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D 2.2 State of the art on enhanced digitisation

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Abbreviations

AMZ: Arheoloski Muzej u Zagrebu

CL: Culture Lab

D: Deliverable

HUJ: The Hebrew University of Jerusalem

IIT: Fondazione Istituto Italiano di Tecnologia

INRAP Institut National de Recherches Archeologiques

KCL: King's College London

MIN: Miningful srls

QB: QBrobotics Srl

UB: Universitat de Barcelona

UBM: Universite Bordeaux Montaigne

UNIPI: Universita di Pisa

UoY: University of York

Executive summary

Deliverable D2.2, *State of the Art on Enhanced Digitisation*, reviews current technologies and methodologies for the digitisation and analysis of ceramic and lithic artefacts. It outlines the current advancements in enhanced digitisation for the AUTOMATA system, which combines high-resolution 3D modelling with non-invasive archaeometric methods. These findings will guide subsequent deliverables, including D2.3 *System Specification* and D2.4 *Ethical Guidelines for Trustworthy AI*, ensuring a robust and ethical implementation.

The document first examines 3D digitisation technologies (Section 2), assessing the several methodologies for capturing artefact geometry and surface details. Section 2.5 reviews large-scale 3D digitisation projects, highlighting advancements and ongoing challenges in automation, interoperability, and long-term data accessibility. Non-destructive archaeometric techniques (Section 3) are then explored, focusing on hyperspectral imaging (HSI), portable X-ray fluorescence (p-XRF), and Raman spectroscopy. These methods enhance material characterisation and provenance studies, and their integration with 3D models is discussed in Section 4, which reviews platforms which enable multi-layered digital artefact representations.

Section 5 explores robotics in cultural heritage digitisation, assessing automated scanning platforms, robotic arms, and mobile systems for improving efficiency and precision. It examines robotic solutions such as Fraunhofer’s CultLab3D and the Italian Institute of Technology’s scanning platform, as well as soft robotics for handling fragile artefacts, with the RePAIR project as an example. Advances in mobile robotics (Section 5.4) and coordinate-recording systems (Section 5.5) further demonstrate the potential for semi-autonomous workflows.

The final sections (Section 6) address data management and processing, evaluating AI applications, statistical classification techniques, and data standardisation to ensure long-term digital record usability. Emphasis is placed on aligning workflows with FAIR principles (Findable, Accessible, Interoperable, and Reusable) (Section 6.3) to support data sharing and reuse.

By consolidating these insights, Deliverable D2.2 defines a structured approach to enhanced digitisation, ensuring that technological developments align with the needs of archaeologists, museum professionals, and cultural heritage institutions. This document provides a roadmap for the AUTOMATA system, supporting the shift from fragmented digitisation methods to an integrated, scalable, and sustainable workflow.

1 Introduction

Deliverable 2.2, *State of the Art on Enhanced Digitisation*, builds upon the foundation established in Deliverable 2.1 (*Methodologies, scenario and user requirements*), which laid the groundwork for the project's aim: enhancing and accelerating the digitisation of ceramic and lithic artefacts through a structured, research-driven approach tailored to user needs. Deliverable 2.1 identified key scenarios, challenges and user requirements, emphasising the necessity for adaptable digitisation workflows to accommodate the diverse demands of the project's stakeholders. The methodologies and scenarios defined in D2.1 have directly informed the scope of this state-of-the-art review, ensuring that the research is aligned with the specific needs of archaeologists, museum professionals, and cultural heritage institutions. By integrating these requirements, this deliverable serves as a reference point for the development and prototyping of the AUTOMATA system.

The content presented in this document is the result of a collaborative effort among specialists from the various consortium partners, each contributing their expertise in archaeology, computer science, material analysis, and robotics. Our combined knowledge has enabled a comprehensive assessment of current methodologies and technologies relevant to the project's goals. The state of the art explored here not only contextualises existing digitisation practices but also identifies technological gaps and challenges that AUTOMATA aims to address through its innovative approach. "Enhanced digitisation" refers to advanced methodologies for capturing, analysing and documenting artefacts through state-of-the-art tools and systems. While 3D modelling, AI, and robotic applications to archaeology, as well as portable non-destructive archaeometric techniques, have already been utilised for the digitisation and study of ceramics and lithics, these approaches have often been applied separately. By building on past experiences and addressing their challenges, AUTOMATA aims to streamline these processes into a cohesive system. The project envisions an integrated solution that combines advanced 3D modelling, AI-driven analysis, robotic automation, and archaeometric data integration to create a comprehensive and adaptive workflow. The combination of these approaches significantly enhances the accuracy, accessibility, and depth of digital records, enabling more comprehensive research and preservation. By combining these methods, the system addresses key research questions about artefacts' identity and origins or manufacturing sequences. For instance, the 3D models will assist in answering typological questions about what an artefact is by providing precise geometric and morphological data or documenting the *chaine opératoire*. Meanwhile, archaeometric analyses will reveal the artefacts' general biography by exploring their material composition and the combinations of components used to create it. Questions about how an artefact was made or whether it reflects community practices and cultural traditions can be explored more effectively when supported by accurate, multi-layered data.

Despite significant progress in the field, challenges remain. Capturing fine details at high resolution, managing the resulting large datasets and combining varied and multiscalar data can be technically demanding. Visual documentation is further complicated by the absence of standardised recording methods for artefact appearance. Additionally, while non-invasive analytical techniques are becoming more accessible, interpreting the data they generate requires specialised expertise and considerable time.

By systematically assessing the technological landscape, this deliverable establishes the scientific and technical framework necessary to guide the next phases of the AUTOMATA project. The findings presented here will directly support the prototyping of the AUTOMATA system, informing the development of the robotic 'work cell' designed for the automated and enriched digitisation of archaeological materials. Furthermore, the insights gained from this research will contribute to subsequent deliverables, particularly D2.3 (*System Specification*) and D2.4 (*Ethical Guidelines for Trustworthy AI*), ensuring that the system's implementation is both technically robust and ethically sound.

This state-of-the-art report not only consolidates the knowledge required for the development of enhanced digitisation methodologies but also reinforces the interdisciplinary nature of the AUTOMATA project. By bringing together expertise from archaeology, engineering, and data science, the project aims to establish a seamless and scalable digitisation framework that advances the documentation, analysis, and preservation of archaeological heritage.

2 Current technologies and methodologies for 3D digitisation of ceramics and lithics

2.1 3D modelling

The application of 3D digitisation technologies in archaeology has advanced significantly, providing new avenues for the documentation, analysis, and dissemination of ceramic and lithic assemblages (Karl et al., 2022; Wyatt-Spratt, 2022). By generating detailed 3D models, researchers can analyse morphometrics, surface properties, and spatial relationships with greater precision and reproducibility. These technologies enable the recording and preservation of information, the creation of reference databases, the production of supplementary data (profiles, sections, etc.), the reconstruction of missing parts, and the dissemination of raw data and/or results. The 3D model becomes a tool to assist in knowledge production, rather than just a support medium. As a consequence, these large datasets allow the weaving of interpretative schemes that aim to reconstruct the production of the artefacts (*chaîne opératoire*), as well as economic and social processes linked to the objects themselves.

Various technologies are employed to precisely capture the geometry and appearance of archaeological artefacts, each producing point-cloud data that can be processed into high-resolution 3D models and enable detailed visualisation and computational analysis (Borderie, 2004). These technologies differ in their methodologies, strengths, and limitations, posing challenges for selecting the optimal digitisation techniques and resolution, often requiring expert judgment to avoid missing crucial details. Several research studies have compared the outcomes of different 3D data capture technologies (e.g., Evin et al., 2016; Porter et al., 2016; Slizewski & Semal, 2009; Zvietcovich et al., 2016). Beyond photogrammetry, structured light and laser scanning addressed here, micro-CT scanning can also be used to produce 3D models of archaeological artefacts intended for in-depth analysis of large assemblages of small, hard-to-capture artefacts (Falcucci & Peresani, 2022; Gomart et al., 2017; Göldner et al., 2022).

Photogrammetry employs overlapping photographic images taken from different angles defined by clear protocols to construct 3D models. Specialised software identifies shared points between images to generate a highly detailed point-cloud. This method is particularly effective for capturing colour and texture, achieving micrometric resolutions with high-resolution cameras and macro lenses (Galantucci et al., 2018). Photogrammetry excels in visual realism, making it suitable for detailed documentation of ceramic and lithic assemblages. However, even lighting is required to avoid shadows and distortions, and external scaling strategies and the computational demands of processing can be substantial (Galantucci et al., 2018). Plus, the use of photogrammetry can pose challenges when capturing complex geometry (objects with sharp angles, the interior of closed pottery, etc.) or with objects whose surfaces are reflective (flint, obsidian, glaze).

Several recent projects concentrate on the application of photogrammetry to pottery assemblages, concentrating on post-acquisition 3D model processing and research such as profile extraction or digital reconstruction of complete vessels based on shards (Di Angelo et al., 2024; Göttlich et al., 2021; Harush et al., 2020; Zvietcovich et al., 2016). Lithic artefacts are rarely modelled using photogrammetry, yet some projects have produced promising results that are dependent on close-range capture and elaborate designated protocols (e.g., Porter et al., 2016).

Laser scanners measure distances using reflected laser beams, creating point-clouds with moderate to high spatial resolution. They excel in geometric accuracy, particularly for complex artefacts, but generally capture less detailed colour information compared to photogrammetry (e.g., Lin et al., 2010; Porter et al., 2016). Reflective and transparent surfaces can introduce errors, and high-quality hardware is often prohibitively expensive.

Structured light scanners project pre-set light patterns onto an object and analyse deviations to triangulate spatial coordinates. These scanners offer a balance between geometric precision and colour accuracy, making them ideal for small-to-medium-sized artefacts (e.g., lithic tools). High-resolution scanners, such as the Polymetric PT-M4, achieve exceptional results for both geometry and texture, as demonstrated in studies on lithics and ceramics (Barone et al., 2018; Di Maida et al., 2023; Grosman et al., 2008, 2022; Karasik & Smilansky, 2008). A similar approach was applied in the digitisation of figurines and moulds from the Autun excavation site, where a high-precision structured light scanner was used to capture minute details with exceptional accuracy (Androuin, Hamon, & Thivet, 2023). However, the technology struggles with shiny, dark, or transparent surfaces, requiring pre-treatment (e.g., dulling sprays, which can, however, partially erase certain clues such as the wear marks studied by the traceologist) to improve capture quality.

While numerous additional 3D scanning tools and methods can be employed beyond those already discussed, a comprehensive analysis of these alternatives falls beyond the scope of this deliverable. For instance, while micro-CT has been mentioned, its application could be expanded to tomography more broadly. Other techniques, such as light field cameras, 3D measurement arms, and digital microscopes — often constrained by proprietary formats that limit 3D model export — offer further possibilities. Multi-view stereophotometry (Laurent, 2024) represents another approach worth considering alongside methods for surface characterisation like Reflectance Transformation Imaging (RTI) and profile characterisation through aided profilers. A more in-depth discussion of 3D digitisation technologies and their potential integration within enhanced digitisation workflows will be provided in Deliverable 2.3.

In ceramic analysis, 3D models integrate with traditional typological methods to enhance classification and morphometric analysis. Tools such as Pottery 3-D software calculate metrics like radius and curvature, supporting typological classifications and morphometric analyses (Karasik & Smilansky, 2011). Structured light scanners are frequently employed for their precision, although photogrammetry can serve as a cost-effective alternative when visual realism is prioritised (Harush et al., 2020). An overview of recent developments in computational analysis of ceramics can be found in Karl et al. (2022).

Similarly, lithic artefacts are typically digitised using structured light scanners due to their ability to capture fine details, such as sharp edges and micro-topographies. Analytical software like Artifact3-D facilitates a range of quantitative analyses, including volume calculations, scar segmentation, and asymmetry measurements (Grosman et al., 2022). Such data are crucial for exploring manufacturing techniques, cultural transmission, and cognitive processes (Richardson et al., 2014; Muller et al., 2022, 2023; Yashuv & Grosman, 2024). An overview of recent computational lithic analyses based on 3D modelling can be found in Wyatt-Spratt (2022).

3D digitisation offers numerous advantages, but it also presents several challenges that need to be addressed. One major issue is the difficulty in capturing certain surface types. As mentioned before, reflective, transparent, and dark surfaces often pose problems for all 3D scanning technologies, frequently requiring pre-treatment to improve accuracy during the capture process (Harush et al., 2020; Grosman et al., 2022; Porter et al., 2016). Another challenge involves lighting conditions. Photogrammetry, for instance, performs best under

bright and evenly distributed lighting, whereas laser scanning and structured light scanning require dimmer environments to ensure optimal data quality.
The resource demands associated with 3D digitisation are also significant. Processing and managing 3D models require substantial computational power and storage capacity, which can be a barrier for smaller institutions with limited resources. Additionally, the management of 3D digital data is a complex task that necessitates skilled personnel. Proper data preservation and re-use involve drafting detailed Data Management Plans (DMPs), selecting appropriate formats, metadata, and files for long-term preservation, depositing these in suitable repositories, and ensuring their ongoing monitoring and accessibility.
Finally, cost remains a critical factor. The expense of high-quality equipment and software often limits the accessibility and widespread adoption of 3D digitisation technologies, particularly in institutions or projects with constrained budgets.

2.2 Appearance acquisition systems

Appearance acquisition systems are technologies designed to capture the visual and physical properties of an object, including its shape, texture, colour, and reflectance behaviour. Traditional digitisation methods, like basic 3D scanning, capture geometry but lack detailed reflectance data. These systems measure how materials interact with light, often using structured lighting, multi-camera setups, and specialised sensors to generate high-fidelity digital representations. A key component of these systems is the Bidirectional Reflectance Distribution Function (BRDF), which records how surfaces reflect light from different angles, allowing for realistic rendering and analysis.
Appearance acquisition systems, particularly for spatially varying BRVF (SV-BRDF), have evolved significantly since the early spectro-goniophotometers of the 1960s (Torrance & Sparrow, 1966; Nicodemus et al., 1977). These devices measured BRDF point-by-point using collimated light and photodiodes but were slow and impractical for dense sampling. The advent of digital photography in the late 1990s transformed these systems into imaging solutions, as demonstrated by Marschner (1998) and Matusik et al. (2003). More recent reviews by Weinmann & Kleiny (2015) and Guarnera et al. (2016) highlight ongoing advancements in BRDF instrumentation.
Despite progress, SV-BRDF measurement for non-planar objects, such as museum artefacts, remains challenging. Systems like those by Schwartz et al. (2013) and Köhler et al. (2013) use domes with multiple cameras and lights to capture shape and reflectance but are limited by fixed camera resolution and object size. Robotic systems (e.g., Holroyd et al., 2010) provide flexibility but are slow and constrained by camera field-of-view. Additionally, challenges persist in re-projecting images onto object geometry and balancing spatial resolution with scalability.
Future advancements will likely focus on improving resolution, speed, and adaptability while reducing costs. Multiplexed systems (e.g., Havran et al., 2017) and novel imaging technologies are promising solutions to overcome these limitations, ensuring more effective applications for cultural heritage.
Within AUTOMATA, a prototyping phase will be conducted employing an advanced appearance acquisition system designed to capture both the geometry and reflectance properties (spatially-varying BRDF) of archaeological artefacts. Our approach will build upon these methodologies, integrating a robotic system similar to La Coupole (Schwartz et al., 2013) with a 6-axis robotic arm, a high-resolution 3D scanner, and an array of directional and uniform LED panels. This system will allow precise alignment of geometry and reflectance

data, overcoming previous limitations in spatial resolution and object size constraints. The combination of high-speed imaging (Ximea CB120CG-CM) and optimised lighting control will ensure an accurate acquisition of surface optical properties, enabling a robust digitisation framework.

2.3 Past and ongoing projects dealing with extended 3D digitisation of lithics and/or ceramics

The digitisation of ceramic and lithic artefacts has become an essential tool in both academic research and cultural heritage management, greatly enhancing analytical capabilities and improving dissemination practices. While traditional 2D views remain important, 3D models contribute valuable insights, with their potential for heuristic analysis making them objects of study in their own right. These models contain rich data that reveal features often hidden in conventional analysis, enabling new forms of engagement with the material (Campanaro et al., 2015; Dell'Unto et al., 2015). To be useful in research and education, however, these 3D models must meet quality standards and be made accessible via platforms that promote interaction and reuse (Dell'Unto, 2018; Scopigno et al., 2017). Also, adhering to the FAIR principles (Findable, Accessible, Interoperable, and Reusable) (Wilkinson et al., 2016) is crucial for ensuring these digital artefacts function as valuable assets for learning and research (see section 6.3).

3D models of artefacts can be used to form digital collections, which have the potential to transform how students, educators, and researchers engage with archaeological data. However, the absence of user-friendly visualisation systems that promote interaction hinders the full potential of these datasets for knowledge creation (Davis, Shrobe, & Szolovits, 1993). To address this challenge, several projects have been developed, focusing on creating accessible and interactive environments for engaging with 3D artefacts. Among them, the Dynamic Collections and BItFROST projects are notable contributions to this field.

The Dynamic Collections project (Ekengren et al., 2021; Callieri et al., 2023), developed at Lund University in collaboration with the Visual Computing Lab at ISTI-CNR, Pisa, and the BItFROST project, which focuses on 3D data reuse in museums, both rely on the 3DHOP framework[1] for high-resolution 3D streaming and interaction. Dynamic Collections provides a 3D web infrastructure designed to enhance education and research in archaeology, offering tools for searching, comparing, and interacting with a collection of 3D artefacts (among them ceramics and lithics). Users can create personalised collections, add annotations, and engage with the objects through advanced analysis tools. Similarly, BItFROST (Bonelli et al., 2024) enables the reuse of 3D data while maintaining control over museum-held datasets through self-hosting. This approach avoids reliance on third-party repositories, ensuring better control over data access and preservation. By integrating with existing digital catalogues and 2D media databases, BItFROST functions within a wider museum data ecosystem, supporting interoperability and long-term accessibility.

These projects align with numerous research initiatives that have been undertaken over the past decade to establish comprehensive 3D digitisation pipelines (e.g., 3D-ICONS), create tools for 3D web services (e.g., ARIADNE), promote 3D recording for long-term

[1] 3DHOP tool is an open-source framework for web-based display of complex 3D models. It provides a customizable interface and interaction tools, allowing the creation of applications tailored to specific project needs. 3DHOP handles intricate 3D geometries with a multiresolution streaming representation, ensuring quick transfer and efficient rendering. This technology has been employed by notable cultural heritage repositories like UoY ADS, Deutsche Exc Cluster TOPOI, and the ARIADNE and ARIADNEplus projects.

documentation (e.g., 3D-coform, scan4reco, Carare), and develop technologies for artefact reassembly, AI-based pottery identification, and best practices for publishing 3D assets (e.g., GRAVITATE (Phillips et al., 2016), ArchAIDE, Europeana pro[2]).

Beyond these academic and research-focused initiatives, museums across Europe are increasingly developing digital collections of 3D artefacts to improve public engagement and accessibility. Institutions such as the Museo Arqueológico Nacional (Spain), MArTA - Museo Archeologico Nazionale di Taranto (Italy), Museo Egizio (Italy), Museo Archeologico Nazionale di Napoli (MANN) (Italy) or The British Museum (United Kingdom) have adopted online platforms to share their collections[3]. While some, like Sketchfab, provide broad accessibility, their reliance on commercial hosting and limited metadata integration present challenges for long-term research applications. However, in many cases, artefacts are studied and reproduced individually in 3D, but they are often not integrated into the specific museum's collections repositories. This separation can hinder the potential for creating cohesive, interactive collections that fully reflect the richness of museum holdings. Systems like Dynamic Collections and BItFROST, which emphasise structured metadata, interactivity, and sustainability, ensure better control over data access and preservation. They offer solutions for integrating 3D models into museum collections, aligning with institutional goals of long-term stewardship while facilitating research and public access.

These developments show that the digitalisation of artefacts, supported by advanced visualisation tools, is not just a supplementary resource but an essential part of modern archaeological research and education. By fostering greater interaction with artefacts, these systems have the potential to transform how archaeological knowledge is generated and shared across disciplines. Ultimately, works like those of Derudas (2023) and digital excavations highlight the transformative impact of 3D visualisation and digital analytical tools on archaeological practice. These approaches, while still in an experimental phase, aim to enhance visual-spatial thinking and conceptual understanding in the field.

[2] More details about these projects can be found in section 6.3.

[3] Examples from the Museo Arqueológico Nacional (Madrid, Spain): https://sketchfab.com/man/collections; Museo Archeologico Nazionale di Napoli (MANN) (Italy): https://sketchfab.com/MANN.

3 Current methodologies and technologies for non-destructive diagnostics in archaeology

Archaeometry covers the vast field of applications of scientific techniques relating to physics, chemistry, biology, and geology to archaeology. It formally emerged in the late 1950s, though its roots can be traced back much earlier. Before this time, the chemical analysis of archaeological materials was already being performed in different contexts, and the emergence of an interest in the composition of ancient objects can be traced back to the end of the 18th century (Caley, 1951; Pollard, 2013). Early studies into the chemistry of materials were mostly driven by curiosity rather than being associated with broader archaeological research projects (Chaptal, 1809; Klaproth, 1798; Pearson, 1796). From the second half of the 19th century, scientists started appreciating the historical value of the compositional analysis of ancient artefacts. During this period, analytical appendices were published that were associated with reports of archaeological excavations (Goebel & Friedemann, 1842; Layard, 1853; Schliemann, 1880). While metals were the primary focus of these early studies, the pioneering work of Damour (1865) on lithic artefacts opened new avenues by linking geological sources with patterns of resource use, population movement, and craftsmanship.

During the second half of the 20th century, the application of archaeological sciences developed and expanded into all types of contexts and chronological frameworks. Since its establishment in 1958, the Journal of Archaeometry, along with the Journal of Archaeological Science (JAS) and major international conferences like the ISA (International Symposium on Archaeometry), has played a pivotal role in fostering the integration of scientific approaches into archaeology, reflecting a growing interdisciplinary focus in journals and conference sessions worldwide. While archaeometry continues to flourish, challenges persist in integrating scientific methods with archaeological practice (Killick, 2015). The evolution of archaeological theory, from the scientific rigour of processual archaeology in the 1960s (Binford, 1962; Binford, 1965; Binford, 1978; Schiffer 1975, 1987) to the interpretative focus of post-processualism in the 1980s (Hodder, 1982, 1988; Shanks & Tilley, 1987), has led to ongoing efforts, such as cognitive archaeology (Mithen, 1996; Whitley, 1992), to reconcile objective analysis with subjective interpretation. In this context, materiality emphasises the active role of artefacts in shaping social processes, with scholars integrating insights on technological choices and resource use to bridge scientific data and cultural interpretations through archaeometry.

The distinction between destructive, non-destructive, invasive, and non-invasive methods is fundamental to archaeometric practice (Vandenabeele & Donais, 2016). Destructive analysis involves methods that compromise the structural and functional integrity of the material, often requiring sampling directly from the object. In contrast, non-destructive analysis avoids material removal, leaving the object entirely intact and available for further investigation. The terms invasive and non-invasive refer to whether or not the analysis requires direct interaction with the artefact's surface or material. Non-invasive techniques do not require any sampling, meaning the object is analysed as a whole, typically causing no damage or only minimal microdamage. These methods often involve the use of energy or particle beams — such as X-rays or lasers — to interact with the artefact, assessing surface characteristics or, in some cases, penetrating deeper for bulk analysis. Surface-focused analyses must account for factors like contamination or historical surface alterations that can obscure the original composition of the material. Furthermore, analyses using particle beams require consideration of variables such as beam penetration depth, the escape depth of signals (which may be reabsorbed before reaching the surface), and the geometric configuration of the detection system. Non-invasive techniques are typically non-destructive or micro-destructive, allowing artefacts to remain intact while still yielding valuable data. They often involve direct analysis, where laboratory instrumentation is brought to the artefact for examination. *In situ* studies are a prime example, employing mobile instruments for investigations conducted outside laboratory settings, such as on archaeological sites, geological outcrops, or within museum exhibition spaces (Potts & West, 2008; Crupi et al*.,* 2018).

AUTOMATA strengthens digitisation by combining 3D modelling with portable, non-invasive, and, therefore, non-destructive, archaeometric techniques for analysing ceramic and lithic artefacts. The system will prioritise flexibility, adapting to the specific needs of archaeologists while integrating emerging technologies. Although some portable, handheld and lighter instruments may offer lower accuracy than advanced systems, they are ideal for initial screenings, assessing visible and physico-chemical characteristics, and efficiently collecting large datasets.

The AUTOMATA system enhances the digitisation of cultural heritage objects through two key phases: 3D modelling for geometry and surface appearance capture, followed by hyperspectral imaging (HSI) for detailed surface analysis. Depending on the results, additional techniques such as portable X-ray fluorescence (p-XRF) or Raman spectroscopy may be applied for further material characterization.

3.1 Hyperspectral Imaging (HSI)

In the hypothesised workflow for the AUTOMATA project, hyperspectral imaging (HSI) is the first screening technique applied to archaeological artefacts. HSI captures reflectance data across hundreds of narrow spectral bands, typically spanning regions of the electromagnetic spectrum from the Near Ultraviolet (NUV) to the Near Infrared (NIR) and, in some cases, the Shortwave Infrared (SWIR). This capability allows researchers to identify and differentiate materials based on their unique spectral signatures, making it especially valuable for detecting pigments, coatings, and other surface features. HSI is particularly effective for objects with flat, well-defined surfaces, since this aspect facilitates the acquisition and treatment of the images, enabling high-resolution data capture without compromising the integrity of the artefact. Its non-invasive nature ensures that no physical sampling is required, preserving archaeological materials and making it an invaluable tool in heritage science.

In the context of AUTOMATA, the evaluation of various sensors for hyperspectral imaging is currently underway. One commercially available sensor is the IQ camera by Specim. This ultraportable camera, weighing just 1.3 kg and with dimensions of 207 x 91 x 74 mm, is designed for use in a variety of settings, including both field and lab environments. Although initially developed for agricultural and food analysis (Behmann et al., 2018), the Specim IQ camera has recently been adapted for archaeological field applications (Sciuto et al., 2022). It features a CMOS sensor that captures images in the 400–1000 nm wavelength range, offering a spectral resolution of 7 nm and a spatial resolution of 512 x 512 pixels per image. The camera is particularly effective when combined with controlled lighting conditions, such as halogen lamps or natural sunlight, ensuring that the spectral data is both accurate and reproducible.

In addition to the Specim IQ camera, several miniaturised hyperspectral sensors are available that could be evaluated for the AUTOMATA project. For instance, Headwall Photonics has developed the Nano-Hyperspec®, a compact hyperspectral imaging platform designed for integration with unmanned aerial systems (UAS). This sensor offers full hyperspectral resolution without compromising performance, making it suitable for applications requiring reduced size, weight, and power (SWAP) characteristics (Hill & Clemens, 2015). Another example is the miniaturised hyperspectral imager utilising a reconfigurable filter array, which addresses the trade-off between spectral and spatial resolution. This design enhances versatility in various applications, including food safety and biomedical fields (Guo et al., 2024). Additionally, advancements in microelectromechanical systems (MEMS) technology have led to the development of handheld hyperspectral imagers for the visible to near-infrared (VNIR) range. These devices are wirelessly connected to mobile platforms, enabling real-time data acquisition and analysis in field applications (Rissanen et al., 2018). These innovations represent promising options for integration into the AUTOMATA project's imaging capabilities.

3.1.1 Applications of HSI for the study of ceramics and lithics

HSI can work across the Visible to Near Infrared (VIS-NIR) spectrum, which is particularly useful for the analysis of bulk materials. This range provides broad absorption bands due to molecular overtones and combinations of vibrational modes, allowing for the analysis of organic compounds and minerals with minimal or no sample preparation. Infrared bands of the electro-magnetic spectrum relate to different geologic information: for example, iron minerals can be identified in the visible/near infrared (VNIR), the Short Wave Infrared region (SWIR) is marked by spectral features of hydroxyls, carbonates and water molecules, while the long wave (or thermal) infrared region (LWIR) is sensitive to silicates and carbonates. In addition, the Short-Wave Infrared (SWIR) range (1700–2500 nm) is particularly useful for identifying and classifying minerals, making it effective for lithic studies, where precise identification of stone materials is essential.

Hyperspectral imaging (HSI) has become a powerful tool in archaeological research, particularly for the study of ceramics, lithics, and other archaeological materials, due to its ability to capture spectral data across hundreds of narrow bands, providing detailed chemical and physical insights. Initially applied in cultural heritage studies to reveal hidden patterns in paintings (Cucci, Delaney, & Picollo 2016; Liang 2012), the combination of HSI and advanced statistical treatments, such as the MHX (Multi-Illumination Hyperspectral eXtraction) technique, has successfully enhanced the visibility of previously invisible features (Salerno et al., 2014; Triolo et al., 2020; Adinolfi et al., 2019). Archaeological applications have expanded to include targeted analyses, such as lithic tool provenance studies, where NIR spectral imaging has proven effective for classifying rock types based on spectral signatures (Andersen et al., 2021; Elliott, 2020; Parish, 2011; Sciuto et al., 2018). The technique has also been employed for heat treatment detection in silica rocks (Schmidt et al., 2013) and the identification of organic residues (Prinsloo et al., 2008). Furthermore, HSI has demonstrated its utility in pigment analysis on ceramics and rock art, aiding in the characterization of red iron-based pigments and other mineralogical components (Bayarri et al., 2021; Linderholm, Geladi, & Sciuto 2015). Applications extend to the analysis of soils and sediments, where HSI can support stratigraphic interpretation and the identification of depositional processes (Choi et al., 2020; Linderholm et al., 2019). Advances in portable HSI devices, such as the Specim IQ camera, have made data acquisition in the field more accessible, facilitating rapid classification of materials and assessments of preservation conditions during excavations (Linderholm et al., 2013; Vincke et al., 2014; Sciuto et al., 2022). However, smaller VIS-NIR devices may compromise spectral resolution compared to bulkier SWIR systems, highlighting the importance of balancing portability with data quality. Standard statistical approaches like

PCA (Principal Component Analysis) remain essential for the reduction of large datasets and pattern identification (Geladi & Grahn 1996; Prats-Montalbán, De Juan, & Ferrer 2011; Eriksson et al., 2013), with tools such as Evince and Python-based workflows increasingly being employed for real-time data analysis. These advancements have positioned HSI as a critical technique for both excavation contexts and field labs, allowing rapid, non-destructive analysis of a wide range of archaeological materials.
Recent research has further demonstrated the applicability of HSI for the study of ceramics and bricks. Galluzzi et al. (2024) employed a VIS-NIR portable HSI camera to analyse Italian maiolica ceramics at the Museo Nazionale del Bargello, effectively distinguishing between original ceramic components and restored elements through multivariate statistical methods such as Principal Component Analysis (PCA) and Spectral Angle Mapper (SAM) classifications. Similarly, Puntin et al. (2022) tested a portable HSI device on Roman bricks from Massaciuccoli, successfully classifying brick compositions and suggesting different sources for raw materials using a combination of spectral imaging, XRF, and visual analysis. These studies emphasise how HSI, combined with statistical models and complementary techniques, can effectively support archaeological research on ceramics and construction materials, contributing to both provenance studies and authenticity assessments. However, balancing spectral resolution and portability remains a challenge when using ultraportable devices compared to larger laboratory systems. Finally, the study by Beauvoit et al. (2023) applied hyperspectral imaging alongside SEM-EDS and PIXE-PIGE to examine 19th-century polychrome glazed ceramics from the Vieillard & Co. manufacturer in France. The HSI method successfully identified pigments in the relief glazes and demonstrated its effectiveness for the non-destructive analysis of ceramic decorations. The research also contributed to building a preliminary spectral database to support future non-invasive studies of ceramics where sampling is not feasible.

3.2 Portable X-Ray Fluorescence (p-XRF)

X-ray fluorescence (XRF) spectroscopy is a technique that identifies and quantifies the elemental composition of artefacts by measuring the characteristic secondary X-rays emitted when primary X-rays create and fill atomic vacancies (Pollard et al., 2007; Pollard & Heron 2008). The portable XRF spectrometer has been widely used in recent archaeological research. As stated by Frahm (2024), its success hinges on a thorough understanding of the methodology and the use of the device. The instrument parameters (e.g., the voltage applied to the tube, the anode metal used inside the X-ray tube, the presence or absence of beam filters, etc.) necessitate careful planning in study design and data interpretation. For example, considering that lower tube voltages are more effective for analysing lighter elements (low-Z), while higher voltages are necessary for detecting heavier elements (high-Z) (Haschke et al., 2021), the Olympus Vanta p-XRF model uses a 2-beam Geochem filter system to optimise element detection, effectively analysing mid-Z elements but struggling with low-Z elements due to low-energy X-ray absorption and requiring high-voltage settings for high-Z elements (Johnson, 2014; Hunt & Speakman 2015). Modern detectors process X-rays far more efficiently than earlier models and have improved in detecting a broader range of elements, including light elements and heavy ones (Shackley 2010; Frahm 2024). Innovations such as gold (Au) anodes (such as the one present in the Thermo Niton 950 XL3t instrument) and graphene windows have enabled the use of higher voltages and improved the detection of lighter elements (Frahm, 2024). However, while p-XRF is a valuable tool for compositional analysis, it is generally considered less suitable for detailed quantitative studies compared to laboratory-based techniques (Barone et al., 2011; Bonizzoni et al., 2013; Ceccarelli et al., 2016; Pirone et al., 2017; Hunt & Speakman 2015; Tykot 2016; Trojek et al., 2010; Romano et al., 2006). Key challenges arise from the surface sensitivity of pXRF, which limits its ability to analyse heterogeneous materials like ceramics and lithics accurately. Factors such as surface alterations, coatings, and contaminants can distort results, requiring careful surface preparation and contextual understanding (Forster et al. 2011; Frahm 2024). Also, calibration and accuracy are critical for reliable results, and periodic external checks with Certified Reference Materials (CRMs) help mitigate drift in the instruments (Frahm 2024; Da Silva et al. 2023). Achieving both accuracy and precision is particularly challenging when analysing materials with complex compositions. Matrix effects can distort elemental readings, especially for materials like ceramics and lithics, which require specific calibration workflows (Da Silva et al., 2023; Fedeli et al., 2024). Penetration depth is another limitation, as pXRF primarily analyses surface layers, with the X-rays not penetrating deep enough to provide a full picture of the material's composition. The theoretical depth is often overestimated, especially for silicate-based materials (Drake & Shannon, 2022; Potts et al., 1997). Morphological factors, such as irregular surfaces or the tilt of the X-ray beam, further complicate measurements. The presence of weathering, glazes, or external coatings can obscure the actual composition of artefacts (Forster et al., 2011; Fornacelli et al., 2021). Moreover, small artefacts can present challenges due to their reduced interaction with the X-ray beam, leading to less accurate readings. Shackley (2010) suggests that specimens larger than 10 mm in their smallest dimension and thicker than 2 mm are ideal for XRF analysis, while smaller samples can be analysed with decreasing accuracy. Additionally, the small detector window only captures a small area of the specimen, which contrasts with destructive methods that provide a more homogenised sample (Speakman et al., 2011). To address this, multiple measurements from different areas of the artefact are recommended, especially for heterogeneous materials like ceramics, where the clay matrix and inclusions may vary significantly (Forster et al., 2011; Odelli et al., 2020).

In summary, while pXRF is a powerful tool for preliminary analyses, especially in provenance studies, its limitations — such as surface sensitivity, calibration challenges, and issues with small or irregular specimens — require careful consideration and complementary approaches to achieve reliable results (Frahm 2024; Frahm 2018; Speakman et al., 2011).

3.2.1 Application of p-XRF for the study of ceramics and lithics

Portable XRF (p-XRF) has been widely adapted for the analysis of diverse materials, particularly inorganic ones, including ceramics, metals, lithics, and glass (Tykot, 2016; Shugar & Mass, 2012). Ceramic studies, in particular, have greatly benefited from the versatility of p-XRF, which has been employed to identify raw material sources, examine production techniques, and therefore explore cultural interactions (Hein & Kilikoglou, 2017; Goren et al., 2011). However, when selecting an analytical method for ceramic analysis, the primary consideration is the range of elements that can be detected. p-XRF is capable of measuring major elements, which constitute the bulk of the material, minor elements that make up most of the remainder, and trace elements, present at levels below 0.1 wt% (1000 ppm) (Artioli, 2010). Major elements, such as silicon (Si), aluminium (Al), calcium (Ca), and iron (Fe) (they can vary slightly depending on the specific ceramic material and the analytical technique used), provide foundational data on the mineralogical composition of clays. For instance, high calcium levels may indicate the inclusion of calcareous materials, like shell temper, in ceramic production (Tykot, 2016). While trace elements, including titanium (Ti), manganese (Mn),

rubidium (Rb), strontium (Sr), and zirconium (Zr), are crucial for provenance studies. Present in minute concentrations, these elements act as geochemical markers, linking ceramics to specific clay sources or tempering materials. For example, research by Forster et al. (2011), Emmitt et al. (2018), and Hein & Kilikoglou (2020) highlights the effectiveness of p-XRF in differentiating between local and imported ceramics, identifying production centres, and mapping trade routes.
In addition, p-XRF has been applied to determine elemental concentrations in surface layers, such as glazes or paints, offering insights into decorative techniques (e.g. Belfiore et al., 2021). However, in this case, due to the shallow penetration depth of X-rays, it may not provide information about the underlying ceramic body. The method has also proven valuable for examining firing techniques and conditions. By analysing iron oxidation states, p-XRF can reveal the atmospheric conditions of ceramic kilns, while changes in trace element concentrations can shed light on post-firing alterations (Hunt & Speakman, 2015). Moreover, p-XRF has provided nuanced insights into specific cultural and regional ceramic traditions. For example, in the study of shell-tempered Chickasaw pottery, the technique has been instrumental in understanding production choices and regional variation (Sorresso & Quinn, 2020).
When it comes to lithic materials, the unique properties of obsidian and certain other stone types make them particularly well-suited for sourcing studies. Obsidian sources are often geochemically homogeneous yet distinctive, allowing them to be differentiated with precision (Sheppard et al., 2011; Tykot, 2017). Among all materials used in provenance research, obsidian remains the most successfully characterised (Craig et al., 2010; Jia et al., 2010; Phillips & Speakman, 2009). Its glassy matrix is especially amenable to quantitative analysis using portable XRF (p-XRF), as demonstrated in numerous studies (Frahm, 2013; Frahm & Doonan, 2013; Speakman & Shackley, 2013). This compatibility with p-XRF enables the rapid evaluation of large and complex datasets with minimal need for additional methodological development. For instance, Sheppard et al. (2011) analysed 565 obsidian fragments from four distinct geological sources, highlighting the efficiency and effectiveness of this approach.

3.3 Raman spectroscopy

XRF, an atomic technique, and Raman, a molecular technique, are highly complementary and form a valuable pair of analytical instruments (Barone et al., 2018). Raman spectroscopy, based on inelastic scattering of monochromatic light, generates vibrational spectra unique to each material, enabling non-invasive analysis of artefacts. Raman spectroscopy has become an essential tool in the study of cultural heritage materials, and its development has significantly transformed the field. Named after its discoverer, Chandrasekhara Venkata Raman, who was awarded the Nobel Prize in Physics in 1930 for this discovery, the technique utilises the interaction of light with matter to reveal the molecular fingerprints of artefacts without causing damage. By measuring the energy shifts that occur when a laser interacts with the vibrations of a material's molecules, Raman spectroscopy provides detailed insights into its chemical composition and crystalline structure. Though the technique spans various scientific disciplines, its contribution to cultural heritage research, especially in the study of ceramics and lithics, has been particularly impactful.
The introduction of portable Raman spectrometers has revolutionised the field further, allowing researchers to bring this technology directly to archaeological sites, museums, and other field settings. This development is particularly significant for immovable or fragile artefacts that cannot be transported to a laboratory. Portable Raman instruments make it

possible to perform high-quality, non-destructive analyses *in situ*, blending laboratory-grade precision with the practicalities of fieldwork (Rousaki & Vandenabeele, 2021; Vandenabeele, 2013).
Traditionally, Raman spectroscopy was confined to laboratories, requiring bulky, stationary equipment. The advent of portable Raman devices has extended the technique’s reach, offering unprecedented flexibility for fieldwork. These instruments vary in size and functionality, ranging from transportable systems requiring vehicles for movement to handheld devices and compact, palm-sized models.

3.3.1 Applications of Raman spectroscopy for the study of ceramics and lithics
Raman spectroscopy, especially in its portable form, offers unparalleled insights into ceramics and lithics. Both material classes benefit from the technique’s non-invasive, high-resolution capabilities, which preserve the artefact's integrity while revealing essential details about composition, manufacturing techniques, and usage. Portable Raman devices are particularly well-suited for identifying pigments on ceramics and lithics, as well as residues and crystalline phases, providing a holistic understanding of these artefacts' production and functional histories (e.g., Mancini, Dupont-Logié, & Colomban, 2016).
In ceramics, Raman spectroscopy can differentiate glazes by identifying compounds like lead silicates, feldspars, or tin-based opacifiers, which are indicative of specific production technologies (Colomban, Sagon, & Faurel, 2001). By analysing the Raman spectra of coloured glazes and paintings, researchers can reconstruct the artistic choices of ancient cultures and gain insights into the evolution of ceramic decoration techniques. Moreover, the identification of crystalline phases such as mullite ($Al_6Si_2O_{13}$) in ceramic bodies provides evidence of firing temperatures and kiln technologies, reflecting the technological advancements of past societies (Mancini et al., 2016).
For lithics, portable Raman devices allow the detection of residues left on tools, such as organic compounds or mineral traces, which shed light on their use and the environments in which they functioned. For instance, residues of lazurite on lithic tools suggest their role in lapis lazuli processing, while diopside traces indicate specific geological sources of the material. Provenance studies benefit greatly from Raman spectroscopy, as comparing the spectra of lithic materials with geological reference samples enables the tracing of raw material sources and the reconstruction of ancient trade routes (Jehlička & Culka, 2022).
The methodologies for analysing ceramics and lithics with portable Raman spectrometers involve careful attention to the choice of laser wavelength to minimise fluorescence from organic contaminants. Fibre-optic probes are employed to deliver the laser light to the sample and collect the scattered signal, ensuring precision even on uneven surfaces. Spectral data are processed using software libraries, which compare observed peaks with reference spectra to identify molecular and mineralogical components. These techniques allow researchers to perform real-time, in situ analyses of artefacts, bridging the gap between laboratory precision and field practicality. By integrating pigment analysis, residue detection, stratigraphy, and wear pattern studies, portable Raman spectroscopy provides a comprehensive approach to understanding the lifecycle of ceramics and lithics, from production to use and eventual deposition.

4 Integration of 3D models and archaeometric data

The digitalisation of artefacts, when paired with archaeometric techniques, has unlocked new possibilities for studying and preserving cultural heritage. This fusion not only provides a cutting-edge platform for analysis but also offers a richer understanding of the artefacts' histories and contexts.

Archaeometry and digitalisation bring together a wide range of disciplines, connecting archaeologists, art historians, engineers, conservators, and more, as highlighted in the previous sections. Today, this field encompasses an immense variety of data, which is often stored and organised in different ways, rarely sharing the same database or ontology. Plus, this collaborative approach not only highlights the technical challenges of heritage research but also prompts reflection on its broader philosophical questions. What does it mean to truly "know" an artefact in a digital world? Can virtual models truly preserve the authenticity of physical objects? Does the move towards digitalisation deepen our understanding of materiality, or does it risk overshadowing it? Rather than diminishing the value of material culture, enhanced digitalisation has the potential to magnify its significance (Gil & Hallot, 2025). By combining the precision of archaeometric analysis with the clarity of 3D visualisation, contemporary projects are not just preserving artefacts — they are reshaping the way they are studied, conserved, and experienced.

Recent advancements, such as the Referenced Information System in 3D (RIS3D) (Dutailly et al., 2023), provide a centralised framework for combining diverse datasets into a cohesive 3D interface. RIS3D allows for the seamless visualisation of hyperspectral imaging, X-ray fluorescence (XRF), Raman spectroscopy, and other archaeometric analyses alongside 3D representations of artefacts. Data is managed through a PostgreSQL database and accessed via a NodeJS web server, with visualisation handled by a Unity-based 3D viewer. As in Abergel et al. (2023) and for the IIIF 3D Community Group[4], the use of JSON for data storage enhances flexibility, enabling hierarchical organisation and efficient querying while supporting user-defined schemas tailored to specific research requirements.

Key features of RIS3D include the ability to anchor archaeometric data spatially through 3D points, surface outlines, volumetric elements, and, more generally, 3D proxy — a simplified geometry used as the position to link information in 3D — as in (Demetrescu & Ferdani, 2021) facilitating detailed analysis and comparison. Automating the integration process — such as aligning sensor outputs with 3D coordinate systems and defining compatible data structures — streamlines workflows and minimises manual input. For example, spectrometric data can be accurately projected onto 3D surfaces using known sensor parameters and iterative calibration methods.

By leveraging tools like RIS3D, researchers can perform dynamic analyses in an interactive environment, bridging the gap between geometric modelling and material science. Despite these advancements, challenges remain in standardising data formats (Lovell et al., 2023), ensuring interoperability across diverse systems (Kuroczynski et al., 2023), and addressing the computational demands of managing and visualizing large, complex datasets.

The *e-thesaurus* project (Gil & Hallot 2025) is another example of the integration of 3D modelling with material analysis, as part of the CPER MAuVE (*Médiations visuelles, culture numérique et création*) initiative. This project focused on the 3D modelling of medieval goldsmithing, addressing the challenges of combining digital and material data over five years of research. One key achievement is the development of interactive holograms for "museums

[4] IIIF 3D Community Group: https://iiif.io/community/groups/3d/

beyond walls" and the *e-corpus* 3D web application, which allows for direct annotation of artefacts. These tools are designed to overcome obstacles such as the high reflectance of gold and silver surfaces and the intricate religious iconography of medieval objects, which often present challenges for modern audiences.

A key example during the *e-thesaurus* collection's digitisation was the extensive analysis of the Saint Bertin Cross Foot at the C2RMF (*Centre de recherche et de restauration des musées de France*). X-ray fluorescence analysis conducted with the New Aglae particle accelerator provided insights into the composition of the enamels, while radiographic imaging offered a clear view of the internal structure. The objective was to directly incorporate these detailed data into the 3D model using e-corpus. Thanks to the precise measurement points, the annotation tool was able to accurately mark the locations of analysis on the object and display the chemical composition results. Additionally, the radiographs were used to model a hypothesis for the reconstruction of the internal assembly, allowing for the simultaneous processing of the scanned 3D object and its individual components. This method enables sectional views, exploded views, and the ability to test the assembly process visually. For example, one can examine the wooden core within the shaft, the attachment point where the original cross was fixed, the lead counterweight beneath the dome, and the techniques used to secure the lost-wax statues of the evangelists (Guillaumont & Dumetz 2025).

In 2020, two research programmes further demonstrated the potential of integrating material and digital data. The first, based at the Institut National d'Histoire de l'Art, explored the "Material Fabric of the Visual" through studies of painted panels in Mediterranean collections, while the second, based at the Bibliothèque nationale de France, examined the relationship between "Colour: Artifacts, Materials, and Cognition." These programmes aimed to make the material data collected through scientific examination of objects more accessible, both to heritage scientists and a broader audience. A key component of these initiatives is the AGORHA meta-database (Mirabaud & Pochon, 2024), a platform designed to structure and link diverse scientific data from museum and library objects. By standardising data from techniques such as X-rays, UV, and infrared imaging, AGORHA makes it easier for researchers to access and integrate datasets, fostering interdisciplinary collaboration.

In a similar way, the Retro-Color 3D project[5], funded by the Nouvelle-Aquitaine region and Université Bordeaux Montaigne, aims to reconstruct the original colours of archaeological objects, particularly sculptures and architecture. By combining historical research, scientific analysis, and digital technology, it addresses the challenges of polychromy restitution. The project begins with collecting data from historical records, photographs, and previous studies, followed by identifying areas on objects that were originally painted. Experiments with ancient pigments and restoration techniques help visualise the original appearance of the objects. Colorimetric measurements are taken for accurate digital reconstruction, which is then integrated into 3D models for interactive visualisations. Case studies include the tympanum of Bordeaux Cathedral's Royal Portal (Schlicht et al., 2013), the *triclinium* at Herculaneum (Dardenay, A. 2020), and the Akhenaten bust at the Louvre (Laboury et al., 2019). Through these efforts, the project enhances our understanding of the original appearance of these artefacts, contributing to both archaeological research and cultural heritage preservation.

[5] https://archeovision.cnrs.fr/retrocolor3d/

5 Robotics for CH digitisation

The integration of robotic systems in cultural heritage digitisation has significantly advanced 3D data acquisition and model generation, addressing challenges related to accuracy, processing time, and automation of scanning techniques. This section presents an overview of robotic solutions that have been developed for digitising cultural heritage, including applications of Structure-from-Motion (SfM) and Structured Light Scanning, as well as state-of-the-art automated systems, such as those developed by Fraunhofer and the Italian Institute of Technology (IIT). The requirements for the robotic arm, as identified in Deliverable 2.1, form the basis for designing a system tailored to the specific needs of archaeological research, ensuring accurate, efficient, and scalable digitisation workflows. This chapter explores the role of soft robotics in handling fragile archaeological artefacts and the potential for autonomous systems to streamline large-scale documentation. Special attention is given to the development of mobile and coordinate-recording systems, which enhance flexibility and precision in artefact digitisation.

5.1 Robotic systems for digitising cultural heritage

The field of cultural heritage digitisation has increasingly benefitted from the integration of robotic systems, which are revolutionising the processes of 3D data acquisition and model generation. The automation provided by robotics tools has helped overcome limitations such as accuracy errors from manual operation and long processing time. Among 3D digitisation techniques, Structure-from-Motion (SfM) and Structured Light Scanning have been automatised through robotic solutions (Traviglia et al., 2024).

SfM, a widely utilised technique in heritage studies, reconstructs 3D models from a sequence of photographs. While its low cost and superior texture quality make it an attractive option, the method is time-consuming and susceptible to operator errors during image capture. The integration of robotic systems into the SfM workflow effectively addresses these limitations by automating image capture and feature identification. Robotic arms equipped with cameras can systematically move around objects, capturing multiple views with precision and consistency. Advanced algorithms further enhance this process by automating the matching and spatial alignment of features, significantly reducing processing times while improving accuracy (Tomasi et al., 1992).

Similarly, Structured Light Scanning, another prominent method, employs a projector and a camera to map 3D surfaces by analysing patterns of light and shadow (see section 2). This technique is particularly valued for its precision and capability to capture intricate surface details. However, its performance can be adversely affected by factors such as ambient lighting conditions, manual misalignment of the equipment, or inconsistent positioning during scanning. The use of robotic solutions optimises this process by automating the positioning and movement of the scanning equipment. A robotic arm can precisely manoeuvre the projector and camera to ensure uniform coverage of the object, maintaining optimal angles and distances. Furthermore, the automation reduces the system’s sensitivity to environmental conditions, as robotic control enables consistent calibration of lighting and positioning. By minimising operator intervention and errors, robotic Structured Light Scanning achieves highly detailed and reliable digitisation of cultural artefacts, even in challenging scenarios (Rachakonda et al., 2019).

Notable advancements in the field of cultural heritage digitisation are led by institutions such as Fraunhofer and the Italian Institute of Technology (IIT). Fraunhofer has been at the forefront of automation in cultural heritage digitisation since 2014, notably through the creation of its Competence Centre for Cultural Heritage Digitisation and the development of the CultLab3D system. This adaptable scanning platform combines autonomous, adaptive robotics with optical scanning technology. The system includes two integrated scanning modules connected by a conveyor belt system for the trays. The CultArm3D module is an autonomous, colour-calibrated scanner that leverages photogrammetry, featuring a high-resolution camera, diffuse lighting, a robotic arm, and a customisable turntable. On the other hand, the CultArc3D module employs an imaging-based scanning method consisting of a light arc with ring lights and a camera arc equipped with ten cameras. These cameras are arranged around the artefact on a tray at different radii, enabling independent rotational movements to achieve detailed imaging (Santos et al., 2014).

The Center for Cultural Heritage Technologies (CCHT) at IIT has developed a new platform for the automated scanning of archaeological objects. This solution is part of the House of Emerging Technologies – Genova project (in Italian, Casa delle Tecnologie Emergenti – CTE) and includes an automated digitisation platform connected to automated robotic handling of artefact trays and their transport to a workstation for digitisation. The system utilises two robotic arms: one arm, equipped with a gripper, holds and rotates a tray on which the object is placed, while the second arm, fitted with a structured light scanner, moves around the artefact at a minimum distance of 60 cm to perform a 360° scan (Babini & Frascella et al., in submission). The platform can be used on 3D and 2D archaeological objects with a minimum size of 10 cm. Different materials can be scanned with the structured light system, including stone, ceramics, metal, textile, and bone, provided that they are opaque. For this reason, glass remains excluded from this application.

When the scanning process is completed, the data is uploaded and processed in the cloud, delivering high-quality 3D scans of the artefacts. Moreover, when objects are manipulated or rescanned, the system can systematically detect and re-identify them, estimating their positions and orientations at new locations thanks to an algorithm explicitly written for this purpose (Ahmad *et al.* 2024). Position and orientation estimation is achieved through an initial transformation using Least Squares Fitting, followed by a "rotate-until-converge" method to ensure ICP convergence. This approach effectively resolves artefact alignment issues when scanned in batches, facilitating seamless 3D scanning and preservation.

The same robotic system is also being employed to explore the possibility of automating hyperspectral imaging acquisitions. A small and compact camera mounted on the robotic arm in place of the structured light scanner and an illumination system purposefully designed to ensure optimal illumination through all the measurements enable the scanning of the object with routines similar to the ones used for the 3D camera. The methodology was successfully tested on selected 2D and 3D cultural heritage objects, providing reliable results (Babini and Frascella et al., in submission).

This robotic platform for automated scanning significantly accelerates the acquisition process, enabling a greater number of digital copies to be produced within the same timeframe and with the same resources compared with traditional methods. This advancement supports the acquisition, documentation, and preservation of extensive data on cultural heritage objects, many of which might otherwise be at risk of loss. Moreover, the collected data provides valuable information on the conservation conditions and potential restoration requirements. Finally, the automated scanning process and the resulting digital replicas enhance accessibility to cultural heritage artefacts, benefiting both specialists and the general public.

These examples demonstrate how robotics provides a transformative approach to cultural heritage digitisation by automating labour-intensive processes, enhancing efficiency, and extending the capabilities of existing 3D modelling techniques. As these systems continue to evolve, they hold the potential to bridge the gap between innovation and preservation, ensuring the safeguarding and accessibility of cultural treasures for future generations.

5.2 Robotic Arm for handling fragile artefacts

In recent decades, robotics has played a fundamental role in automating tasks that are harmful and/or repetitive for humans. In various sectors, such as pharmaceuticals, agriculture, electronics, and the food industry, handling fragile objects has become a crucial challenge. Soft Robotics has emerged as one of the most promising solutions, capable of delicately handling irregular and fragile artefacts (Rus & Tolley, 2015), making it a suitable fit for applications in archaeology as well.

Vision-based grasping techniques, powered by deep learning and computer vision, have significantly advanced artefact recognition and improved precision in locating artefacts (Mahler et al., 2017). Additionally, the development of dexterous robotic hands, mimicking human dexterity, enables intricate artefact handling (Dollar et al., 2010). Human-robot collaboration, especially with collaborative robots, enhances safety and efficiency in artefact manipulation (Ajoudani et al., 2018). Reinforcement learning techniques refine grasping skills, while bio-inspired approaches draw inspiration from nature to devise innovative grasping solutions. A notable example is the Pisa/IIT SoftHand, developed by the Italian Institute of Technology (IIT) (Catalano et al. 2014). The applicability of the SoftHand in the archaeological field has been demonstrated by the EU-funded RePAIR project. This initiative is developing an intelligent robotic system for handling and processing archaeological fresco fragments, collecting 3D recordings and hyperspectral imagery, and reassembling the fragments using robotic arms equipped with the Pisa/IIT SoftHand (REpair, 2023[6]; fig. 1).

Another remarkable project is OceanOneK (OceanOne, 2022[7]), the latest generation of underwater humanoid robots designed by Stanford University for deep-sea exploration with bimanual manipulation capabilities and the IIT's SoftHand (fig. 2). In February 2022, in collaboration with the *Département des recherches archéologiques subaquatiques et sous-marines* (DRASSM), an expedition was carried out off the coast of Corsica. Among the various explorations, one mission focused on recovering fragments of vases and lamps from a Roman shipwreck dating back to the 2nd century AD (Corsica Expedition, 2022[8]).

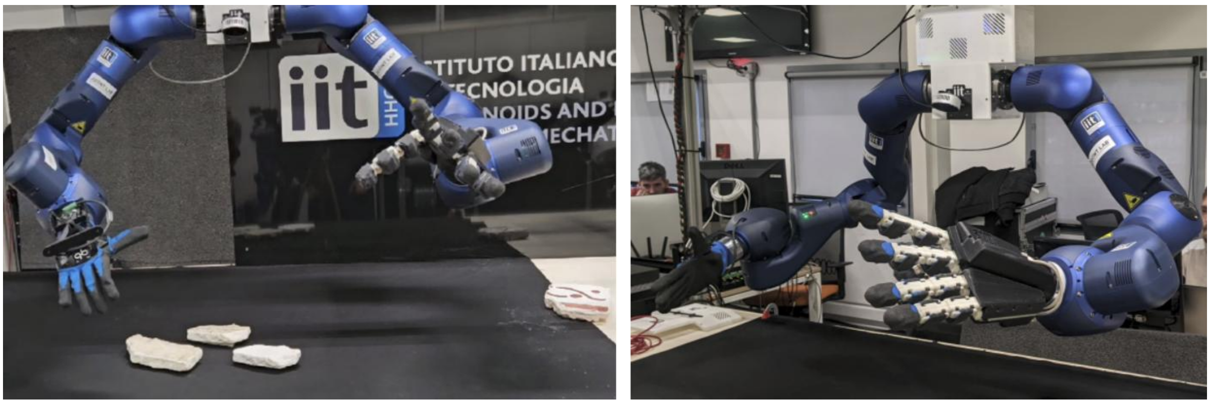

Fig. 1 - RePAIR: testing phase at the laboratories of the Italian Institute of Technology.

[6] RePAIR 2023: REPAIR Project, available at: https://www.repairproject.eu/project/, last accessed 15-09-2023\
[7] OceanOne, available at: https://khatib.stanford.edu/index.html
[8] O2K Corsica Expedition 2022, available at: https://cs.stanford.edu/groups/manips/ocean-one-k.html

Fig. 2 - OceanOneK: Pisa/IIT SoftHand grasping archaeological artefacts during the 2022 Corsica Expedition.

5.3 Autonomous system for large-scale documentation

In nature, the ability to efficiently reorder objects and information following a specific protocol, starting from a disordered and heterogeneous set, has always been a prerogative of beings endowed with intelligence. This ability has always been present in human evolution and has played a fundamental role in industrial evolution, where the organisation and logistics of production flows are essential.

The progress of technology and the increase in production volumes have led man to delegate these reorganisation operations to automatic systems: first purely mechanical, such as separators exploiting inertial principles, magnetic forces and dimensional constraints, then systems with the integration of sensors for additional information such as brightness, colour and temperature. These systems are, therefore, used in the most disparate fields for picking objects (e.g. mechanical components, electronics) and continuous flows, such as in agriculture and small parts.

Further progress in robotics, especially in the collaborative field, has made it possible to have more tools available for the design of such systems, such as easily reconfigurable and highly dexterous robots, adaptive and soft gripping devices capable of interacting with a wide range of objects in a safe and reliable way, increasingly high-performance software and sensors and Artificial Intelligence algorithms.

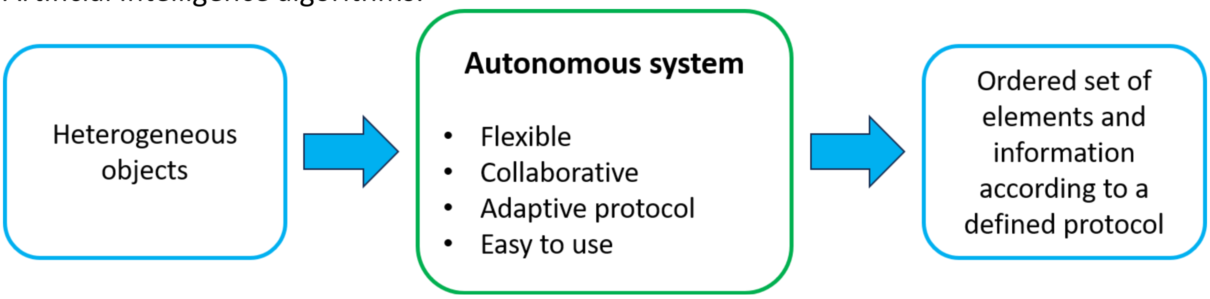

Fig. 3 - Input and output scheme for the autonomous system.

The synergy of these tools allows us to design autonomous and intelligent systems capable of managing a wide range of heterogeneous objects, manipulating and analysing them, and then obtaining a series of information organised according to a precise protocol associated with each object. It is precisely the coordinated integration of all those technological elements that constitutes the heart of the design of the robotic cell in the AUTOMATA project, which will allow the transformation of a set of heterogeneous objects into an organised digital database shared in the cloud and the cataloguing process to be speeded up and standardised.

5.4 Mobile System that can work on batteries

The third industrial revolution was characterised by the introduction and extensive use of industrial robots in factories in 1961, where robots have subsequently evolved to perform increasingly complex tasks. This introduction has been achieved by creating dedicated work environments, such as production lines in the automotive sector, where high speeds and inertia can be managed and exploited safely to maximise productivity. Placed along the assembly line, a robotic manipulator can perform tedious and repetitive tasks such as welding, painting, moving or cutting with immense speed and incredible precision. However, this approach has led to the definition of a robot-friendly environment, which is well delimited and separated from a human-friendly environment, where more delicate and complex operations are performed.

Afterwards, with the aim of further automating production, we have come to the birth of the fourth industrial revolution, or Industry 4.0, characterised by the use of increasingly advanced, interconnected and rapidly programmable systems.

One of the enabling technologies of Industry 4.0: "advanced manufacturing solutions", is based in particular on the concept of human-machine collaboration, where robots are not necessarily confined within barriers. The main element of this evolution was the birth of the first collaborative robots (cobots, as defined on Universal Robot website[9]) in 2008, capable of safely collaborating with an operator to perform shared tasks.

Cobots are, therefore, designed to work next to the operator and have small sizes to adapt to existing applications and contexts designed for humans. Their size has allowed the creation of mobile systems that, unlike fixed industrial robots that have unlimited movement. As a result, mobile robots can operate in a large workspace and even explore unknown environments. Robot operating environments can be classified into three categories:

- **Predefined and structured environment** - The robot has full knowledge of the environment and the objects it interacts with;
- **Semi-structured environment** - The robot has some prior knowledge (e.g. GPS maps) about the environment. An example could be a surveillance robot that travels its familiar territory, but the environment and the objects within it can change spatially and temporally; or the exploration of a house to verify its usability after an earthquake, which may have caused collapses or structural failures (Negrello *et al.* 2018);

[9] Universal Robot, available at: https://www.universal-robots.com/it/informazioni-su-universal-robots/centro-notizie/storia-dei-robot-collaborativi/#:~:text=Nel%202008%2C%20Universal%20Robots%20ha,questa%20classe%20emergente%20di%20robot.

Fig. 4 - Field Experiments in a Post-earthquake Scenario with WALK-MAN, a Humanoid Robot, in Amatrice, Italy. On the top line, the pilot station is visible, while on the bottom line, the robot WALK–MAN executes the commanded actions.

● **Unstructured environment** - The robot has no *a priori* knowledge about it, for example, underwater or in an open environment (OceanOne, 2022). The robot must rely on its powerful sensory and navigation system to operate autonomously. A practical approach would be a semi-autonomous system that occasionally accepts remote intervention.

Fig. 5 - In 2022, off the coast of Corsica, the O2K underwater robot explored a 2nd-century AD Roman shipwreck site discovered in 2012 near Aléria.

Due to the need to be able to operate in unknown and/or uncertain environments, mobile robots require a much higher level of intelligence than traditional industrial robots. These requirements have been met by the phenomenal progress in electronics and artificial intelligence technology. However, this is still not enough to provide the system with the necessary flexibility and dexterity; in fact, a concomitant evolution of self-adaptable and soft end-effectors has allowed a further increase in application possibilities. Consequently, a mobile robot is a complex assembly of fundamental building blocks, each of which must be carefully chosen based on specifications such as environment, autonomy, tasks to be performed, flexibility and reconfigurability.

A mobile robot is not only a system capable of autonomously moving but also a compact system with the possibility of being moved from one environment to another without the need for significant reconfigurations of the environment, but to be harmonized in any human-scale environment: laboratory, workshop, offices, etc. This last concept will be developed in the AUTOMATA project, therefore creating a collaborative and mobile robotics station that can be easily transported by an operator and positioned in different work environments intended for cataloguing archaeological finds. The collaborative nature of the robot, end-effector and integrated sensor systems will constitute a harmonised system for safety work close to humans.

5.5 Systems that could record coordinates of point analysis on objects

Most generic object pose estimation systems in the state-of-the-art rely on recognising the object prior to estimating its position and orientation, thus depending on prior knowledge of the object in the scene (Kybic et al., 2009). However, this becomes challenging when dealing with cultural artefacts, which often feature complex geometries and irregular shapes due to corrosion, degradation, or breakage (Soler et al., 2018). Several unsupervised approaches have attempted to address classification (Grilli et al., 2019), point labelling (Hackel et al., 2018), and semantic segmentation (Grilli et al., 2017) of cultural heritage materials. Despite these methods' advancements, they have not succeeded in achieving accurate pose estimation, as handling archaeological fragments requires a high degree of precision, especially for tasks that depend on accurate grasping for proper manipulation.

If a soft robot needs to grasp the artefact at specific points for designated tasks, situations may arise where the object is initially grasped but subsequently rotates within the grip. In some cases, the grasp might fail entirely, necessitating a reattempt. The system must continuously track the object's pose to determine, using 3D scanning via RGB-D or other commercial sensors, the coordinates of every point on the surface. Having precise knowledge of the position of points on the artefact's surface can be immensely valuable for mapping archaeometric data gathered by sensors during the information collection process.

A notable contribution is the work by Javed Ahmad et al. (2024), who introduced the novel Automated Artifact Position and Orientation Estimation (AAPOE) system. This system detects artefacts, re-identifies them if moved, and estimates and tracks their poses within the workspace.

6 Data treatment

The AUTOMATA project adopts a comprehensive approach to data treatment, integrating traditional statistical methods, artificial intelligence (AI)-driven classification, and advanced data curation strategies to enhance the digitisation and analysis of cultural heritage artefacts. Traditional statistical techniques, such as principal component analysis (PCA) and multivariate image analysis, remain fundamental in processing archaeometric data from methods like p-XRF, hyperspectral imaging, and Raman spectroscopy, enabling pattern recognition and provenance studies. Building upon these techniques, AI methodologies, including machine learning and deep learning, provide automated solutions for artefact classification, predictive modelling, and feature extraction, addressing the challenges of scalability and subjectivity inherent in traditional approaches. Finally, AUTOMATA ensures that digitised data are curated following FAIR principles, with a focus on interoperability, metadata standardisation, and long-term reuse within European research infrastructures. This structured approach not only enhances archaeological research but also supports the broader objectives of sustainable and accessible cultural heritage data management.

6.1 Statistics and classification techniques

Data treatment plays a fundamental role in non-destructive archaeometric analysis, ensuring the accurate interpretation of complex datasets generated by techniques such as portable X-ray fluorescence (p-XRF), hyperspectral imaging (HSI), and Raman spectroscopy. In provenance studies, chemical data from p-XRF analysis are commonly processed using multivariate statistical methods, including principal component analysis (PCA) (Baxter 2015; Grahn and Geladi 2007), dendrograms (Papageorgiou and Liritzis, 2007), cluster analysis (Ikeoka et al., 2012), and artificial neural networks (Barone et al., 2018). These chemometric approaches help identify patterns and clusters within large datasets while reducing the dimensionality of variables to facilitate interpretation. PCA, for instance, projects data into a multivariate space based on the covariance of recorded values, allowing the identification of spectral signatures and distribution patterns (Brown 2007). However, statistical errors, particularly with small fluctuations in intensity, could lead to exaggerated differences in heterogeneous materials. Ensuring transparency and reproducibility in published studies requires proper documentation of analytical parameters, including calibration, sample preparation, and metadata (Johnson et al., 2024).

Similarly, hyperspectral imaging (HSI) generates extensive datasets that require advanced statistical treatment for effective interpretation. HSI enables spectral mapping and provides geochemical information across surfaces, aiding in the identification of material compositions through fingerprinting approaches (Koehler et al., 2002). However, challenges such as overlapping spectral peaks and the limited availability of reference libraries necessitate alternative solutions, including consulting spectral databases (Baldridge et al., 2009; Clark et al., 1993; Rossel et al., 2016). Multivariate Image Analysis (MIA) is widely used in HSI data processing to reduce dimensionality and enhance pattern recognition (Geladi & Grahn, 1996; Grahn & Geladi, 2007; Prats-Montalbán, De Juan, and Ferrer, 2011; Eriksson et al., 2013). Tools such as Evince by Prediktera facilitate this process through clustering algorithms, while Python-based software like Spectral Python allows for real-time spectral analysis and preprocessing tasks such as shadow correction. These techniques improve the visualisation and interpretation of hyperspectral datasets, making them more accessible for archaeological applications, including the enhancement of wall paintings and the mitigation of scattering effects (Grifoni et al., 2019; Legnaioli et al., 2013; Triolo et al., 2020; Sciuto et al., 2019).

Raman spectroscopy data also benefit from statistical treatments to enhance spectral resolution and facilitate material identification. Given the complexity of Raman spectra — often affected by noise and fluorescence interference — chemometric techniques such as dimensionality reduction and hierarchical clustering analysis (HCA) are employed to distinguish subtle variations between samples. These methods allow for the identification of characteristic vibrational modes associated with specific pigments or mineral compositions, supporting provenance studies and material classification. The integration of these multivariate statistical approaches across different non-destructive techniques significantly enhances the robustness and accuracy of archaeometric investigations, providing a more comprehensive understanding of the material properties of cultural heritage artefacts.

6.2 AI applications

Archaeological research and practice, including systematic excavations and occasional discoveries, yield vast quantities of artefacts, requiring meticulous analysis and classification for meaningful interpretation. Traditional approaches to these problems heavily rely on human expertise, are time-consuming, prone to subjectivity, and face serious difficulties in keeping up with the rapid progression of discoveries. Therefore, there is a growing demand for alternatives, such as the application of new technologies and Artificial Intelligence, to fill the capacity gaps in the field. As listed below, different AI technologies and machine learning techniques are applied to artefact classification and digitisation workflows, providing significant results and demonstrating the potential of the application of AI in archaeology (Gattiglia, 2025).

Machine learning has found multiple applications in archaeology, where data are inherently numerical or categorical. In Orengo et al. (2020), a random forest algorithm was used to detect archaeological mounds by working on multitemporal synthetic-aperture radar and multispectral image data. In Guyot et al. (2018), using aerial laser scanning (ALS, lidar) data, automated classification of megalithic funerary structures was conducted. Machine learning was applied in Eberl et al. (2023) to the identification of Lithic microdebitage. Neural network analysis has been applied by Nobile et al. (2024) to predict the original metrics of fragmented, reused, or damaged laminar artefacts.

The advent of modern deep learning techniques, particularly Convolutional Neural Networks (CNNs) (LeCun et al., 1998), coupled with advancements in hardware performances, allowed highly effective applications of computer vision to archaeology.

Different deep neural networks were used to detect objects (Verschoof-van der Vaart et al., 2020), restore ancient texts (Assael et al., 2022), find similarities, build 3D models and perform site detection (Gattiglia, 2025). In (Bewes et al., 2019), a neural network is trained to recognise, starting from photos of skulls, the sex of the individual. In Orengo et al. (2021) the authors implemented a specific class of CNN (R-CNN) to identify pottery fragments in drone imagery. In Emmitt et al. (2022), deep neural networks were used to distinguish worked stone objects from naturally occurring lithic clasts.

Gualandi et al. (2021) developed machine learning tools for automatic pottery classification based on shape and decoration. In Pawlowicz & Downum (2021) the authors exploited identifiable decorative patterns on ceramic vessels to improve ceramic dating processes with the help of deep learning AI. In Anichini et al. (2021) and Núñez Jareño et al. (2021), the authors demonstrated the possibility of using appropriately trained deep neural networks to identify archaeological artefacts from just a single photo. Manitsaris et al. (2014) showed how a system called ArtOrasis may provide real-time feedback on pottery-making techniques,

aiding in the acquisition of gestural skills. In Chetouani et al. (2020), a classification of patterns of ceramic sherds was carried out by combining deep learning-based features extracted from some pre-trained CNNs. Arch-I-Scan realised a prototype system for the detection and classification of whole pottery vessels (Tyukin et al., 2018). All the machine learning and deep learning techniques have proven to be fundamental to approach digitisation workflows or being part of it, including extraction from archaeological drawings, that represent a source of knowledge that is essentially standardised, including information on shape, decoration, and dimensions of artefacts (Navarro et al., 2021, 2022; Parisotto et al., 2022; Cardarelli, 2022).
However, notwithstanding the significance and promise of applications in archaeology, there are important challenges and issues raised by AI technologies.
High-quality, well-curated datasets are crucial for training and validating AI models. However, archaeological data can be fragmented, incomplete, and subject to biases introduced during collection or analysis. Moreover, securing large volumes of high-quality labelled content for the development of AI models based on state-of-the-art architectures remains a hard theoretical and practical challenge. On the one hand, labelling processes based entirely on human expert input are prohibitively expensive and using surrogate simulated data creates issues of its own. A recent study (Tyukin et al., 2024), through a series of numerical experiments, suggests that replacing real data with simulated data (constructed from geometric models) may create biases (due to e.g. the lack of capturing sufficient variability, etc.) and, as a result, lead to decreased accuracy of the final model. A similar observation but in a more general setting and for *generative AI models* was made by Alemohammad et al. (2023). In fact, in Alemohammad et al. (2023) the authors proved that exclusive usage of *generative models* to produce simulated data may lead to the collapse of variance and strong bias. They suggested that maintaining appropriate levels of variability through the presence of sufficient amounts of expert-labelled data may be necessary to avoid both bias and overfitting.
A recent work (Bastounis et al., 2023) shows that serious obstacles exist in verifying both the robustness and accuracy of a trained deep neural network model. The obstacle is the need for potentially exponentially large (in the size of the data's domain – the number of relevant features used in the analysis) volumes of labelled data to produce simultaneous accuracy and robustness certificates. This, however, applies to unstructured representations. Therefore, a way out could be to design an AI classification model which does not attempt to combine all decisions into a single stage. Instead, it could output a sequence of decisions, each reporting objects' categories based on data with gradually increasing dimensions. That way, the end-user and the designer may be able to control the risks of instability and lack of robustness. Such an organisation may also help with reducing the need for large volumes of carefully labelled datasets. Such an approach will also allow the exploitation of AI error correction methodology (Tyukin et al., 2024) at appropriate stages of decision-making.
In recent years, the field of archaeometry has been transformed by the integration of AI and machine learning techniques. While traditional statistical analyses have long been a cornerstone of archaeometric research, AI and ML methodologies are now offering novel and enhanced capabilities. In Guglielmi et al. (2024), the statistical analyses of materials were followed by post-processing, taking advantage of neural network prediction capabilities. In López-García & Argote (2023), cluster analysis for the selection of discriminatory variables in an archaeometry setting is powered by machine learning techniques, producing a more effective variable selection method. In Oonk & Spijker (2015), data fusion of multi-element

XRF results was applied to assess the complementary value of geochemistry and machine learning on predictive modelling in archaeology.

Another distinctive trait of many AI models, particularly deep learning networks, lies in their "black boxes" behaviour, making it difficult to understand the rationale behind their decisions. This lack of transparency can hinder the acceptance of AI-driven interpretations within the archaeological community (Gattiglia, 2025). In recent years, explainable artificial intelligence (XAI) has become increasingly popular, as a set of techniques making AI systems simpler to understand and interpret (Sharma et al 2024). Such techniques are also evolving, including interactive dialogues, simulating human-like interactions, where users ask questions and get relevant explanations (Mindlin et al 2025). Moreover, employing a combination of purely data-driven AI (including for non-causal and counterfactual explanation) with logic-based solutions, like in Costa et al. (2021), could present an acceptable compromise and balance between the capabilities of modern AI models and the conservative and evidence-based nature of research.

6.3 Standardisation and solutions for data capture, curation, dissemination, tracking, and reuse

The increasing reliance on digital methodologies in archaeology has led to significant advancements in data curation and reuse, but it has also highlighted persistent challenges related to the preservation, accessibility, and interoperability of digital archaeological records (Richards et al., 2021). Digital archiving is crucial for safeguarding archaeological information, as many excavations are destructive, leaving digital records as primary sources for future research (Richards et al. 2021; Huggett 2020). However, the absence of standardised approaches to data curation across institutions and countries results in inconsistencies in the quality and availability of archaeological datasets (Richards et al. 2021; Kintigh et al. 2014).

One of the most widely accepted frameworks to address these challenges are the FAIR (Findability, Accessibility, Interoperability, and Reusability) Principles, which have been increasingly integrated into digital archaeological data management (Richards et al., 2021). Considerable work has been done to define best practices for the implementation of the FAIR Principles for archaeological data, and due to the very diverse types of data created by the domain, it is often used as an exemplar across the humanities and social sciences (Wright et al., 2022). The FAIR Principles set out not only technological standards but the need to create community standards specific to the domain. These decisions permeate all aspects of the archaeological data management workflow, from the point of capture to use and future reuse.

Nevertheless, digital archives still face usability issues, including limited export options, unclear licensing, inconsistent metadata, and documentation gaps (Seaton et al., 2023; Bevan, 2015). Seaton et al. (2023) propose the 'quality-in-use' approach as a method to assess usability in digital archaeological datasets, considering factors such as effectiveness, efficiency, satisfaction, context coverage, and overall usability. Their findings highlight the necessity for improved documentation, enhanced user interfaces, and more standardised data formats (Seaton et al., 2023; Huggett, 2019).

In archaeometry, data are no longer viewed as static or given but as dynamic and co-created, shaped by the tools, methodologies, and researchers involved. This perspective highlights the complexity of defining and producing data, emphasising the need for robust frameworks to ensure accuracy and relevance. Archaeometric research faces the challenge of balancing data quality, time, and cost (Artioli, 2010). High-quality data require substantial investments in sample preparation, measurement time, and financial resources, necessitating a strategic approach in selecting analytical methods. Cost-effective screening techniques are often used for large sample sets, while more detailed analyses are reserved for selected specimens, ensuring meaningful comparisons with established databases (Artioli, 2010; Pollard & Heron, 2008).

One of the major challenges in digital archaeological data curation is the integration of 3D data and archaeometric datasets. While Geographic Information Systems (GIS), 3D pottery data, and radiocarbon data have demonstrated the potential for digital integration, variations in data formats, licensing conditions, and metadata standardisation continue to hinder reuse (Seaton et al., 2023; Kansa & Kansa, 2018). Moreover, there are gaps in current data infrastructures regarding the harmonisation of high-resolution imaging and material characterisation techniques, which are critical for advancing archaeometric research (Atici et al., 2013; Bevan 2015).

Initiatives such as the COST Action SEADDA (Saving European Archaeology from the Digital Dark Age), SSH Open Marketplace, and the ARIADNE RI have played a crucial role in advancing data management practices in archaeology and cultural heritage. SEADDA has emphasised the long-term preservation and accessibility of archaeological data, while the ARIADNE RI has significantly contributed to the development of interoperable infrastructures, enabling standardised access to diverse archaeological datasets. The SSH Open Marketplace, funded by the Social Sciences and Humanities Open Cloud (SSHOC) project, was developed to support the integration and consolidation of thematic e-infrastructure platforms, preparing them for connection to the European Open Science Cloud (EOSC). As a domain-oriented discovery portal and an aggregator of the SSHOC project, it supplements existing services such as the EOSC Catalogue & Marketplace, facilitating the seamless exchange of tools, services, data, and knowledge within the broader European research landscape. Despite these efforts, additional refinements are required to ensure seamless integration of visual, chemical, and physical data into existing infrastructures, addressing the unique needs of both archaeological and cultural heritage research.

The AUTOMATA project builds upon existing frameworks, including the implementation of the FAIR Principles and the Heritage Digital Twin (HDT) framework, to develop eco-responsible and interoperable solutions for enhanced data curation and reuse. AUTOMATA aligns its efforts with European infrastructures such as ARIADNE, Europeana, EOSC, and ECCCH, ensuring that high-quality digitisation outputs contribute to a sustainable digital ecosystem. A key aspect of AUTOMATA's approach is selective digitisation tailored to research needs, avoiding unnecessary high-resolution captures and reducing data storage demands while maintaining scientific accuracy. By implementing 3D data compression, targeted high-detail analysis, and robust metadata strategies, AUTOMATA aims to streamline digitisation workflows while enhancing long-term data reuse and interoperability (Quantin et al., 2023).

Moreover, AUTOMATA integrates metadata standards such as the Web Annotation Data Model (W3C) and structured vocabularies like PeriodO, VAIF, Geonames, and PACTOLS, ensuring compatibility with European research infrastructures. The project also emphasises workflow documentation, detailing equipment settings, data collection protocols, and preservation formats to support transparent and reproducible research practices. Additionally, AUTOMATA's 3D referencing and annotation strategies align with ongoing efforts in projects like the ARIADNE RI and ECCCH, further supporting interoperability and reuse in digital archaeology. The overall data strategy for AUTOMATA is defined by adherence to the FAIR Principles and best practices for archaeology as developed by the Archaeology Data Service and set out in D10. 1 *Data management plan.*

Through its comprehensive approach, AUTOMATA advances the standardisation of data management processes in archaeological digitisation, ensuring that datasets remain robust, reusable, and interoperable. This not only addresses the evolving needs of archaeological research but also strengthens cultural heritage preservation efforts by promoting sustainable and accessible digital archiving practices.

7 Conclusions

The comprehensive state-of-the-art review presented in this deliverable highlights the significant advancements achieved across all relevant fields, including 3D digitisation, archaeometric analysis, robotics, and data management. The continuous development of methodologies and technologies in these domains has laid a strong foundation for the AUTOMATA project, confirming both the feasibility and the innovative potential of the proposed system. The integration of 3D modelling, archaeometric analysis, and robotic automation builds upon advancements made by initiatives such as CultLab3D (Santos et al., 2014), RIS3D (Dutailly et al., 2023), RePAIR project (REpair, 2023) and ArchAIDE (Anichini et al., 2021), which have significantly enhanced digital documentation and automated artefact analysis. These projects illustrate the growing need for comprehensive digitisation workflows that not only capture high-resolution geometry but also incorporate material composition data, ensuring a holistic understanding of archaeological objects.

The adoption of non-destructive analytical techniques, including hyperspectral imaging (HSI), portable X-ray fluorescence (p-XRF), and Raman spectroscopy, has been pivotal in refining artefact classification and provenance studies (Sciuto et al., 2022; Galluzzi et al., 2024). Previous research has demonstrated the potential of HSI for pigment and material identification (Bayarri et al., 2021; Beauvoit et al., 2023), while p-XRF and Raman spectroscopy have proven effective for elemental and molecular analyses in both ceramics and lithics (Tykot, 2016; Hein & Kilikoglou, 2017). AUTOMATA capitalises on these developments by integrating these techniques into a single workflow, enhancing the accuracy and accessibility of cultural heritage studies.

Another fundamental aspect is the role of AI and robotics in automating digitisation processes. The work of Fraunhofer on automated scanning (Santos et al., 2014) and the Italian Institute of Technology's robotic handling systems (Babini & Frascella, in submission) demonstrate how machine learning and robotic arms can streamline data acquisition and ensure high-precision artefact manipulation. Similarly, ArchAIDE (Anichini et al., 2021) has paved the way for automated ceramic classification using AI-based shape recognition, significantly reducing manual input in typological studies. AUTOMATA aligns with these advancements by designing an adaptable system capable of processing and analysing large datasets while maintaining high standards of reproducibility.

Despite these technological advancements, challenges remain, particularly in terms of data standardisation, interoperability, and long-term preservation. Initiatives such as IIIF 3D (Abergel et al., 2023) and e-thesaurus (Gil & Hallot, 2025) have underscored the importance of structured metadata and linked data for ensuring digital heritage sustainability. AUTOMATA seeks to address these challenges by establishing a robust framework for data integration and dissemination, ensuring that digitised artefacts remain accessible and reusable across different research domains.

The findings outlined in this document reinforce the feasibility of the AUTOMATA system. The technological landscape presented here confirms that the core elements required for its development are not only available but are also evolving in ways that align with the project's objectives. By leveraging recent breakthroughs in these fields, the project can design and prototype a highly adaptive and efficient robotic work cell capable of performing enhanced digitisation at an unprecedented level of precision and automation.

Furthermore, interdisciplinarity and dialogue are at the heart of the AUTOMATA project. The diverse expertise of the consortium partners — spanning archaeology, engineering, AI, spectroscopy, and cultural heritage management — ensures a dynamic and collaborative approach to system development. The continuous exchange of knowledge between these disciplines is not only essential for refining the system’s functionalities but also for pushing the boundaries of what enhanced digitisation can achieve. This collaborative framework fosters innovation and strengthens the project’s ability to anticipate challenges, optimise methodologies, and refine workflows to meet the needs of end-users. The research presented here provides a structured and well-informed basis for the prototyping of the AUTOMATA system, ensuring that its design is grounded in the latest technological advancements and best practices. Additionally, by maintaining a strong interdisciplinary dialogue throughout the project’s duration, AUTOMATA will not only achieve its immediate goals but also contribute to the broader evolution of digitisation practices in archaeology and cultural heritage.

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