WHERE THE DATA IS: AN EXPLORATORY STUDY OF MIXED-REALITY IN THE WET LAB DOMAIN

Research Paper

Peter Hoghton, Monash University, peter.hoghton@monash.edu

Henry Linger, Monash University, henry.linger@monash.edu

Maxime Cordeil, Monash University, max.cordeil@monash.edu

Tim Dwyer, Monash University, tim.dwyer@monash.edu

Kim Marriott, Monash University, kim.marriott@monash.edu

Luke Visser, Agilent Technologies, luke.visser@agilent.com

Abstract

In this paper we present the first naturalistic (in-situ) exploratory study seeking to apply mixed-reality (MR) technologies within the industrial chemical laboratory (wet lab) domain with the aim of identifying opportunities and challenges for such applications. This research was conducted in partnership with Agilent Technologies (Agilent), an industry leader in the wet lab domain, which allowed us to draw on domain expert knowledge of actual work practices to inform the design of our system and its subsequent evaluation. This naturalistic approach is in stark contrast to most existing MR research, which usually involves tightly controlled experimental conditions. Despite this, designing and evaluating solutions in-situ must be explored in order to better understand how these systems succeed or fail to meet user requirements in an industrial environment involving actual work practices. This approach enabled the discovery of a new construct which we term "physically embedded data". We conclude that existing process models need to be extended to facilitate the design of effective MR systems for knowledge work practices by explicitly incorporating this phenomenon. This understanding also forms the basis for further research opportunities into a new system design methodology for industrial MR support systems for knowledge work practices.

Keywords: Mixed-Reality, Augmented Reality, Virtual Reality, Knowledge Work, Wet Lab.

Acknowledgements

The authors would like to express our sincere thanks to Mr. Kingsley Stephens for his contributions to the mixed-reality prototypes used during this study. We would also like to thank Agilent Technologies for funding and supporting this research project. Finally, we would like to thank all the participants from Agilent and Monash University's Faculty of Pharmacy and Pharmaceutical Sciences.

1 Introduction

Industrial work environments are complex in many respects and require a high level of domain expertise. Effective support for industrial work requires appropriate technology that is designed in collaboration with domain experts in order to understand actual work practices, rather than prescribed process definitions, within a specific work environment. This proposition underpins the Industry 4.0 movement where the objective is to use "smart" technologies to increase efficiency and reduce human errors in industrial activities. Manufacturing, assembly and maintenance industries, with their relatively linear and discrete work activities, were among the early adopters of Industry 4.0.

However, other industry sectors deal with more complex human-centred activities. In this context, work activities focus on human decision making and judgement, informed by diverse data and mediated by environmental, contextual and social factors. In work environments involving such knowledge work (Iivari & Linger, 1999), the challenge is to design technology to support those activities in a way that people retain control of the work, rather than automate that work.

We were approached by our industry partner, Agilent Technologies (Agilent), who believed that mixed-reality (MR) technologies could potentially improve knowledge work practices in the context of an industrial chemical laboratory (wet lab) - a laboratory which may be used in the preparation of liquid chemicals for scientific research. Our study uses design science to explore this issue. In this paper we use MR as an encompassing term for all technologies on the reality-virtuality continuum (Milgram et al., 1995), most notably augmented-reality (AR) and virtual-reality (VR). MR offers the possibility of supporting work activities by bridging digital and physical worlds. This includes providing digital information directly overlaid on the surrounding physical work environment and reconstructing accurate digital representations of physical environments and activities. Our overarching research project addresses the question 'What are the opportunities and challenges for deploying an industrial mixed-reality support system for knowledge work practices?'.

Our collaboration with Agilent situates our research within an actual wet lab environment. In this paper we address the specific research question:

How can mixed-reality support knowledge work practices in the wet lab domain?

The significance of our study is that it is the first naturalistic (in-situ) study investigating the use of MR in this domain and draws on the domain knowledge of the workers performing actual work practices. This contrasts with the artificial experimental conditions that characterize most MR research. Our research setting allows us to explore individual and collaborative work practices, identify tacit and explicit knowledge that informs those practices, prototype MR applications and evaluate the technology together with the domain workers.

We discovered that the performance of knowledge work practices relies on data which is "physically embedded". We define *physically embedded data* as data or information inherent in the form and state of physical context, objects, people, or other (non-digital) artifacts involved in the activity. Examples of such physically embedded data in the context of a wet lab (as discussed in this paper) are experiment notes written in a paper logbook, contamination in a test-tube indicating the need to sterilize it, and scratches in the paint from which it is possible to infer that the radio frequency (RF) shielding of a mass-spectrometer is damaged. Another important aspect of our study was the collaboration between domain experts which points to the role of tacit knowledge and social learning in the performance of knowledge work practices.

Our reflection on the deployment of our MR systems highlighted the need to incorporate relevant embedded data in the design of the MR systems. This points to the need to extend how work processes (and practices) are formally represented. Process models need to explicitly represent physically embedded data and the learning loops inherent in the collaboration between the domain experts. Such models would identify the interface between data as an abstract entity and its real-world representation. Moreover, these models would facilitate the design of MR applications by clarifying what aspects of the practice can be appropriately supported by MR systems.

The insights gained from our study provide the basis for articulating a new system design methodology. This methodology would include observation of work practices, elicitation of tacit knowledge from domain experts and representation of process and practice in models incorporating physically embedded data. Such a methodology would support the industrial deployment of MR technologies and systems for knowledge work practices.

The next section discusses related work in this area and justifies our design science methodological approach. It is followed by a detailed account of each stage of our exploratory study in Section 3. We then provide a discussion of the impact of this research, including possible avenues for further research, in Section 4.

2 Related Work

In this study we theorize the activities within the wet lab domain as knowledge work. Knowledge work is defined by Iivari & Linger (1999) as work that is based on a body of knowledge and produces outputs which are primarily knowledge. Knowledge work practices require a deep understanding of 'objects of work' - physical artefacts or abstract phenomena essential to the practice. Work practices within the wet lab domain rely on human decision making and judgement, informed by diverse data and mediated by environmental, contextual and social factors, and as such can be considered knowledge work practices. The diversity of data within knowledge work practices is contextual, therefore a system designed to support these practices must compliment this (Burstein & Linger, 2003). MR offers the possibility of supporting knowledge work practices by providing contextual information directly overlaid on the surrounding physical work environment and reconstructing accurate digital representations of physical environments and activities, bridging digital and physical worlds.

The divide between the digital and physical world has been a long-standing concern in MR research. The established approach in MR to bridge this divide is to create a "Digital Twin" model of the physical world. In this paper, we propose an alternative approach based on the physically embedded data construct where data is conceptualised as an abstract entity represented in a variety of forms, from the tacit contextual state of physical objects to tacit and explicit knowledge. Our approach extends the work of researchers like Dourish (2004) in which data are seen as purely digital entities with links to a tangible object.

Existing MR research largely focuses on interaction techniques, devices, perception and applications (Marriott et al., 2018). However, there is currently a need to explore how MR can be used effectively in the workplace and how to integrate it in collaborative industrial workflows, including knowledge work practices.

Ens et al. (2019) explored 110 research papers on collaborative MR from the past three decades. They found that 95% of papers focused on synchronous collaboration, with 68% focusing on distributed collaboration. Real-time remote support tasks were the most common application explored. They conclude, however, that most studies undertaken in this area have been controlled laboratory experiments containing artificial tasks with the intent of uncovering general design principles (Masood and Egger, 2019; Schmalstieg and Hollerer, 2016). For example, a popular substitute for industrial assembly tasks involves getting participants to assemble Lego models by following step-by-step instructional guides (Gavish et al., 2015; Paelke, 2014). This extends to collaborative MR research, with much of the focus on dedicated collaborative research spaces (Müller, 2015; Müller, 2019), CAVE Automatic Virtual Environments (CAVEs) (Cordeil et al., 2016) or other self-contained areas with built-in tracking systems (Isenberg, 2010).

It is not uncommon for researchers to conclude that modern MR technology simply has too many limitations to be effectively implemented in real world contexts (in-situ) in its current state. Some of the most cited limitations being bulkiness (Franklin, 2006), tracking instability (Marner et al., 2013), and a narrow field of view (Bork et al., 2018). While the certainty and replicability of a controlled study environment can overcome, or at least alleviate, such limitations, another likely reason that studies are rarely conducted in-situ is due to the level of industry access required by researchers, adding to the logistical complexity of the study. Despite this, designing and evaluating solutions in-situ must be explored in order to better understand how these systems succeed or fail to meet user requirements in an industrial environment involving actual work practices.

There is also a need for additional research into conceptual frameworks for the design of MR systems which support industrial knowledge work practices. Dourish (2004) discusses the importance of the relationship between both the physical and symbolic nature of interaction and how this relationship should be a principal design consideration of digital support systems. They also introduce the concept of data objects being mapped onto physical objects in the user's environment. However, this is largely explored in the context of tangible computing whereby data objects can be displayed and allow interaction through a physical interface. This idea should be extended to consider the role of data more broadly in an industrial MR support system.

3 Methodology

Currently, there is a distinct lack of practical "informing" (Gill and Bhattacherjee, 2009) provided to the industries from which most MR research problems are drawn. To address this, we have chosen a Design Science Research (DSR) approach (Hevner et al., 2004). A distinguishing feature of DSR is the relevance of research results to real-world applications (Straub and Ang, 2011). DSR researchers (Lee et al., 2011; Myers and Baskerville, 2009) acknowledge the need for researchers to publish both theoretical and practical contributions. We achieve this through the situated design and implementation of an artefact (MR prototypes) (Gregor and Hevner, 2013), followed by a naturalistic evaluation of the artefact (Carlsson and Johansson, 2010), and are ultimately able to demonstrate "proof of value" (Gregor and Hevner, 2013) to industry through domain expert testimony. Despite the logistical complexities and technological limitations faced, this approach enabled us to obtain a greater understanding of MR design and deployment for actual industrial workflows, rather than general design principles. This understanding also forms the basis for further research opportunities into a new system design methodology for industrial MR support systems for knowledge work practices.

As discussed in the previous section, most existing MR research is characterized by tightly controlled laboratory studies which uncover general design principles without practically "informing" the industry from which the research problem was drawn. We address this by conducting the first naturalistic (in-situ) exploratory study of MR in the wet lab domain in partnership with Agilent. This approach enabled us to explore work practices, identify tacit and explicit knowledge informing those practices, and prototype and evaluate MR solutions together with domain experts.

The study was conducted in three distinct stages, as shown in Figure 1. The first stage, Domain Knowledge Acquisition *(Section 3.2)*, involved embedding researchers within the wet lab domain. We co-designed the MR prototypes by conducting a brainstorming workshop with domain experts to identify the work activities which presented the greatest opportunity for MR support. The second stage, Iterative Prototyping *(Section 3.3)*, involved the development, deployment and evaluation of MR prototype systems. The third stage, Learning & Reflection *(Section 3.4)*, was a self-reflection on the design and implementation of the MR prototypes.

Each of these stages is informed by steps in the DSR methodology introduced by Gregor and Hevner (2013). That is, stage (1) includes problem identification and definition of solution objectives; stage (2) design, development and demonstration; stage (3) is evaluation and communication of "proof of value" to stakeholders.

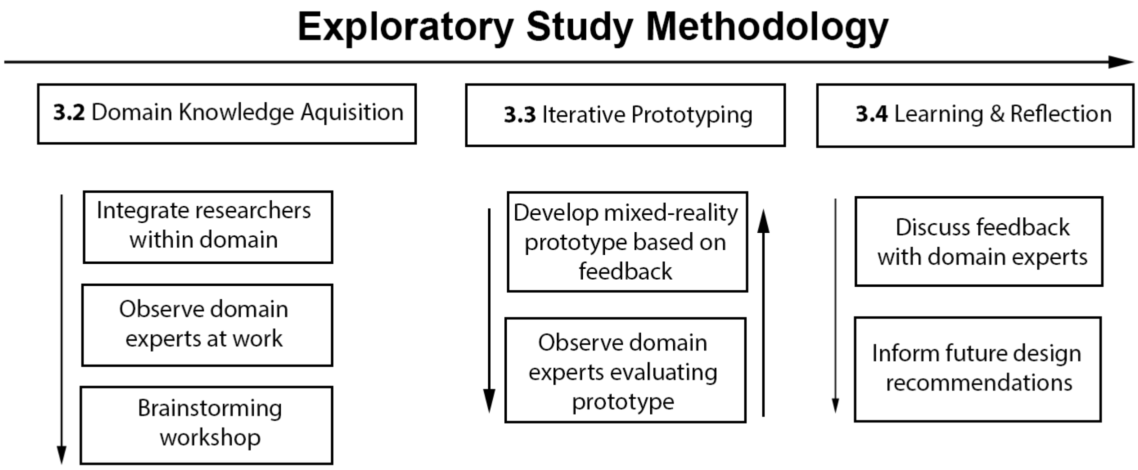

Figure 1. The study methodology.

3.1 Study Setting

The exploratory study lasted approximately 24 months in total, beginning in late 2017. The study setting was a wet lab. Wet labs are highly collaborative environments, with complex shared workspaces, where domain experts are required to cooperate and interact with numerous physical objects including complex scientific instrumentation and potentially hazardous chemicals.

The study was conducted in partnership with Agilent, an industry leader in the wet lab domain, and one of their customers; Monash University's Faculty of Pharmacy and Pharmaceutical Sciences (Monash). Monash was primarily chosen for logistical reasons, an existing legal agreement between Agilent and Monash, facilitating researchers' access to the wet labs and domain experts. Moreover, Monash has a large volume of Agilent instruments. The need to observe the customer setting emerged from our interaction with Agilent domain experts who saw MR systems to be most beneficial to their customers.

Our study had access to domain experts (more than 50) when the researchers were embedded in Agilent. In addition, at Monash, the study focused on two participants who regularly used the Agilent instruments during a typical day, as well as an Agilent technician who was on-site performing routine maintenance. We also had access to other users of the wet lab at Monash.

3.2 Domain Knowledge Acquisition

Initially the researchers were integrated within Agilent for approximately 6 months in order to gain a deep understanding of the day-to-day work practices and environments of Agilent and the intricacies of Agilent's signature spectroscopy instrumentation. During this time, we conducted a brainstorming workshop, as outlined in the requirements gathering process introduced by Goodwin et al. (2016), with domain experts to explore the potential value and requirements of an MR support system.

During the workshop, participants were tasked with brainstorming and storyboarding existing work practices with their ideal MR support solutions. From this, it was determined that customer focused work practices provided the greatest opportunity for MR intervention. Specific activities that were discussed included remote technical support and sample preparation.

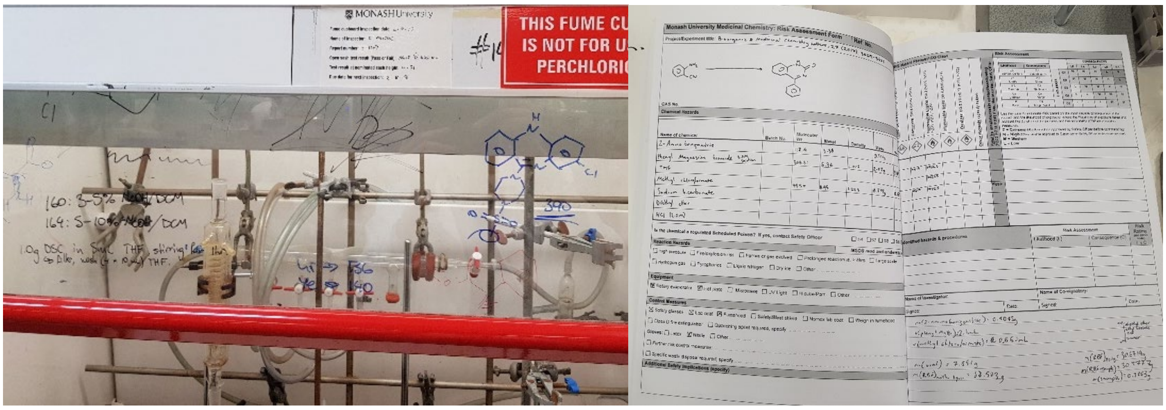

Figure 2. *Chemical formulas written on a fume cupboard window (left) and experiment data written in a paper logbook (right) within a wet lab at the customer site.*

At Monash, each participant was observed during a typical workday. Of particular interest during the observations was engagement with physical objects and data in various forms. Participants wrote notes on a fume cupboard window and in a physical logbook to record important information about their work, including how samples were prepared *(Figure 2)*. When asked, participants stated that there were no digital alternatives and that this was considered common practice in the domain.

A more subtle example was the choice of scientific equipment. One of the participants stated, *"I use this [instrument] because there is usually no waiting time, even though the [instrument] at the back [of the laboratory] is better"*. This was particularly noteworthy as both instruments were of the exact same make and model. When asked why one instrument was considered better than another the participant was unable to give a clear reason. However, the Agilent technician explained that the instrument was likely to be perceived as "better" because some of its internal components had recently been replaced. This information was unknown by other participants, who entered the laboratory to use this particular instrument. This example shows that participants form a particular mental model of the activity based on their knowledge of their environment and the physical objects in that environment.

In another example, the Agilent technician identified potential issues with an instrument that the internal diagnostics failed to detect. This included listening for a particular sound being emitted from the instrument to determine if it were functioning correctly and observing damaged paint on one of the internal components that if left damaged could have negatively affected the results obtained from the instrument.

Our interaction with Agilent domain experts and close observations of work practices at Monash provided a rich picture of the deployment potential for MR systems. At the same time, it gave us an insight into the complexity of the work practices and the importance of both tacit and implicit knowledge of the work environment, even if it is not recorded in the prescribed process definition. The challenge is to incorporate the data to represent such knowledge in the design of MR support systems.

3.3 Iterative Prototyping

The brainstorming workshop was the basis on which we determined that most value would flow from an MR system that could directly interface with the complex spectroscopy instrumentation found in Agilent customer wet labs. The first prototype was designed to provide remote technical support for the customer using the instrumentation. The Agilent support technician could remotely interact with the customer's instrument through virtual reality (VR), while the customer used augmented reality (AR) overlays to see what the technician was doing in real-time. The prototype system displayed an augmented hologram of a single instrument and could highlight individual internal components and display real-time diagnostic information about them *(Figure 3)*. This system allowed users to monitor an instrument in real-time without having to rely on the complex onboard software through the connected workstation. The system also had some collaborative capabilities, allowing multiple users to connect to the same session and view the same instrument data remotely.

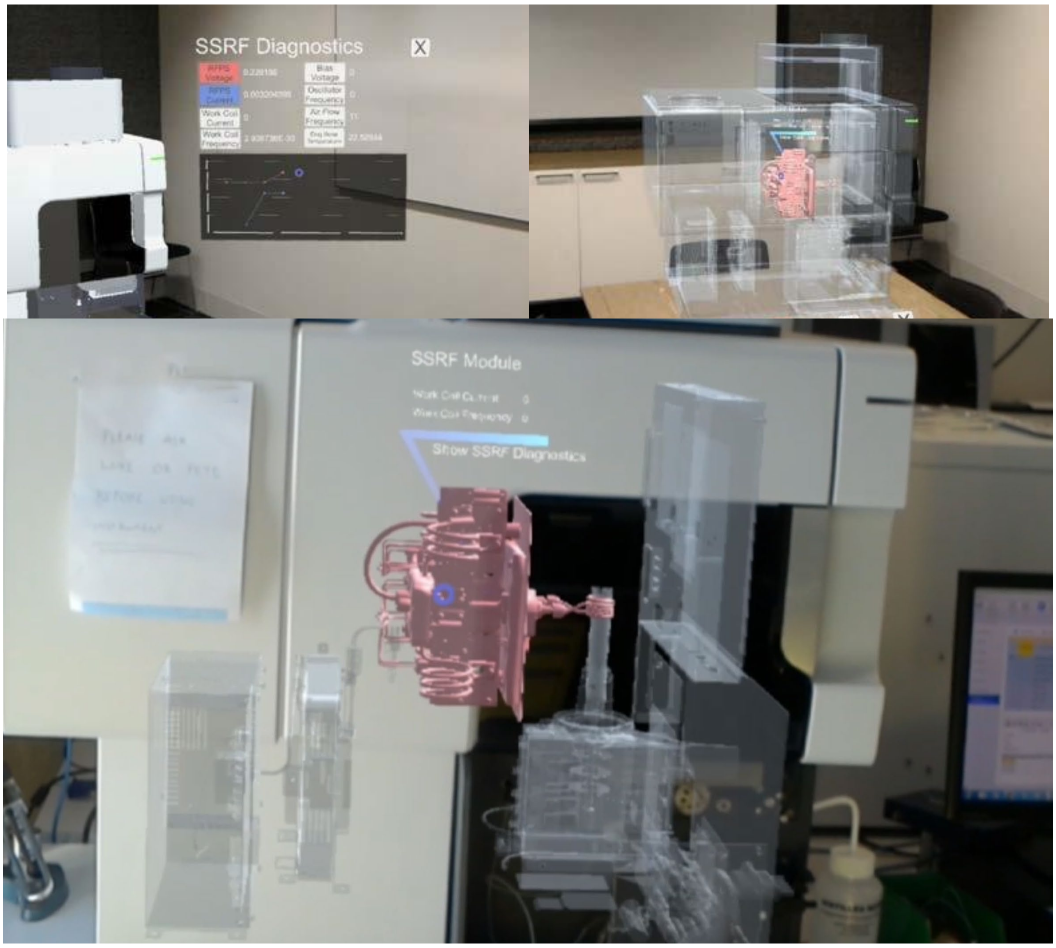

Figure 3. Screenshots of the first MR prototype developed during the study showcasing a remote support activity. The remote technician can view real-time diagnostic information about the customer's instrument (top left) and view a hologram of the instrument and it's internal components at 1:1 scale (top right). The customer can then be guided through simple maintenance tasks by the technician via 'x-ray' style holographic overlays (bottom).

Our observations and discussions with domain experts at Monash led to the development of a second prototype. However, due to technological limitations with current AR technology at the time, such as difficulties tracking small glass test tubes, we developed this prototype entirely in VR. Incorporating the surrounding lab environment into the solution also presented a challenge in determining which objects of work were relevant to the activity (Kalkofen et al., 2007) and then tracking them. VR enabled us to overcome these challenges by reproducing a complete virtual wet lab, with spectroscopy instrumentation, fume cupboards, and test tubes *(Figure 4)* ensuring all objects of work were present and tracked without the need for complex tracking systems. Within the virtual lab, users could interact with artefacts, see real-time instructional overlays, and prepare samples for analysis. The information overlays provided in this prototype were based on the object's interaction history. This allowed the user to be made aware of relevant information, such as potential contamination of a test tube during sample preparation.

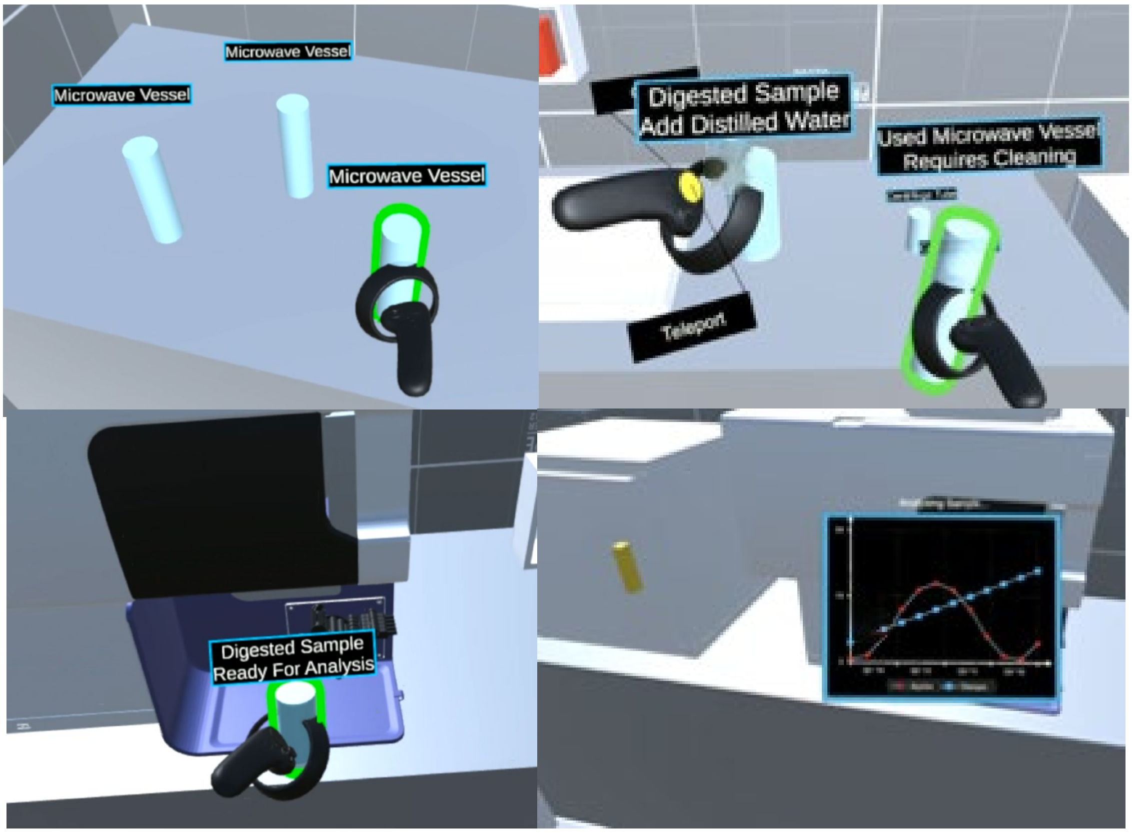

Figure 4. Screenshots of the second MR prototype developed during the study showcasing a sample preparation activity. The user can interact with small glass test tubes (top left), prepare samples (top right), analyse samples (bottom left), and analyse results (bottom right).

Development of both prototypes took approximately one year, throughout which researchers conducted iterative evaluations of each system with Agilent domain experts and Monash lab users. These evaluations focused on how the prototypes met the needs of the workers when performing actual work practices. Two formal evaluations were conducted with a subset of participants from the brainstorming workshop, as this group had been involved in determining the requirements of the MR support system. In addition, several informal evaluations took place throughout the year. In the formal evaluations, domain experts were given a brief 10-minute training session on how to use the system and were then observed by researchers while they used the system in a real wet lab to complete actual work tasks for approximately 30 minutes. In the informal evaluations, participants were given unlimited time to use the system without prior training or set tasks. In each case participants were then asked for verbal feedback.

Feedback about the first prototype suggested that domain experts wanted a broader view of the customer's work environment. Multiple participants specifically mentioned that they needed to see the pump tubing connected to the instrument and the contents of any nearby samples. All participants agreed that they would prefer to see a "first person" point of view representing exactly what the customer sees in their work environment. There was also feedback on the technological limitations of the system, including it's narrow field of view and tracking instability, which is consistent with prior MR research as outlined in Section 2.

The second prototype addressed this feedback by incorporating additional aspects of the surrounding wet lab environment into a VR simulation of a virtual wet lab. Participants stated that the virtual wet lab was "surprisingly immersive". Additional feedback suggested that participants still required further information about the state and context of objects within the lab. One user stated that they wanted to be able to see "more detail [about] the workflow" as it was being undertaken.

3.4 Learning & Reflection

A key problem with the prototypes was that they attempted to directly translate existing support systems into MR instead of utilizing the advantages of the MR technology to improve the technological support for the user. As such, users who were already familiar with the existing systems did not see added value of the MR system beyond the novelty of the new technology.

Our reflection was that our prototypes failed to demonstrate the potential for MR to identify, track and incorporate data to represent knowledge and information inherent in the environment and the objects in that environment. Many of the observations of in-situ work practices made during the study need to be recorded to articulate the implicit or incidental knowledge and information which is relevant in those practices. Our prototype evaluations suggest that a conventional approach to MR system co-design fails to add value to knowledge work practices which rely on such information and knowledge.

We use the term *physically embedded data* as an encompassing term representing data, information and knowledge inherent in the form and state of objects, people, context or other (non-digital) artifacts involved in an activity. Our observations suggest that knowledge work practices, such as those in a wet lab, rely on physically embedded data even when such data is not made explicit to those involved in the activity. Designing effective MR systems to support knowledge work practices requires the relevant physically embedded data to be identified so that actual work practices can be better understood and incorporated into the design of the system.

As discussed in Section 1, we were originally approached by Agilent who believed that MR technologies could potentially improve knowledge work practices in the context of a wet lab and their spectroscopy instrumentation. As part of our design science approach, the relevance of this research to real-world applications must also be acknowledged. The following is a statement provided by a senior manager at Agilent demonstrating the "proof of value" of this research to Agilent:

> *"MR technology research has considerable value to Agilent in our capacity to provide assisted, augmented solutions to our customers. This comes in two forms, one visionary in that it scouts and researches the future to see what could be and the other determining a feasible path that leads us to those customer outcomes in the future. There is the capacity to use this technology to train a naïve user through to supporting an expert one. One of the most obvious examples is that of supporting customers during the COVID-19 pandemic, MR technology gives us a way of being there with the customer when they need assistance.*
>
> *Laboratory customers face two problem domains that this research addresses. The first is dealing with digitally silent lab items that hold information the user needs to cognitively manage (e.g., what is in this glassware? Is it clean?). The second is helping them in a workflow that sits in an emerging MR domain, but which needs to incorporate digitally silent items.*
>
> *This body of research helps Agilent understand a laboratory more fully, it's workflow and the ability to design future solutions to ease the cognitive load of our customers in their labs."*

4 Discussion

The overarching aim of this research project was to identify opportunities and challenges for MR support within knowledge work practices. Our collaboration with Agilent enabled us to explore this within the context of the wet lab domain.

As discussed in the previous section, our prototypes had failed to properly understand and utilise the physically embedded data relevant to the work practices that we explored. In fact, current process and practice models do not account for this phenomenon at all. These models need to be extended to account for the coupling of artefacts and their physically embedded data. While this is outside the scope of this research paper, here we provide a discussion of how process modelling may incorporate physically embedded data to increase understanding of knowledge work practices and identify opportunities for MR support.

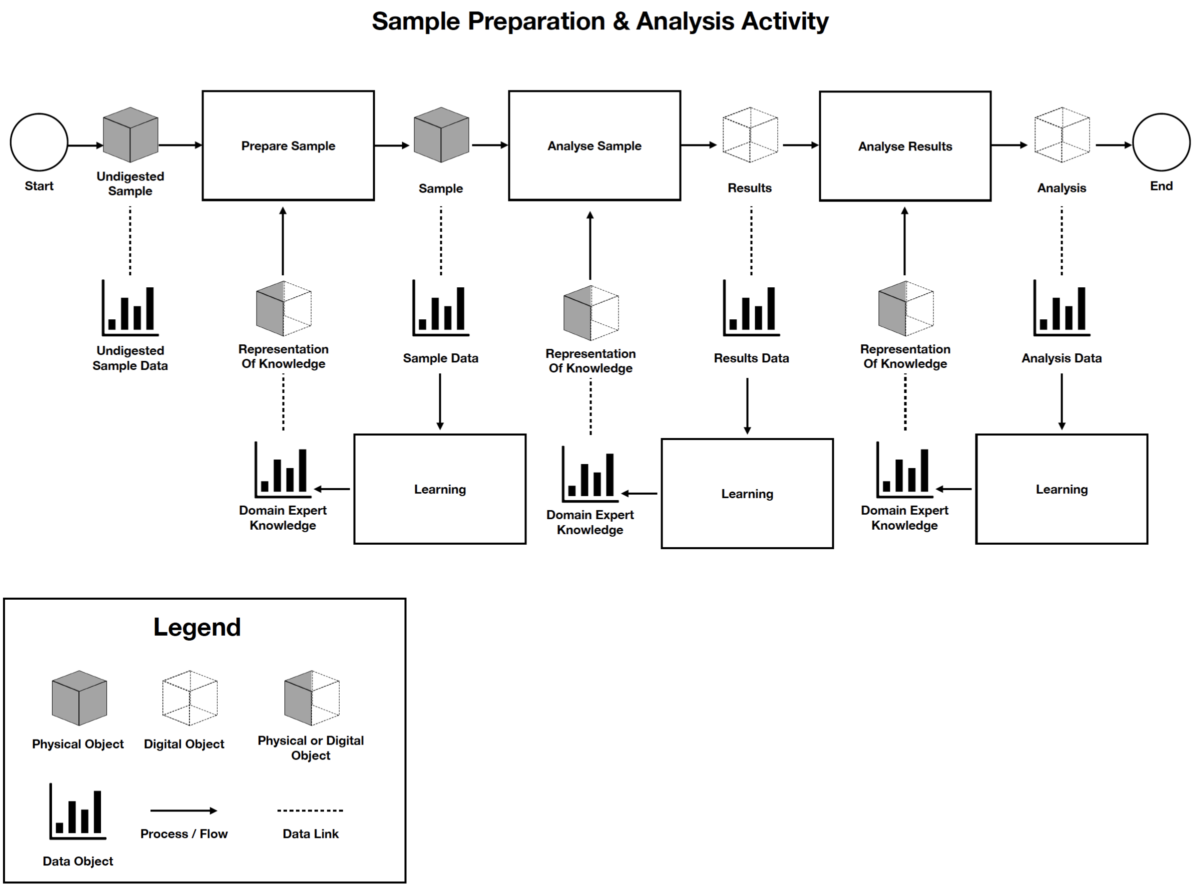

Figure 5. An example process model of the sample preparation & analysis activity, demonstrating the explicit incorporation of data objects and their linked representations, as well as the learning loops inherent in the activity.

The abstraction of a data object from its physical or digital representation, as shown in Figure 5, provides several clear advantages. It enables us to more clearly visualise the role that an MR system would have when integrated within the activity. Currently, the user would be required to identify and maintain the link between a data object and its representation. This not only increases the cognitive load required to perform the task but is also inherently more prone to human error. This is especially significant when one considers the complex and contextual nature of knowledge work practices.

By integrating MR within the activity however, the role of identifying a data object, and maintaining the link to its representation could theoretically be handled entirely by the system, thus reducing cognitive load and lowering the chance of human error (Küçük et al., 2016; Yang et al., 2019). For example, in the above activity an MR system could potentially track the interaction history of a glass test tube and inform the user of a potential contamination. There are also scenarios where the representation of data may not actually be integral to the activity at all, but rather only the data itself is required, such as the mental model formed by weather forecasters as a result of hand-drawing weather charts rather than relying solely on computer-generated charts (Linger & Aarons, 2005). As a further example, as observed in this study, domain expert knowledge about a process may be written in a logbook. However, the logbook itself only serves as a representation of that knowledge, only the knowledge itself (the data object) is integral to the activity. In such scenarios, MR could potentially remove or digitise physical representations altogether and display them contextually in-situ, thus simplifying the activity process (Funk et al., 2016; Werrlich et al., 2018).

Another potential advantage involves the identification of learning loops within the activity. For example, the data object output by a task may itself become an input in a parallel learning task. The output of the learning task could be actual knowledge, such as the weather forecasters' mental model discussed above. In the context of our observations this would apply to the domain expert recognising the RF shielding of a mass-spectrometer to be damaged due to scratches in the paint as a result of their prior experience.

The insights gained from our study present further research opportunities for articulating a new system design methodology. Informed by the methodological approach of this study, a new methodology would include observation of work practices, elicitation of tacit knowledge from domain experts and representation of process and practice in models incorporating physically embedded data. Such a methodology would clearly identify the aspects of a knowledge work practice which could be effectively supported through MR and enable the implementation of effective MR systems to support those practices.

5 Conclusion

Supporting collaborative industrial activities has been a major focus of MR research for some time now. The maintenance, assembly and manufacturing industries were among the early adopters of MR technologies due to the relatively linear and discrete nature of their work practices. However, other industries with work practices which rely on human decision making informed by environmental, social and contextual factors introduce a new challenge. The tightly controlled experimental conditions of most existing MR research fails to "inform" those industries on the potential value of MR support as these studies are unable to address the complexities of actual work practices.

In this paper we explored the potential of MR to support knowledge work practices within the wet lab domain. Unlike most existing MR research, we took a DSR approach by conducting the first naturalistic (in-situ) exploratory study of MR in the wet lab domain. This enabled us to utilize domain expert knowledge during the design, development and evaluation of prototype systems to focus on the needs of workers undertaking actual work practices within the domain. This approach ultimately led to the discovery of a new construct, which we term physically embedded data.

Our reflection and subsequent discussion indicate the need to formally represent this phenomenon in process and practice models to facilitate the design of industrial MR systems by highlighting areas where MR could provide effective support for knowledge work practices. We also present a research opportunity for a new system design methodology which would include observation of work practices, elicitation of tacit knowledge from domain experts and representation of process and practice in models incorporating physically embedded data. This methodology could then be applied in other domains (or with other technologies) to further explore the physically embedded data phenomenon.

References

Bork, F., Schnelzer, C., Eck, U. and Navab, N., 2018. Towards efficient visual guidance in limited field-of-view head-mounted displays. *IEEE transactions on visualization and computer graphics*, *24*(11), pp.2983-2992.

Burstein, F. and Linger, H., 2003. Supporting post-fordist work practices. Information Technology & People.

Carlsson, S. and Johansson, B., 2010, June. Naturalistic and artificial evaluations of personas and role-based enterprise systems. In *International Conference on Design Science Research in Information Systems* (pp. 558-562). Springer, Berlin, Heidelberg.

Cordeil, M., Dwyer, T., Klein, K., Laha, B., Marriott, K. and Thomas, B.H., 2016. Immersive collaborative analysis of network connectivity: Cave-style or head-mounted display?. *IEEE transactions on visualization and computer graphics*, *23*(1), pp.441-450.

Dourish, P., 2004. *Where the action is: the foundations of embodied interaction*. MIT press.

Ens, B., Lanir, J., Tang, A., Bateman, S., Lee, G., Piumsomboon, T. and Billinghurst, M., 2019. Revisiting collaboration through mixed reality: The evolution of groupware. *International Journal of Human-Computer Studies*, *131*, pp.81-98.

Franklin, M., 2006. *The lessons learned in the application of Augmented Reality*. QINETIQ LTD FARNBOROUGH (UNITED KINGDOM).

Funk, M., Kosch, T. and Schmidt, A., 2016, September. Interactive worker assistance: comparing the effects of in-situ projection, head-mounted displays, tablet, and paper instructions. In Proceedings of the 2016 ACM International Joint Conference on Pervasive and Ubiquitous Computing (pp. 934-939).

Gavish, N., Gutiérrez, T., Webel, S., Rodríguez, J., Peveri, M., Bockholt, U. and Tecchia, F., 2015. Evaluating virtual reality and augmented reality training for industrial maintenance and assembly tasks. *Interactive Learning Environments*, *23*(6), pp.778-798.

Gill, G. and Bhattacherjee, A., 2009. Whom are we informing? Issues and recommendations for MIS research from an informing sciences perspective. *Mis Quarterly*, pp.217-235.

Goodwin, S., Mears, C., Dwyer, T., de la Banda, M.G., Tack, G. and Wallace, M., 2016. What do constraint programming users want to see? Exploring the role of visualisation in profiling of models and search. *IEEE Transactions on Visualization and Computer Graphics*, *23*(1), pp.281-290.

Gregor, S. and Hevner, A.R., 2013. Positioning and presenting design science research for maximum impact. *MIS quarterly*, pp.337-355.

Hevner, A.R., March, S.T., Park, J. and Ram, S., 2004. Design science in information systems research. *MIS quarterly*, pp.75-105.

Isenberg, P., Fisher, D., Morris, M.R., Inkpen, K. and Czerwinski, M., 2010, October. An exploratory study of co-located collaborative visual analytics around a tabletop display. In *2010 ieee symposium on visual analytics science and technology* (pp. 179-186). IEEE.

Iivari, J. and Linger, H., 1999, January. Knowledge work as collaborative work: A situated activity theory view. In Proceedings of the 32nd Annual Hawaii International Conference on Systems Sciences. 1999. HICSS-32. Abstracts and CD-ROM of Full Papers (pp. 10-pp). IEEE.

Kalkofen, D., Mendez, E., Schmalstieg, D.: Interactive focus and context visualization for augmented reality. In: Proceedings of the 2007 6th IEEE and ACM International Symposium on Mixed and Augmented Reality. pp. 1–10. IEEE Computer Society (2007)

Küçük, S., Kapakin, S. and Göktaş, Y., 2016. Learning anatomy via mobile augmented reality: Effects on achievement and cognitive load. Anatomical sciences education, 9(5), pp.411-421.

Lee, J.S., Pries-Heje, J. and Baskerville, R., 2011, May. Theorizing in design science research. In *International conference on design science research in information systems*(pp. 1-16). Springer, Berlin, Heidelberg.

Linger, H. and Aarons, J., 2005. Filling the Knowledge Management Sandwich: An Exploratory Study of a Complexwork Environment. In Information Systems Development (pp. 501-513). Springer, Boston, MA.

Marner, M.R., Irlitti, A. and Thomas, B.H., 2013, October. Improving procedural task performance with augmented reality annotations. In *2013 IEEE International Symposium on Mixed and Augmented Reality (ISMAR)* (pp. 39-48). IEEE.

Marriott, K., Schreiber, F., Dwyer, T., Klein, K., Riche, N.H., Itoh, T., Stuerzlinger, W. and Thomas, B.H. eds., 2018. *Immersive Analytics* (Vol. 11190). Springer.

Masood, T. and Egger, J., 2019. Augmented reality in support of Industry 4.0—Implementation challenges and success factors. *Robotics and Computer-Integrated Manufacturing*, *58*, pp.181-195.

Milgram, P., Takemura, H., Utsumi, A. and Kishino, F., 1995, December. Augmented reality: A class of displays on the reality-virtuality continuum. In Telemanipulator and telepresence technologies (Vol. 2351, pp. 282-292). International Society for Optics and Photonics.

Müller, T., 2015, August. Towards a framework for information presentation in augmented reality for the support of procedural tasks. In *International Conference on Augmented and Virtual Reality* (pp. 490-497). Springer, Cham.

Müller, T., 2019. Challenges in representing information with augmented reality to support manual procedural tasks.

Myers, M.D. and Baskerville, R.L., 2009. Commentary on Gill and Bhattacherjee: Is there an informing crisis?. *MIS Quarterly*, *33*(4), pp.663-665.

Paelke, V., 2014, September. Augmented reality in the smart factory: Supporting workers in an industry 4.0. environment. In *Proceedings of the 2014 IEEE emerging technology and factory automation (ETFA)* (pp. 1-4). IEEE.

Schmalstieg, D. and Hollerer, T., 2016. *Augmented reality: principles and practice*. Addison-Wesley Professional.

Straub, D. and Ang, S., 2011. Editor's comments: Rigor and relevance in IS research: Redefining the debate and a call for future research. *MIS quarterly*, pp.iii-xi.

Werrlich, S., Daniel, A., Ginger, A., Nguyen, P.A. and Notni, G., 2018, October. Comparing HMD-based and Paper-based Training. In 2018 IEEE International Symposium on Mixed and Augmented Reality (ISMAR) (pp. 134-142). IEEE.

Yang, Z., Shi, J., Jiang, W., Sui, Y., Wu, Y., Ma, S., ... & Li, H. (2019). Influences of Augmented Reality Assistance on Performance and Cognitive Loads in Different Stages of Assembly Task. Frontiers in psychology, 10, 1703.