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Connected Laboratory Instruments: An analysis of user adoption within the Widefield Microscopy market

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ABSTRACT

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In scientific institutions, the pathway to digital transformation and IoT adoption requires laboratory automation as well as informatics. Connectivity of instruments is key to both, and hence it has become a crucial avenue in the product roadmaps of instrumentation manufacturers in life sciences. This thesis focuses on the market of manual widefield microscopes. These imaging systems are currently being developed to perform multiple smart functions and to be individually connected to cloud services. In general, connected instruments allow for scientists to remotely access their data in real time, share their results, collaborate with peers, and get prompt access to analysis and support tools provided by vendors. However, despite these potential benefits, the adoption of connected manual microscopes remains in general limited. In addition, not a single manufacturer has emerged as the clear leader in this space.
The overall aim of this investigation is to gain a better understanding of the variables impacting adoption of connected microscopes, at the user level. A hypothetical model, using the general framework of the Technology Adoption Model (TAM), is proposed, and quantitatively tested here. The dimensions of perceived usefulness, perceived ease of use, perceived safety and perceived responsiveness are studied in relation with the intention to use connected microscopes. Statistically significant positive correlations are demonstrated to exist between either the perceived usefulness or the perceived safety and the intention to use connected instruments. Positive correlations are also observed between each of the two remaining dimensions (perceived ease of use and perceived responsiveness) and the intention to use, but they are not statistically significant. For these two cases it could be argued that the survey applied here is unable to capture the nuances associated to these constructs. Finally, an additional exploratory analysis allows to tentatively conclude that age and years of experience of the scientists are negatively correlated with their intention to use connected microscopes, albeit not in a statistically significant manner.
Given the increasing rate at which connected instruments are being developed, the outcome of this investigation is relevant to shed light into drivers, patterns, and concerns, as well as to identify individual barriers impeding adoption of these instruments amongst the community of scientific users. Thus far, to the best of our knowledge, no other study has specifically addressed factors influencing adoption of connected manual widefield microscopes, at the user level.

Keywords: Technology Adoption Model, connected microscopes, user adoption, intention to use, perceived usefulness, perceived safety.

LIST OF CONTENTS

LIST OF ABBREVIATIONS

2D	Two-dimensional
3D	Tri-dimensional
AI/ML	Artificial Intelligence and Machine Learning
CPU	Central Process Unit
ELN	Electronic Laboratory Notebooks
HW	Hardware
IoT	Internet of Things
IT	Information Technology
IU	Intention to Use
M2M	Machine-to-Machine
MCU	Microcontroller Unit
PE	Perceived Ease of Use
PR	Perceived Responsiveness
PS	Perceived Safety
PU	Perceived Usefulness
SW	Software
TAM	Technology Adoption Model

1 INTRODUCTION

The term ‘Internet of Things’ (IoT) was coined on the late 1990’s to refer to the interconnectedness of physical objects, which could communicate to each other and through the internet (Gill, 2018). Since then, the IoT has grown to include an overwhelming number of so-called smart connected devices that have become essential for us humans to be connected to each other and to our workplaces. The IoT market size was estimated to be worth ~ $ 309 Billions in 2020 with 25% CAGR forecasted for 2021-28 and it is currently dominated by the smart cities (26%) and the industrial IoT (24%) segments (Nižetić et al., 2020).

In scientific institutions, the pathway to digital transformation and adoption of IoT has primarily been centered around two areas: laboratory automation and laboratory informatics (Bhuiyan et al., 2022). Because connectivity of instruments is key to both areas, this has become a crucial avenue in the strategic product roadmaps of instrumentation manufacturers in life sciences. As a result, manufacturers in life sciences have developed instrumentation that can perform multiple smart functions and that can be individually connected to cloud services to benefit the customer experience. In general, connected instruments allow for scientists to remotely access their data in real time, share their results, collaborate with peers, get prompt access to analysis as well as service support tools provided by manufacturers, all of which can potentially increase work productivity and reduce lab downtimes.

During the last 5 years, there has been a significant uptick of connected instruments that are intended for general use (such as refrigerators or centrifuges), which allow laboratories to remotely monitor sample storage or workflow conditions in real-time (Gardner, 2022). However, despite the benefits indicated above, the user uptake of connected devices in more specialized life science instrumentation, such as widefield microscopes, has proceeded very cautiously. This has been hypothesized to be partly due to users’ concerns related to security and privacy, but also due to other reasons that span beyond individual attitudes, such as difficulties in integrating end-to-end solutions and the existence of fragmented legacy systems (Ali et al., 2022).

To create a truly user centric IoT in the life sciences market that successfully connects scientists and their instruments in a sustainable ecosystem, multiple elements are important to be considered, among of which are: the establishment of trusted and standardized communications, the proper management of huge amounts of data and services, and particularly the individual willingness of users to adopt connected instruments. Within life sciences, this thesis will particularly address the Widefield Microscopy market. Widefield microscopes are regarded iconic instruments, and they are often used to represent life sciences in the public domain. Some of the well-established brands in this space include Olympus (now Evident), Nikon, Leica Microsystems, Zeiss and Thermo Fisher Scientific. Companies in the Widefield Microscopy space have adopted various strategies to develop their connected microscope platforms, and their success has differed between manufacturers. Thus far, not a single manufacturer has emerged as the clear leader in this space, and connectivity adoption remains in general limited.

The overall aim of this investigation is to gain a better understanding of the variables impacting adoption of connected microscopes, at an individual user level. A hypothetical model, using the general framework of the Technology Adoption Model (TAM), is proposed, and tested here, to describe factors that could impact adoption of connected microscopes. Using quantitative correlation analysis, this thesis attempts to answer the following research questions:

- Question 1 (Q1): To what extent does a relationship exist between the perceived usefulness of connected microscopes and the intention to use them?
- Question 2 (Q2): To what extent does a relationship exist between the perceived ease of use of connected microscopes and the intention to use them?
- Question 3 (Q3): To what extent does a relationship exist between the perceived safety of connected microscopes and the intention to use them? and finally,
- Question 4 (Q4): To what extent does a relationship exist between the perceived responsiveness of connected microscopes and the intention to use them?

Given the increasing rate at which laboratory instruments are been developed with connectivity functionalities, the outcome of this investigation is relevant to shed light into drivers, to understand patterns and concerns, as well as to identify individual barriers impeding adoption of this new type of instruments amongst the scientific community of users. Thus far, to be the best of our knowledge, no other study has specifically addressed factors influencing adoption of connected manual widefield microscopes, at an individual level.

2 REVIEW OF THE LITERATURE

2.1 Introduction to the Landscape of Connected Instruments

To understand technology adoption of connected instruments it seems essential to begin by defining what such devices are. In this section, the general concept of ‘Internet of Things’ is presented, followed by the specific definition and components characterizing smart connected devices. Finally, an overview of the supporting technology infrastructure, otherwise known as ‘technology stack’, is outlined.

2.1.1 “Internet of Things” and Smart Laboratories

The term “Internet of Things” or IoT was originally proposed by Kevin Ashton, a computer scientist that founded the MIT’s Auto ID Center, where the concept of radio-frequency identification (RFID) was initially developed (Porter and Heppelmann, 2014). Today, IoT is widely used to reflect the interconnectedness of physical devices with smart and connectivity capabilities, which can interact with each other via Machine-to-Machine communications (M2M), enabling collection and exchange of data (Baker et al., 2017). While both the ‘smart’ and ‘connected’ terms seems to be obvious to most readers and product users, an exact definition will be covered in the next section to help navigate this topic, from a theoretical standpoint. Suffice to say, these devices typically have some degree of on-board computational power as well as internet-enabled functionality for communication purposes. By an estimate from Cisco in 2020 (“Cisco Annual Internet Report - Cisco Annual Internet Report (2018–2023) White Paper - Cisco,” 2020), the number of smart connected devices was largely to surpass in 2023 the global population. Newer estimates are predicting it may reach 75-80 billion by 2025 (Ali et al., 2022).

The importance of IoT has been considered so high that some authors have referred to it as the driver for the Fourth Industrial Revolution (Baker et al., 2017). Connected devices forming the IoT are widespread, as schematically represented in FIGURE 1. They are used in areas such as healthcare monitoring, commercial retail, smart city networks, robotics, intelligent transportation, video surveillance, logistics and package tracking. Similarly, they include smartphones and house devices, such as TVs and gaming consoles (Ali et al., 2022; Porter and Heppelmann, 2014). The application of IoT has already proven to be successful in well-known areas such as smart parking, but extensive research is currently ongoing on other such as traffic congestion minimization (El-Sayed and Thandavarayan, 2018), smart grids (Tan et al., 2017) and healthcare (Baker et al., 2017).

About 50% of the connections that are created when these devices are in use, are regarded to be M2M type. The so-called M2M connections can be defined as those involving automated exchange of information between devices, without any human intervention (Porter and Heppelmann, 2015). This includes, but it is not limited, to information that is collected directly from devices for the purposes of monitoring or controlling them.

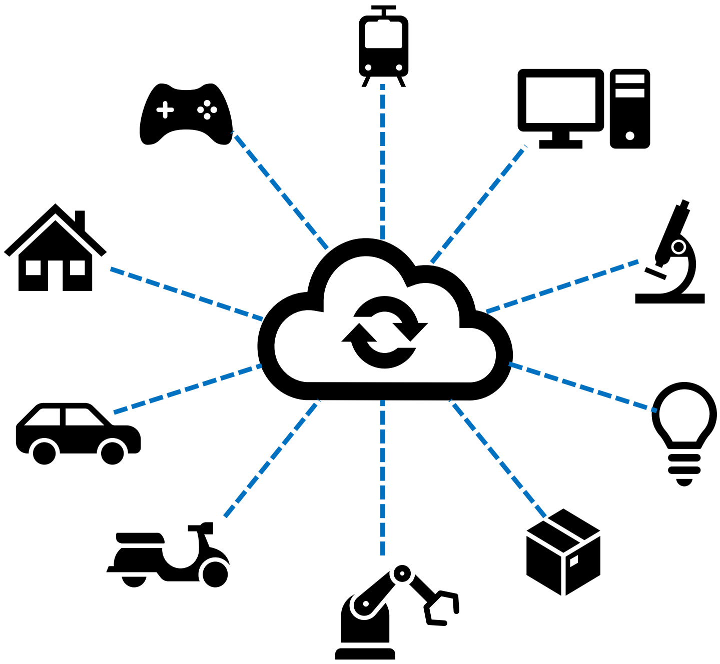


FIGURE 1. Schematic representation of the variety of smart, connected devices currently available.

In scientific institutions, connected devices are one key component of the digital transformation landscape, which is essential for the creation of IoT centric laboratories. There is no one single accepted definition for ‘smart laboratories’ but it is generally accepted that this term refers to laboratories where the latest technology is used to manage scientific activities (Gill, 2018; Knight et al., 2020). Overall, smart laboratories are characterized by the implementation of laboratory automation and/or laboratory informatics. Laboratory automation relates to the use of technology that replaces manual processes, using laboratory instruments. Laboratory informatics, on the other hand, refers to the digitalization of the process of handling laboratory data and information obtained from multiple laboratory instruments, to optimize lab operations (Poongothai et al., 2018).

Smart, connected instruments in laboratories are essential in both avenues, and their utilization is expected to have a significant positive impact in increasing scientific productivity and data sharing. Productivity can be improved by simplifying procedures, reducing manual hands-on and instrument down times as well as minimizing human errors and providing higher data reproducibility (Rochi, 2023). Sharing, on the other hand, is improved by allowing remote data access, facilitating easier collaboration and data integration (Gardner, 2022), which is also particularly important to enhance the reusability of scientific data (Kemmer et al., 2023). Expectedly, such benefits are not exempt of disadvantages. Overall, the major challenges that have been identified are related to data security and privacy, the difficulties of technical integration and the existence of a fragmented legacy of traditional instruments that are still in use across multiple sectors, which hampers standardization efforts (Ali et al., 2022). In addition, the differential degree to which data transfer can take place among different instruments is a concern (Rochi, 2023). However, thus far, no scientific study has specifically addressed the factors influencing adoption of these instruments in the Widefield Microscopy field, at an individual level. This will be the focus of current investigation.

2.1.2 What are Smart Connected Instruments?

To begin with, it is important to define what smart, connected instruments are, and how they differentiate from their conventional (non-smart and non-connected) counterparts. Smart connected devices can be defined as those that consist of three primary components (Porter and Heppelmann, 2014):

- Physical hardware (HW) components: These consist of the mechanical and electrical parts. These are typically the same components present in conventional devices.

- Components supporting smart functions: Smart functions are defined as those that help facilitate the interaction of the user with the device and amplify the capabilities of the physical components in a manner that provide ‘smartness’. Digital components in this group, supporting intelligent functions include microprocessors, data storage solutions, instrument- embedded operating systems having dedicated User Interfaces (UI) or companion computers having a dedicated application to control the device. The digital UI of a smart connected device can even reside into a tablet or a smartphone application, even eliminating the need for physical controls in the instrument (Siggelkow and Terwiesch, 2019).

- Components supporting connectivity functions: Components in this category refer to elements such as ports, antennae as well as protocols which support the wired or wireless connections to a cloud ecosystem where the device data is stored. Connectivity functions further amplify the instruments capabilities in a manner that expands the value outside the boundaries of the physical device. These components can enable for example one-to-one connections (i.e. one device connecting to the user or the manufacture cloud ecosystem) or one-to-many connections (i.e. a central system simultaneously connecting to many devices) (Porter and Heppelmann, 2015).

As discussed earlier, a staggering rise of smart connected devices has taken place over the last 10 years (Ali et al., 2022). Such increase has coincided with the latest wave of Information Technology (IT)- driven business transformation, in which IT has become part of the devices. These smart and connectivity components have significantly improved the functionality of the devices and have even created new capabilities. As described in FIGURE 2, these capabilities can be broadly divided into four types: monitoring, control, optimization, and autonomy functions, with an increasing level of complexity (Nižetić et al., 2020). Devices can have all four functions, but in the instruments used by scientists in life sciences these capabilities are currently limited primarily to monitoring and control.

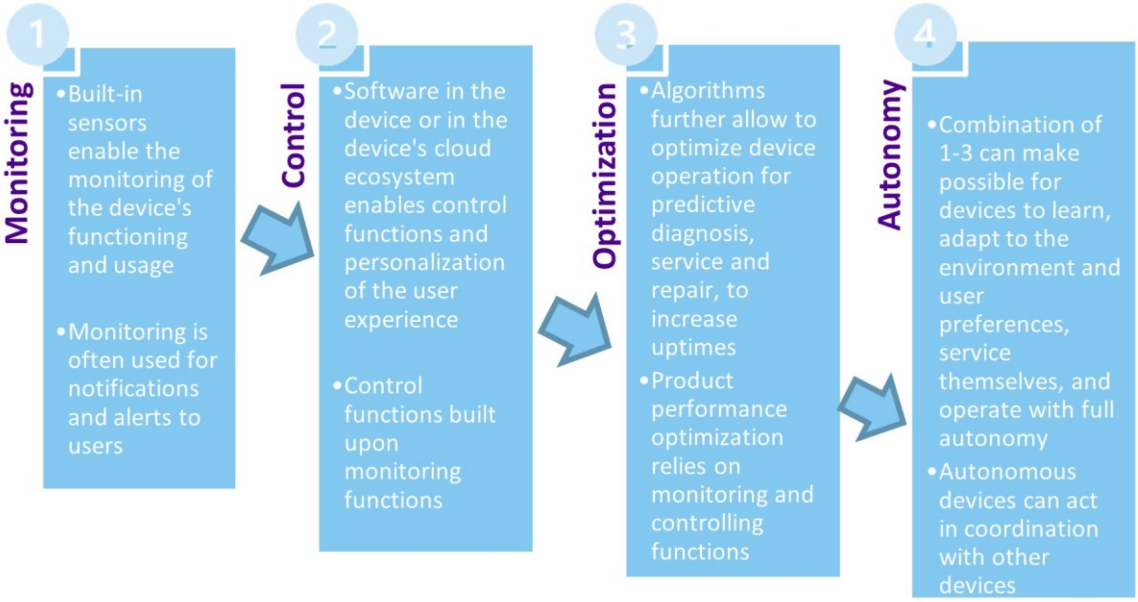


FIGURE 2. Capabilities of smart connected devices, increasing in complexity from 1 to 4, adapted from (Porter and Heppelmann, 2014).

2.1.3 What is the Technology Stack?

The existence of smart, connected devices within the IoT is only possible via a supporting technology infrastructure that is commonly referred to as ‘Technology Stack’ (Porter and Heppelmann, 2014). FIGURE 3 presents a three-tier architectural model for smart connected devices consisting of layers that include the product, the communication network (or connectivity) and the cloud.

The products (or ‘things’) are the primary layer of the model and given the variety of existing connected devices, this layer is consequently highly diverse. There is a multiplicity of components that are vendor-specific, as well as various modules and operating systems found at this level. As highlighted by (Ali et al., 2022), this layer is responsible for translating and propagating the heterogeneity of the entire technology stack. In the second layer, devices are connected to the cloud, and this includes all the protocols that enable such network communication. Lastly, the third, cloud technology layer, oversees handling raw data from smart connected devices. This includes, among others, big-data databases, that handles real-time and historical data captured from the product, application platforms to enable connected business applications using data access and visualization tools, as well as smart product applications, which are not embedded in the products, but significantly expand their functionality for users

(Baker et al., 2017). The cloud layer is populated by broad enterprise solutions such as Amazon, Azure and IBM, that offer a variety of IoT network applications (Ali et al., 2022) as well as niche, product-specific cloud services, that can be highly tailored to specific markets and specialized customer needs, as it will be later discussed, in the case of life scientists.

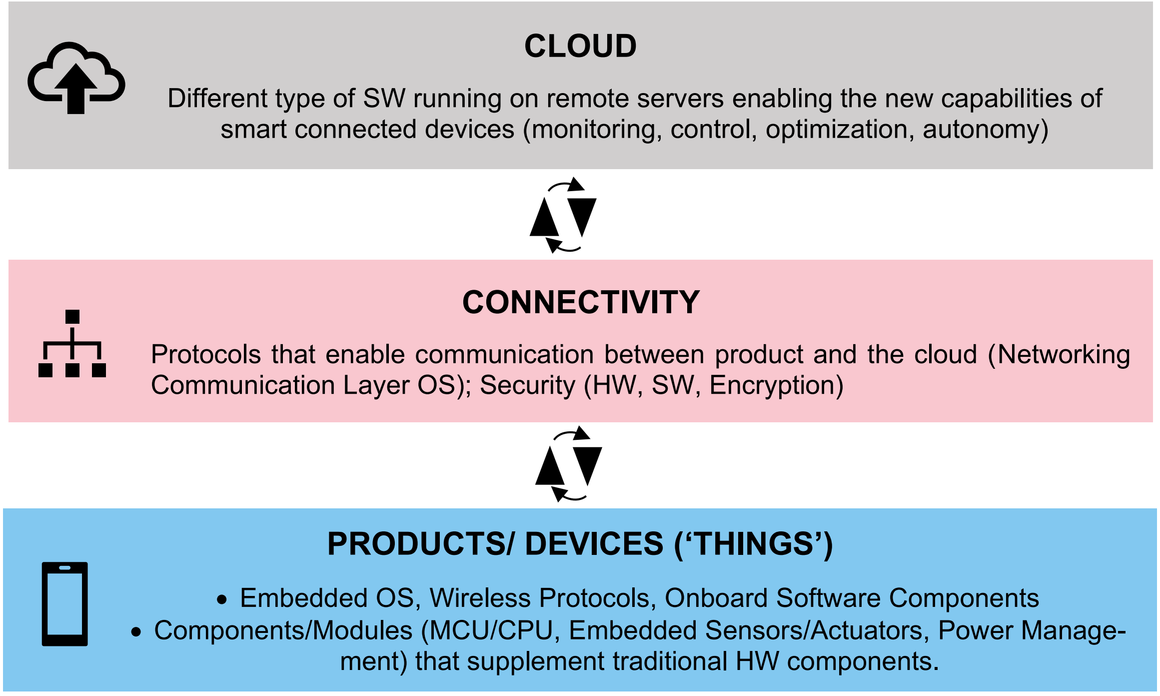


FIGURE 3. Simplified representation of the Technology Stack, adapted from (Ali et al., 2022; Porter and Heppelmann, 2014). For abbreviations in the scheme, please refer to the List of Abbreviations.

The technology stack has enabled significantly faster product development, and it has permitted the gathering, analysis and sharing of extremely large amount of data that can provide entirely new insights into the use of devices (Bhuiyan et al., 2022; Porter and Heppelmann, 2014). From a development perspective, the smart and connectivity functionalities allow for a full exploitation of customization, which can ensure that product variability is successfully achieved at a very low cost. For instance, earlier, if new product functions were required to be introduced, new physical controls needed to be added to the hardware (HW) of the instrument with the high associated costs of developing new physical components and entirely new physical product generations. However, with the addition of the technology stack, the same changes are now entirely possible to accomplish through updates in software (SW) instead of HW, and such improvements can be effectively delivered directly through the cloud ecosystem. Similarly, products can be localized for different language needs just via the SW, also minimizing the need for HW changes (Porter and Heppelmann, 2015). From a service and support perspective, the myriad of information that is constantly collected on the products, allows for systematic monitoring of the device's health, making it often possible to implement remote service and/or to improve the remote troubleshooting capabilities, all of which can reduce instrument's downtimes as well as improve the user experience (Ali et al., 2022; Bhuiyan et al., 2021).

As some physical device components become more simplified and are replaced by SW improvements, several aspects of the HW product development as well as manufacturing have consequently become more straightforward. By contrast, on the other hand, devices have now a larger number of sensors and ever-growing SW capabilities, all of which drives the continuous needs for proper SW support infrastructure (Fountaine et al., 2019). As a result, building and supporting the technology stack for smart, connected products requires substantial financial investments and a change on company culture towards a more IT-driven organization, both of which cannot not be underestimated (Mann et al., 2022).

2.2 Introduction to the Widefield Microscopy Market

This investigation particularly focuses on specialized instruments used by life scientists to visualize microscopic biological samples, known as widefield microscopes. In this chapter, it is first covered the general definition of this microscopy modality, followed up by a comparison between connected and traditional widefield microscopes. Next, it is reviewed the most important companies that are currently playing in this space, and a summary of the strategies they have utilized to implement connectivity on their products. Finally, it is examined how the introduction of connected microscopes has shaped and will continue to shape the competition within this industry. For this analysis, the classical Porter's Five Forces model is utilized (Porter, 1979).

2.2.1 What are Connected Widefield Microscopes?

Technically speaking, widefield refers to a microscopy modality in which the whole specimen is exposed to a light source on a microscope stage. The most basic form of widefield microscopy is 'brightfield microscopy' in which the entire specimen can either be illuminated by white light either from above – what is known as an inverted configuration, or from below – what is referred to as an upright configuration (Wilson et al., 2017).

An important type of widefield microscopy is the so-called 'fluorescence microscopy', in which the specific property of certain compounds that can be used to stain the cells, known as fluorophores, is utilized (Ockenga, 2011). In fluorescence microscopy, the specimen is illuminated with a light of a specific wavelength, instead of white light as in brightfield microscopy, which then excites the fluorophores, causing them to emit at longer wavelengths, creating fluorescent images. Scientists working in life sciences rely on the use of widefield microscopy, including both brightfield and fluorescence, to study live and fixed cells as well as tissues. Those cell-based assays using brightfield or fluorescence imaging are essential to address key questions in the fields of cancer biology, immunology, neuroscience and drug discovery, among many others (Lichtman and Conchello, 2005).

From the perspective of their components, there are clear differences between traditional and smart connected microscopes. A components-based comparison is schematically shown in FIGURE 4. Both traditional and smart connected microscopes share physical components which include mechanical, electrical, and optical parts, enabling the basic magnification and visualization of cells and tissues. The addition of smart components allows improved or new functions that can be accessed through a customized UI either with an embedded computer, or a companion computer. These functions were earlier either unavailable or available to a certain extent only via direct interaction with the physical HW components. Examples of smart functions, are those that allow safety-proofing the instrument, thus minimizing errors that users can often make with traditional devices. For example, a smart microscope can automatically switch off the light when the user does not need it, to preserve the instrument lifetime and, more importantly, to protect the biological samples, as they can be altered by continued light exposure. A smart microscope can also recognize the objective installed and correctly add scale bars that match the exact used magnification. Functions that were previously only available via the HW can now also be replaced by smart components. One example is the image focus, which in smart instruments can be done digitally on the UI, as opposed to using a manual knob in a traditional instrument.

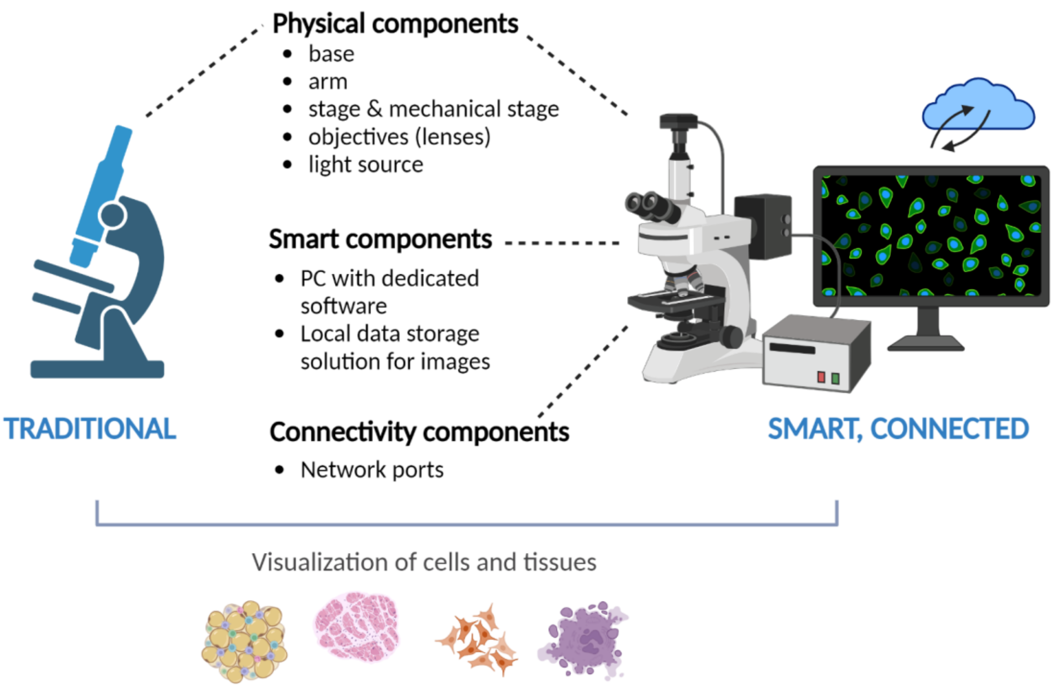


FIGURE 4. Comparison between traditional and smart, connected microscopes. This list of components is not comprehensive, as it is shown here only with illustration purposes.

While in traditional microscopes the usage of the instrument relies exclusively on the physical product, the addition of connectivity components, allows for the functionality of the imaging device to further exist also outside of it. The instrument operation can be recorded and monitored remotely, and users can be alerted if a malfunction has taken place, without having to be in the physical vicinity of the microscope. The user can also have access to other remote functionalities for instance to control the instrument operation, and instrument-generated images can be sent to a dedicated or a generic cloud ecosystem, where the user can have access to image analysis tools.

2.2.2 Landscape of Players in the Widefield Microscopy Market

The Widefield Microscopy market is divided into the Manual and the Automated segments, in relation to the instrument capabilities for only manual (user-driven) or automated (user-independent) functions. The segment that will be the focus on this investigation is the manual segment, which has been valued at ~$170M in 2023, with a forecasted 5 years CAGR of ~5%, according to various market reports ("Cell Analysis Market 2022– Global Forecast to 2027," 2022; "Cell Culture Market – Global Forecast to 2025," 2020; "Market Reports: Microscopy Global – Global Forecast to 2026," 2021). This market accelerated significantly during the period 2020-22 owned to the acceleration of the Cell Culture market, which was strongly associated to the SARS-CoV-2 (COVID-19) pandemics.

Manual microscopes are primarily used to evaluate the health of cells and tissues used by life scientists. It was estimated in late 2020 that the Cell Culture market is roughly worth $19B and is rapidly growing, with a forecasted CAGR of 11-12.0% for the 2020-25 period ("Cell Culture Market – Global Forecast to 2025," 2020). Some examples of microscope models and their manufacturing companies competing in the cell culture imaging space, are shown in FIGURE 5. The basic cell culture imaging space is populated by established brands, particularly the four big renowned optical companies in the world, which include Olympus (since 2022, the microscopy business now belongs to Evident, a newly created, wholly owned subsidiary of Olympus), Nikon, Leica Microsystems (since 2005, the company is part of the Danaher Corporation) and Zeiss. These four companies alongside another established brand, Thermo Fisher Scientific, represent about the majority (estimated over 70%) of the manual microscopy market. In addition, there are other relevant emerging players, such as ECho Labs (acquired in 2021 by CELLINK), as well as Bio-Rad Laboratories. Altogether, these players offer multiple manual instrument choices for customers, varying in functions as well as purchase prices, generally within the range between $5K and $15K.

FIGURE 5. Some examples of instruments currently available in the manual widefield microscopy space.

The competition in this space has been traditionally characterized by a technical performance race, accomplished by manufacturers through continuous improvements in the optical or other hardware components and accessories. However, with digital transformation and IoT gaining traction in life science labs, players in the widefield microscopy space are also now competing in improving the user experience through the addition of smart as well as connectivity functions (Poger et al., 2023). From the connectivity perspective, the two most common strategies are summarized in FIGURE 6, followed by a description on what they encompass.

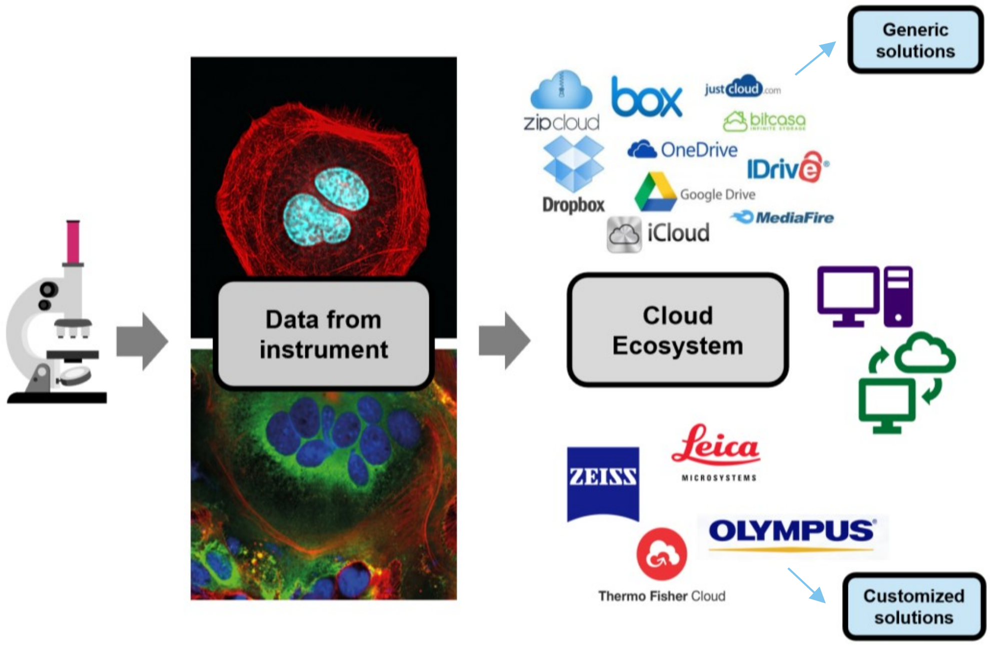


FIGURE 6. Main connectivity strategies utilized by widefield microscopy manufacturers.

Large companies have opted for investing financial resources in developing their own customized cloud ecosystems, such for instance in the case of the Zeiss's Labscope ("Share Your Microscopic Samples with Labscope for Windows," 2023), the Olympus Scientific Cloud ("The Olympus Scientific Cloud | Olympus IMS," 2023) or Thermo Fisher Connect ("Thermo Fisher Connect Platform - FI," 2023). By connecting their microscopes to their own cloud environments, users can storage their acquired images while simultaneously having access to image analysis SW and remote service tools specifically developed by those manufacturers.

Other often smaller companies have simply opted to leverage existing (generic) cloud platforms. That is the case for instance of ECho Labs which only offers connectivity to DropBox from their widefield microscopes. The strategy in this case has been to avoid any large investments associated to developing their own cloud ecosystems or SW analysis solutions, at the disadvantage of basically restricting their offering to third-party image sharing. It could be hypothesized that a combination of both strategies would probably provide the best outcome for users. Interestingly, despite encountering the same challenges in the marketplace, the adoption of connected instruments has differed between manufacturers, and thus far, not a single manufacturer has emerged as a clear leader in this space.

There are additional drivers behind the efforts of microscope manufacturers towards improving image sharing capabilities, which are at least partially associated to the volume of the produced data. The increasingly large amount of images that is being generated by microscopes (including widefield microscopes) has resulted in larger and more complex imaging datasets (Poger et al., 2023). As a result, microscopy has progressively moved into the so-called 'big data' era, which requires more rigorous standards for metadata, data management as well as dissemination procedures (Kemmer et al., 2023). In addition, there have been well-known reproducibility concerns that has justified the need for the release and reuse of scientific data in general (including imaging), and the development of minimum reporting guidelines (Sansone et al., 2012). Because of that, microscopy has begun to improve the Findability, Accessibility, Interoperability and Reusability of data by adopting to so-called FAIR guidelines (Wilkinson et al., 2016). The FAIR data principles are a concise and measurable set of principles, applicable in a broader sense to biological research. They evolved from discussions between multiple stakeholders representing academia, industry, publishers, and funding agencies. When applied to microscopy, they have served as a foundational guiding tool to enhance the reusability of imaging data.

Companies in the widefield microscopy space need to play an essential role in the dissemination and sharing of image acquisition tools and software, and they should work towards the development of better and more intuitive metadata acquisition (Kemmer et al., 2023). In practice, it has been primarily the larger companies (Zeiss, Evident, Nikon, Leica Microsystems and Thermo Fisher Scientific) that have actively participated in these efforts. For example, in Europe, research infrastructures have interacted closely with these five companies through the Euro-BioImaging Industry Board (www.eurobioimaging-industryboard.com) in order to assist scientists in standardization efforts. The manner in which different manufacturers in this space react to the ongoing image data transformation, and how they develop strategies to improve acquisition and data sharing with their instruments, in accordance with the FAIR principles, will have a significant impact on their future competitiveness.

2.2.3 How Connected Microscopes Shape Industry Competition?

As we earlier mentioned, digital technologies are profoundly impacting the nature of competition across multiple markets, including life sciences. Particularly, this widespread introduction of smart, connected devices has caused a dramatic shift in the manner companies operate and it has reshaped the structure of industries and their boundaries (Kavadias et al., 2016). The widefield microscopy market is no exception, and to further understand this impact, it is very useful to conduct an analysis using the classical Porter's Five Forces model (Porter, 1979). The Porter's five forces model considers all types of actors, not only the players already covered in previous section, which have a potential or interest in the said industry. This analysis is summarized in FIGURE 7 and each of the five forces are explained below.

Bargaining Power of Buyers

It can be assumed that smart connected microscopes can have, at least theoretically, a mixed and complex impact in the bargaining power of buyers. On one hand, they cause a reduction on this power, given the wealth of information that is available to manufacturing companies, which can provide an in-depth understanding of instrument's usage, thus allowing the relationships between companies and users to potentially be more customized. For example, if a certain developed cloud application is repeatedly engaging more users than others for certain microscopes, the company can focus their development efforts into adding new functionalities on that cloud SW solution, thus creating even more reasons for users to be engaged, and consequently increasing their costs of switching to another manufacturer (Mann et al., 2022).

Of note, this is a scenario that can have multiple effects: it can also allow companies to de-prioritized cloud development efforts when no significant user traction is gained, thus it can guide companies towards what to do, and what not to do (Siggelkow and Terwiesch, 2019). When solutions can constantly be made fit-for-their needs, users are less likely to abandon their existing manufacturers, assuming that companies are sufficiently agile in adjusting to those needs.

FIGURE 7. Five Forces Analysis for smart connected instruments in the manual widefield microscopy market

On the other hand, the bargaining power of buyers can also be increased, because having access to remote SW analysis tools can empower users to better understand the competitive landscape and play one manufacturer off another (Ali et al., 2022). Getting access to microscope performance data can, also at least theoretically, allow users to judge the ‘true’ technical reliability of the instrument, also allowing them to better judge manufacturers’ quality. However, it is important to note, that in this manual widefield microscopy segment, customers may not necessarily be as technology-savvy as in other microscopy segments, for instance as in the case of automated microscopy, and therefore they may be less likely to focus on the technical performance of the instruments.

In making decisions, scientists could be also nowadays influenced by the willingness of manufacturers to contribute to ‘common good’ initiatives, such as those improving adherence to the FAIR principles (Kemmer et al., 2023; Wilkinson et al., 2016) as discussed in section 2.2.2. It could be expected that buyers will also bargain in the favor of those companies which make more meaningful commitments to enhance data quality and sharing with their connected instrumentation. Based upon this, in my opinion, it is likely that the overall impact on bargaining power of buyers will remain mixed, at least for the near future.

Bargaining Power of Suppliers

The bargaining power of suppliers evaluates the ease with which suppliers can increase the prices of microscopes. Smart connected microscopes have also caused a redistribution of the bargaining power of suppliers. Because of the decline on the use of hardware, these traditional suppliers are more likely to experience a loss in their bargaining power. In contrast, suppliers of sensors, and embedded operating sensors and software components, which are increasingly more essential for manufacturers to maintain and develop the technology stack, are gaining bargaining power.

Threat of New Entrants

The introduction of smart connectivity has also impacted the entry of new players, in a mixed manner. It can reduce their threat because new entrants wishing to break into the market with new microscopes face now even higher development costs, given the need for product-embedded technology as well as costs of developing and maintaining the technology stack. However, the shift towards more advanced smart functionalities have also opened the door to new product-less players, offering highly advanced SW analysis solutions, that can be instrument agnostic and thus attractive to a larger customer base (Siggelkow and Terwiesch, 2019). Because of this increased threat, the large microscopy companies have responded with an increased number of acquisitions and/or collaborations with these product-less, SW providers.

For instance, Zeiss acquired in December 2020 a majority equity in arivis AG, which was previously a highly specialized image analysis company, with solutions tailored to life sciences ("ZEISS invests by acquiring majority stake in arivis AG," 2020). The acquisition allowed Zeiss to be better positioned in 3D image visualization, image processing and analysis software offering, while also reducing altogether the threat of a potential competitor. Because of the arivis AG acquisition, Zeiss has been able to adopt a broader competitive strategy and has now rebuilt its image analysis platforms to offer a full suite of SW tools applicable to Zeiss microscopes but also instrument agnostic, as presented in FIGURE 8.

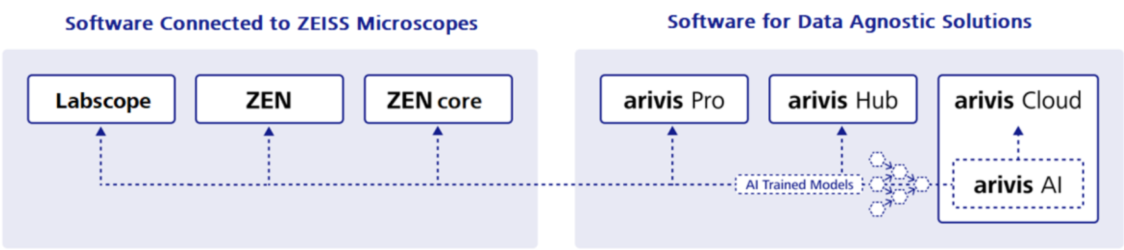


FIGURE 8. "Zeiss arivis" image analysis platform launched as the global Zeiss solution to scale, integrate and connect all image analysis pipelines, reproduced from ("arivis and APEER go ZEISS," 2023)

The new brand Zeiss arivis, was announced in April 2023 and it includes all the Zeiss SW products, toolkits and modules for all image analysis pipelines, thus generalizing Zeiss approach as a provider of end-to-end image analysis solution ("arivis and APEER go ZEISS," 2023). This new approach is also particularly important in consolidating Zeiss's path for further development of smart, connected widefield microscopes.

Another relevant example highlighting the higher impact of new product-less entrants in this space is offered by Leica Microsystems, which in 2021 acquired the SW-only provider Aivia ("Leica Microsystems acquires Aivia, a leading AI-enabled 3D microscopy, image visualization and analysis software solution," 2021). The acquisition of Aivia, which had been founded in 2017, brought to Leica a wide range of Artificial Intelligence/Machine Learning (AI/ML) and Deep Learning algorithms for 2D and 3D image visualization, cloud-based model training modules and web applications, among others, while also eliminating a competitive threat. This approach mirrors the strategy applied by Zeiss in consolidating smart connected functions through advanced software and cloud computing.

Threat of Substitute Products

The threat from substitutes occurs when buyers in the market can achieve a similar result by using means other than the products/solutions available in the market under consideration (Porter, 1979). Overall, the addition of intelligence and connectivity-capability to microscopes increases the performance and customization of the instrument relative to their traditional counterparts. As a result, it is expected that substitution threats are lowered, and industry growth increased.

It should be noted though, that an interesting phenomenon is also taking place here. Because manufacturers are developing microscope intelligence and connectivity capabilities, such as those provided by cloud's imaging analysis apps and peer collaboration tools, they can in parallel lower the demand for other types of products such as Electronic Laboratory Notebooks (ELNs), thus increasing the threat of substitute products in other adjacent life science markets. The ELNs are SW tools enabling researchers to move towards digitally documenting their experiment, instead of using conventional laboratory notebooks. These ELNs also typically include collaboration tools, protocol templates and they support the tracking of results from laboratory instruments (Kwok, 2018). In this sense, their offering highly overlaps with the cloud platforms that some life science manufacturers have developed, such as Thermo Fisher Scientific ("Thermo Fisher Connect Platform - FI," 2023), which also include image analysis tools. Thus, developments in the field of smart connected microscopes can increase the threat of substitute products in other life-sciences associated markets.

Rivalry among Existing Players

It is not surprising, in view of what was discussed above, that the competitive rivalry among existing players in the Widefield Microscopy market has increased, as the primary battlefront has shifted from hardware to software, and new avenues has been created for product differentiation and customer engagement. Compared to the rivalry that existed on times of traditional microscopes, new competitive dynamics have now emerged, characterized by, for example:

- The rate of acquisitions by bigger brands of smaller product-less players offering differentiating SW functionalities has become more commonplace as well as the establishment of partnerships. This is in response not only to a need to improve the SW offering, but also as a strategy to reduce the threat that such product-less companies can pose to the established brands in this market.

- There is an increased pressure for more frequent SW releases delivered in connected instruments. This takes place in a continuous manner, in between product launches as part of multigenerational product plans. The aim is to keep customer engagement and provide greater level of advanced functionality for the instruments. Software updates are also extremely convenient for users as they require nearly no effort and are generally exempt of any costs.

- The continuous access to companies' large image databases allows users to investigate cloud analysis tools. Players are racing for offering the better suited, more sophisticated set of image analysis tools in the cloud.

- More recently, companies are similarly competing to reduce customer pain points by leveraging AI/ML.

The latter point is particularly interesting as it benefits companies with long history and access to large diverse image repositories. Algorithms using AI/ML can be trained in large image datasets to be able to perform multiple functions, particularly image enhancement and object segmentation (Tran, 2022). In both cases, users can access tools to speed up their image analysis and increase the quality of their imaging results, thus boosting their productivity. During a recent public survey published by Zeiss, it was found that users are generally interested in using AI/ML to improve their data quality, speed and resolution, with the first one being the most important application, as indicated by 60% of the study participants (SelectScience, 2023).

2.3 Introduction to Technology Adoption

The previous chapters have covered the basic aspects of connected devices, and particularly of connected widefield microscopes. In this chapter, the attention is shifted towards technology adoption. To be able to shed light into the process of adoption of connected manual microscopes by scientists, it is imperative to understand how innovations are typically adopted. The topic of technology adoption is complex, and can be studied at an individual, organizational as well as a societal level. It includes the acceptance, implementation and utilization of new technologies, with the general goal of improving performance (Dearing and Cox, 2018). In the following sections, it is outlined the basis of innovation adoption, and then it is reviewed, in greater detail, the most widely used theory providing a framework for technology adoption at an individual level.

2.3.1 The basis of Innovation Adoption

A great deal of innovation research has been aimed at understanding how and why people adopt new technologies. For most successful technological innovations, despite of how different they may look to be, adoption seems to follow an S-shaped curve, as illustrated in FIGURE 9 (curve highlighted in dark blue).

The adoption is initiated by early adopters, which are followed by an early and then a late majority, and finally taken on by laggards. This model initially presented by (Rogers, 1983) proposed that users adopt technologies at different times, with an inflexion point after which an exponential flattening takes place that generally indicates market saturation. However, it should also be noted that competing or complementary innovations are also relevant since potential adopters usually can select what to adopt. In addition, failures are important since many innovations do not ever get adopted or ‘diffuse’, particularly if they are perceived to be new but not necessarily better (Dearing and Cox, 2018).

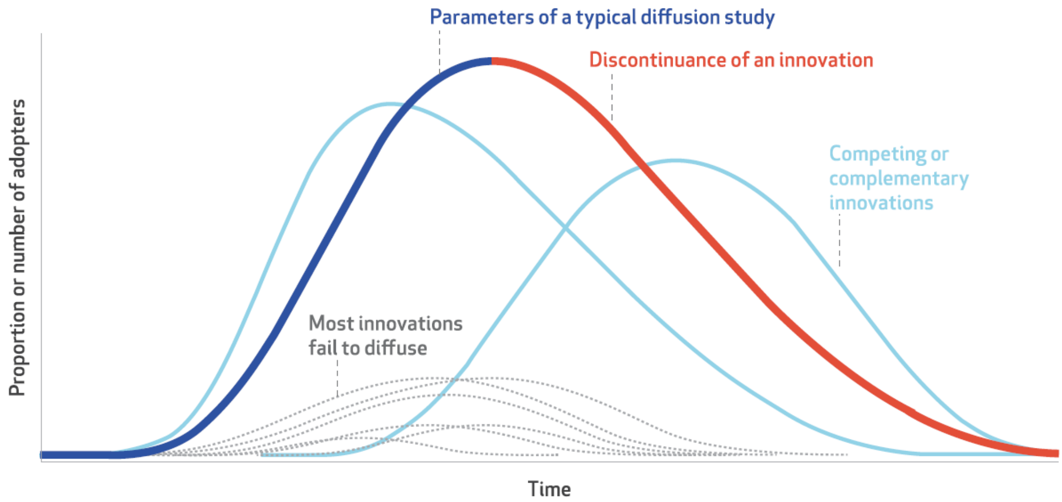


FIGURE 9. Innovation adoption curves, with each curve representing a separate hypothetical technological innovation, reproduced from (Dearing and Cox, 2018). The dark S-shaped curve represents an example of a successful adoption curve.

An extensive number of articles has been published with a focus on developing and testing models that can predict technology use, starting as early as in the 1970’s. The study by (Attié and Meyer-Waarden, 2022) has recently reviewed in detail the main accepted technology adoption theories, particularly in the context of the adoption of smart connected objects. Among these theories, the **Technology Acceptance Model (TAM)** (Davis, 1985) has been highly used and recommended in the literature for studying the adoption of disruptive technologies. This theory was first developed upon the introduction of email technology during the 1980’s, and its goal was to improve the understanding of user acceptance processes related to the new computer-based information systems. Thus far, TAM is regarded as the most influential theoretical framework for studying human behaviour when adopting new technologies (King and He, 2006; Marangunić and Granić, 2015; Taherdoost, 2018). Because of that, the Technology Acceptance Model was selected for this investigation, and it will be covered in detail in the following chapter.

2.3.2 Technology Acceptance Model (TAM) and its Evolution

The pioneering work conducted by Fred Davis to understand the adoption of email technology in a corporate organization (IBM), led to the proposal of the first version of the TAM (Davis, 1985). In this first model, Davis suggested that the usage or adoption of a new system (or technology) was primarily determined by the *attitude* of a user towards the system, which in turn was influenced by the *perceived usefulness* and the *perceived ease of use* (FIGURE 10).

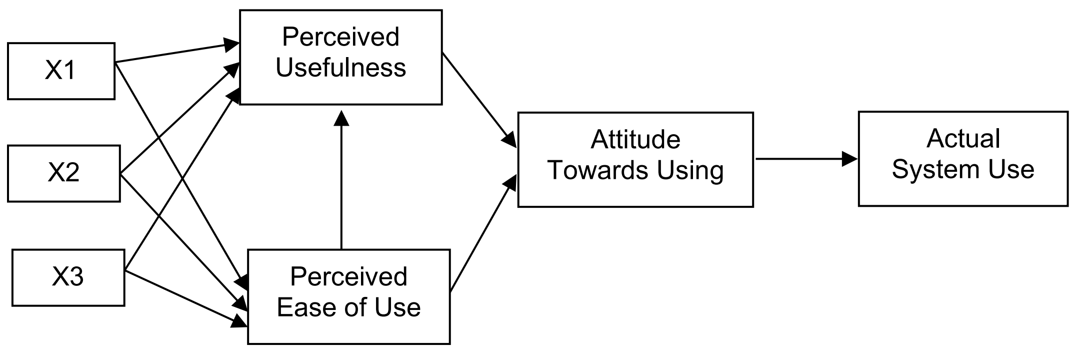


FIGURE 10. Original Technology Acceptance Model proposed by Fred David. The figure was redrawn from the original publication (Davis, 1985).

The ‘perceived usefulness’ was regarded as the degree to which a user believes that using a new system or technology can benefit their job performance (or life overall). In the case of instruments used for scientists this could be considered the extent to which a user believes the new system can help solve a specific pain point and improve his/her lab work experience. The second element, ‘perceived ease of use’, was found by Davis to contribute directly to the perceived usefulness, and it was defined as the degree to which the user believes that using the new system is effortless. The model also postulated that perceived usefulness and ease of use were both influenced by the *system design* characteristics (schematically represented in FIGURE 10 by certain system-dependent factors X1, X2, X3).

With research that was subsequently performed, the relationships presented in the original model were modified, some variables were removed, and new ones were added. For example, the *attitude* variable was found not to be directly mediating the relationship between perceived usefulness and perceived ease of use on the actual system usage, and thus it was entirely eliminated from the model (Davis, 1989). In turn, a new variable was added, namely *behavioural intention* (or *intention to use*) which was found to be directly influenced by the perceived usefulness of the system (Davis et al., 1989). In many parallel studies that were carried out during the following years, it became consistently clear that perceived usefulness is a key determinant on the intention to use. Thus, after further exploring which specific variables could influence the perceived usefulness, a new extension of the TAM model was developed (FIGURE 11), which is nowadays known as TAM2 (Venkatesh and Davis, 2000).

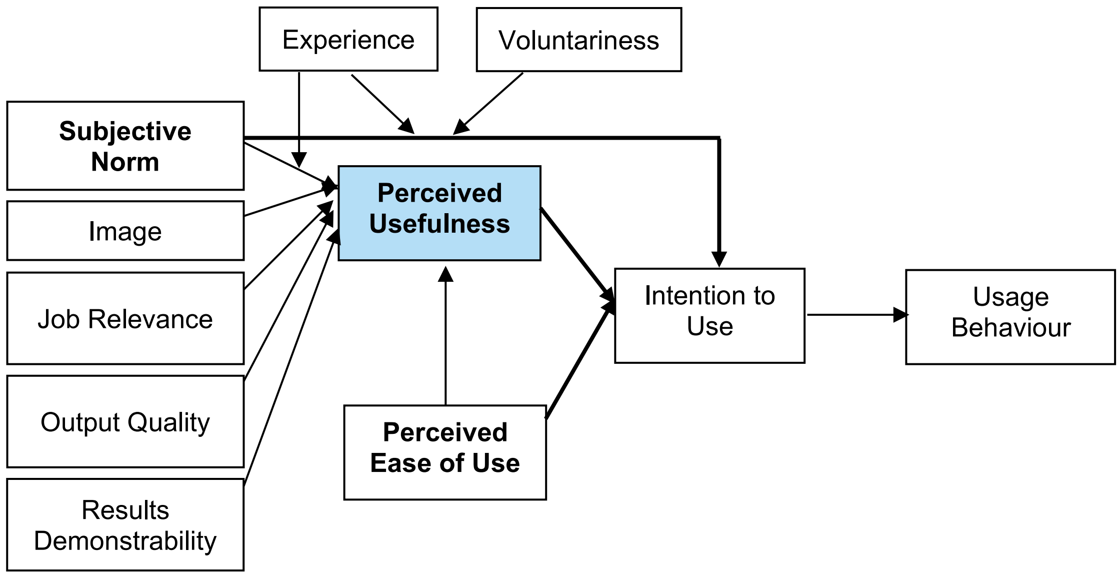


FIGURE 11. Extension of the Technology Acceptance Model known as version 2 (TAM2). The figure was redrawn from the original publication (Venkatesh and Davis, 2000). This model focused on identifying variables influencing the perceived usefulness (indicated in blue).

In this new model, new variables were found to influence the perceived usefulness, and they were defined as follows:

- *Subjective norm*: refers to the influence of other individuals on the user's decision to use or not the technology.

- *Image*: related to the desire of the user to maintain a favourable standing among others.

- *Job relevance*: corresponds to the extent to which the new technology is applicable and relevant to the user's job.

- *Output quality*: the degree to which the technology can deliver the promised results.

- *Results demonstrability*: the extent to which the technology can produce or influence the generation of tangible results.

This new extended model also identified the mediating effect of *voluntariness* and experience on the subjective norm by including two voluntary and two involuntary environments in a longitudinal research study (Marangunić and Granić, 2015; Venkatesh and Davis, 2000). The study conclusively demonstrated that intention to use is directly modulated by subjective norm, perceived usefulness (as in previous studies) as well as perceived ease of use. Those relationships are highlighted with thicker arrows in FIGURE 11.

Another relevant extension of TAM was published the same year by one of the authors of TAM2, Viswanath Venkatesh (Venkatesh, 2000). In this model, now broadly known as TAM3, the focus was instead on the contributing factors to the perceived ease of use. As shown in FIGURE 12, two different types of variables are highlighted: the so-called *anchors* and the *adjustments* (Venkatesh, 2000).

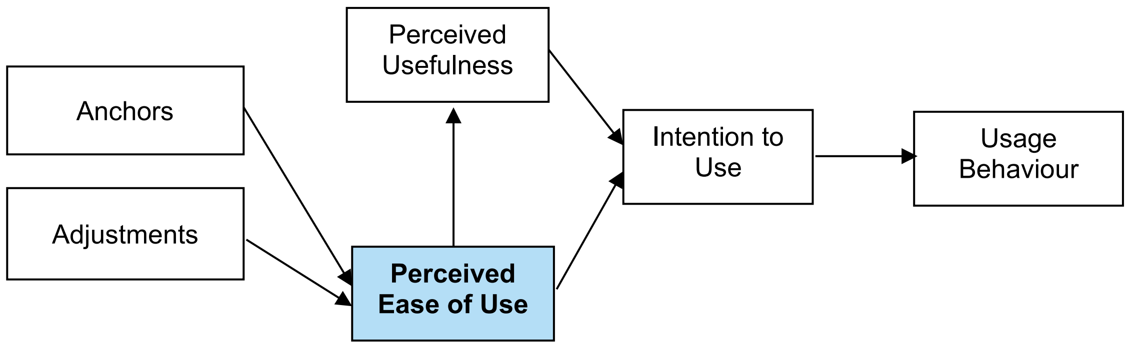


FIGURE 12. Extension of the Technology Acceptance Model known as version 3 (TAM3). This model focuses on identifying variables influencing the perceived ease of use (indicated in blue). The figure was redrawn from the original publication (Venkatesh, 2000), but in a more simplified manner.

The ‘anchors’ were defined as general beliefs about computers and computer usage. The category of anchors includes variables, such as computer-self efficacy, computer anxiety and computer playfulness. On the other hand, ‘adjustments’ are regarded as beliefs that are constructed based on the direct hands-on experience with the new system or technology. That category comprises variables such as perceived enjoyment and objective usability. In both cases, the variables, as defined by (Venkatesh, 2000), were not entirely new, but they were derived from previous research (Marangunić and Granić, 2015).

Following these efforts, and in view of the growing body of work around TAM in multiple different fields, a unified theory of acceptance and use of technology (UTAUT) was formulated in 2003 (Venkatesh et al., 2003). This theory integrates multiple elements across eight prominent TAM-based models. Furthermore, the Technology Acceptance Model has continued to evolve as more research has been conducted on the acceptance of information and digital technologies (a.o. Creaser et al., 2022; Dutot et al., 2019; King and He, 2006; Marangunić and Granić, 2015; Yanto et al., 2023). The modifications that have introduced to the TAM model are summarized in FIGURE 13.

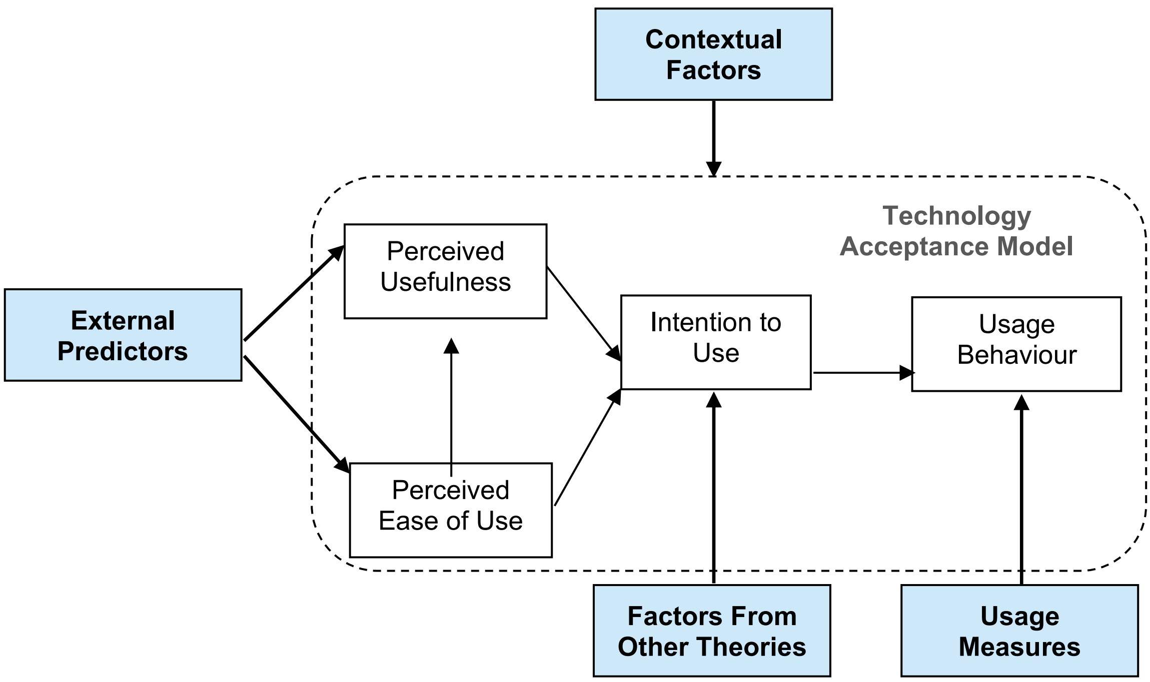


FIGURE 13. Summary of the types of modifications that have been introduced in the Technology Acceptance Model (modifications are shown in blue and relationships with thicker arrows). The figure was redrawn from (Marangunić and Granić, 2015).

These modifications can be sub-divided into four major types:

- *External predictors*: this refers to the multiple variables that have been identified as influencing the perceived usefulness and the perceived ease of use, some of which were discussed above for TAM1 and TAM2 models (FIGURE 11 and FIGURE 12).

- *Factors from other theories*: this relates to factors derived from other theories of technology acceptance, like risk (Featherman and Pavlou, 2003), trust (Wu et al., 2011) and user participation (Amoako-Gyampah, 2007).

- *Usage measures*: included here are actual measures of usage of the system or technology, which may not be interchangeable when applying TAM in different studies (Horton et al., 2001).

- *Contextual factors*: comprise specific factors, including also environmental factors, which could have a moderating effect on adoption, such as gender, cultural differences, age, personality differences, etc. In particular, age is one important factor that can play a key role in the interaction with technology (Marangunić and Granić, 2015).

It is important to note, however, that the Technology Acceptance Model is not exempt of limitations (Chuttur, 2009). For example, some studies using TAM have only included self-reported usage data, which is subjective and unreliable. In addition, different approaches to technology use (voluntary vs obligatory) have been shown to produce entirely different results (Chuttur, 2009). Furthermore, some authors have questioned the theoretical relationships between the different constructs of the model (a.o. Bagozzi, 2007). Therefore, it is important to be aware of these limitations when applying it to a new area, such as the adoption of connected microscopes.

3 METHODOLOGY

In this section it is introduced the methodology that was used to carry out this investigation, including the theoretical model that was proposed, as well as the methods that were used for quantitative data collection as well as analysis.

3.1 Research Model

As discussed in section 2.3.2, TAM is considered the most influential theoretical model for studying factors driving human acceptance of new technologies (Taherdoost, 2018) and it was therefore the model selected for this investigation. Building specifically from TAM3 and taking into consideration the assumptions that will be discussed below, this investigation proposed the model presented in FIGURE 14 to help explain adoption of connected microscopes. It can be safely assumed that connected microscopes have multiple smart functions, but for the purpose of this investigation, the attention was exclusively directed towards connectivity. In FIGURE 14, Q1-Q4 indicate the research questions that are postulated in this investigation, as already presented in the Introduction chapter.

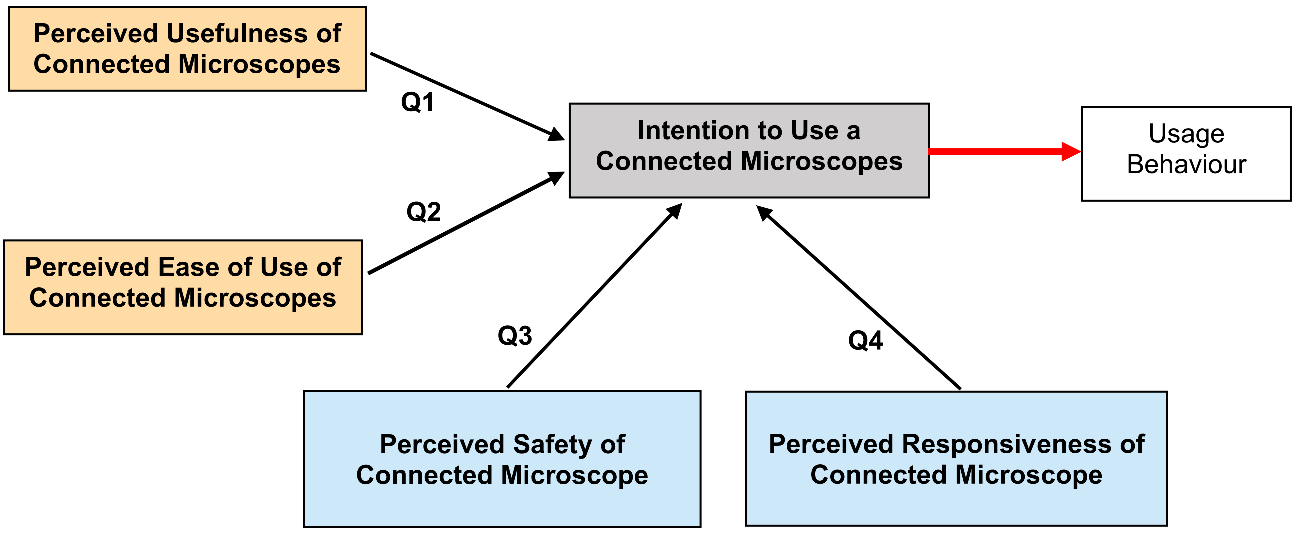


FIGURE 14. Research model used in this investigation. The blue, yellow and gray shadowed rectangles represent the constructs that were tested as part of this quantitative research. The relationship indicated with the red arrow was not part of this study.

After an extensive literature search, no publications directly focusing on studying adoption of connected laboratory instruments were identified. Therefore, other reference studies focusing on adoption of smart devices, particularly those with connected functionalities, were utilized instead to draw theoretical parallels and assist in the development of the quantitative survey applied here. The selected reference studies covered adoption of self-driving cars (Nees, 2016; Koul et al., 2018), smartwatches (Dutot et al., 2019), e-services in healthcare settings (Nazari-Shirkouhi et al., 2023) and virtual reality laboratories for educational purposes (Estriegana et al., 2019; Yanto et al., 2023).

A total of five dimensions or constructs were tested in this investigation. These specific studies mentioned above, as well as the general body of work around TAM, have confirmed the relationship between perceived usefulness, perceived ease of use and the intention to use new technologies. It was therefore hypothesized similar relationships would also apply in the case of connected microscopes. In addition to those dimensions, it is also hypothesized here that a direct relationship exists between either *perceived safety* or *perceived responsiveness,* and the intention to use connected microscopes. These two last specific constructs were introduced in this investigation as they are considered general challenges of connected laboratory instruments (Ali et al., 2022; Rochi, 2023). Thus, it was of great interest to test its relevance in the context of connected microscopes.

Definitions of constructs are not always included in published TAM studies. However, building from those TAM studies where definitions have been explicitly outlined (Holden and Karsh, 2010; Estriegana et al., 2019; Dutot et al., 2019), the following definitions of the constructs were developed and used on the course of this investigation:

- *Intention to use*: Defined as a scientists' inclination or willingness to use connected microscopes. In the TAM framework it is assumed that the higher the intention to use connected microscopes, the higher the actual usage will be.

- *Perceived usefulness*: Defined as use of the connected microscopes that leads to enhancement or gains in the job performance of a scientist.

- *Perceived ease of use*: Defined as either the lack of physical or mental efforts, or simply as the individual perception of how user-friendly a connected microscope is to utilize, in comparison with traditional (non-connected) instruments.

- *Perceived safety*: Defined as the lack of risk, or the existence of only minimal risks, when using connected microscopes. This is associated with a scientist's *trust, willingness to rely,* and sense of *security* with this new type of instrument.

- *Perceived responsiveness*: Defined as the capability of the instrument for fast and seamless data transfer to and from a cloud ecosystem, thus ensuring data preservation. The fastest this data transfer would occur, the more responsive the instrument is assumed to be.

To ensure clarity in the quantitative survey presented to participants, the term '*connected microscopes'* was always explicitly stated as '*microscope(s) connected to a cloud ecosystem*'.

3.2 Data Collection

In this section, all relevant aspects of the quantitative data collection process that were undertaken in this investigation are presented. This includes general aspects of the respondent's population, the survey design and the scenarios that were presented as part of the survey.

3.2.1 Participants

Participants in this quantitative study were all required to be scientists in any field within life sciences currently working with manual brightfield microscopes. The first question in the study served to qualify those that were active current users of the instruments and to exclude those that were not. Participants who responded negatively to the qualifying question, were immediately disqualified from responding to the survey. The total number of qualified respondents was 37. None of the users received any monetary compensation for their participation, and they were all contacted via the collaborative network of the author of this thesis.

Responders were all scientists working in academic and biotech/pharma institutions across Europe and the United States. Those institutions included the University of Helsinki in Finland, Uppsala University in Sweden, Institute for Cancer Research (ICR) in the UK, Research Center of the CHU de Québec, Université Laval, Canada, and companies such as Thermo Fisher Scientific, Zeiss and Evident (former Olympus). Basic demographic information was collected from all participants: age, years of experience using microscopes, academic degree, and the region of the world where they currently work.

3.2.2 Quantitative Survey

The survey was prepared and hosted on SurveyMonkey, and a link to it was distributed via email. The survey remained open for 10 business days. Each participant was randomly assigned to either a Control condition, coded C (no vignette, n= 11), the Idealized vignette condition, I (n= 14) and the Realistic vignette condition, coded R (n= 12). The vignette conditions are described in section 3.2.3. The study tested five dimensions and two to four statements were prepared for each dimension, as detailed in TABLE 2. Responses were measured on a 7-point Likert scale with anchors of ‘strongly disagree’ and ‘strongly agree’. The neutral scale was set at 4 with ‘neither agree nor disagree’. Participants were faced with a total of 18 statements, which were designed to assess the scientist’s attitude and willingness to adopt connected instruments.

The statements related to the general dimensions (Intention to Use, Perceived Usefulness and Perceived Ease of Use) were directly adapted from the corresponding references listed in TABLE 1. Given the specialized target audience of this study, when adapting the statements specific attention was given to re-wording key terms that are essential for scientific comprehension. The statements related to the constructs of Perceived Safety and Perceived Responsiveness were created *di novo*. A catch question was added towards the middle of the questionnaire, to ensure participants were fully engaged. It stated: ‘*This question is a check to make sure you are reading the questions. Please select the answer ‘I am reading carefully’ below*’. The correct answer was inserted at the ‘Neither agree nor disagree’, which is the neutral position on the Likert scale.

TABLE 1. Constructs and statements included in this quantitative survey utilized in this investigation.

Construct	Statement	Reference
Intention to Use Connected Microscopes (IU)	IU 1. I would like to have a microscope in my laboratory that is connected to a cloud ecosystem	(Nees, 2016)
	IU 2. Given that I would have access to a microscope connected to a cloud ecosystem, I foresee that I would use it.	(Koul et al., 2018)
Perceived Usefulness of Connected Microscopes (PU)	PU 1. I think using a microscope connected to a cloud ecosystem will allow me to work more productively.	(Koul et al., 2018; Nees, 2016)
	PU 2. A microscope connected to a cloud ecosystem will allow me to easily access and share my data.	
	PU 3. Using a microscope connected to a cloud ecosystem will enhance my effectiveness.	(Sagnier et al., 2020)
	PU 4. I believe that using a microscope connected to a cloud ecosystem will improve the service that I can receive from the	

	instrument manufacturer.	
Perceived Ease of Use of Connected Microscopes (PE)	PE 1. I believe I would find a microscope connected to a cloud ecosystem easy to use.	(Koul et al., 2018; Nees, 2016)
	PE 2. I think it will be easy for me to become skillful at using a microscope connected to a cloud ecosystem.	(Koul et al., 2018)
	PE 3. I think learning to operate a microscope connected to a cloud ecosystem will not be more difficult than learning to use a not-connected microscope.	(Koul et al., 2018)
	PE 4. I foresee that my interaction with a microscope connected to a cloud ecosystem will be clear and understandable.	(Nazari-Shirkouhi et al., 2023)
Perceived Safety of Connected Microscopes (PS)	PS 1. Using a microscope connected to a cloud ecosystem will be safe.	
	PS 2. I think there are no major security risks associated to using a microscope connected to a cloud ecosystem	
	PS 3. I feel comfortable using a microscope	

	connected to a cloud ecosystem even though I am aware that there are some associated risks.	
	PS 4. I think that using a microscope connected to a cloud ecosystem is secure enough for my work in the lab.	
Perceived Responsiveness of Connected Microscopes (PR)	PR 1. I believe a microscope connected to a cloud ecosystem will be fast to use.	
	PR 2. I think a microscope connected to a cloud ecosystem will allow me to save my data easier than a non-connected microscope.	
	PR 3. I think that a microscope connected to a cloud ecosystem will be convenient for uploading and downloading relevant data.	
	PR 4. I feel a microscope connected to a cloud ecosystem will be more reliable to preserve my original data than a non-connected microscope.	

3.2.3 Scenarios

The vignettes prepared for the study are presented in TABLE 2. They consisted of two hypothetic scenarios involving a scientist friend whose laboratory had acquired a fluorescence microscope one year ago. Their rationale was inspired by (Nees, 2016). The participants were asked to assume that the presented scenario was accurate. The realistic scenario was written to emphasize two main challenges associated to the use of connected microscopes, namely data security and instrument responsiveness. However, to ensure a balanced portrait, it also included some of the expected benefits of adopting these systems, specifically improved sharing, and collaboration as well as higher convenience. A control group received no vignette. In this case, participants were directly presented with the following text, which was common to all scenarios: *'In this survey, statements will be presented, and you will be given options to express your agreement or disagreement'.* Selection of each scenario was randomized in the survey, as described in previous section.

TABLE 2. Vignettes randomly presented to participants in the quantitative survey.

Idealistic vignette	**Realistic vignette**
Imagine that in the cell culture laboratory of one your scientist friend, a manual fluorescence microscope was purchased about 1 year ago. This microscope can connect to cloud ecosystems (such as OneDrive) as well as to a cloud provided by the instrument manufacturer. Getting the instrument connected took no time and it was handled smoothly by the IT Department. Now, when your friend uses the instrument, he uploads his images at a high speed to the cloud. He can then access his images later, from his own computer or mobile phone, and analyze them remotely. Your friend enjoys that he can share his data with his supervisor in a more convenient	Imagine that in cell culture laboratory of one your scientist friends, a manual fluorescence microscope was purchased about 1 year ago. This microscope can connect to cloud ecosystems (such as OneDrive) as well as to a cloud provided by the instrument manufacturer. Getting the instrument connected took some months, as they were some hurdles related to restrictions of the IT department. Now, when your friend uses the instrument, he often uploads his images to a cloud environment, and he shares and analyze them more easily. However, when working with many files, especially from time-lapsed or higher plex experiments, he has noticed

way. He feels the instrument is safe and his data is secured, even when working in confidential projects. Your friend also likes that he does not need to worry anymore about carrying an USB drive into the cell culture laboratory. Additionally, he now quickly downloads software upgrades, when they become available from the instrument manufacturer, to keep the instrument up-to-date.	that data transferring is not always fast. Thus, when he is in a hurry, he takes a USB drive into the cell culture lab. In few cases during the last month, he needed to wait for another user to finish this data uploading to the cloud before he could use the microscope. When working on confidential projects, he still uses the instrument offline due to concerns on data security.

3.3 Data Analysis

A D'Agostino & Pearson test was first applied to determine if the data was normally distributed. Once this was confirmed, parametric tests were subsequently selected to perform the relevant statistical comparisons. Means and standard deviations (SDs) for all survey constructs were calculated. To evaluate how a presented scenario could influence the acceptance of connected microscopes, differences between the responses across all survey items in the three tested groups (C, I or R) were subjected to one-way Analysis of Variance (ANOVA). To specifically establish the differences between pairs of groups, an unpaired t-test with Welch's correction was applied. Welch's correction was selected on the basis that it does not assume equal standard deviations (SDs).

The relationships between PU, PE, PS, PR and IU for connected microscopes were investigated using Pearson Correlation. Descriptive statistics were used to assess the demographic variables tested in the study. Furthermore, an exploratory analysis was undertaken to assess if two of other variables measured as part of the survey (age and years of experience with microscopes) could have any correlation with the intention to use. For such exploratory analysis both descriptive statistics as well as Pearson Correlation were applied. In all cases, statistical significance for this study was set at $p \leq 0.05$. All statistical analysis were performed using GraphPad Prism software version 10.2.1.

4 RESULTS

Results that were obtained in this quantitative study are summarized in this section, alongside a discussion of key aspects associated to the data analysis.

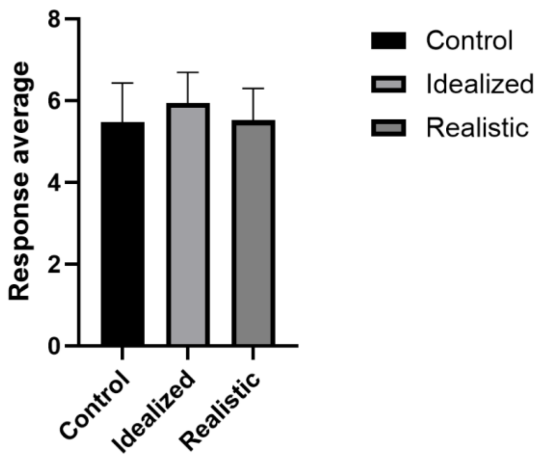
4.1 Vignette Effect and General Data Trends

Prior to initiating any analyses, all scores obtained for all five constructs in the three tested groups (C, I or R), were subjected to a D'Agostino & Pearson test. As presented in TABLE 3, the data is binomially distributed across all groups. Based upon this, it was deemed adequate the application of parametric statistics for all statistical analysis performed in this investigation.

TABLE 3. Results of D'Agostino & Pearson normality test for the survey results on the three tested scenarios (C, I and R).

	Control (C)	Idealized (I)	Realistic (R)
K2	1.227	3.869	0.050
p value	0.541	0.145	0.975
Passed normality test? (α =0.05)	Yes	Yes	Yes
p value summary	ns	ns	ns

The average scores for all survey items were then compared across the three tested groups using one-way ANOVA, and results are presented in FIGURE 15.



One-Way ANOVA Summary	
F (2, 178)	5.933
p value	0.0032
p value summary	**

FIGURE 15. Statistical comparison of the overall survey scores obtained for the three tested scenarios (C, I and R). The ANOVA results are shown as an insert in the figure.

Higher scores in the survey indicated higher acceptance of connected microscopes. The obtained ANOVA results demonstrates that there is a significant difference between the three conditions. In particular, the overall scoring of participants on the idealized vignette (5.941 $\pm$ 0.753) is significantly higher than in the control group (5.486 $\pm$ 0.948), p= 0.0049 **) and higher as well than in the realistic condition (5.525 $\pm$ 0.779, p= 0.0028 **). This is not surprising, as humans can be more accepting of new technologies under idealized scenarios, as reported for instance in adoption studies of self-driving cars (Nees, 2016). By contrast, the realistic vignette and the control conditions are not significantly different from each other (p= 0.8112). Thus, it can be concluded that the realistic vignette does not negatively impact the outcome of the participant's scores.

An individual analyses of the five dimensions across the three groups was also conducted and the results are shown in TABLE 4.

TABLE 4. Means and standard deviations calculated for all responses in each of the three tested scenarios (C, I and R) across the five measured dimensions.

Dimensions	**Control (C)**	**Idealized (I)**	**Realistic (R)**
Intention to Use (IU)	6.09 $\pm$ 0.89	6.43 $\pm$ 0.73	5.96 $\pm$ 0.72
Perceived Usefulness (PU)	6.11 $\pm$ 0.28	6.00 $\pm$ 0.50	5.44 $\pm$ 0.70
Perceived Ease of Use (PE)	5.38 $\pm$ 0.81	6.00 $\pm$ 0.85	5.73 $\pm$ 0.73
Perceived Safety (PS)	4.66 $\pm$ 0.78	5.21 $\pm$ 0.53	4.98 $\pm$ 0.76
Perceived Responsiveness (PR)	5.18 $\pm$ 1.79	6.08 $\pm$ 0.58	5.53 $\pm$ 0.73

Via this descriptive analysis, it can be further concluded that participants in the idealized scenario score the highest for IU, PE, PS and PR across the three groups, but not for PU. This is an interesting observation as it suggests that usefulness of connected microscopes is clearly perceived and accepted among scientists, regardless of the vignette. Another observed noticeable pattern is that IU remains the highest scored attribute in the idealized group as well as in the realistic group, whereas PS is the lowest scored attribute in each of the three groups. The realistic scenario presented to participants included statements highlighting the two main barriers commonly associated to connected instruments (data security and instrument responsiveness, see TABLE 2). However, the scores of participants for the corresponding dimensions of PS and PR, respectively, are higher in the realistic scenario when compared to the control condition. Overall, although idealized participants seem in general more willing to adopt connected instruments and to better perceive their ease of use, safety and responsiveness, the vignette condition is not the only one explaining the differences across the three groups.

It is important to note that around 54% of the survey participants identify themselves as being at least '*somewhat familiar*' with the topic of connected microscopes. Additionally, 57% of all participants possess at least 10 years of experience using brightfield microscopes, with that percentage being the highest (at 90%) for the control group. Thus, it is reasonable to also assume that across all groups, participants have formed an opinion on the topic of connected microscopes, that could be independent of the scenario that they were confronted with, during the survey.

4.2 Descriptive Statistics for all Survey Variables

Means, standard deviations, and medians for all individual items in the survey were calculated and they are presented in TABLE 5.

From a descriptive standpoint, responses to most items in the survey (17 out of 18) tend to positive agreement in the Likert scale, based on their medians being 5 or higher. The highest received scores are for statement PU2 (*A microscope connected to a cloud ecosystem will allow me to easily access and share my data*), which emphasizes the benefits of better data access and shareability that is provided by connected instruments. None of the statements tend to negative agreement in the Likert scale, based on none of the medians being below 4. The only item in the survey having a median of the responses at the neutral position (4) is PS2, as respondents were in general unable to agree nor disagree with the statement: *I think there are no major security risks associated to using a microscope connected to a cloud ecosystem*. Overall, a comparison between variables indicates that PS scores are lower than the rest of the variables, as already mentioned in previous section 4.1 (when describing TABLE 4). However, the overall score considering all four items within PS on was clearly above neutral (4.97).

TABLE 5. Descriptive statistics calculated for all constructs in the survey across all participants.

Construct	Statement	Mean	SD	Median
Intention to Use Connected Microscopes (IU)	IU 1. I would like to have a microscope in my laboratory that is connected to a cloud ecosystem	6.11	0.81	6.00
	IU 2. Given that I would have access to a microscope connected to a cloud ecosystem, I foresee that I would use it.	6.24	0.89	6.00
Perceived Usefulness of Connected Microscopes (PU)	PU 1. I think using a microscope connected to a cloud ecosystem will allow me to work more productively.	5.73	0.99	6.00
	PU 2. A microscope connected to a cloud ecosystem will allow me to easily access and share my data.	6.43	0.87	7.00
	PU 3. Using a microscope connected to a cloud ecosystem will enhance my effectiveness.	5.73	0.93	6.00
	PU 4. I believe that using a microscope connected to a cloud ecosystem will improve the service that I	5.22	1.34	5.00

	can receive from the instrument manufacturer.			
Perceived Ease of Use of Connected Microscopes (PE)	PE 1. I believe I would find a microscope connected to a cloud ecosystem easy to use.	5.60	1.17	6.00
	PE 2. I think it will be easy for me to become skillful at using a microscope connected to a cloud ecosystem.	5.92	1.04	6.00
	PE 3. I think learning to operate a microscope connected to a cloud ecosystem will not be more difficult than learning to use a not-connected microscope.	5.46	1.66	6.00
	PE 4. I foresee that my interaction with a microscope connected to a cloud ecosystem will be clear and understandable.	5.76	1.12	6.00
Perceived Safety of Connected Microscopes (PS)	PS 1. Using a microscope connected to a cloud ecosystem will be safe.	4.78	1.00	5.00
	PS 2. I think there are no major security risks associated to using a microscope connected to a cloud ecosystem	4.14	1.18	4.00
	PS 3. I feel comfortable using a microscope connected to a cloud	5.45	0.99	6.00

	ecosystem even though I am aware that there are some associated risks.			
	PS 4. I think that using a microscope connected to a cloud ecosystem is secure enough for my work in the lab.	5.57	0.77	6.00
Perceived Responsiveness of Connected Microscopes (PR)	PR 1. I believe a microscope connected to a cloud ecosystem will be fast to use.	5.14	1.48	6.00
	PR 2. I think a microscope connected to a cloud ecosystem will allow me to save my data easier than a non-connected microscope.	5.76	1.36	6.00
	PR 3. I think that a microscope connected to a cloud ecosystem will be convenient for uploading and downloading relevant data.	6.08	0.95	6.00
	PR 4. I feel a microscope connected to a cloud ecosystem will be more reliable to preserve my original data than a non-connected microscope.	5.00	1.55	5.00

4.3 Correlation Analyses

Most TAM studies have centered on the study of the relationships between PU, PE and the anticipated IU of many different types of new technologies (Holden and Karsh, 2010; Horton et al., 2001). The applications have been very broad, ranging from online learning and virtual laboratories (Estriegana et al., 2019), smartwatches (Dutot et al., 2019), to driverless cars (Koul et al., 2018), near-field communication allowing mobile payments (Dutot, 2015) and e-services across multiple industries, such as healthcare (Nazari-Shirkouhi et al., 2023), just to mention a few.

To test the relationships between the variables hypothesized in the initially proposed model (FIGURE 14), Pearson correlations were calculated. A matrix showing the correlation among all research variables is displayed in TABLE 6. The PU and the PS were found to be both positively correlated, in a statistically significant manner, with the IU connected microscopes. On the other hand, PE and PR were both positively correlated with the IU, but not in a statistically significant manner. More specific details on the research questions analyses are presented in TABLE 7.

TABLE 6. Correlation matrix indicating relationships among all variables tested in this study. The shadowed cells correspond to the relationships studied as part of the research questions of this investigation.

	Intention to Use (IU)	Perceived Usefulness (PU)	Perceived Ease of Use (PE)	Perceived Safety (PS)	Perceived Responsiveness (PR)
Intention to Use (IU)	1.000				
Perceived Usefulness (PU)	**0.487****	1.000			
Perceived Ease of Use (PE)	0.124	0.2070	1.000		
Perceived Safety (PS)	**0.354***	-0.0884	-0.0406	1.000	
Perceived Responsiveness (PR)	0.207	-0.0601	0.0708	0.4890**	1.000

*$p < 0.05$; **$p < 0.01$; *** $p < 0.001$

TABLE 7. Specific statistical analyses performed to answer the research questions addressed in this study.

Research Question	**Statistical Analysis Result**
Q1: To what extent does a relationship exist between the perceived usefulness (PU) of connected microscopes and the intention to use (IU) them?	The PU of connected microscopes and the IU have a moderate, statistically significant positive relationship: $r = 0.4873$, $R^2 = 0.2375$, $p = 0.0035$ (** $p < 0.01$)
Q2: To what extent does a relationship exist between the perceived ease of use (PE) of connected microscopes and the intention to use (IU) them?	The PE of connected microscopes and the IU have a positive but not statistically significant relationship: $r = 0.1237$, $R^2 = 0.01531$, $p = 0.4856$ (ns, $p > 0.05$)
Q3: To what extent does a relationship exist between the perceived safety (PS) of connected microscopes and the intention to use (IU) them?	The PS of connected microscopes and the IU have a weak, statistically significant positive relationship: $r = 0.3538$, $R^2 = 0.1252$, $p = 0.0371$ (* $p < 0.05$)
Q4: To what extent does a relationship exist between the perceived responsiveness (PR) provided by connected microscopes and the intention to use IU) them?	The PR of connected microscopes and the IU have a positive but not statistically significant relationship: $r = 0.2069$, $R^2 = 0.04280$, $p = 0.2480$ (ns, $p > 0.05$)

With respect to **Question 1**, it was demonstrated in this study the existence of a **positive and significant correlation between PU and the IU** for connected microscopes. The statements used in this survey emphasized the main benefits expected from connected microscopes, among them: easier access to data, better data shareability (which also provides better capabilities for data traceability), better access to the services that are received by the instrument manufacturer as well as higher productivity. In particular, the highest scores obtained for PU2 serves as a key indication of the importance of remote data access and shareability for scientists. This is a finding that can be likely beneficial for manufacturers looking for effective ways to promote their connected microscopes. It is also significant that the usefulness statement associated with manufacturer's services (PU4) received the lowest score within this dimension. It would be worthwhile for manufacturers to gather more convincing evidence of the true benefits of using connected instruments from a service and support standpoint, to further increase the perception of usefulness among potential future users.

In relation to **Question 2**, it was, unexpected, on the other hand, that PE and IU correlated positively but not in a statistically significant manner. In general, it is assumed that the ease of use of a system improves the self-confidence and self-efficacy of an individual, which in turn creates a positive attitude towards the use and adoption of a new system (Nazari-Shirkouhi et al., 2023). The statements utilized in current survey emphasized, as in several earlier studies (Koul et al., 2018; Nazari-Shirkouhi et al., 2023; Nees, 2016) multiple relevant aspects of this dimension, such as: the intrinsic easy to use; how easy would be to become skillful with a connected microscope, how easy would be to learn and operate a connected microscope (when compared to a traditional instrument) and how interactions would be clear and understandable.

It is not immediately obvious why a significant positive relationship between PE and IU could not be demonstrated here. When looking at this specific correlation graph (shown in FIGURE 16), it could be noted that users who showed a high intention to use connected microscopes (with high IU scores, multiple overlapping datapoints ranking around 7 in the Likert scale), did not perceive connected instruments as easy to use, as they responded with lower PE scores.

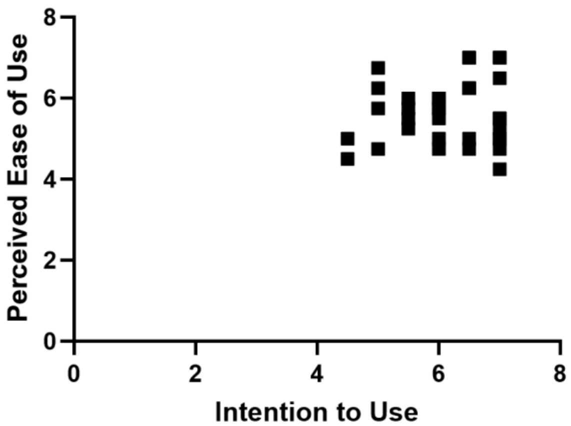


FIGURE 16. Correlation graph between dimensions of IU and PE, as recorded in this quantitative survey.

It could be hypothesized that user's perceptions of ease of use for connected microscopes extents to *'ease of installation'*, even though this was not explicitly included in any of the survey PE statements. Engagement of IT and technical hurdles that need to be overcome during the installation of connected microscopes are often challenging aspects that have been known to impact adoption of connected lab instruments (Gill, 2018). Confounding *'ease of use'* and *'ease of installation'* could potentially explain why lower scores were obtained for PE. From instrument manufacturers standpoint, these results highlight the need for more development efforts to improve usability, particularly around design elements that are specifically associated to microscope connectivity. Lastly, it should also be kept in mind that the reduced size of the study population is a limitation of this present study. With a broader sample size, it is possible to have a more reliable result of any possible relationships between PE and the IU for connected microscopes.

Another interesting outcome was the demonstration of a **positive, albeit weak correlation, between PS and the IU** for connected microscopes, which answers **Question 3** of this investigation. The perception of safe usage is essential for instruments in which data is transferred outside of the physical location of the instrument to a cloud ecosystem, and/or shared, and it often associates with user trust. Trust has been shown to play a key role in the individual's decision to develop a long-term relationship with a particular product, or a manufacturer/brand and it is thus essential for new technology adoption (Seong-Ha and Ha-Kyun, 2023). In a prior study covering the adoption of smartwatches (a different, but yet also connected, device type), trust was defined as 'willingness to rely' on the other partner, which in that case was the smartwatch manufacturer brand (Dutot et al., 2019). Similarly, perceived safety can be associated with security, and research has suggested that customers, in this case scientists, need to be convinced that their data is secured and it cannot be intercepted, for them to be willing to use the products (Dutot, 2015).

Many studies have demonstrated that trust is positively correlated to PU and PE, which in turn are both positively correlated to IU, in the TAM framework (Dutot, 2015; Dutot et al., 2019; Sagnier et al., 2020). The PS statements in current study focused on the acceptance of risks, assuming that they are not major, as well as in the willingness to accept that using a cloud ecosystem is 'secure enough' for the work in the lab. Once more this can be useful information for instrument manufacturers, in trying to offer proof points for scientists that their connected microscopes are safe. In future studies, it would be interesting to gather more insights into what can be considered *'secure enough'.* Similarly, it would be good to gather more insights into the PS perspectives of academic vs industrial users, as scientists working in industry, for instance in pharma or biotech, are often involved in confidential projects, and can therefore have more safety concerns than academic users. In our survey we unfortunately did not collect information on user segments, and thus it was not possible to perform any exploratory correlations around PS and end-user work segment.

Finally, in assessing **Question 4** of this study, it was demonstrated that PR and IU have a positive but not statistically significant correlation. Responsiveness was a variable selected for this study given the important implications of data transfer effectiveness for connected instruments (Poger et al., 2023). However, finding similar quantitative survey studies in the literature proved difficult, and thus the statements that were utilized here were created by the author based upon her own expertise. As a result, they lacked any direct validation from any previously published investigation. Additionally, it needs to be kept in mind, that PR is an attribute that could be challenging to gauge in a quantitative investigation, such as current study. This is because responsiveness in terms of *'uploading and downloading'* or *'saving data'*, could be very differently perceived by users depending on their specific experiences in speed connectivity at their respective institutions. In retrospect, the survey should have included one or two open questions for the PR dimension, to gather a more nuanced understanding of what the responsiveness perceptions were among participants. For future investigations, it would be important to expand this type of investigations not only to a larger sample size, but also to include qualitative insights of users, on the topics of PR and PE.

Finally, even though it was not initially intended as a research question in this study, it was also demonstrated the existence of a moderate, statistically significant positive relationship between PS and PR, with r = 0.4890, R^2= 0.2391, p= 0.0039 (** $p < 0.01$). This relationship is worth exploring in further studies.

4.4 Demographic Analyses

The collected demographic data in this study included participant's age, years of experience in using brightfield microscopes, region of the world where they work, and their educational degree. A summary of this data is presented in TABLE 8.

From participant's age perspective ~43% of participants belonged to the 25-34 age group, while another 45% was distributed across 35-44 and 45-54 ranges. None of the participants was under 24, which could be regarded as 'too young' (from a scientific standpoint) as it is where undergraduates would be primarily included. Also, roughly 43% of participants had accumulated up to 9 years of experience working with brightfield microscopes and the vast majority (over 86%) had at least 5 years of experience. In addition, 50% of them had completed a Doctoral degree. In general, this indicates that the surveyed population, despite its limited size (n=37), provided a good representation of knowledgeable, skilled, and well-versed microscopy users.

TABLE 8. Demographics data overview of survey's participants.

Variable	Ranges	Number	Percentage
Age	18-24	0	0.0%
	25-34	16	43.2%
	35-44	11	29.7%
	45-54	6	16.2%
	55-64	4	10.8%
	65+	0	0.0%
Years of Experience	< 5 years	5	13.5%
	5-9 years	11	29.7%
	10-14 years	12	32.4%
	15-20 years	8	21.6%
	> 20 years	1	2.7%
Region	Europe	20	54.1%
	North America	16	43.2%
	Asia	1	2.7%
Educational degree	BSc	3	8.1%
	MSc	13	35.1%

	PhD	19	51.4%
	Adjunct (Docent) or Associate/Assistant Professor	1	2.7%
	Professor	0	0.0%
	Other	1	2.7%

4.5 Additional Exploratory and Correlational Analyses

In several new technology adoption studies, age has been found to influence the intention to use (Marangunić and Granić, 2015; Straub, 2009). In some specific cases, such in the adoption of driver-less cars, it has been demonstrated that age is negatively correlated with the usage intent (Koul et al., 2018; Nees, 2016). Thus, it would be plausible to assume that younger scientists, having spent less years of lab experience with traditional (non-connected) instruments, may show a higher disposition, be keener and more willing to use newer, connected microscopes. Correlations between the intention to use connected microscopes and the age as well as years of experience, were then separately investigated, and results are presented in TABLE 9.

TABLE 9. Exploratory correlational analyses between IU and two other variables (age and years of experience).

Additional Research Question	**Statistical Analysis Result**
To what extent does a relationship exist between the user age and the Intention to Use (IU) connected microscopes?	The age of the user has a negative but not statistically significant relationship with the intention to use connected microscopes: $r = -0.1134$, $R^2 = 0.01286$, $p = 0.5166$ (ns, $p > 0.05$)
To what extent does a relationship exist between the years of experience of the user and the Intention to Use (IU) connected microscopes?	The years of experience of the user has a negative but not statistically significant relationship with the intention to use connected microscopes: $r = -0.03616$, $R^2 = 0.001308$, $p = 0.8366$ (ns, $p > 0.05$)

In alignment with previous studies, a negative correlation was identified in both cases, but they were not found to be statistically significant. It is possible that by increasing the sample size, more reliable correlations could be established between these variables.

To further investigate a possible impact of age with the limited sample size that was gathered in this study, the responses were divided into two groups: under 34 (representing 43% of participants) and over 34 (representing the remaining 57%). By dividing into only two groups, it was also possible to have a larger number of respondents in each group which would increase the statistical confidence of the test. Scoring results for each of the five survey dimensions were then compared between the groups (FIGURE 18). No statistically significant differences were identified in any of the cases.

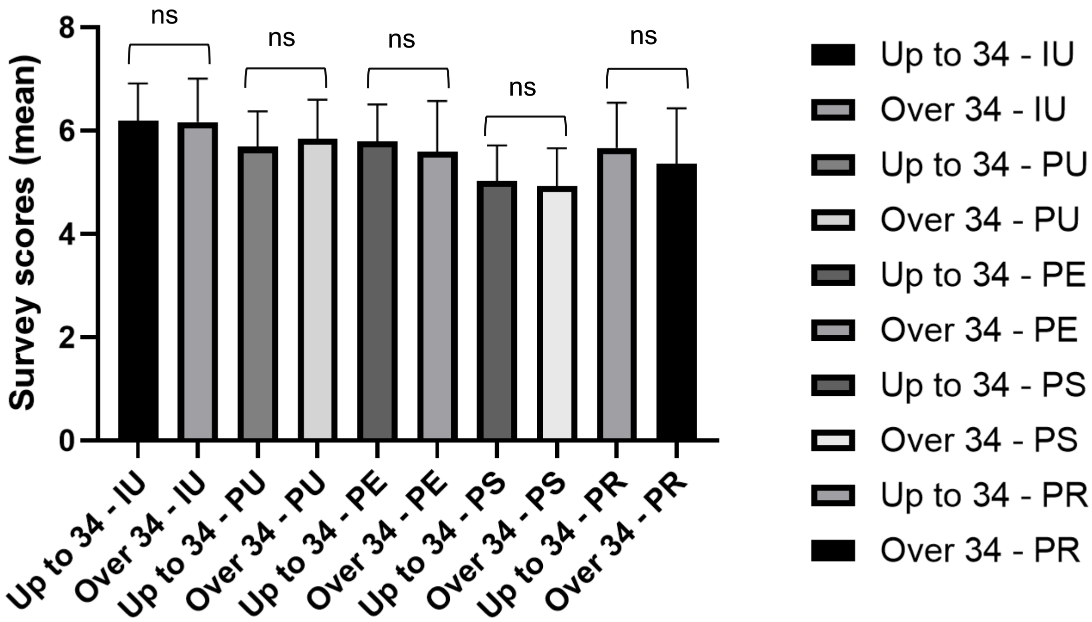


FIGURE 17. Comparison of results (mean ± standard deviations) obtained for each of the survey variables, between respondents who were up to 34 years old and those who were above.

A similar comparison was performed considering years of experience using brightfield microscopes. The responses were also divided into two groups: those who had up to 9 years of experience (also representing 43% of participants, like in the case of the users under 34 years old) and at least a decade of experience (the remaining 57%). In this manner, it could be exactly considered the user experience with microscopes. Scoring results for all survey dimensions are presented in FIGURE 18. As in the age effect, there was no statistically significant differences on the overall acceptance of connected instruments as measured across all constructs between both groups.

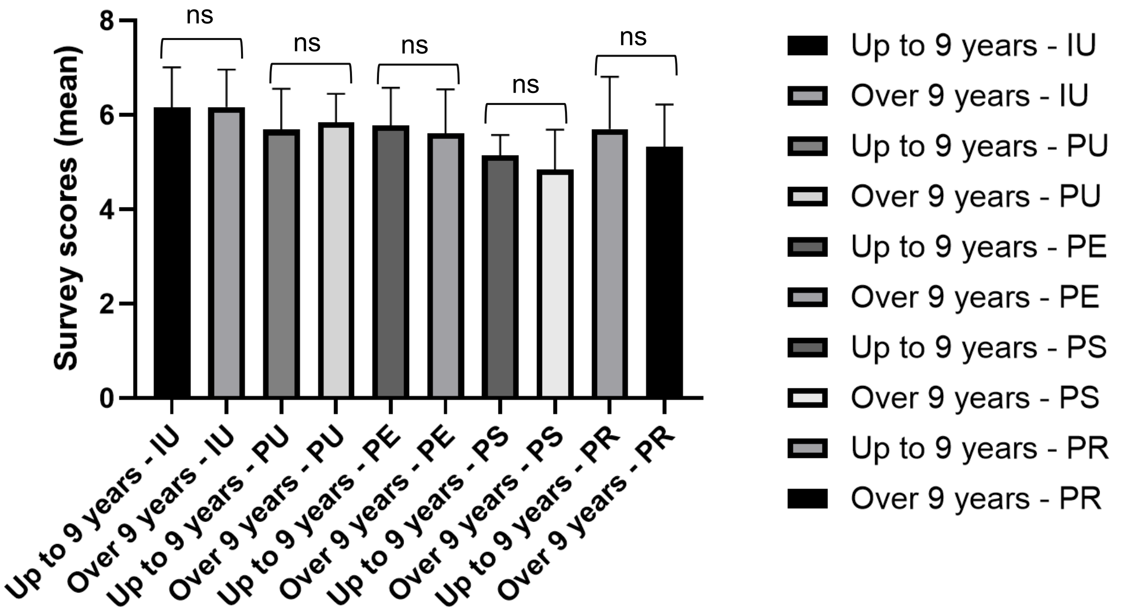


FIGURE 18. Comparison of results (mean ± standard deviations) obtained for each of the survey variables, between respondents who had up to 9 years of experience and those with at least a decade of experience.

5 DISCUSSION AND CONCLUSIONS

This chapter includes a summary of the main actionable findings of this thesis, alongside the repercussions that they may pose for instrument's manufacturers wishing to succeed and continue to grow in the manual widefield microscopy market. To maintain an objective perspective of the implication of this thesis, the limitations of this investigation are also critically assessed, followed by key recommendations on opportunities for future investigations.

The survey carried out in this investigation served to test an adoption model that helps explaining the main drivers behind adoption of connected manual widefield microscopy market, within the framework of the TAM and at an individual user level (FIGURE 14). This initially proposed model was revisited, and the confirmed and/or unconfirmed correlations accordingly reviewed, as shown in FIGURE 19. The statistically significant relationships demonstrated here (black straight arrows) serve to identify two main drivers for user adoption.

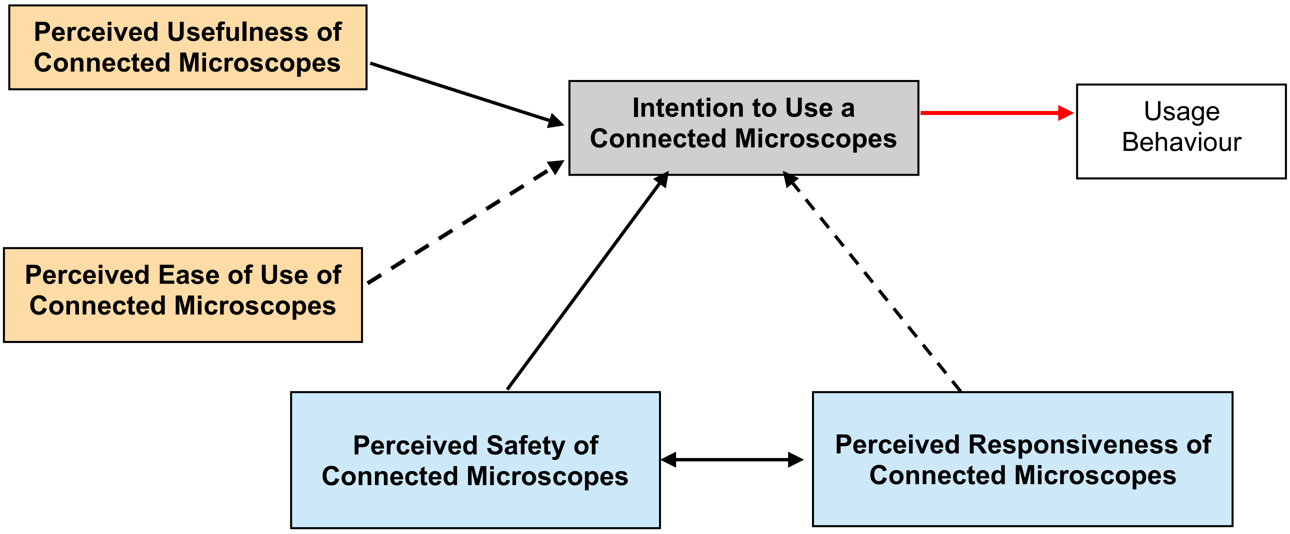


FIGURE 19. Model for adoption of connected microscopes, as demonstrated in current study. The straight black arrows correspond to positive and statistically significant relationships confirmed during this study, whereas the dotted arrows correspond to positive, but not statistically significant correlations.

In first place, the usefulness of connected microscopes, as perceived by scientists who currently are active users, correlates positively and significantly with their intention to use these instruments. Regardless of the vignette that they were shown during this quantitative survey, scientists tended to agree with statements associated with connectivity benefits, in particular higher productivity, increased data sharing, and enhanced work effectiveness. Given that findability, accessibility, interoperability and reusability of data, as per the FAIR guidelines (Wilkinson et al., 2016) have gained increasingly more importance in the biological imaging field, it is expected that the perceived usefulness of connected microscopes will only continue to grow. It is important to note that the specific benefit of improved service by manufacturers received the lowest score within the perceived usefulness construct. For instrument manufacturers, this provides an important guidance for their development and marketing strategies. It needs to be credibly and convincingly demonstrated to users that connecting their microscopes to cloud ecosystems indeed improves the service and support they could receive from vendors. From a communication standpoint, case studies could be highly valuable to convince scientists, for instance by using examples of installed instruments whose users have directly benefited from truly faster and more effective vendor support.

In second place, the perception of safe usage correlates also positively and significantly with the intention to use connected microscopes. In other words, the safer a connected microscope is perceived to be, the more intention to use a scientist shows. Consequently, to ensure adoption, connected microscopes need to be demonstrably safe and solutions for storing data need to be proven secure to customers. For large companies that have developed their own customized cloud ecosystems, such as Zeiss, Evident and Thermo Fisher Scientific, data protection becomes imperative, and continuous investment to maintain secure platforms need to be prioritized, which consequently increases development costs in the long run. Interestingly, unlike usefulness, perception of safety on connected microscopes is less obvious for scientists across all the three scenarios that were tested in this thesis. Once more, this provides actionable guidance to manufacturers in the manual microscopy market. As shown in other studies Seong-Ha and Ha-Kyun, 2023), building a sense of trust and security ensures a long-term relationship with a provider. For connected microscopes, this is proven not to be an exception.

Additionally, this study demonstrates that there is a positive correlation between perceived ease of use and the intention to use connected microscopes, as well as between perceived perceived responsiveness and the intention to use such instruments, although in both cases the correlations are not statistically significant. It could be argued that the survey applied here was unable to capture the nuances associated to both dimensions. For example, the perception of 'ease of use' could have been confounded with 'ease of installation' or 'ease to maintain'. It is plausible to expect that scientists could perceive a more complex instrument (a connected vs a traditional one) as more complicated to maintain. Similarly, the assessment of perceived 'responsiveness' using terms such as *'uploading and downloading'* or *'saving data'* could be interpreted differently by users, based upon their specific individual experiences. Thus, other investigation approaches, possibly involving qualitative research, may be needed to confirm current findings.

Finally, this study allows to tentatively conclude that age and years of experience of the scientists are negatively correlated with their intention to use connected microscopes, but not in a statistically significant manner. Consequently, targeting adoption to specific younger audiences does not seem to be an absolute pre-requisite for manufacturers willing to increase their market share. By contrast, it could be potentially better not to prioritize age-targeted marketing, since decision making in instrument purchases is typically in the hands of more experienced scientists in senior positions, such as Principal Investigators, Group Leaders or Professors. In that direction, it seems better to simply create better proof points for scientists that connected microscopes do indeed increase individual productivity.

Despite the reduced sample size, the quality of the responses in this survey could be regarded as high, judging from the fact that over 50% of surveyed participants expressed familiarity with the topic of connected microscopes and close to 90% of respondents had at least 5 years of experience with the target instruments. In addition, 50% of them were already in the post-doctoral phase of their careers. However, for future investigations it is recommended to broaden the sample size. It is also advisable to include a combination of both quantitative (such as surveys) as well as qualitative methods (such as interviews) when examining perceived ease of use and perceived responsiveness. Similarly, it is important to specifically capture segmentation data among participants. For instance, discrimination between academic and industrial (pharma/biotech) users can be essential to better understanding the perceived safety dimension, and to better outline security needs for connected manual microscopes.

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