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"DON'T JUDGE COARSE WARES BY THEIR UGLINESS…" THE BENEFITS OF FABRIC ANALYSIS AND THE USE OF SUPERVISED DEEP LEARNING ALGORITHMS FOR THE STUDY OF ROMAN POTTERY (FABRICAI)

Basandosi su ampie collezioni di riferimento di ceramica romana, ricercatori francesi e belgi hanno classificato correlazioni per le ceramiche prodotte localmente distribuite nel Nord della Gallia. Questo approccio alle varianti di impasti mediante confronto macroscopico ha portato alla definizione di zone di produzione, consentendo l'analisi delle rotte di trasporto e degli scambi economici, o riflessioni sulla romanizzazione, lo status dei siti di consumo, le identità culturali. Dal 2014, un approccio multi-analitico allo studio degli scarti di produzione consente di rispondere a domande sulla tecnologia e sul trasferimento di conoscenze. Tuttavia, è necessario molto di più prima fare in modo che tutti i siti di produzione regionali siano caratterizzati. Inoltre, lo scavo dei siti di consumo porta a quantità di frammenti difficili da identificare a livello macroscopico. Nel 2021, Arteka e il dipartimento di progettazione Arkeocera hanno sviluppato un programma analitico, utilizzando il riconoscimento delle immagini con un algoritmo di Deep Learning, che consente di affrontare questi problemi e che si unisce ad altri progetti recenti in cui l'IA è applicata ai dati archeologici (per esempio, ArchAIDE). Il punto di partenza è l'implementazione di un database di impasti identificati scientificamente, che porterà poi allo sviluppo di un'applicazione che offre un guadagno di tempo durante la fase post-scavo, la formazione degli specialisti e la mappatura estensiva della distribuzione.

1. Introduction

Ceramic vessels are one of the most important witnesses of everyday life as they withstand burial conditions well and are discarded when broken, while rarely recycled. They have the potential to yield a wide range of information about production techniques, potter's choices, cultural influences, or commercial activities. For instance, long distance trade patterns are revealed by studying large quantities of amphorae or table wares, such as Samian or slipped wares. However, the bulk of pottery assemblages comprises cooking wares, and their study is less popular than that of amphorae or table wares, because they reflect local or regional trade patterns. This means that opportunities for understanding local and regional market systems remain underexploited.

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Building on the work of David Peacock[1] or Roberta Tomber and John Dore’s reference collection for Romano-British pottery[2], researchers have a long history of characterizing common wares from Roman Gaul and they agree on the need to focus on this group of understudied material culture.

Northern Gaul, or *Gallia Belgica*, close to the Rhine *limes* and Britannia, was an economically thriving region, and producer of cereals, salt, and other important victuals. Following from the Roman Conquest, new markets developed, including ceramic workshops, first by South-Gaulish immigrant potters[3], soon followed by local North-Gaulish potters.

The Nervian and Atrebates region in Northern Gaul is an interesting research area because of the numerous workshops (*fig.* 1), many of which have been recently excavated. For instance, new kiln sites have been discovered in Bavay, the Nervian capital[4], in Famars[5], Montescourt-Lizerolles[6] and Vermand[7]. These recent surveys permit the development of new integrated approaches, elaborating broad research questions. For instance, the study of wasters allows to examine potters’ gestures and choices, the technical evolutions of their products as can be seen in paste recipes, or their skill to adapt to demand, shown by differences in the management and lay-out of pottery workshops.

Similarly, the characterization of fabric variants opens possibilities for understanding technological knowledge transfer, and their identification on consumption sites makes it possible to identify distribution patterns and understand markets.

2. The benefits of an in-depth study of coarse wares using a multi-disciplinary approach

To tackle broad research questions, it is necessary to integrate different methods. Pottery specialists from Northern Gaul have combined cross-field approaches, such as macroscopical description, petrography, chemical analyses, typology, chronological aspects, technological traces, archaeomagnetic analysis, anthracology, or study of kiln structures and workshop lay-out. The results are manyfold, yielding possibilities for understanding the organization of workshops on an intra-site, inter-site as well as an extra-site level.

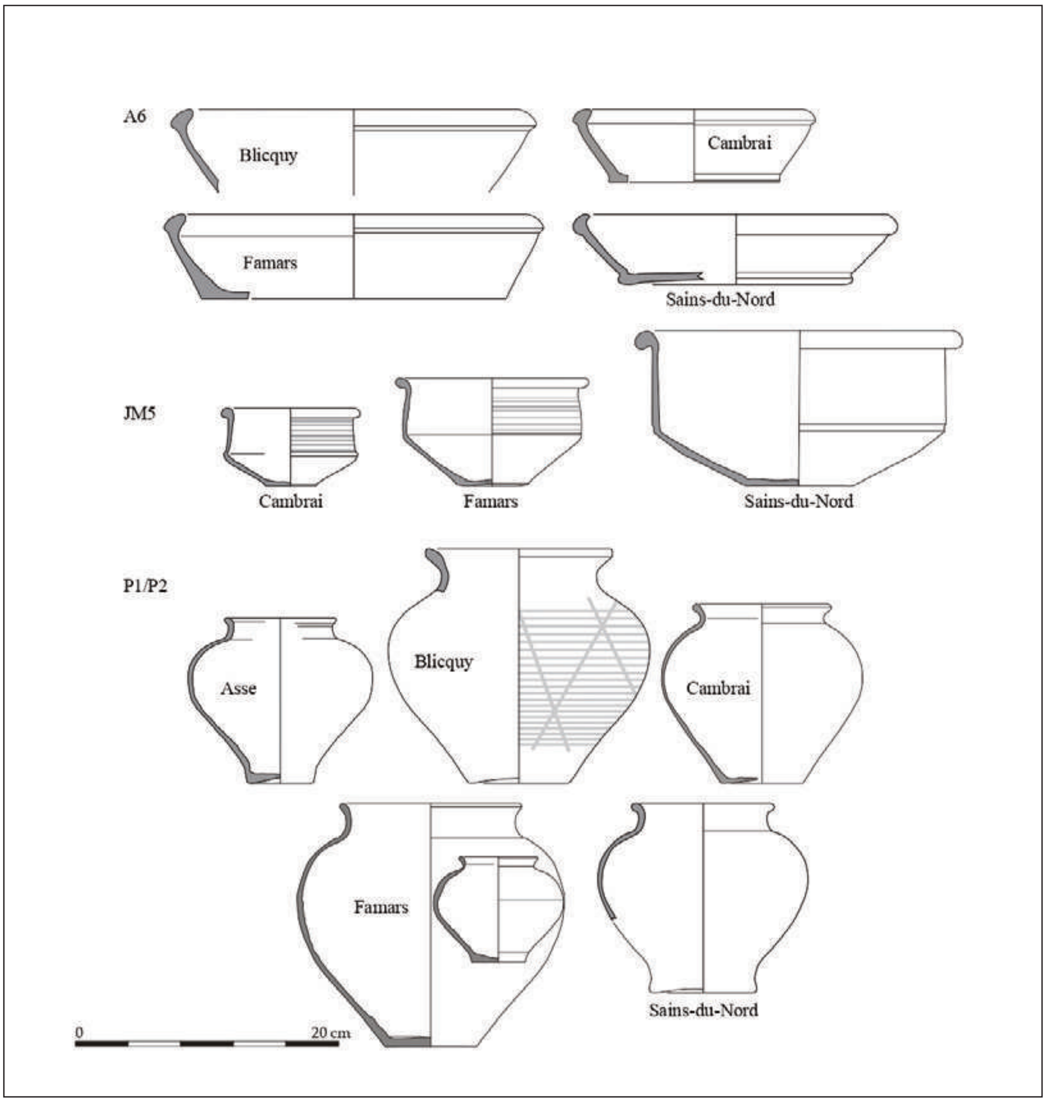
The present article concentrates on the purpose and method of extensive fabric analysis and how it can evolve. Extensive sampling and study of wasters from kiln sites within a specific production region is necessary to grasp the evolution of technological choices, reflecting periods of testing, innovation, adaptation, standardization as well as transfer of techniques.

Coarse ware types often stay in the repertoire for a long time, only slowly evolving, and most of them are feeble chronological indicators. For instance, the southern Nervian repertoire comprises a wide range of types, produced in most regional workshops from the 1st to the 3rd or even 4th centuries AD. At various workshops in the Nervian territory, including Asse, Blicquy, Cambrai, Famars and Sains-du-Nord, similar shapes of plates, bowls and pots were produced (*fig.* 2).

When exclusively types are acknowledged, small variations might indicate a different origin or chronological evolution, however, the overall date remains mostly imprecise. Linking the typological information to fabric descriptions can tackle the question on an inter-site level as well as an intra-site level.

[1] Peacock 1977.
[2] In general, Tomber, Dore 1998.
[3] Willems, Borgers 2017.
[4] Labarre, Willems 2019.
[5] Favennec *et al.* 2019.
[6] Maréchal *et al.* 2019.
[7] Hosdez *et al.* 2019.

1. LOCALIZATION OF THE KILN SITES IN THE STUDIED REGION. IN RED THE KILN SITES THAT WERE PUBLISHED IN THE ATLAS VOLUME; IN BLUE THE KILN SITES THAT WILL BE PUBLISHED IN A NEXT VOLUME (elaboration by P. Lefèvre, Inrap)



2. TYPICAL TYPES OF THE NERVIAN TERRITORY, PRODUCED IN SEVERAL KILN SITES (elaboration by S. Willems)

2.1. Results on an inter-site level

The comparison of fabric variants from different workshops with typo-chronological data enables their differentiation on an inter-site level and permits interpretation of knowledge transfer. A case in point are the workshops at Bavay, Pont-sur-Sambre and Famars, mostly identified as one large group of “Bavay-productions”[8] . Indeed, workshops were installed in Bavay, the *civitas* capital (*fig.* 1, n. 6), in the Augustan period, when the town was constructed *ex nihilo*.

The main production consisted of *mortaria* (grinding bowls) and jugs, which were exported outside the *civitas* borders from the middle of the 1st century AD onwards[9]. To the south-east of the capital, Pont-sur-Sambre (*fig.* 1, n. 18), located on one of the important rivers of the region, the Sambre, permitting export towards the Meuse River and thus the *limes* region, also housed a ceramic production, which concentrated on highly standardized *mortaria*[10].

[8] Borgers *et al.* 2021.
[9] Labarre, Willems 2019.
[10] Loridant, Ménard 2002.

To the south-west, Famars was located near the Scheldt River, which permitted to export its cooking wares and jugs, and from the 3rd century AD onwards also *mortaria* to the North (*fig.* 1, n. 12)[11]. Compositional analysis of the *mortaria* and jugs from these three production sites indicated that potters used calcareous raw materials, rendering their inter-site differentiation quite difficult.

The results of fabric analysis showed that four different paste preparations were used (e.g., Fabrics 1, 2, 9 and 16), albeit with a broadly similar chemical signature. Analysis of the pottery waste and stamped *mortaria* from the workshops showed the presence of the same paste recipes among the three workshops. More specifically, at Bavay, Fabrics 1 and 16 were used to produce *mortaria*, Fabric 9 for jugs, while at Pont-sur-Sambre Fabric 16 was indicative for *mortarium*-production, and at Famars Fabrics 1 and 2 for *mortaria* and jugs respectively[12].

Typo-chronological differences had to be considered to identify the origin of sherds from consumption sites. Excavations at Bavay have yielded numerous kilns situated in the south of the city, and all of them seem to have been exclusively active during the 1st century AD. As for Pont-sur-Sambre, information from consumption sites suggests that the production and use of its *mortaria* can be dated to the 2nd century AD.

At Famars, the workshops were evenly installed from the end of the 1st century onwards, when they mainly produced jugs or cooking ware; in the 3rd century AD, however, they seem to have taken control over the production (and distribution) of *mortaria,* when Pont-sur-Sambre stopped.

Combining this chronological information with extensive fabric analyses then, permits to infer interaction between the three workshops. The technology of Fabrics 1 and 16, which were in use at Bavay to produce *mortaria*, was transferred to the other workshops at Pont-sur-Sambre (e.g., Fabric 16) and Famars (e.g., Fabric 1), which were active during the 2nd and 3rd centuries AD (*fig.* 3). Moreover, at Famars, Fabric 16 has also been observed in cult pots.

The use of the same raw materials and paste preparation techniques indicates a high level of shared technological practices. On the one hand, the movement of potters from Bavay to Pont-sur-Sambre and Famars can be imagined, when pottery production at the capital stopped. On the other hand, knowledge transfer in the form of kinship is an alternative suggestion, whereby 3rd century AD potters from Famars reproduced gestures of preparation from previous generations[13].

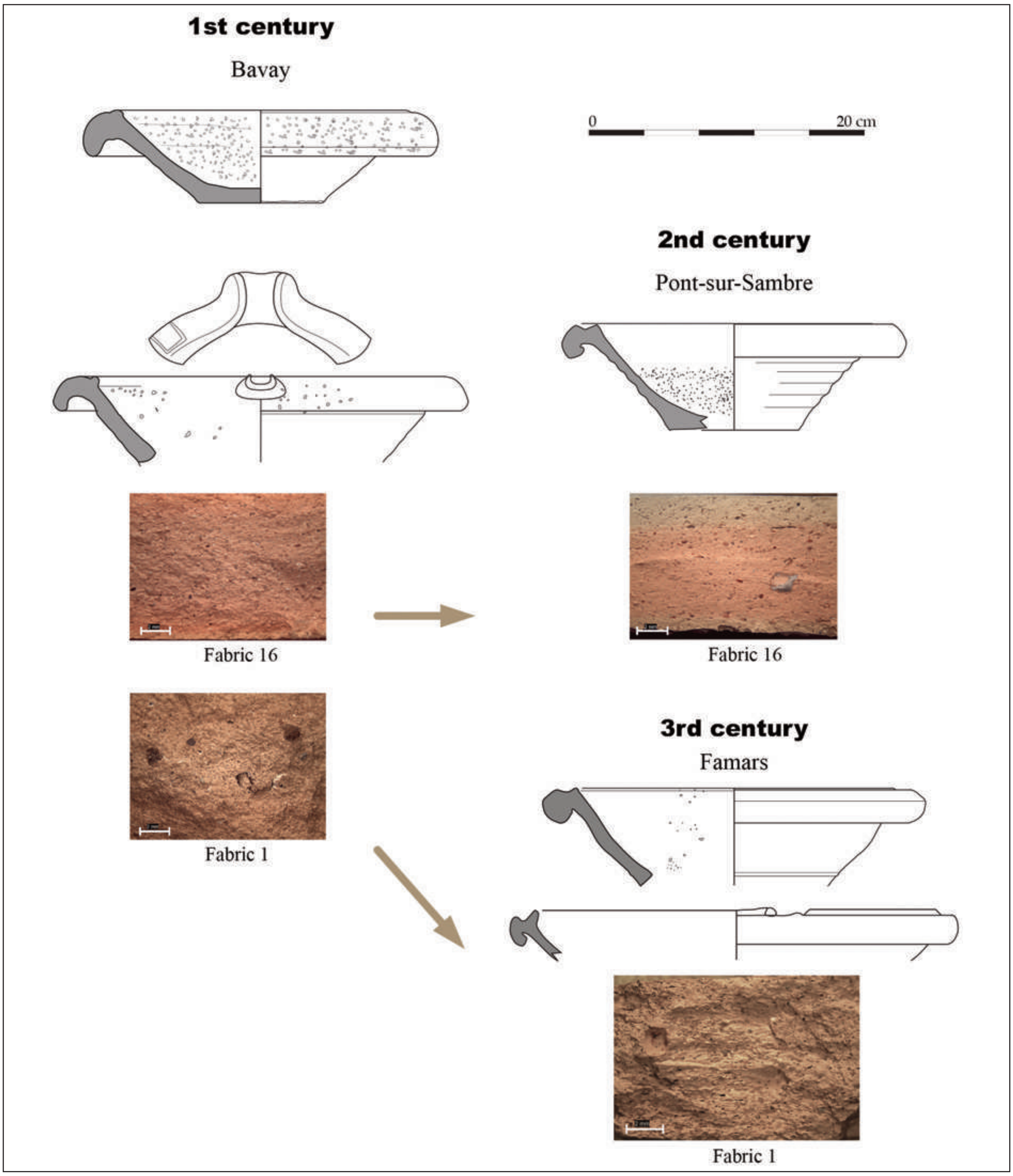
2.2. Results on an intra-site level

On an intra-site level, study of fabric evolution, or fabric variants, within the same workshop[14], permits specification of the chronology of coarse wares within a region. In-depth study of the coarse ware fabrics from Famars[15] has brought to light a complex evolution of paste preparation techniques, reflecting periods of testing, abandoning and standardization.

This interpretation was only obtained by the study of extensive samples of pottery waste from 12 kilns. Almost 300 samples were petrographically or chemically analyzed, and their selection was based on macroscopic variants, as well as function, type, and chronology, as well as archaeomagnetic dating.

In the beginning of the production period, potters seem to have discarded pottery because of the presence of clay pellets in their products (*fig.* 4, fabric 3).

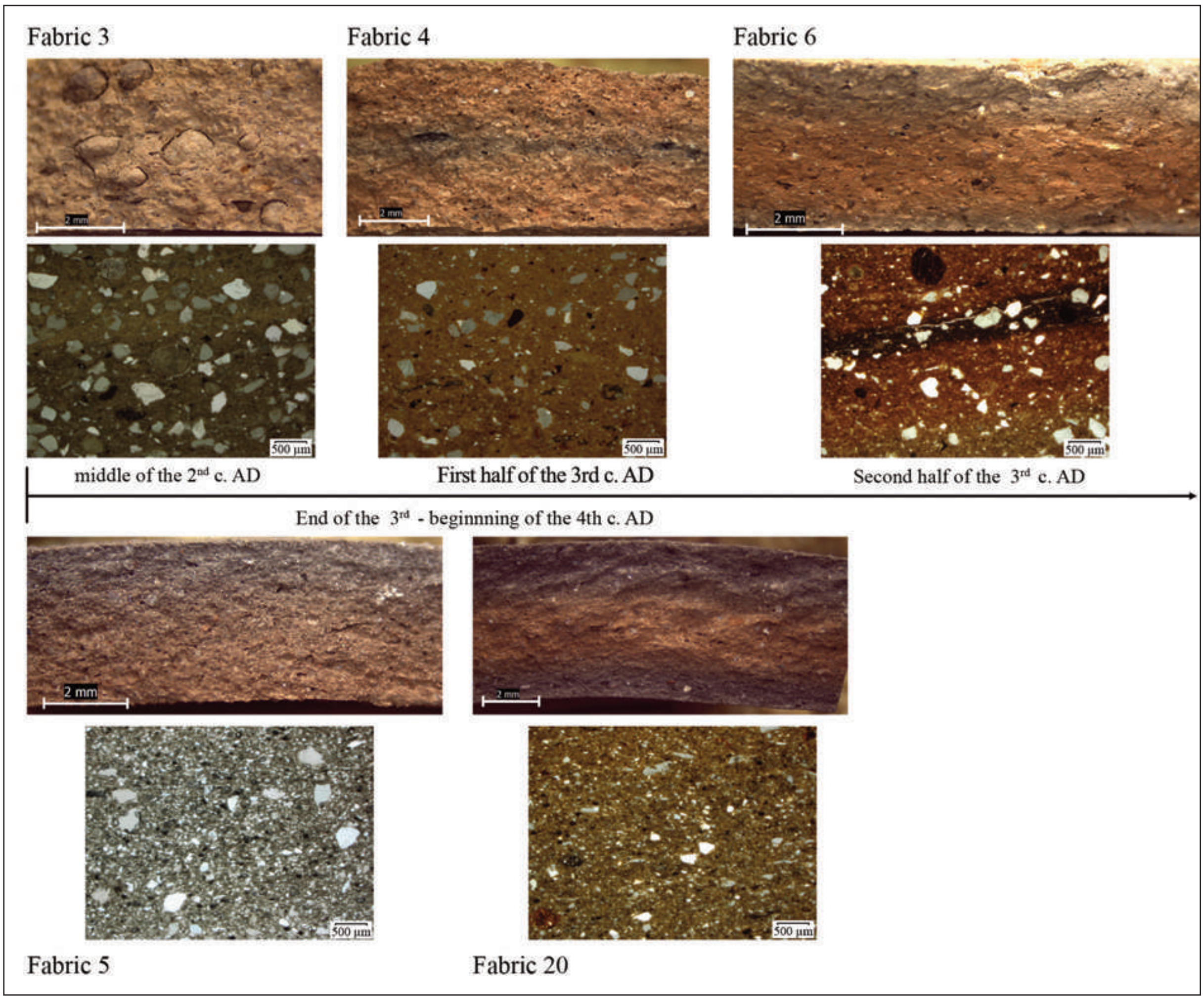
[11] Willems *et al.* 2019
[12] Willems, Borgers 2017.
[13] Borgers *et al.* 2021.
[14] Favennec *et al.* 2019.
[15] Borgers *et al.* 2020.



3. THE MOVING OF POTTERS OR THE KNOWLEDGE TRANSFER BY KINSHIP ILLUSTRATED BY THE IDENTIFICATION OF THE SAME PASTE PREPARATIONS WITHIN THREE KILN SITES (elaboration by S. Willems)

This preliminary paste preparation technique was highly calcareous, not always adapted to cooking purposes. Gradually, however, potters seem to have mixed various clays and added sand to obtain less calcareous variants. By the end of the 3rd century AD, potters seem to have employed two standardized sandy variants (*fig.* 4, Fabrics 5 and 20), which were the result of a long learning process of cleaning, mixing and tempering clays.

Knowledge of the chronological evolution of these fabric variants, as well as differentiation with other kiln sites, enables to specify the dating of cooking wares that have slowly evolving type variation.



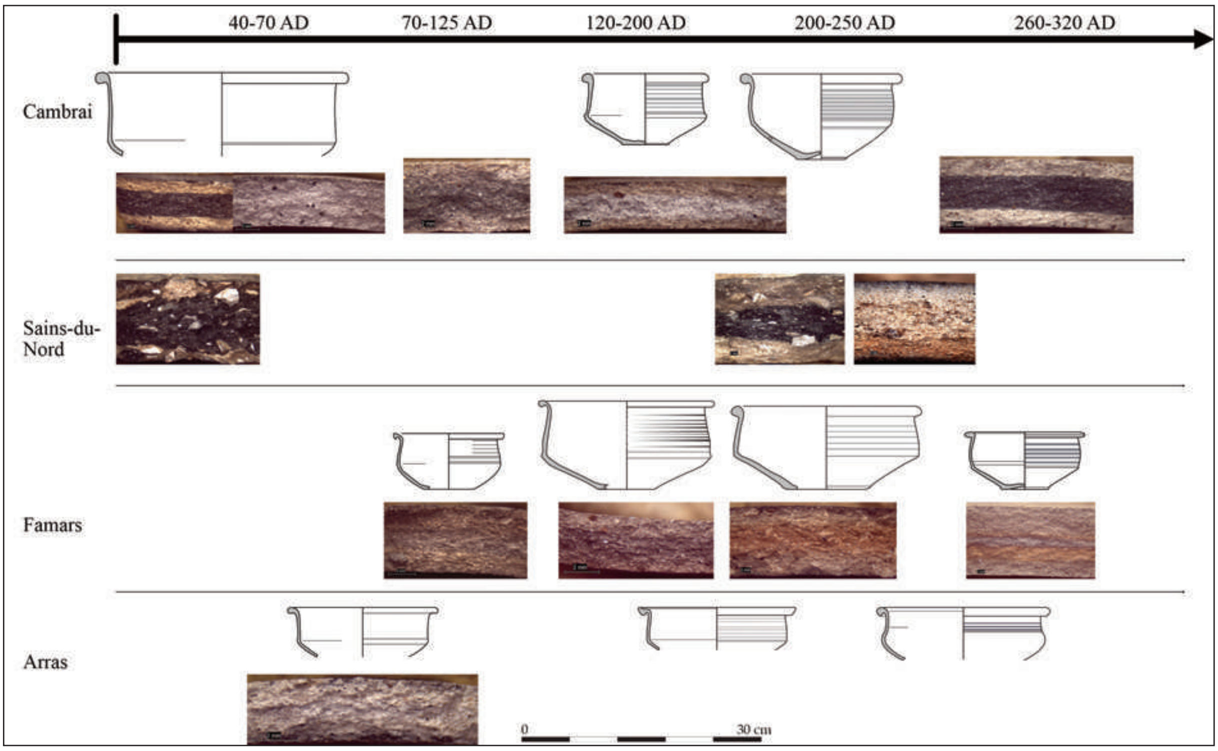
4. THE EVOLUTION OF PASTE PREPARATION WITHIN THE FAMARS KILNS FROM THE 1ST TO THE BEGINNING OF THE 4TH C. AD (elaboration by S. Willems and B. Borgers)

For instance, the slow evolution of the carinated bowl, from the middle of the 1st century AD to the beginning of the 4th century AD, can be specified by distinguishing their origin and fabric evolution (*fig.* 5). The earliest productions of carinated bowls are encountered in the kilns at Cambrai and Arras, while at Famars they were only produced from the end of the 1st or beginning of the 2nd century AD onwards. From this follows that the date of a bowl in a typical fabric from Famars is restricted to the 2nd and 3rd centuries AD, while the fabric variations help to further refine its chronology.

2.3. Results on an extra-site level

The systematic identification of pottery fabrics also enables the interpretation of consumption patterns. By mapping the distribution of pottery productions, market mechanisms and strategies can be perceived. Historians are reluctant to accept the existence of concepts such as economic competition or sharing and division of markets for the Roman period[16]. However, when the production origin of ceramics on consumption sites is identified, and the presence/absence of all these productions is compared, new insights can be gained, showing a complex interaction between kiln sites or, at least, merchants.

[16] Tchernia 2011, pp. 170-172; Genin 2011, p. 427.



5. FABRIC VARIATIONS OF DIFFERENT KILN SITES PERMITTING TO CHRONOLOGICALLY SPECIFY THE DATING OF A SAME TYPE, SUCH AS THE NERVIAN CARINATED BOWL JM5 (elaboration by S. Willems)

We observe that, even if most kiln sites produced a wide variety of forms and categories, production sites are often complementary and large(r) workshops tend to dominate the markets with specific vessels. The reason for the domination is access to specific raw materials, enabling the production of high-quality wares, such as cooking wares in kaolin-rich clays and jugs or *mortaria* in calcareous clays. The Cambrai kilns, as well as the Arras kilns, dominated the markets of Northern Gaul during the entire 1st century AD, as they had access to kaolin-rich clays, with good refractory qualities and thus well adapted to thermal shocks[17]. Arras (*fig.* 1, n. 1), *civitas* capital of the *Atrebates*, exported to the south from the middle of the 1st century AD onwards, supplanting the Noyon-region imports tempered with limestones. Consumption contexts from Amiens, capital city of the *Ambiani*, the neighboring people, show that Arras products dominated the local market at least until the beginning of the 2nd century AD.[18] The installation of a new kiln site to the east of Amiens, at Beuvraignes, localized within the *civitas* borders of the *Ambiani* and using kaolin-rich clays, changed the market completely in this part of *Gallia Belgica*. The Arras productions, taking up 60% of the cooking ware imports around AD120, fell back to between 3 and 5% between AD130 and 150, while Beuvraignes overtook 53 to 67% of the market of cooking wares[19].

A similar image has been obtained for the Cambrai productions, whose cooking wares and baking plates in kaolin-rich clays were popular. The main difference is that the pottery was not totally supplanted, as competition came from workshops using sandy clays. For instance, at the consumption contexts at Famars cooking wares from Cambrai are dominant during the 1st and 2nd centuries AD. Nevertheless, the local sandy wares from Famars gained in importance and took over 50% of the repertoire by the end of the 2nd and during the 3rd century AD[20].

[17] D'Anna *et al.* 2003, p. 8.
[18] Dubois 2010a; Dubois 2010b; Dubois 2010c.
[19] Dubois 2010c.
[20] Willems 2019, p. 304.

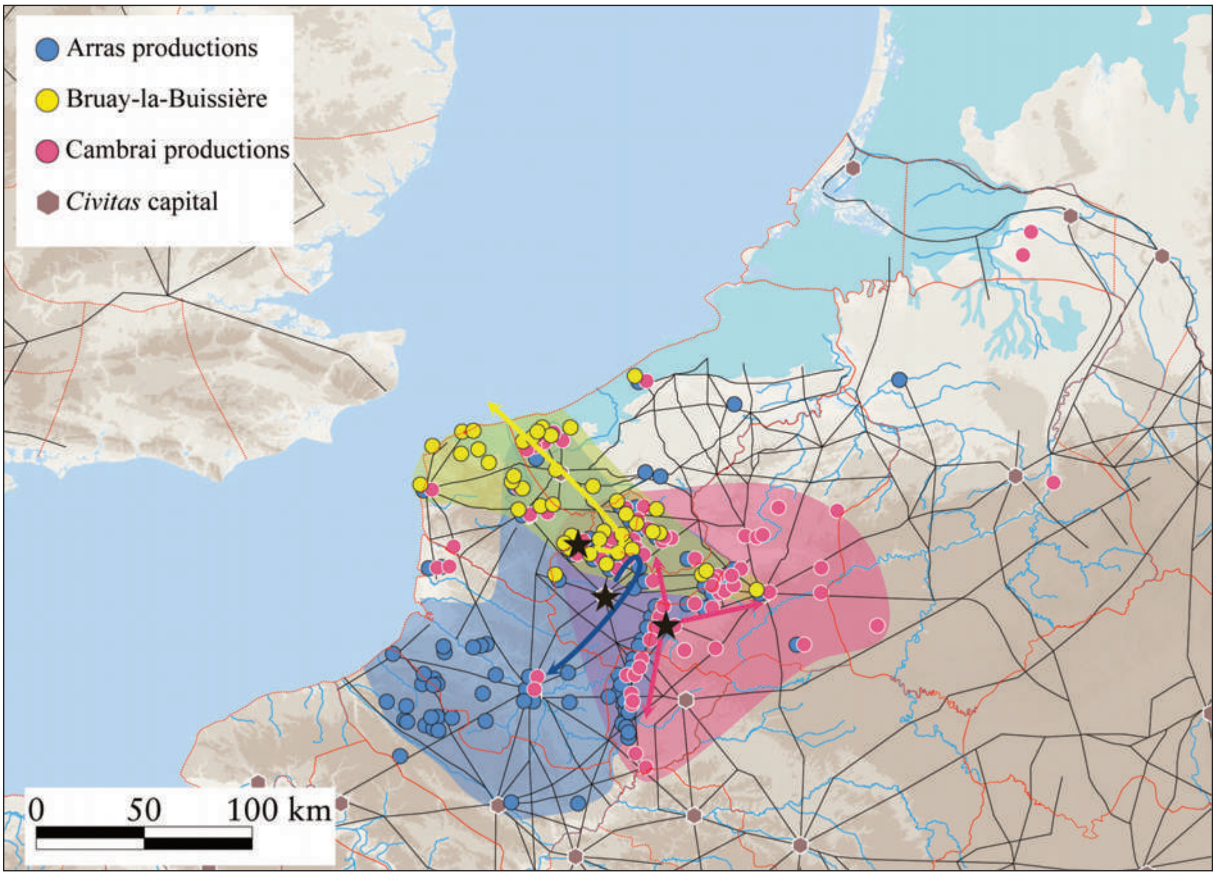
Moreover, the export of Cambrai products was limited towards the north, and was blocked to the south by the pottery from Arras and Beuvraignes, and to the west by a third important workshop, Bruay-la-Buissière (*fig.* 1, n. 9). Bruay-la-Buissière is situated in the north-western part of the *Atrebates* region and is known to having produced grey wares. Calculations following excavations suggest the presence of hundreds of kilns[21].

The distribution maps of the ceramics from these three production sites show a clear division of markets. This could be the result of their geographical positioning and an elaborated road system.

However, it does not explain why Bruay-la-Buissière did not export towards the south, where Arras maintained a strong position as a supplier of cooking wares on the *Ambiani* territory. On the other hand, it seems significant that major workshops developed at Beuvraignes, and later, at Beauvais, where kaolin-clays are available.

Mapping and interpreting these dynamics as situations of mere economic competition is difficult (*fig.* 6) as more research is required on the nature and status of the workshops, particularly regarding potters' movement or knowledge transfer. What is clear, though, is that the markets were divided and controlled by important workshops, that exploited good quality clays.

Nevertheless, other workshops were viable as they developed complementary ceramic wares, using sandy clays, which did not have to resist to thermal shocks.



6. MARKET DIVISION OF COARSE WARES BY THREE MAJOR KILN SITES, ARRAS, CAMBRAI AND BRUAY-LA-BUISSIÈRE (elaboration by S. Willems and R. Clotuche, Inrap)

[21] BLAMANGIN 2019.

Examples of workshops include Dourges[22], Ostricourt[23], Ploegsteert[24], Bourlon[25], Blicquy[26] or Howardries[27], that produced *dolia* (food containers) and regional amphorae, each of them varying and adapting their repertoire to the local markets as well as to the export of locally produced victuals.

Finally, the kiln sites disposing of calcareous clays specialized in the fabrication of *mortaria* and jugs, their popularity reflected by the long-distance trade patterns. In Northern Gaul, two major production groups of *mortaria* and jugs in calcareous clays dominated the markets: the Bavay-Pont-sur-Sambre-Famars group and the Noyon region group. Study of fabrics, potters’ stamps and typology have shown a shared ownership of the two production groups[28]. Similar potters’ stamps from two craft families from the region of Lyon, the *Valerii* and the *Atisii*, have been identified on *mortaria* that were produced in Bavay and Noyon, suggesting that potters moved from the south to the newly created markets in the north. Moreover, the repertoire seems to have been inspired by Mediterranean types[29].

The distribution maps of these stamped *mortaria* show two clear export models: one towards the Rhine, Meuse, and northern territories, and the other the west and Britannia (*fig.* 7). The two distribution patterns overlap slightly in a zone of 30 km around the production sites, reflecting mixed commerce on the local and regional markets, but the long-distance export seems to have been clearly divided.

As both kiln groups seem to have belonged to the same owners, this is probably not a result of competition, but more a question of sharing export facilities, adapting to the position of roads and rivers, or the existing network of the owner’s middlemen. We can conclude that a first mapping of extensive fabric identification across Northern Gaul is promising to reveal local and regional market strategies in Roman times.

3. The drawbacks and how to tackle them: towards new solutions

3.1. The drawbacks

Although the results of integrated fabric studies are promising, some drawbacks should be noted and inspire new development of alternative ways to examine coarse wares.

Firstly, this kind of integrated research requires a vast experience of pottery specialists, to correctly identify local productions. Knowledge of literature, typo-chronology, technology as well as macroscopic observation is time-consuming.

The results of pottery studies highly depend on the specialist’s experience and the methodology applied, often leading to disparate and unequal human-gathered information, which remains to be interpreted, transformed, and adapted to analysis. Creating a network of well-trained specialists, using the same method, requires time and effort and depends on collaboration. Moreover, information from consumption sites is often dispersed in grey literature, such as private companies’ excavation reports, not easily accessible.

Secondly, this approach calls for extensive reference collections, for which a network of researchers with access to kiln material is needed. Publication of reference collections on paper or on websites, updating information and enabling real-time access is time-consuming and costly, demanding for long-time funding and personnel.

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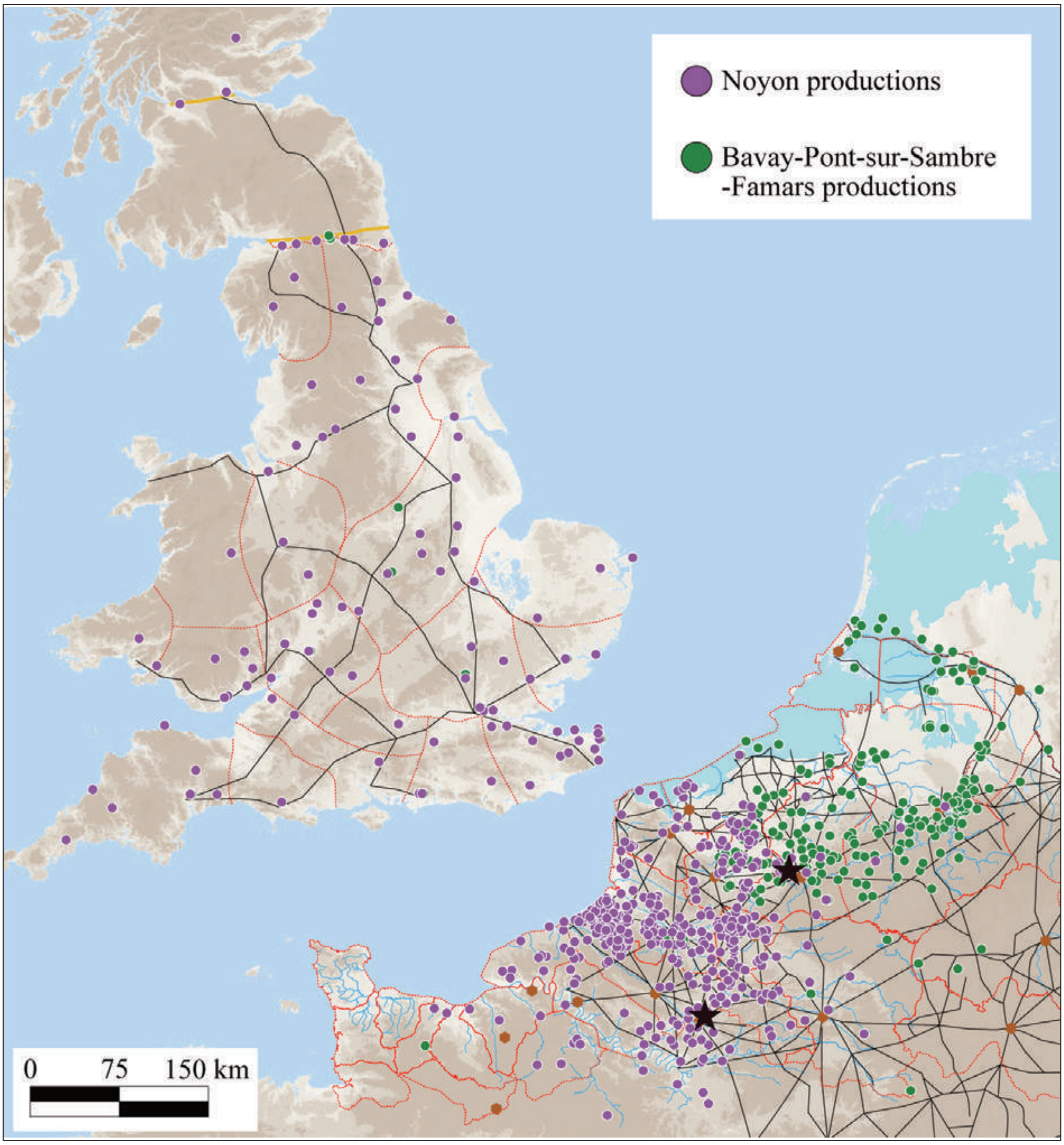
22 Thuillier 2001; Leroy *et al.* 2012.
23 Lantoine 2020.
24 Bourgeois 1989.
25 Chauwin, Tuffreau-Libre 1973.
26 Deru *et al.* 2012.
27 Amand 1971.
28 Dubois *et al.* 2009.
29 Willems, Ledauphin 2019.



7. MARKET SHARING; THE EXAMPLE OF THE NOYON GROUP AND THE BAVAY/PONT-SUR-SAMBRE/FAMARS GROUP, PROBABLY BELONGING TO THE SAME FAMILY OF OWNERS (elaboration by S. Willems and R. Clotuche, Inrap)

A good example of a major joint effort is the *National Roman Fabric Reference Collection*[30] which was first published in 1998, reprinted in 2002 and is currently out of print. The project resulted from a collaboration between *Historic England*, the *Museum of London Archaeology*, and the *British Museum*. Previously, from 2009 to 2014, the online database was hosted at molas.org.uk. In the meantime, it was and still is linked to the work by Paul Tyers, author of the monograph *Roman Pottery in Britain*[31].

[30] Tomber, Dore 1998; https://romanpotterystudy.org.uk/nrfrc/base/index.php (last access march 15th, 2024).
[31] Tyers 1996, with reprint in 1999 and 2003, out of print since 2005; https://potsherd.net/atlas/concordance/nrfrc (last access march 15th, 2024).

The physical collection is housed in the Museum of London, former *Specialist Services*, and the full text and images are now available on the *Roman Pottery Studies Group* website, thanks to funding from the *Roman Research Trust.*

3.2. New Solutions for Museums

The use of Artificial Intelligence (AI) for heritage management and research is expanding, especially in museum contexts since the Covid pandemic, when it was necessary to digitally give access to collections. Moreover, the European Commission published a recommendation[32] to accelerate the digital transition, with the aim to create a European data space or digital platform for cultural heritage, building upon the European digital library.

Production of high-quality images of objects or archives, sound and audio-visual data are shared to preserve and promote cultural objects. Important goals are the protection, preservation, and reuse of heritage for future generations (e.g., education, tourism). Creating a sustainable digital infrastructure, obtaining digital skills, and developing cutting-edge technologies thus contribute to the objectives of the "Digital Decade"[33].

The promotion of important monuments and archaeological sites through 3D images is one of many examples of how to digitally disseminate cultural heritage. Nevertheless, the huge number of data seems underexploited, as the main objective is to promote, and not analyze the objects and archives.

In the last two decades, web information systems have been widely used for the management of archaeological sites and data sets. GIS-based applications, 3D and the development of a Virtual Research Environment help managing very different data, from digitally retrieved information to paper documents[34].

Most recently, Machine Learning has been implemented as one of the new ways of analyzing big data, and archaeology has not been left out. The use of AI is now part of everyday life, as applications for social media, health care management or marketing chatbots indicate. Cultural heritage is no exception. Large museums, such as Paris' Quay Branly Museum or London's Tate Gallery, have developed AI applications, which are popular on social media, and increase their visibility.

Several Italian museums use cameras to monitor the emotions visitors have when interacting with art. The algorithm has learned how to recognize gender, age, interact with the public, think of museum walk through using virtual reality (Dali Theatre Museum) or chatbots answering visitor's questions, whether practical or related to the cultural object itself[35].

3.3. What about analyzing artefacts? A State of the Art

The examples indicate the importance of AI applications for public promotion and interaction, but what about the study of cultural objects using digitalization?

Several interesting projects aim to classify sites and landscapes, e.g., through LIDAR[36]. Other approaches focus on objects, such as rock carvings[37], mosaics[38] or ancient pottery decoration patterns, of which The Tusayan White Wares from Northeast Arizona is a good example[39].

[32] https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:32011H0711&from=EN (last access march 15th, 2024).
[33] https://hadea.ec.europa.eu/calls-proposals/data-space-cultural-heritage-deployment_en (last access march 15th, 2024).
[34] Meyer *et al.* 2007.
[35] Villaespesa, French 2019.
[36] Bonhage *et al.* 2021; Van der Vaart-Verschoof, Lamberts 2019.
[37] Tsigkas *et al.* 2020.
[38] Felicetti *et al.* 2021.
[39] Pawlowicz, Downum 2021.

It shows how AI can be used to classify pottery within an already existing typological framework. Doubtless, one of the most important projects is ArchAIDE[40], which is funded by the European Union's Horizon 2020 research and innovation program. The project unites several universities (Pisa, York, Cologne, and Barcelona), and provides a mobile application as well as an internet solution for the recognition of pottery forms, decoration styles and stamps. The goal is to optimize the classification and characterization of pottery, facilitating the time-consuming work of comparing finds with extensive catalogues. The main goal of the project is to develop a specific tool for archaeologists, facilitating their tasks during excavation, as well as post-excavation[41].

This works via an image recognition system of form and decoration, resulting in an identification of the proposed photograph, with linked information that is stored within a database to be shared online. The catalogue is based on a corpus of existing digital collections, published typologies and images, which is linked to a multilingual thesaurus. Different algorithms were developed for the two main criteria used by archaeologists: (pottery/vessel) profile and decoration.

Currently, the tool can recognize the shape of Roman *terra sigillata* and amphorae, as well as the decoration of Medieval pottery (e.g., Majolica). One of the difficulties of the project, however, concerns the use of comparative data from a variety of sources, which might have restricted licenses and copyrights.

Another project to be mentioned is the Arch-I-Scan project from Leicester University, which uses Machine Learning to model foodways in the Roman period through the enhancement of the ceramic data[42]. The difference with the ArchAIDE program is that Arch-I-Scan not only includes shape as a criterium, but also ceramic fabrics. The project specifically concentrates on the occurrence of Roman table wares, and especially *terra sigillata*, to interpret the existence of Roman foodways. The chosen criteria focus on vessel shape and fabric, but do not consider molded decoration[43].

Another project emanating from the Römisch-Germanisches Zentralmuseum at Mainz also aims at modelling the distribution of samian wares[44]. All these interesting projects use AI solutions for the study of long-distance trade of pottery, by analyzing decoration, form, or fabrics of table wares.

4. The FabricAI project

The amount of visual archaeological data has strongly grown since the development of public satellite image platforms in the 2000s, such as Google Earth, Bing Maps or Géoportail. In the 2010s, the GlobalXplorer project, led by Sarah Parcak[45] uses a Convolutional Neuron Network (CNN) called AlexNet[46], to analyze the huge number of visual datasets yielded by satellite imagery, revolutionized the approach[47]. As early as 2013, several researchers working in the Somme territory in France developed a program that permitted to localize and georeference archaeological sites to highlight occupational dynamics[48].

[40] http://www.archaide.eu (last access march 15th, 2024).
[41] Wright, Gattiglia 2018.
[42] Van Helden *et al.* 2022.
[43] Núñez Jareño *et al.* 2021.
[44] Mees, Thiery 2021.
[45] Parcak 2009; Parcak 2019; Parcak *et al.* 2017; https://medium.com/@globalxplorer/welcome-to-globalxplorer-7bfb555260a1 (last access march 15th, 2024).
[46] https://medium.com/analytics-vidhya/concept-of-alexnet-convolutional-neural-network-6e73b4f9ee30 (last access march 15th, 2024).
[47] Küçükdemirci, Sarris 2020.
[48] Chaidron, Lermenier 2023, p. 89.

Technological developments, such as RGB (Red Green Blue) ortho-photography, LIDAR, or thermography, using infrared and thermal cameras led to a combination of techniques to obtain the best results.

The start-up Artéka developed a protocol based on satellite multi-spectral imaging technologies yielding more accurate information than the results from satellite imagery. Various wavelengths and sensors on drones were tested during four seasons, overflying different types of terrain, permitting to calibrate the protocol according to the parameters. The mass of data recovered during these tests motivated the creation of a research program within the University of Picardie-Jules Verne, using AI with a supervised algorithm to locate archaeological sites on satellite images. In 2021, engineers from Artéka[49], launched an image recognition analysis program based on a Deep Neural Networks (CNN), for the recognition of bladder cancerous tumors[50.]

In collaboration with pottery specialists from Arkéocéra, it was decided to apply this very same program to archaeological objects. This research program is now linked to the FabricAI project, resulting from a collaboration of researchers from the universities of Paris Nanterre (France), Picardie Jules Verne (Amiens, France), Vienna (Austria), Louvain (Belgium) and the Art and History Museum Brussels (Belgium).

The in-depth knowledge of coarse ware fabrics in Northern Gaul, builds upon extensive reference collections, such as the "*International Fabric Reference Collection*" housed at the Catholic University of Louvain[51], or the reference collection of the *French National Institute for Preventive Archaeology* (Inrap), and has resulted in the first publication of the Atlas of pottery productions[52].

The origin of ceramics is recognized using an integrated approach of fabric descriptions, using macroscopy, petrography, chemical analysis, and combines this with typo-chronology. In the context of the drawbacks, such as time-consuming data-collecting and human-generated heterogeneous information, it was decided to use Artéka's AI approach to automate fabric recognition.

The FabricAI approach is comparable to the method used in a study undertaken at the University of Barcelona[53], where archaeometry is combined to AI for provenance identification. It differs in its specifically geological approach, not considering macroscopic descriptions or typo-chronology - something which we consider necessary to differentiate workshops, that might have exploited similar, if not the same, clay sources. Consequently, our project combines typo-chronological (textual) data with image-based (visual) information, such as macroscopic photographs and micrographs of thin sections.

4.1. General AI methodology

Deep Learning is a subtype of Machine Learning, inspired by the information processing and communication patterns of the brain. Computer power is thus linked to specific neural networks to learn complicated patterns in large amounts of data, also called "big data". It replaces manually created interpretations by analyses resulting from vast amounts of annotated data. Hundreds of thousands of parameters are repeatedly evaluated in the deep graph, using efficient algorithms, to obtain learning. This is specifically used for pattern recognition in visual information.

[49] https://arteka.tech/#dap (last access march 15th, 2024).
[50] https://www.clinicaltrials.gov/ct2/show/NCT05415631 (last access march 15th, 2024).
[51] https://uclouvain.be/fr/instituts-recherche/incal/cran/laboratoire-de-ceramologie.html (last access march 15th, 2024).
[52] Willems *et al.* 2023.
[53] Anglisano *et al.* 2022.

The neural network, processed by the algorithm, receives an input image, and learns to differentiate its characteristics. The more images you feed the algorithm, the more it gets trained, reduces errors, and enhances its precision of recognition. Different types exist, such as Supervised, Unsupervised, Semi-supervised and Reinforcement Learning. In the case of Unsupervised Learning, the algorithm is fed with as much information as possible, without guidance, which means that the algorithm choses how and which patterns will be captured. In the case of Supervised Learning, the input is labelled with correct information to guide the algorithm. The latter will learn by comparing outputs to find errors.

Through classification, regression, prediction and gradient boosting during the feeding and testing periods, the algorithm uses patterns to predict the values of unlabeled datasets. This way we program the computer to vision the world in a similar manner as humans, but by automating it through pattern recognition it rules out a subjective vision.

An important step in the creational process is the development of the database, combining visual and textual information. The choice of relevant data and how to combine them is essential as the researcher decides what information will be used and what the algorithm should learn. A dataset of thousands of labelled images forms the visual database, feeds the AI algorithm, and serves for testing.

The testing stages enable to understand what is relevant or not. We should bear in mind that the final application will generate new images and information, enriching the dataset and permitting extensive comparison and mapping of occurrences through linked GIS-applications. The textual database, therefore, should contain at least the following subsections: scientific classification information (category, typology, chronology), contextual information (site's geographical coordinates, site name and context) and administrative information (collection, inventory number). The visual database is linked to the textual database via information, such as site name, origin, and ceramic category.

To develop a well-working automatic pattern recognition, the algorithm should be fed by homogeneous visual information, including 2D-images that answer to a set of characteristics. Different criteria should be tested and analyzed, resulting in an image protocol. It is important to obtain a dataset of images with the same format and width, including the same sort of features (e.g., decorations, fabrics…), and obtained following the same capture criteria.

The second step is the choice of the neuron network, the development of the algorithm and training. Several deep learning architectures, such as Deep Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN) have been applied to computer vision, speech recognition, automatic natural language processing, and auditory recognition, to produce outstanding results for multiple tasks. CNNs are at present most performant for the detection of objects[54]. On the visual data, this is the captured images, specific zones are indicated and annotated. It consists of providing the algorithm the zone that should be recognized, with an identification that will serve to train the neural network. The training itself consists of an analysis of the image pixels. Indication and identification of the specific zones means that the training is supervised and thus needs fewer datasets than an automatic non-supervised training. The algorithm processes the information provided by the image annotations and verifies its correctness and percentage of correspondence with the model. In Supervised Machine Learning, the models are based on datasets provided by human operators, producing the image annotations. Before the training, a final manual sorting of the resulting labelled images is carried out following a specific protocol, ensuring the quality of the dataset, automatically enhancing the quality of the resulting models. 15% of the images serves to test the algorithm and grouping or indexing the information can be necessary after this feedback.

[54] Le Cun 2019.

4.2. The project's specific methodology

In this specific case the project aimed at the analysis of pottery fresh break images by an online AI image analysis platform. The first step was to lean on a cloud-based image analysis to test the feasibility of AI fabric recognition, and the next stage – if funding is obtained – will concern the development of a mobile system connected to a microscope that would identify pottery fresh breaks in real time[55].

The main objective is to create a tool that would enable stakeholders (students, researchers, curators, archaeologists in private companies…) to identify pottery origin by AI image analysis and to link it to GIS-applications. This would mean time-gain, but also a deeper understanding of the commercial networks, as well as pin down fabrics for which an origin is still uncertain, without having resort to expensive large-scale petrographic and chemical analyses.

The fresh break images are captured by a stereomicroscope, type Leica EZ4, enabling to insert a scale indication and producing illustrations generally under 2Mo size. The visual composition of the fabric is studied according to criteria such as firing atmosphere (oxidized, reduced), appearance of the clay matrix, nature of the inclusions (type, size, form, density). Only sherds from kiln sites are used, validated by petrographic and chemical analysis, to obtain the best characterization of each fabric.

The database contains the description of the fabrics, comprising a visual characterization by the user and a textual description based on the analyses. The images are first classified per production group, and where possible on the level of a specific kiln site: "Arras" productions are the general group; if the characteristics enable recognition the kiln site is specified e.g. "Dainville", one of the kiln sites forming the Arras group. This kind of grouping of fabrics has been applied since the '70s in Great-Britain, and in Northern Gaul[56], using visual combined criteria that are sufficiently identifiable to enable the use of a CNN.

For the first step of testing, the tool Custom Vision (Microsoft Azur suite) was chosen, because it is easy to use and low cost. This is an important criterium as the start-up Artéka led by C. Chaidron, was created in October 2020, and so far, benefited neither from public nor private funding. Moreover, the platform was in use since 2019 for a satellite imagery analysis program, in the context of the research team "Trame" (University of Picardie, Jules Verne, France)[57] .

The Custom Vision service enables users to create, form and deploy vision models, obtaining results with precise metrics, without the necessity for profound knowledge or in-deep learning process. It simplifies the process, without requiring the user to manually adjust computer vision programs, but proposes models that can be fine-tuned according their specific needs. Custom vision uses a convolutional neural network (CNN) for the processing of images.

The detailed architecture is owned by Microsoft, but it is widely known to be based on tested models such as ResNet and AlexNet. These models are characterized by a variable number of layers, from a few tens to several hundreds of layers, enabling in-depth analysis of visual features.

As mentioned before, Custom Vision has the capacity to enable the user to personalize the models, using their own databases. The system learns and adapts itself according to specific examples, enhancing the pertinence and exactness of the results. The training of the models is performed through the addition and adjustment of a personalized layer to the pre-trained model, thus in this case, optimizing the model to the recognition of pottery fabrics.

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[55] This tablet is a solution in case you need a portable analysis system that can be connected to a computer without an Internet connection. The Azur solution may be preferred if you want to use an Internet-connected platform.
[56] See Peacock 1977, but also De Laet, Thoen 1969; Bayard 1980; Dubois 2002; Willems *et al.* 2023 and many others.
[57] https://greymatter.com/content-hub/use-case-how-bing-maps-satellite-imagery-finds-ancient-sites/ and https://greymatter.com/content-hub/using-azure-custom-vision-in-archaeology/ (last access march 15th, 2024).

The interface allows the downloading and labelling of images, thanks to delimitation boxes (bounding-boxes). In Supervised Deep Learning, the researcher must select the information to be learned by the algorithm. The dataset can consist of combinations of segmented images. A macroscopic image linked to an illustration of a surface decoration, or a potter's stamp linked to a fabric image are good examples. The more information is presented, the more the algorithm has to perform.

Once the labelling completed, it is possible to choose the training time and the financial cost. New images can be added to the model and new training can be carried out, each one being numbered and with access to the training measurements that enable comparison and analysis of the evolution of the models' performances. These are measured using different metrics such as precision, recall and F1 scoring. In empirical tests, these models have shown important effectiveness for classification and detection, even if results may vary depending on the training data[58].

4.3. First results

As mentioned, the first tests have been carried out with the Custom vision Azur Microsoft suite (usually ResNet), using the default parameters. The database comprised visual and textual information about pottery waste from four different workshops, including Beuvraignes, Cambrai, Arras and Famars (see *fig.* 1).

The first three workshops are interesting because of their exploitation of kaolin-rich clays. As for Famars, this workshop allows good testing and comparison, because potters used both sandy and calcareous clays. Thus, the Famars dataset provides the algorithm with a totally different kind of information, enabling testing. The weakness of the corpus lies in the requirement for each sample to be validated by chemical and petrographic analyses, which was the case for the aforementioned productions.

The visual dataset of the four workshops was organized according to the following principals or variables: Production group (coarse wares), Category (oxidized wares, reduced wares), Origin (production site) (*fig.* 8).

The structured and grouped visual data facilitate the work of the algorithm, its training and testing, and direct it towards the right research questions. This is also indicated by studies that have focused on heterogeneous data[59].

The visual data were then labelled in such a way that the algorithm knew which information to process and recognize. Specific zones (bounding-boxes) were meticulously indicated on the captured image, using a mouse (*fig.* 9, A). Designating these boxes is essential for CNN analysis. It indicates the zone that the algorithm should recognize. The image is then indexed or annotated with information that will serve to train the neural network and link the image to the right answer (*fig.* 9, B).

This consists of an analysis of the image pixels. Labelling and indexing specific zones mean that the training is supervised and thus needs fewer datasets than an automatic non-supervised training. The algorithm processes the information provided by the image annotations and verifies its correctness and percentage of correspondence with the model. Before the training, a final manual sorting of the resulting labelled images is carried out following a specific protocol. It ensures the quality of the dataset right before the training starts. It is a mandatory and time-consuming step that automatically enhances resulting models.

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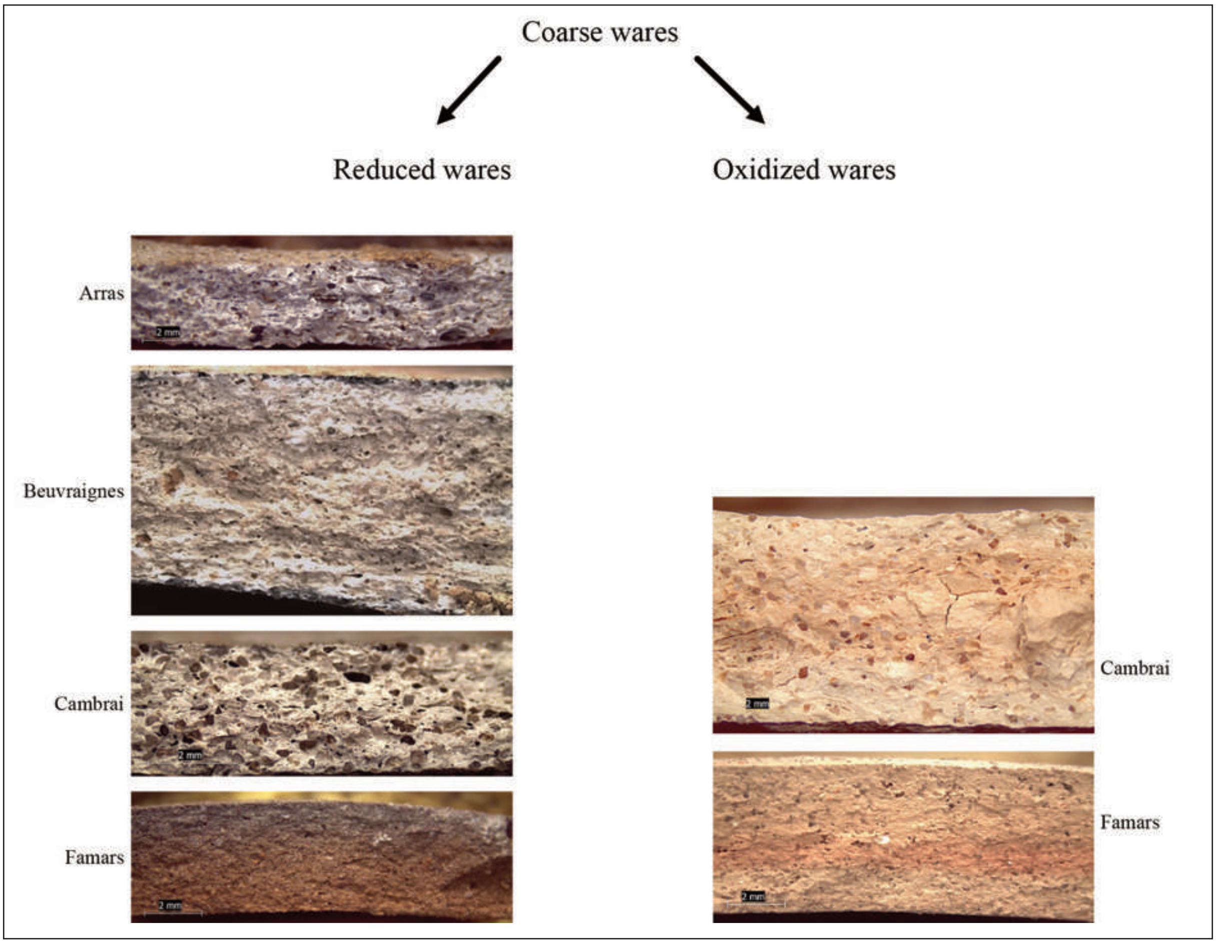
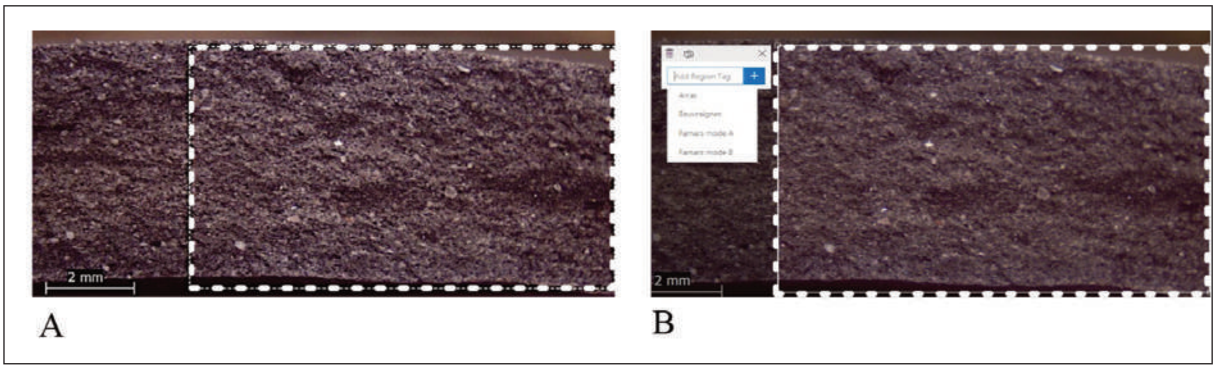
[58] https://techcommunity.microsoft.com/t5/ai-customer-engineering-team/building-image-classifiers-made-easy-with-azure-custom-vision/ba-p/1547844 (last access march 15th, 2024).
[59] Liang *et al.* 2009; Baochen *et al.* 2016.



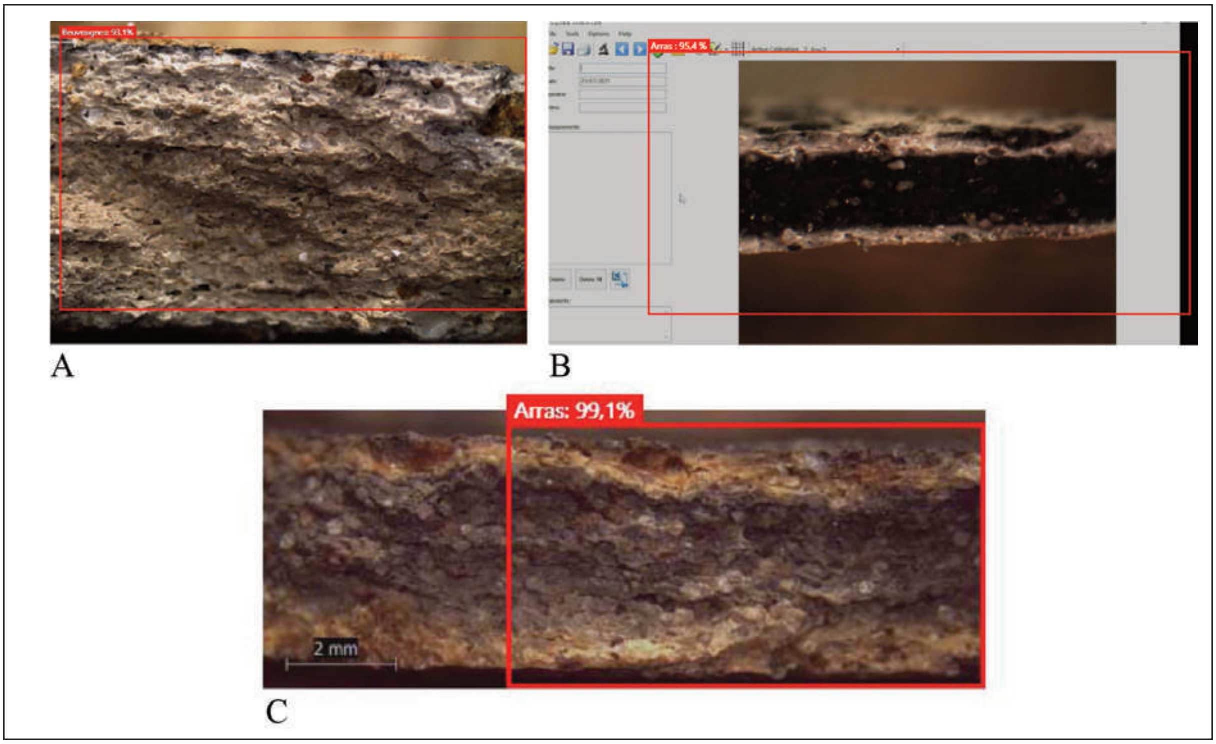
8. ORGANIZATION OF THE FIRST DATASET (elaboration by S. Willems and C. Chaidron)



9. A: LABELLING OF THE SPECIFIC ZONE ON THE FABRIC ILLUSTRATION; B: ANNOTATION OR INDEXING OF THE LABELLED IMAGE (elaboration by C. Chaidron)

The first training of the model has been done using at least 50 images per production group. With only 20 images per group, the algorithm easily gets it right, but precision increases when more images are fed, thus providing more information.

The algorithm can be powered by existing backed-up images or by using the tablet and application linked to a stereo microscope. In the latter case, the AI application analyses the image directly by comparing it with labelled and annotated datasets, without the need for an internet connection. The first input enabled a fabric recognition with up to 93,1% accuracy. After this initial input, the algorithm was tested by feeding images that were not part of the initial dataset. The precision of the next set augmented to a promising 95,4 %, and even 99,1% in the recognition of Arras coarse wares (*fig.* 10).



10. RESULTS OF THE THREE STEPS OF TRAINING AND TESTING: A: FIRST DATASET LEADING TO A 93,1% OF ACCURACY; B: SECOND DATASET LEADING TO 95,4% OF ACCURACY; C: TESTING WITH A THIRD DATASET INCREASED THE ACCURACY TO 99,1% (elaboration by C. Chaidron)

The testing period is extremely important, because in Supervised Learning, the algorithm follows the indicated information. It can become biased due to poor dataset input and an incorrectly organized database. Therefore, feeding images of strongly deviating fabrics permits extensive learning during the different stages of classification, regression, prediction and boosting, and avoids bi-algorithmic problems.

At this stage, the database is too small to make statistical data relevant. The tests focused on the feasibility of using a convolutional neural network to address the problem of identifying the provenance of ceramic samples. Training was carried out on about 100 images. The last results should be seen as a proof of concept, and the last neural network training results are indicative (Accuracy 91,3%, Recall 100%, mAP 100%). Several supplementary trainings are planned at different phases of the compilation of the database. The publication of the Atlas of pottery productions[60], with an inventory of numerous kiln sites, will provide the necessary data for further training.

[60] Clotuche *et al.* 2010; Willems *et al.* 2023

A first proof of concept was published[61], but a multiplication of new research projects focusing on the use of AI and pottery identification is noticeable[62], motivating our initiative.

5. Conclusion

The many advantages of AI have been extensively discussed in recent literature. In the case of automating fabric recognition, it means an enormous time-gain for pottery specialists, often operating in a private context where post-excavation deadlines are strict. It asks for years of experience before knowledge of the reference collections is broad enough to fluently identify different pottery productions. Moreover, the accuracy of identification by a Deep Learning Machine algorithm is probably more performant than what can be expected from a researcher, even if it is a very experienced one.

The application can be linked to a GIS-application with a centralized database. This permits to automatically generate more accurate distribution maps, which would enable an in-depth analysis of the economic system of the study region. This way, Artéka’s tablet and application proposes an interactive research tool, offering, on the one hand, an automatic identification, and in return, a collection of information for research.

Finally, the application can also serve as an educational tool for beginning pottery specialists or students, enabling them to recognize productions, which they were not familiar with.

The first tests are very promising. The algorithm was able to differ among three workshops, where potters used the same kaolin-rich clays but employed different fabric variants through clay preparation. This is an important step forwards, as fabric differentiation might be subjective or questionable, something which is ruled out by automating origin recognition. New datasets, based on the petrographic and macroscopic identifications of pottery waste in the different reference collections (e.g., Atlas, IFRC…) will be included in the FabricAI research program, to further test and develop the application before its commercialization[63].

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[61] Chaidron, Lemenier 2023.
[62] Chetouani *et al.* 2020; Lyons 2021; Resler *et al.* 2021; Agapiou *et al.* 2021.
[63] The authors would like to thank Caterina Paola Venditti, Eugenio Polito, Thomas Froelich and Maria Taloni, for the kind invitation and support to publish the research presented at the EAA Budapest 2022 session #346 “Bringing the Coarse Wares to the Point: The Challenge of a Common Approach”. We would also like to thank the two reviewers who helped us improve the first version of the document with their useful remarks and suggestions for supplementary references on AI.

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