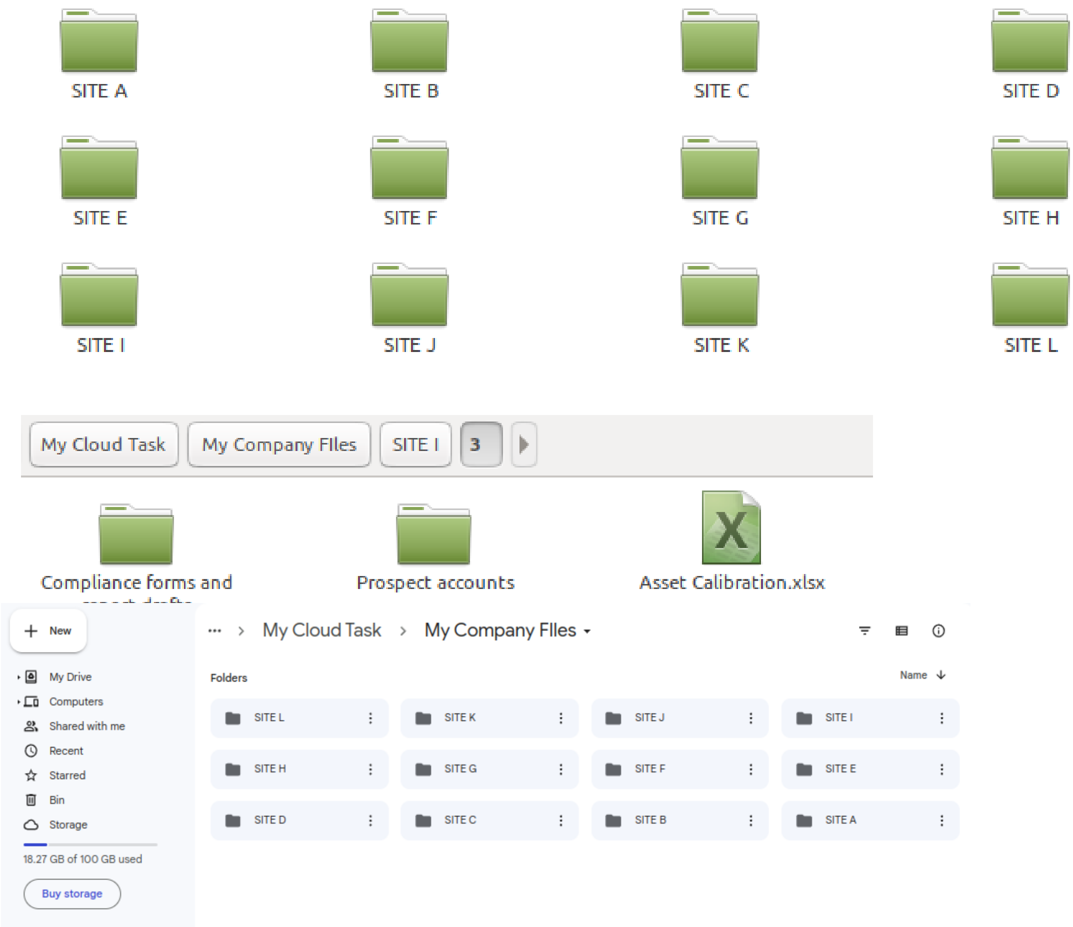


Figure 9: Designing the folder structure and SOP referencing system to capture the TCR rating as participants complete the procedure

4.2. Design stage 2: Designing the quantitative tools for capturing visual values

4.2.1. Literary analysis: identifying system parameters for visual variations

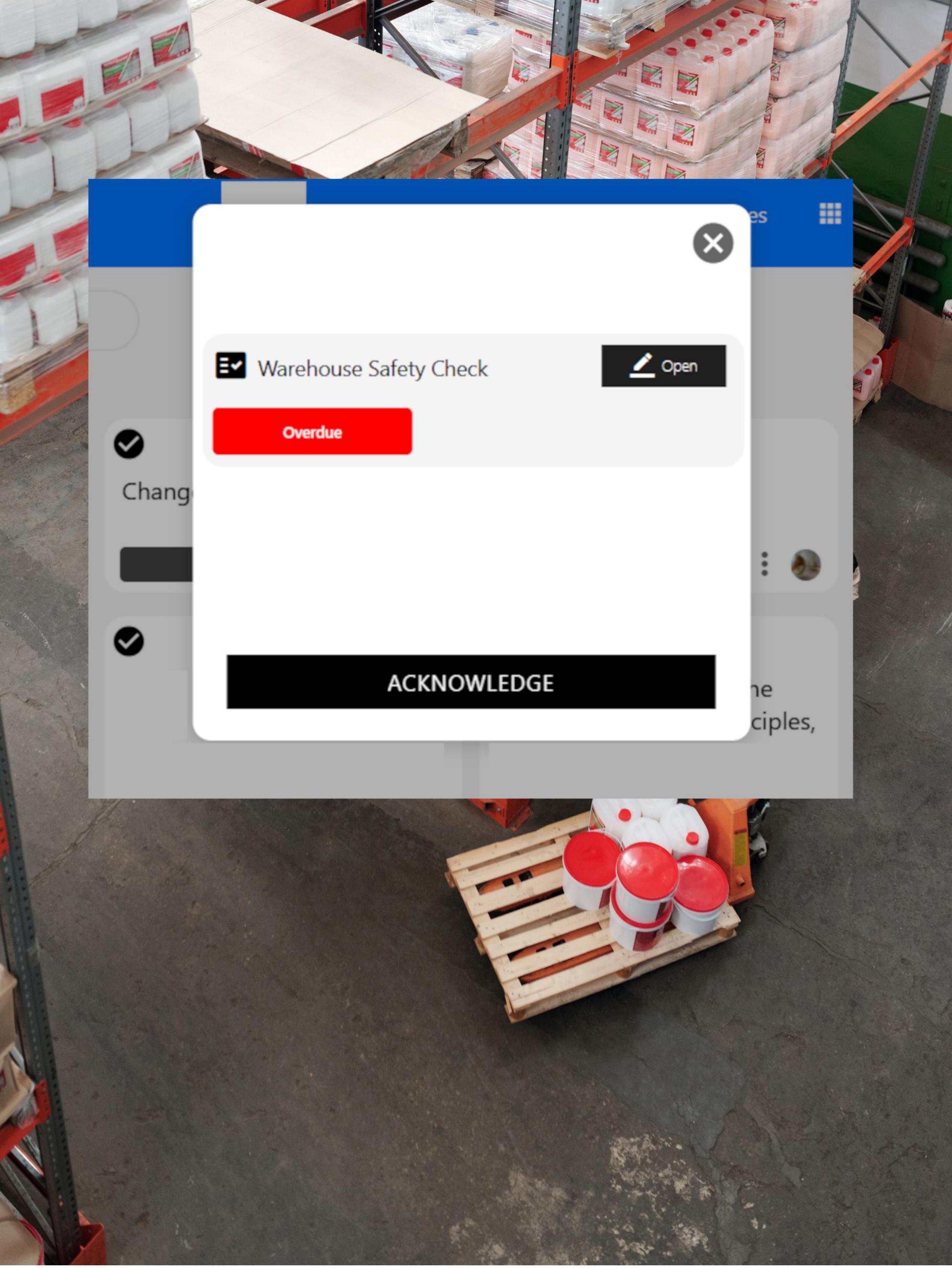
At this stage, the researcher applied the literary analysis method of causal inference to derive each of the theorised behavioural KPIs using the same three-stage process in the previsous stage: 1) identify a qualitative phenomenon related to learning psychology that, if tracked, could be universal across workplaces irrespective to socio-economic or cultural influences on working patterns; and 2) identify a metric that, if tracked by the predictive model, would directly infer the presence of this behaviour in direct relation to a compliance outcome (Nogueira et al, 2022). As a result, the researcher then completed a validation stage, resulting in the 5 behavioural KPIs below. Moreover, over the course of this literary analysis, 21 earlier behavioural KPIs were identified (see Appendix D), which were in-turn modified to create the KPIs below that informed the design of the following data collection tools that would work with the previous information management system.

In addition to the importance of investigating the percentage of procedure steps completed as a means of measuring compliance: the potential relationship highlighted between the visual attributes of training material and task compliance suggested an opportunity to use a procedure referencing system developed using the principles of Dai (2020) to assess the percentage of procedure events successfully navigated by the learner (see inferred KPI A5-1 in Figure 10 below); and contrast this TCR value with changes in graphical variations in the training material (see inferred KPIs A6-1, A6-2, A6-3, A6-4 and A6-5 in Figure 10 below).

KPI number	Measured effect & name	Primary variable A	Primary variable B	Primary variable C	Proposed KPI using the literature
A6-1	Percentage of compliance digital folder locations followed vs required number by the SOP vs graphics format A and B	KPI A5-1 rating for graphics format A	KPI A5-1 rating for graphics format B	Average KPI A5-1 rating for an analogous graphics format	((A/C)-(B/C))X100
A6-2	Percentage of compliance physical workplace locations followed vs required number by the SOP vs graphics format A and B	KPI A5-2 rating for graphics format A	KPI A5-2 rating for graphics format B	Average KPI A5-2 rating for an analogous graphics format	((A/C)-(B/C))X100
A6-3	Percentage of self-setup of desktop and workstation errors vs SOP format when following the SOP vs graphics format A and B	KPI A5-3 for graphics format A	KPI A5-3 for graphics format B	Average KPI A5-3 rating for an analogous graphics format	((A/C)-(B/C))X100
A6-4	Percentage of digital folder locations memorised vs number required by the SOP vs graphics format A and B	KPI A5-4 rating for graphics format A	KPI A5-4 rating for graphics format B	KPI A5-4 KPI rating for an analogous graphics format	((A/C)-(B/C))X100
A6-5	Percentage of physical workplace locations memorised vs graphics format A and B	KPI A5-5 rating for graphics format A	KPI A5-5 rating for graphics format B	Average KPI A5-5 rating for an analogous graphics format	((A/C)-(B/C))X100

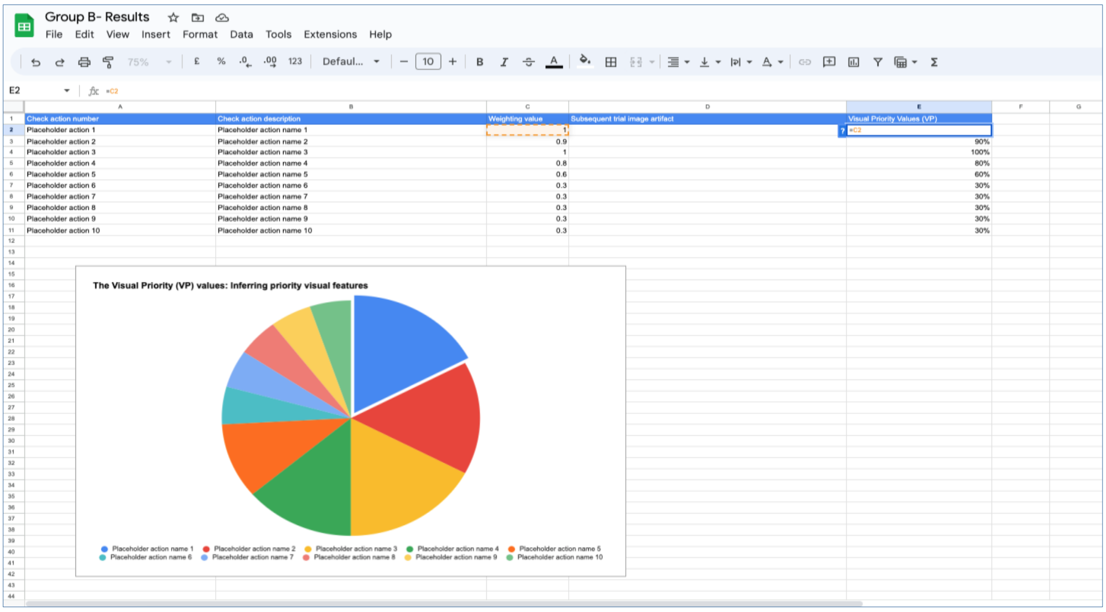
Figure 10: Proposed key performance indicators for LMS presentation design: limitations focus and working memory

4.2.2. Deriving the Visual Priority (VP) value


Warehouse Safety Check
Open
Overdue
ACKNOWLEDGE

characteristics to be compared against *Perceived Visual Priority (PVP)* values shared by the user in the questionnaire. Consequently, in designing this part of the data collection infrastructure, the researcher applied the concept design and stress-test methods of Krishnan Nallaperuma (2003) to conceptualise and design this part of the tool using the following considerations:

Stage 1- The concept design stage: At the concept design stage, the researcher created a table to capture the priority weight values for each of the defined task stages, enabling the user of the predictive model to hypothesise the respective significance of each step when represented visually in the training material (Hayble-Gomes, 2022): this tool would in-turn be used by an organisation applying this model during the design of a trial training image, but representing each different step (i.e. completing the ISO log) with a different spatial percentage than a step with a lower rating (access folder L). In addition, as with the previous the self-correction technique in the predictive model of Kang et al (2021): this tool would enable the organisation to modify these percentage values over time in response to performance data from each of the tested images at a later stage of the applying the procedure (see Figure 11 below).



Check action number	Check action description	Weighting value	Subsequent trial image artifact	Visual Priority Values (VP)
Placeholder action 1	Placeholder action name 1	1		=C2
Placeholder action 2	Placeholder action name 2	0.9		90%
Placeholder action 3	Placeholder action name 3	1		100%
Placeholder action 4	Placeholder action name 4	0.8		80%
Placeholder action 5	Placeholder action name 5	0.6		60%
Placeholder action 6	Placeholder action name 6	0.3		30%
Placeholder action 7	Placeholder action name 7	0.3		30%
Placeholder action 8	Placeholder action name 8	0.3		30%
Placeholder action 9	Placeholder action name 9	0.3		30%
Placeholder action 10	Placeholder action name 10	0.3		30%

Figure 11: Example weight values and subsequent Visual Priority (VP) values for each identified procedure action

Stage 2- The concept testing phase: At stage 2, the researcher designed the table to include 10 check actions that would be added by the user of the predictive model when selecting the universal stages of the compliance procedure suggested by Hayble-Gomes (2022): in-turn, this would enable said steps to be added into the spreadsheet and given a weight value between 0 and 1 and used to generate a respective Visual Priority (VP) value (See formula in Appendix, 8.1.1.) by using their ratio. In turn, this enabled the tool to calculate a Visual Priority (VP) value using the chosen ratios ratios; enabling the tool to suggest which stage of the procedure should be given the most space within the image as part of the designed test image (See Figure 12 below). However, in addition to to deriving values for percentage of the surface area within a test image: the importance of considering varying perceptions of the resulting visual elements in the design process due to differences in culture, social environment and social incentives within the workplace context (Hristov et al, 2019) would mean that the user of the predictive model would have the freedom to interpret each of these percentages within the context of the worker environment.

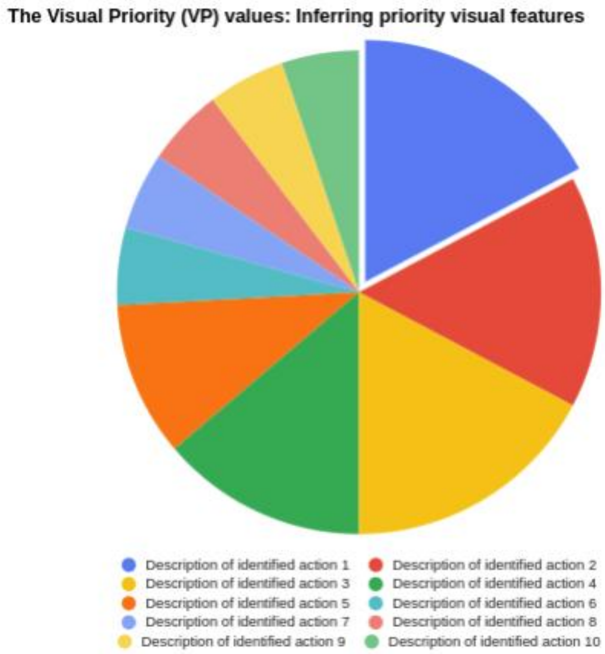
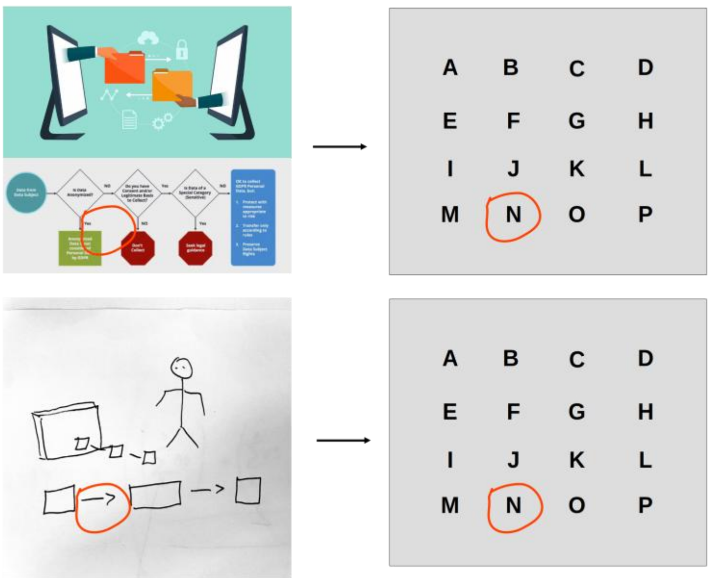


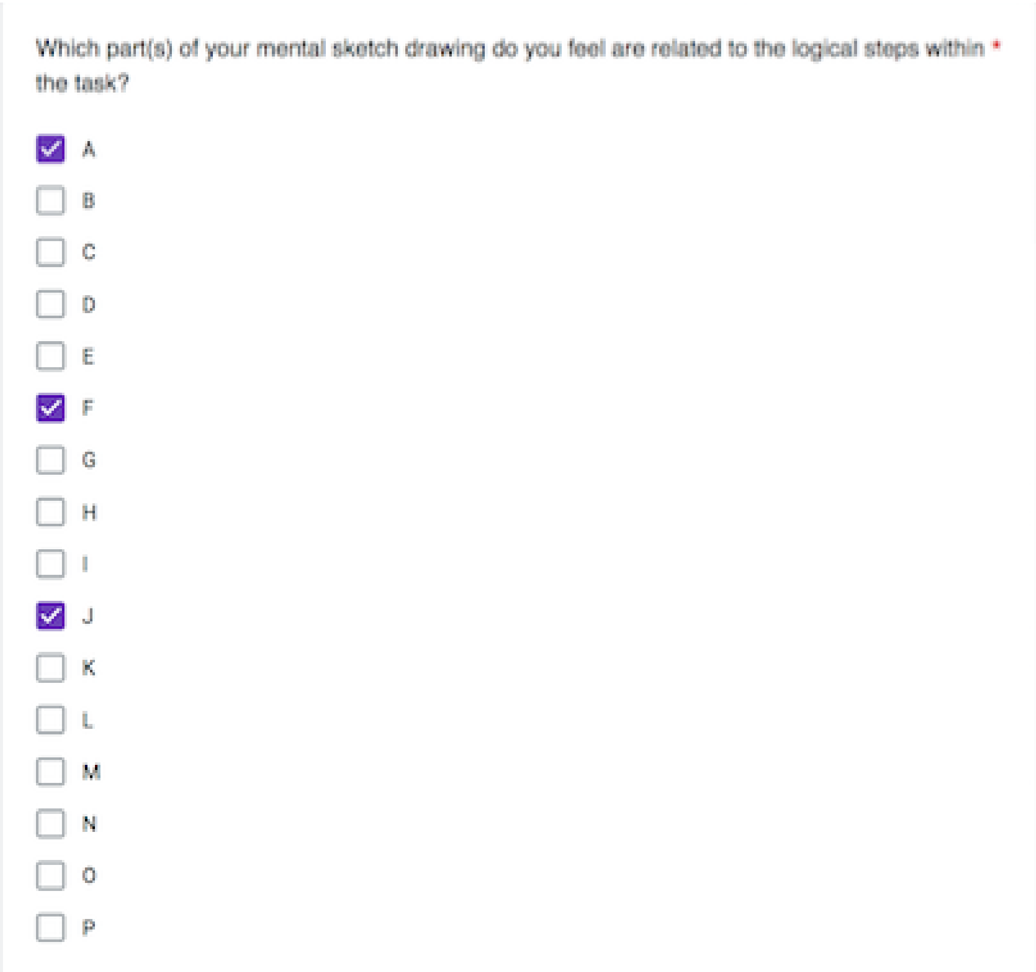
Figure 12: Example of generating the pie chart based on the ratios between the Visual Priority (VP) values for each identified procedure action

4.2.3. Deriving the Perceived Visual Priority (PVP) value

With the above tool enabling the predictive model to hypothesise which visual characteristics should take priority when designing the test image using the ontology of the 10 steps within the procedure: this stage involved designing the tools needed to capture the *Perceived Visual Priority (PVP) value* using the questionnaire (see Appendix B), which would define the extent to which a section of a trial image is perceived by the participant to be relevant to the training topic. Due to the past predictive model of systematic marketing logo design, capturing perceptions of 'perceived priority' from participant interactions to continually modify attributes within a draft image design (Tian, N et al, 2022); and the role of a quantitative questionnaire in capturing user perceptions as discrete values in order to apply cluster analysis to represent attributes with the highest perceived value (Liu et al, 2021): this led the researcher to design a tool for the predictive model that borrowed these methods of systematic commercial image design, but to test how participants would react to variations of training imagery:

Stage 1- Designing the A-P grid system for the questionnaire: At this stage, the researcher designed the structure of the quantitative questionnaire (see Appendix C) that a user of the predictive model could distribute across five participant groups; with four of the groups exposed to variation of the test training image, and one group that would be asked to sketch a drawing their perceive as best representing the concepts of the training material. On the one hand, a categorical framework independent of attributes of one image would enable multiple image variations to be tested against the same set of criteria be contrasted across groups of participants (Maass et al, 2022); and due to the risk of misinterpreting qualitative data when asking each participant group to describe the sections of their training image they perceive most cognitively relevant to the compliance task (Campell et al 2014), this would require the design of a new method for contrasting attributes across the test images. Consequently, the researcher designed a separate grid image containing letters A-L was that would be added underneath where the test training image would be placed in the questionnaire design (see Appendix); enabling the participants of each group to refer to the area of the image using the corresponding letter in the grid below. In turn, this would enable a user of the predictive model to add these recorded values to the participant results log (See Figure 13 below), and update the priority value (See formula in Appendix, 8.1.1.) of the letter(s) the participant has selected.

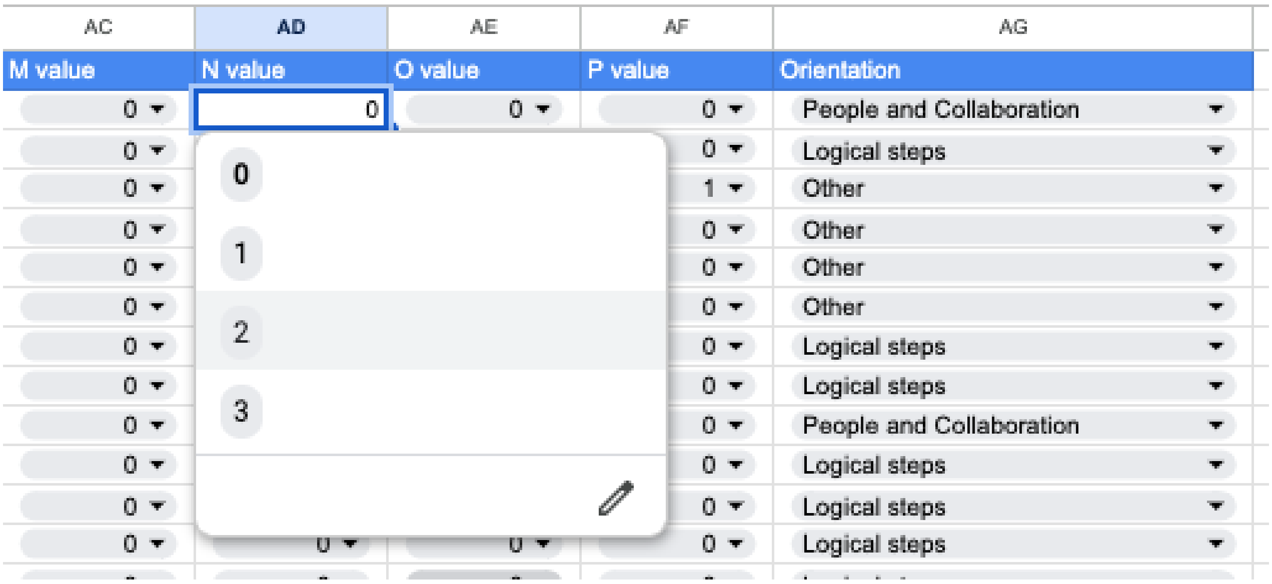



Which part(s) of your mental sketch drawing do you feel are related to the logical steps within the task? *

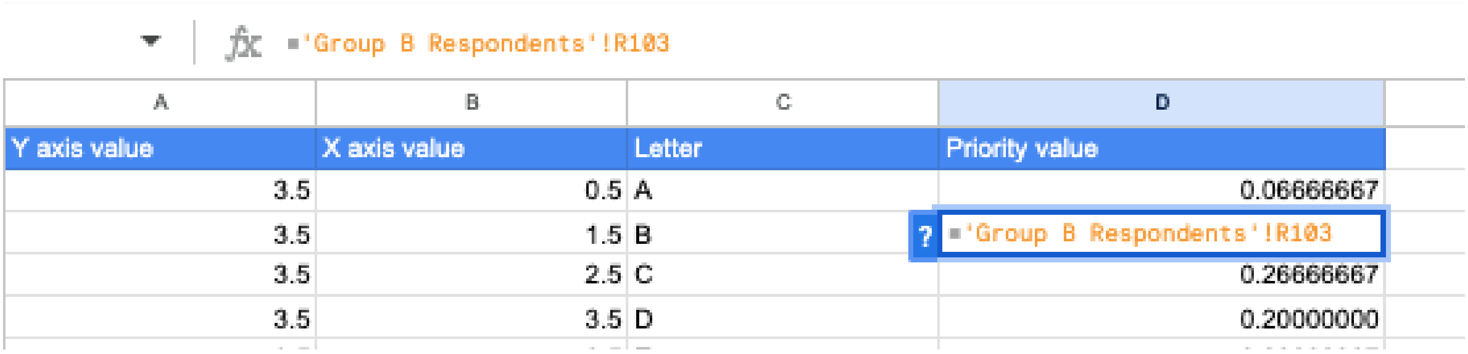
- [x] A
- [ ] B
- [ ] C
- [ ] D
- [ ] E
- [x] F
- [ ] G
- [ ] H
- [ ] I
- [x] J
- [ ] K
- [ ] L
- [ ] M
- [ ] N
- [ ] O
- [ ] P

Figure 13: Designing the image-agnostic grid system for capturing the Perceived Visual Priority (PVP) values in the trial images presented to the participants

Stage 2- Designing the tool to calculate hot zones of Perceived Priority (PVP): After designing the quantitative questionnaire and the A-P grid system in the previous stage, the researcher used this stage to design a scatter graph generator that would be used to calculate the average Perceived Priority Value (PVP) of the image presented to one of the five participant groups. In turn, the researcher designed the participant log sheet (see Figure 14 below) to contain 0/1 values for each of the letters on the grid image: this would enable a user of the predictive model to record the letters selected in the questionnaire by the participants of each of the five groups, where the spreadsheet would generate a priority values between 0 and 1 for each of the letters A-L.



	AC	AD	AE	AF	AG
	M value	N value	O value	P value	Orientation
	0	0	0	0	People and Collaboration
	0			0	Logical steps
	0			1	Other
	0			0	Other
	0			0	Other
	0			0	Other
	0			0	Logical steps
	0			0	Logical steps
	0			0	People and Collaboration
	0			0	Logical steps
	0			0	Logical steps
	0	0	0	0	Logical steps



='Group B Respondents'!R103

A	B	C	D
Y axis value	X axis value	Letter	Priority value
3.5	0.5	A	0.06666667
3.5	1.5	B	='Group B Respondents'!R103
3.5	2.5	C	0.26666667
3.5	3.5	D	0.20000000

Figure 14: An example of how the recorded letter selections from the questionnaire inform the Perceived Visual Priority (PVP) value for each participant

In turn, in considering the scatter graph technique explored in the data model of Tian, N et al (2022): these priority values were connected to the Y and X values of each letter on the scatter graph generator (see Figure 15 below), enabling the tool to generate hot zones for each letter based on their Perceived Priority Value (PPV); in-turn quantitatively representing the areas of the corresponding training image for the group perceived as most cognitively relevant to the participants.

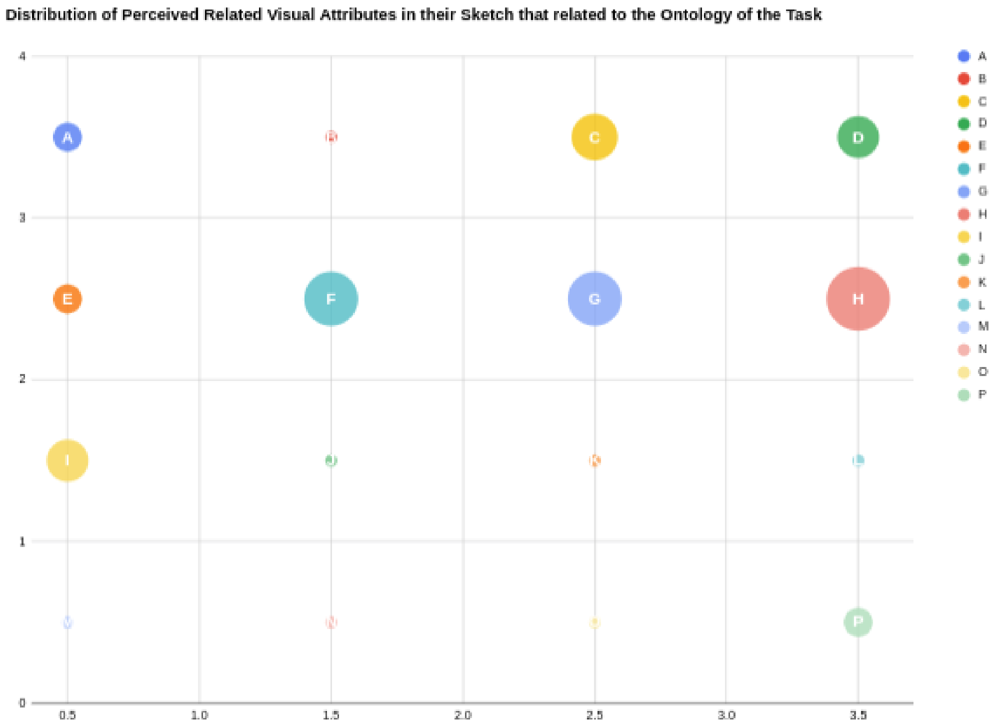
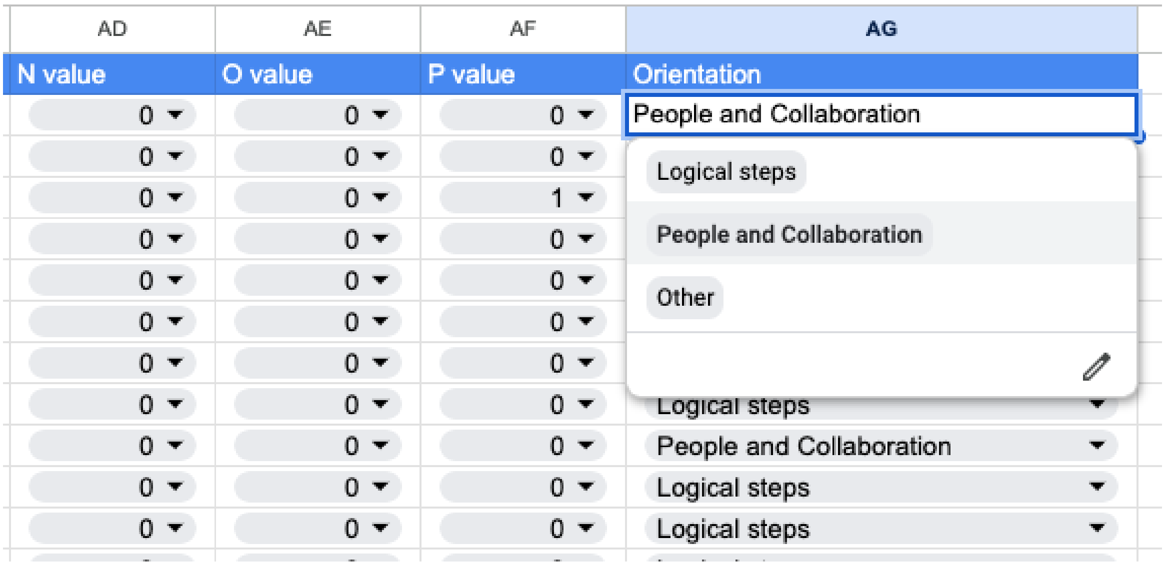


Figure 15: Example of spatially representing the results captured by the questionnaire using a scatter graph to identify the areas of the trial image with the highest Perceived Visual Priority (PVP) value

4.2.4. Deriving the Perceived Orientation Category (POC) value

Stage 1- Adding the additional column: After developing the information system and file structure needed to capture the Task Completion Rating (TCR) among each of the five participant groups, and after having designed the tools to identify the area of the training image in each group perceived as relevant to the training material: the researcher added a final column (see Figure 16 below) to the participant log sheet (see Appendix) that would enable the participants within each group to specify a from of learning they perceive as most relevant to the ontology of the activity. In addition, due to the importance of enabling the classification model to combine quantitative user data to infer pre-determined mode of qualitative category during the design process (Sanborn et al, 2010): the selected options for POC were 1) people and collaboration, whereby selecting this option would indicate that the participant perceives the ontology of the task as relating to social and qualitative phenomenon; and 2) Logical steps, whereby the participant perceives the ontology of the task as relating to procedural stages.



AD	AE	AF	AG
N value	O value	P value	Orientation
0	0	0	People and Collaboration
0	0	0	
0	0	1	
0	0	0	
0	0	0	
0	0	0	
0	0	0	
0	0	0	Logical steps
0	0	0	People and Collaboration
0	0	0	Logical steps
0	0	0	Logical steps

Figure 16: Example of capturing the Perceived Orientation Category (POC) choices by each participant

Stage 2- Comparing final values and identifying optimum visual characteristics: After completing the previous stage, this would enable a user of the predictive model to assess the participants across the five groups with the highest Task Performance Rating (TCR); identify the visual characteristics within the image under section of the grid with the highest Perceived Visual Priority (PVP) value; and then compare these highest performing visual characteristics with a *Perceived Orientation Category (POC)* value (see Figure 17 below) to identify whether this higher performing attribute was caused either by the procedural or declarative form of cognition argued by Reppa et al (2020). Therefore, in considering the original research questions 1 and 2 of this study, this enabled the researcher to design this concept stage of the predictive model to analyse participant data across multiple image variations; identify shared visual characteristics across images tied to the highest-performing participants in TCR; and then to attribute a likely category of cognition to these visual characteristics. Consequently, this will enable a future version of this predictive model to collect visual design features (such as specific image shapes or diagrammatic characteristics) that are most likely to trigger either the procedural or declarative forms of memory argued by Reppa et al (2020), therefore enabling the predictive model to suggest visual design features for compliance training modules that are more procedure-oriented versus visual features for modules related to tasks centred around people and collaboration.

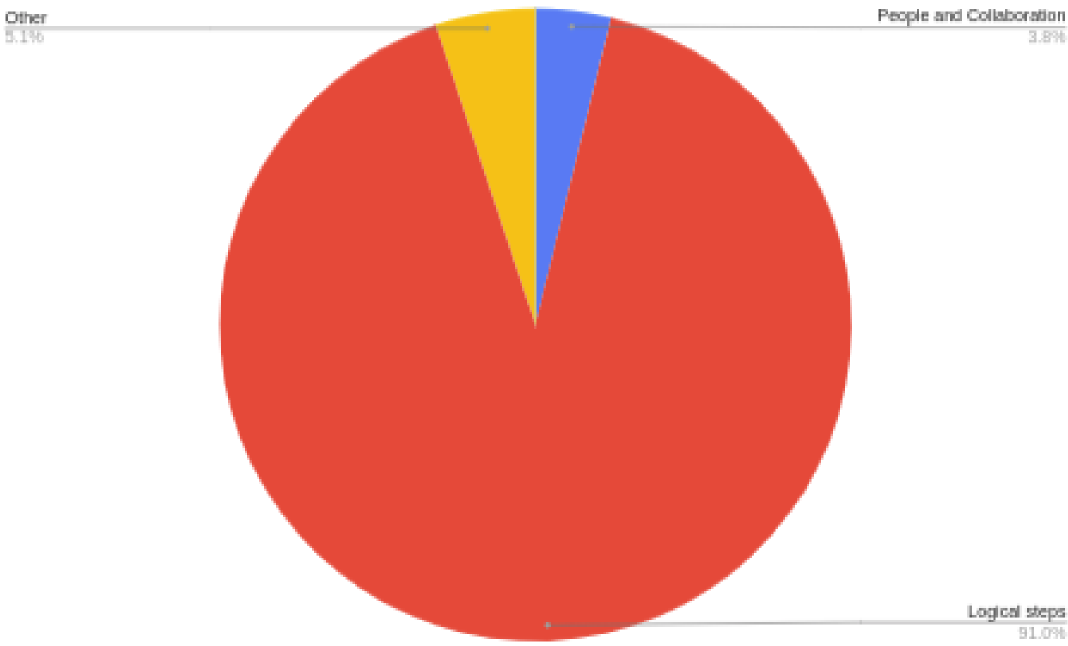


Figure 17: Example of identifying the Perceived Orientation Category (POC) by calculating the ratio between responses

4.3. Design stage 3: The data collection stages for the predictive model concept design

After designing the above tools for the concept design of the predictive model: the researcher used the implications on multiple participant groups for each of the five test images to design the 13 stages of the predictive model procedure (see Figure 18 below); and the structure of the cloud folder that would be accessed by a user of the predictive model for both distributing a cloud folder containing the information management system to the participants; and to access the collected data for each of the participant groups separately (see Appendix C).

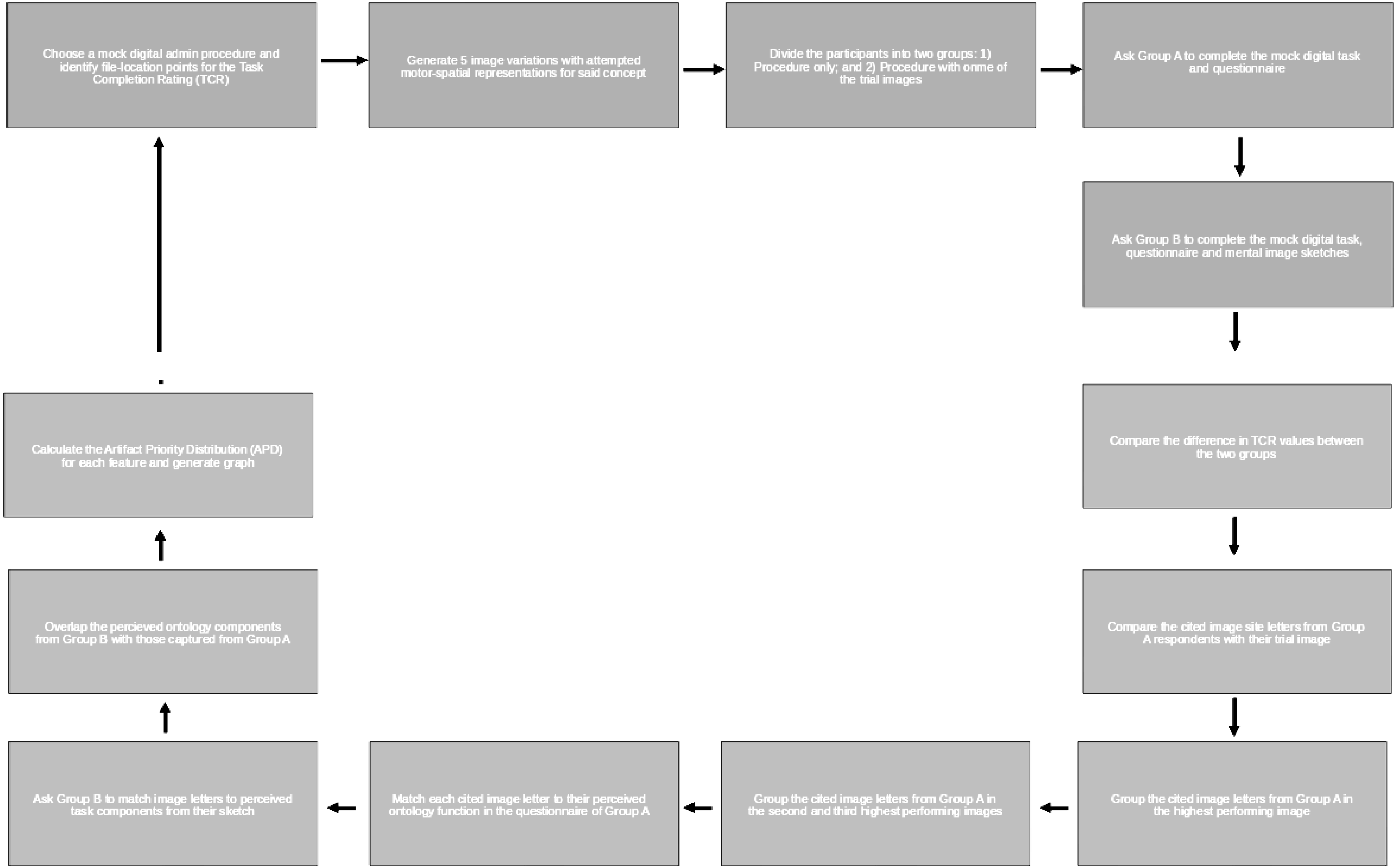


Figure 18: The 15 stages of the draft predictive mode

4.4. Testing the predictive model: The participating organisation and data analysis

4.4.1. Testing the predictive model with participating organisation Tellus Group Limited

After completing the above design for the predictive model at the conceptual level, the researcher tested the conceptual model by following the 13 stages established in the previous section (see Figure 18 above)

Applying stage 1: Choosing a procedure and identifying major actions 1-10

In applying stage 1 of the procedure, the researcher used the referencing format of the designed referencing system to create a back-up procedure as the task that would be tested with the participating company Tellus Group. First, after preparing the test training document PDF, this was uploaded to the cloud folder provided to the participant (see Appendix C). Second, after preparing the cloud folder and confirming ethics documentation from the participant (see Appendix B), the 10 checking stages to measure the KPI of Task Completion Rating (TCR) were decided as follows:

- **Check 1- Initial sign in**: This would confirm whether the participant has completed the initial sign-in task, implying that the presentation format of the training is at least enabling him or her to access the first sub-folder and mock database successfully
- **Check 2- Photos taken of the desk surfaces**: This would confirm whether the participant has successfully taken the photos of the documents on the desk surfaces asked in the procedure, implying success of the presentation format in automating the explanation of another major action key to the overall outcome of the SOP. However, despite retaining this in-person component of the procedure design: the participant was reminded to interpret physical actions as imaginary events to avoid confusion when completing the exercise in an unexpected setting (Campell et al, 2014); and to instead provide text-based updates that they had understood this stage.
- **Check 3- Adding an entry to the document control log**: This would confirm whether the participant has added the required entries to the ISO document control log databases asked at different stages of the protocol, again implying success of the presentation format in automating the explanation of this part of the task.
- **Check 4- Uploading the prepared folder to the cloud unit backup folder**: This would confirm whether the participant has understood the context of the backup procedure, and has correctly interpreted the different stages of preparation required for this stage to be reached, again implying the ability of the presentation format automate the explanation of this part of the process.

- **Checks 6- 10- Miscellaneous contact actions during the task**: This would confirm whether the presentation format of the training interface is at least automating the explanation of the regular contact actions throughout the protocol.

Applying stage 2: Identifying the visual priority values

In applying stage 2 of the procedure, the above checking events were provided the following weight values and subsequent Visual Priority (VP) values:

- **Check 1- Initial sign in**: Weight value: 1; VP value: 100%
- **Check 2- Photos taken of the desk surfaces**: Weight value: 0.9; VP value: 90%
- **Check 3- Adding an entry to the document control log**: Weight value: 1; VP value: 100%
- **Check 4- Uploading the prepared folder to the cloud unit backup folder**: Weight value: 0.8; VP value: 80%
- **Checks 6- 10- Miscellaneous contact actions during the task**:Weight value: 1; VP value: 100%

Applying stage 3: Designing the five trial images using the above priority values

As the participating education company Tellus Group represented 1 participant rather than the minimum of 25 participants that would be required to test the predictive model in full: it was not possible to design any trial images. However, in response part 3 (see Appendix E) from the feedback document (see Appendix E), the participant suggested a preference for ‘squiggly lines’ when considering how to depict the concept behind the training module, suggesting a subconscious preference towards visuals that may trigger procedural as opposed to declarative memory (Reppa et al, 2020); which may be explained by the perceived procedural nature of this compliance task.

Applying stages 4, 5 & 7: Capturing the Perceived Visual Priority (PVP) values & Identifying the visual artefacts within the mental sketch image.

In response to Part 3- Question 1 in the questionnaire (see Appendix B), the participant selected zones A, F and J when asked to articulate the sections of the mental sketch (see Figure 19 below) they perceived as most relevant to ‘logical steps’ within the task; and zone J for the when asked to articulate any sections more relevant to ‘people and collaboration. When considering the sketch image provided by the participant, this revealed two squiggle-like features that may infer a subconscious understanding of the sequence of how the digital folder should be accessed (see Figure 19 below):

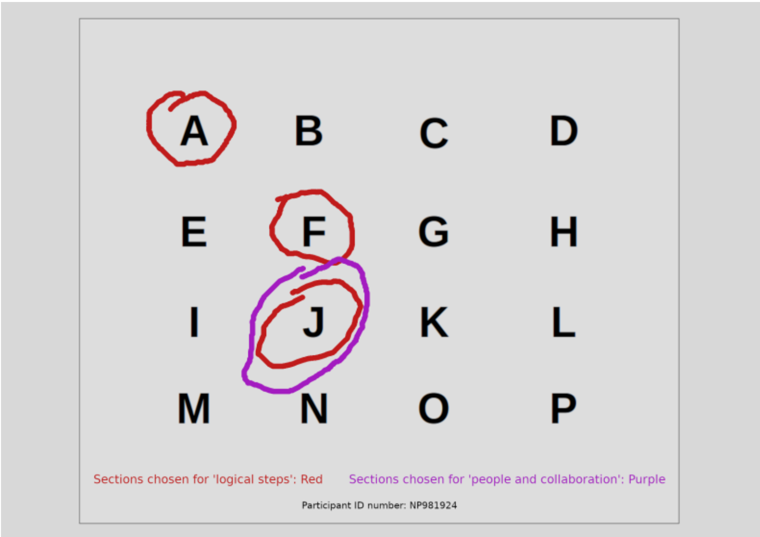


Figure 19: The comparison between the hot zones selected by the participant and the elements of interpreted sketch image representation

5.0. Implications for OnePal

5.1. Exploring contributions of the Visual Interface Iteration System (VIIS)

In considering Q1 of this study (see below): the tools designed as part of the conceptualised predictive model attempted to use a Task Completion Rating (TCR) value collected using a custom-designed information management system, which could then be compared against metrics related to perceived relevance across different areas of separate tested images. In turn, the researcher designed further tools to enable a future user of the predictive model to categorise groups of visual design characteristics suspected to trigger the cognitive binding process of Reppa et al (2020), and therefore enable a HR department to suggest visual design characteristics suited to different compliance tasks based on their ontology and preference towards procedural or declarative memory. Furthermore, in considering H1, H2 and H3 of this study (see below): although the data phase of the analysis was not successful in testing all 13 stages of the predictive model – where visual characteristics derived from TCR performance across a large group of participants could derive element of a repeatable visual design language for training imagery – the responses in the questionnaire provided by the participating organisations did suggest that visual stimuli do in-fact impact the ability for a learner to comprehend a new procedure; but did cause the researcher to re-evaluate the underlying assumption that a static training image would be the primary visual stimulus impacting learning cognition, and instead indicated that the visio-interactional elements of the holistic training experience were the variables that a future developed version of the A-L grid system should test.

'' Visual stimuli do in-fact impact the ability for a learner to comprehend a new procedure''

***Q1**. Can varying the visual attributes within a digital learning interface impact learning performance?*

***H1**: Varying visual features of imagery within a training environment will either negatively or positively impact the cognitive processes of learning in the user;*

H2: A system designed to capture participant data can on the one hand identify optimum visual features of a training interface;

***H3**: A portion of these visual learning processes can be replicated in a digital training interface.*

Furthermore, in considering Q2 of this study (see below): the stages of designing the information management system in stage 1 of the analysis did demonstrate that the folder structure designed using the referencing system of the information management system could be used to capture values C1-10 contributing towards the TCR value of the participant, with the participant able to log their activity using their participant ID number. This consequently suggests an opportunity for organisations to use their information management server structure simultaneously as a data collection mechanism for collecting TCR data, which – in a more advanced implementation of the predictive model concept design of this study – could continually inform the attributes of training imagery using these values. In addition, when considering H0 of this study (see below): although the results collected from the participating organisation were limited in demonstrating the ability to generate visual attributes of the training material, the task performance of the participant (TCR = 0.32) did demonstrate that the referencing system and cloud folder implementation was capable of automating the training process for specific tasks in ISO 9001 spreadsheets; suggesting that the information management system itself can increase the accuracy of compliance training.

''This did demonstrate that the cloud implementation could automate the training process for specific tasks in ISO 9001''

Q2. *Can a predictive modelling framework developed to iterate towards optimum visual attributes be used simultaneously as an information management system for tracking compliance among employees?*

H0: A procedure referencing system and digital file structure developed as part of the predictive model will increase the accuracy of compliance training;

And lastly, in considering Q3 of this study: the questionnaire responses and interpreted mental sketch image provided by the participant suggest that procedural memory is favoured over declarative memory, suggesting that a design language generated by the predictive model for compliance training may be limited to sketches and lines as opposed to the attributes of colour and social imagery for tasks that favour declarative cognition during the learning process. On the one hand, although this may indicate a limitation of predictive model on tasks specific to compliance: the visual experience and interaction with the cloud folder structure may in-fact represent the visual attributes that can be optimised in a compliance training environment, with the logic of the information management system undertaking the responsibility of ensuring compliance irrespective of its visual presentation.

Q3. *To what extent does the visual component of the training experience impact the overall compliance rate of the employee when completing a digital task?*

5.2. Suggesting the Inferred Orientation Category (IOC) values and future applications

In considering the KPIs identified at the beginning of the analysis (see Appendix D) to inform the design of the tools within the predictive model: the ability to generate Percieved Orientation Category (POC) values for visual characteristics collected across repeated training images may enable future applications of the model to derive an *Inferred Orientation Category (IOC)* value for a given image by comparing the performance across KPIs groups separate according to whether procedural or declarative memory is being most utilised (See Figure 20 below): in-turn, this would enable the data model suggested by Ganesan et al (2009) to be modified to collect data analogous to TCR data; but also combined with the below KPI groups to simultaneously monitor over a given project, and then select the pre-determined training image variation based on the inferred orientation.

Consequently, the former inferred Orientation Category (IOC) formulas (see Appendix A) have been arranged into the following formula, and in an excel format for if a future version of this predictive model is applied in an app-like interface in enterprise.

$$(\mathrm{ITIR}) = (\max(\{f(\mathrm{IOC\text{-}L}), (\mathrm{IOC\text{-}P}), (\mathrm{IOC\text{-}N})\})) \div \mathrm{TCR}$$

$$(\mathrm{ITIR}) = (\max(\{f(\mathrm{IOC\text{-}N1}), (\mathrm{IOC\text{-}N2}), (\mathrm{IOC\text{-}N3})\})) \div \mathrm{TCR}$$

Figure 20: The proposed behavioural KPI framework to identify the Inferred Orientation Category (IOC)

6.0. References

Alahmari, S., Renaud, K. and Omoronyia, I. (2022) “Moving beyond cyber security awareness and training to engendering security knowledge sharing,” *Information Systems and e-Business Management* [Preprint]. Available at: https://doi.org/10.1007/s10257-022-00575-2.

Abdi, S. *et al.* (2020) ‘Complementing educational recommender systems with Open Learner Models’, *Proceedings of the Tenth International Conference on Learning Analytics & Knowledge* [Preprint]. doi:10.1145/3375462.3375520.

Abolgasem , M. (2023) *A theory-based content-based image retrieval approach for capturing user preferences during query formulation*. thesis. University of Bedfordshire

ASPINALL, R. (1992) ‘An inductive modelling procedure based on Bayes’ theorem for analysis of pattern in Spatial Data’, *International journal of geographical information systems*, 6(2), pp. 105–121. doi:10.1080/02693799208901899.

Alén, R. (2019) *Measuring the Effectiveness of Information-Security Education, Training, and Awareness*. dissertation. Stockholm University.

Amare, G. (2022) “Reviewing the values of a standard operating procedure,” *Ethiopian Journal of Health Sciences* [Preprint]. Available at: https://doi.org/PMC3511899.

Arrabales, R., Ledezma, A. and Sanchis, A. (2010) “On the practical nature of artificial qualia,” *De Montfort University, Leicester, UK* [Preprint].

Asyraff, A. *et al.* (2021) “Stimulus-independent neural coding of event semantics: Evidence from cross-sentence fmri decoding,” *NeuroImage*, 236, p. 118073. Available at: https://doi.org/10.1016/j.neuroimage.2021.118073.

Balduzzi, D. and Tononi, G. (2009) “Qualia: The Geometry of Integrated Information,” *PLoS Computational Biology*, 5(8). Available at: https://doi.org/10.1371/journal.pcbi.1000462.

Basten, D. and Haamann, T. (2018) “Approaches for organizational learning: A literature review,” *SAGE Open*, 8(3), p. 215824401879422. Available at: https://doi.org/10.1177/2158244018794224.

Bellamy, R.K. *et al.* (2007) “Seeing is believing: Designing visualizations for managing risk and compliance,” *IBM Systems Journal*, 46(2), pp. 205–218. Available at: https://doi.org/10.1147/sj.462.0205.

Beynon-Davies, P. and Lederman, R. (2016) “Making sense of visual management through affordance theory,” *Production Planning & Control*, 28(2), pp. 142–157. Available at: https://doi.org/10.1080/09537287.2016.1243267.

Bobek, E. and Tversky, B. (2016) “Creating visual explanations improves learning,” *Cognitive Research: Principles and Implications*, 1(1). Available at: https://doi.org/10.1186/s41235-016-0031-6.

Bonney, E. *et al.* (2017) “Learning better by repetition or variation? is transfer at odds with task specific training?,” *PLOS ONE*, 12(3). Available at: https://doi.org/10.1371/journal.pone.0174214.

Brady, T.F. *et al.* (2008) “Visual long-term memory has a massive storage capacity for object details,” *Proceedings of the National Academy of Sciences*, 105(38), pp. 14325–14329. Available at: https://doi.org/10.1073/pnas.0803390105.

Cegarra-Navarro, J.-G. *et al.* (2017) “Linking procedural memory with organizational learning through knowledge corridors,” *Journal of Knowledge Management*, 21(6), pp. 1503–1522. Available at: https://doi.org/10.1108/jkm-01-2017-0018.

CAMPBELL, L., LOVING, T.J. and LEBEL, E.P. (2014) ‘Enhancing transparency of the research process to increase accuracy of findings: A guide for relationship researchers’, *Personal Relationships*, 21(4), pp. 531–545. doi:10.1111/pere.12053.

Choudhary, A. *et al.* (2021) ‘An integrated fuzzy intuitionistic sustainability assessment framework for Manufacturing Supply Chain: A study of UK based firms’, *Annals of Operations Research* [Preprint]. doi:10.1007/s10479-019-03452-3.

Cohen, I.G. *et al.* (2014) ‘The legal and ethical concerns that arise from using complex predictive analytics in health care’, *Health Affairs*, 33(7), pp. 1139–1147. doi:10.1377/hlthaff.2014.0048.

Chaudhary, S., Gkioulos, V. and Katsikas, S. (2022) “Developing metrics to assess the effectiveness of cybersecurity awareness program,” *Journal of Cybersecurity*, 8(1). Available at: https://doi.org/10.1093/cybsec/tyac006.

Cruz Villazón, C. *et al.* (2020) “Identification of key performance indicators in project-based organisations through the Lean Approach,” *Sustainability*, 12(15), p. 5977. Available at: https://doi.org/10.3390/su12155977.

Cohen, M.D. and Bacdayan, P. (1994) “Organizational routines are stored as procedural memory: Evidence from a laboratory study,” *Organization Science*, 5(4), pp. 554–568. Available at: https://doi.org/10.1287/orsc.5.4.554.

Dabholkar, A.U. (2020) “How Visual Management can help in improving Productivity in Manufacturing Operation ,” *International Journal of Scientific & Engineering Research*, 11(9).

Dai, Q. (2022) “Designing an accounting information management system using Big Data and Cloud Technology,” *Scientific Programming*, 2022, pp. 1–11. Available at: https://doi.org/10.1155/2022/7931328.

De Treville, S., Antonakis, J. and Edelson, N.M. (2005) "CAN standard operating procedures be motivating? reconciling process variability issues and behavioural outcomes1," *Total Quality Management & Business Excellence*, 16(2), pp. 231–241. Available at: https://doi.org/10.1080/14783360500054236.

Dhakal , R. (2018) *Measuring the Effectiveness of an Information Security Training and Awareness Program*. dissertation.

Doelle, M. (2019) "MEA compliance procedures: Overview of key design and implementation issues," *SSRN Electronic Journal* [Preprint]. Available at: https://doi.org/10.2139/ssrn.3371915.

Dottorato, T.D. (2010) *Human Resource Information Systems and the performance of the Human Resource Function*. thesis. LUISS Guido Carli.

Feldman, J. (2012) "The neural binding problem(s)," *Cognitive Neurodynamics*, 7(1), pp. 1–11. Available at: https://doi.org/10.1007/s11571-012-9219-8.

Fusar-Poli, P. *et al.* (2022) 'Ethical Considerations for Precision Psychiatry: A roadmap for research and clinical practice', *European Neuropsychopharmacology*, 63, pp. 17–34. doi:10.1016/j.euroneuro.2022.08.001.

Ganesan, E. and Paturi, R. (2009) "Key Performance Indicators Framework - A Method to Track Business Objectives, Link Business Strategy to Processes and Detail Importance of Key Performance Indicators in Enterprise Business Architecture," *MCIS 2009 Proceedings. 736* [Preprint].

Gray, O., McCance, T. and Brown, D. (2021) 'Exploring how key performance indicators influence nursing and midwifery practice: A mixed-methods study', *Journal of Advanced Nursing*, 77(12), pp. 4900–4918. doi:10.1111/jan.15049.

Gressgård, L.J. (2014) “Knowledge management and safety compliance in a high-risk distributed organizational system,” *Safety and Health at Work*, 5(2), pp. 53–59. Available at: https://doi.org/10.1016/j.shaw.2014.03.002.

Hashmi, H., Casanovas, P. and Koker, L. (2012) “Legal Compliance Through Design: Preliminary Results of a Literature Survey,” *La Trobe Law School, La Trobe University, Melbourne, Australia* [Preprint].

Harris Mohamed. (2020) ‘’Employee Satisfaction Dataset’’. Available at: https://www.kaggle.com/datasets/mohamedharris/employee-satisfaction-index-dataset?resource=download

Hatfield, G. (2007) “The reality of qualia,” *Erkenntnis*, 66(1-2), pp. 133–168. Available at: https://doi.org/10.1007/s10670-006-9030-1.

Hayble-Gomes, E. (2022) ‘The use of predictive modeling to identify relevant features for suspicious activity reporting’, *Journal of Money Laundering Control*, 26(4), pp. 806–830. doi:10.1108/jmlc-02-2022-0034.

Hristov, I. and Chirico, A. (2019) ‘The role of Sustainability Key Performance Indicators (kpis) in Implementing Sustainable Strategies’, *Sustainability*, 11(20), p. 5742. doi:10.3390/su11205742.

He, D. (2019) “Design and implementation of resource information management based on B/S structure,” *Journal of Physics: Conference Series*, 1345(5), p. 052028. Available at: https://doi.org/10.1088/1742-6596/1345/5/052028.

Hemingway, C.J. (1999) *A socio-cognitive theory of Information Systems and initial applications*. thesis. University of Leeds .

Kang, K. and Bae, C. (2021) “Memory model for morphological semantics of visual stimuli using sparse distributed representation,” *Applied Sciences*, 11(22), p. 10786. Available at: https://doi.org/10.3390/app112210786.

Kelly, L. M., & Cordeiro, M. (2020). Three principles of pragmatism for research on organizational processes. Methodological Innovations, 13(2). https://doi.org/10.1177/2059799120937242

Khan, B. *et al.* (2011) “Effectiveness of information security awareness methods based on psychological theories,” *African Journal of Business Management*, 5(26). Available at: https://doi.org/10.5897/ajbm11.067.

Li, C.-L. *et al.* (2018) “Memory shapes visual search strategies in large-scale environments,” *Scientific Reports*, 8(1). Available at: https://doi.org/10.1038/s41598-018-22731-w.

Li, Z.S. *et al.* (2022) “Towards privacy compliance: A design science study in a small organization,” *Information and Software Technology*, 146, p. 106868. Available at: https://doi.org/10.1016/j.infsof.2022.106868.

Loorits, K. (2014) “Structural qualia: A solution to the hard problem of consciousness,” *Frontiers in Psychology*, 5. Available at: https://doi.org/10.3389/fpsyg.2014.00237.

Lum, J.A. and Conti-Ramsden, G. (2013) “Long-term memory: A review and meta-analysis of studies of declarative and procedural memory in specific language impairment,” *Topics in Language Disorders*, 33(4), pp. 282–297. Available at: https://doi.org/10.1097/01.tld.0000437939.01237.6a.

Liu, J., Chen, Q. and Tian, X. (2021) ‘Illustration design model with clustering optimization genetic algorithm’, *Complexity*, 2021, pp. 1–10. doi:10.1155/2021/6668929.

Maj, S.P. (1991) “Analysis and design of Laboratory Information Management Systems,” *Chemometrics and Intelligent Laboratory Systems*, 13(2), pp. 157–162. Available at: https://doi.org/10.1016/0169-7439(91)90005-m.

Maass, W. (2022) ‘Concept Superimposition: Using Conceptual Modeling Method for Explainable AI’, *ConferencAAAI 2022 Spring Symposium on Machine Learning and Knowledge Engineering for Hybrid Intelligence* [Preprint].

Machajdik, J. and Hanbury, A. (2010) ‘Affective image classification using features inspired by psychology and art theory’, *Proceedings of the 18th ACM international conference on Multimedia* [Preprint]. doi:10.1145/1873951.1873965.

Majeed, Z.A. and Özyer, S.T. (2016) “Implementation of the human resources information systems and comparative study of various platforms,” *Universal Journal of Engineering Science*, 4(4), pp. 66–78. Available at: https://doi.org/10.13189/ujes.2016.040402.

Miri, S.A. *et al.* (2014) “Staff organization training: Designing, stages, and methods,” *Procedia - Social and Behavioral Sciences*, 129, pp. 227–235. Available at: https://doi.org/10.1016/j.sbspro.2014.03.671.

Murata, K. (2018) “A Study on Digital Visual Management for Providing Right Transparency against Emergencies,” *Nihon University, College of Industrial Technology, Department of Industrial Engineering and Management, Chiba, Japan* [Preprint].

Nallaperumal, K. (2013) ‘Engineering Research Methodology A Computer Science and Engineering and Information and Communication Technologies Perspective’, *PHI Learning Private Limited, New Delhi, India* [Preprint].

Nogueira, A.R. *et al.* (2022) ‘Methods and tools for causal discovery and causal inference’, *WIREs Data Mining and Knowledge Discovery*, 12(2). doi:10.1002/widm.1449.

Olszewski, L., Bhattacharya, A. and Harrington, T.S. (2019) “Exploring Visual Management and Continuous Improvement in a Manufacturing Context: A Structured Bibliometric Analysis,” *Norwich Business School, University of East Anglia* [Preprint].

Pedell, B.J. (1996) “Examining the role of Visual Discourse Analysis in multimedia instructional design,” *Proceedings of the 14th annual international conference on Systems documentation Marshaling new technological forces: building a corporate, academic, and user-oriented triangle - SIGDOC '96* [Preprint]. Available at: https://doi.org/10.1145/238215.238265.

Pedell, B.J. (1996 “An approach to designing online help for pictorial instruction sets,” *IPCC 94 Proceedings. Scaling New Heights in Technical Communication* [Preprint]. Available at: https://doi.org/10.1109/ipcc.1994.347544.

Perši, N. (2008) ‘Conceptual Modelling of Complex Production Systems ’, *JIOS*, 32(2).

Puhakainen, P. and Siponen, M. (2010) “Improving employees' compliance through Information Systems Security training: An action research study,” *MIS Quarterly*, 34(4), p. 757. Available at: https://doi.org/10.2307/25750704.

Ramaraju, S., Roula, M.A. and McCarthy, P.W. (2020) “Transcranial direct current stimulation and working memory: Comparison of effect on learning shapes and English letters,” *PLOS ONE*, 15(7). Available at: https://doi.org/10.1371/journal.pone.0222688.

Redner, G. and Ndungu, E. (2014) “Process and Tools for Assessing Compliance with Standard Operating Procedures,” *PharmaSUG 2014 Conference Proceedings* [Preprint].

Reppa, I. *et al.* (2020) “The relative contribution of shape and colour to object memory,” *Memory & Cognition*, 48(8), pp. 1504–1521. Available at: https://doi.org/10.3758/s13421-020-01058-w.

Roza Albareta, A. and Mursanto, P. (2019) “Design of standard operating procedure for requirement engineering in software development: Case study data processing integration subdirectorate statistics Indonesia,” *Journal of Physics: Conference Series*, 1175, p. 012081. Available at: https://doi.org/10.1088/1742-6596/1175/1/012081.

Reijers, W. *et al.* (2017) ‘Methods for practising ethics in Research and Innovation: A Literature Review, critical analysis and recommendations’, *Science and Engineering Ethics*, 24(5), pp. 1437–1481. doi:10.1007/s11948-017-9961-8.

Rezaei, M. (2022) *Machine Learning in Regulatory Compliance Software Systems: An Industrial Case Study*. dissertation. Faculty of Computing.

Roman, L.C. *et al.* (2017) ‘Navigation in the Electronic Health Record: A review of the safety and usability literature’, *Journal of Biomedical Informatics*, 67, pp. 69–79. doi:10.1016/j.jbi.2017.01.005.

Ruvini, J.-D. and Dony, C. (2000) “APE: Learning User’s Habits to Automate Repetitive Tasks,” *Proceedings of the 5th international conference on Intelligent user interfaces* [Preprint]. Available at: https://doi.org/10.1145/325737.325854.

Sanborn, A.N., Griffiths, T.L. and Navarro, D.J. (2010) ‘Rational approximations to rational models: Alternative algorithms for category learning.’, *Psychological Review*, 117(4), pp. 1144–1167. doi:10.1037/a0020511.

Seyffarth, T. and Kuehnel, S. (2020) “Maintaining business process compliance despite changes: A decision support approach based on process adaptations,” *Journal of*

Decision Systems, 31(3), pp. 305–335. Available at: https://doi.org/10.1080/12460125.2020.1861920.

Squire, L.R. and Zola, S.M. (1996) "Structure and function of declarative and nondeclarative memory systems," *Proceedings of the National Academy of Sciences*, 93(24), pp. 13515–13522. Available at: https://doi.org/10.1073/pnas.93.24.13515.

Staats, B.R. and Gino, F. (2012) "Specialization and variety in repetitive tasks: Evidence from a Japanese bank," *Management Science*, 58(6), pp. 1141–1159. Available at: https://doi.org/10.1287/mnsc.1110.1482.

Stöber, T., Kotzian, P. and Weißenberger, B.E. (2018) "Design matters: On the impact of compliance program design on corporate ethics," *Business Research*, 12(2), pp. 383–424. Available at: https://doi.org/10.1007/s40685-018-0075-1.

Tian, N. *et al.* (2022) 'Clustering- and transformer-based networks for the style analysis of logo images', *Computational Intelligence and Neuroscience*, 2022, pp. 1–11. doi:10.1155/2022/2090712.

Trubetskaya, A. and Mullers, H. (2021) "Transforming a global human resource service delivery operating model using lean six sigma," *International Journal of Engineering Business Management*, 13, p. 184797902110512. Available at: https://doi.org/10.1177/18479790211051267.

Tschakert, K.F. and Ngamsuriyaroj, S. (2019) "Effectiveness of and user preferences for Security Awareness Training Methodologies," *Heliyon*, 5(6). Available at: https://doi.org/10.1016/j.heliyon.2019.e02010.

Tsuchiya, N., Taguchi, S. and Saigo, H. (2016) "Using category theory to assess the relationship between consciousness and integrated information theory," *Neuroscience Research*, 107, pp. 1–7. Available at: https://doi.org/10.1016/j.neures.2015.12.007.

Tull, K. (2018) “Designing and Implementing Health Management Information Systems,” *K4D Helpdesk Report 376. Brighton, UK: Institute of Development Studies* [Preprint].

Victoria, L.W., Pyles, J.A. and Tarr, M.J. (2019) “The relative contributions of visual and semantic information in the neural representation of object categories,” *Brain and Behavior*, 9(10). Available at: https://doi.org/10.1002/brb3.1373.

Williams, L., Brady, T. and Störmer, V. (2021) “Category labels do not improve working memory performance for ambiguous shapes,” *Journal of Vision*, 21(9), p. 2778. Available at: https://doi.org/10.1167/jov.21.9.2778.

Williams, T.R. (1993) “Text or graphic: An information processing perspective on choosing the more effective medium,” *Journal of Technical Writing and Communication*, 23(1), pp. 33–52. Available at: https://doi.org/10.2190/1gvh-3c6r-4rt1-jfqm.