



Review Article

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From Traditional Recognition to Digital Traceability and Artificial Intelligence: A Review of Orthopedic Implant and Instrument Identification Technologies

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Abstract

Background: Before revision or implant-removal surgery, the orthopedic surgeon needs to identify the implant present because the required instruments and removal technique may depend on the device. Before modern digital records and standardized device-identification systems, identification of unfamiliar orthopedic implants often depended on radiographic appearance, available operative documentation and clinicians' familiarity with implant designs. Although this problem persists, medical imaging, implant databases, digital traceability systems and artificial intelligence now provide additional approaches to implant identification.

Scope: This narrative review examines established and emerging approaches to orthopedic implant and surgical-instrument identification. It covers visual recognition, paper labels and implant stickers, linear barcodes, Unique Device Identification (UDI), Data Matrix and direct part marking, QR codes, Near-Field Communication (NFC), Radiofrequency Identification (RFID), implant-embedded passive RFID and transcutaneous near-field communication prototypes, artificial-intelligence-based radiographic recognition, and sensor-enabled smart implants. For each approach the review considers function, documented orthopedic use, evidence base and principal limitations, so that clinicians and researchers can compare technologies according to their intended application.

Conclusions: Orthopedic implant and instrument identification has progressed from memory-dependent visual recognition to machine-readable and digital approaches. These technologies are complementary rather than interchangeable: they differ in permanence, line-of-sight requirements, infrastructure needs, ability to function through tissue, suitability for implanted devices versus reusable instruments, and degree of clinical validation. Their use should therefore be matched to the specific clinical application and supported by appropriate evidence. Hybrid workflows that combine documentary records, machine-readable identifiers and, where necessary, image-based recognition currently offer the most practical path forward.

Keywords: Orthopedic implants, Implant identification, Revision surgery, Unique device identification, RFID, Data matrix, Artificial intelligence, Smart implants, Traceability

Background

The Historical Context: Memory-Based Identification

Before comprehensive electronic medical records, identification of unfamiliar orthopedic implants often depended on the visual memory and procedural experience of senior surgeons. A patient might present years after fracture fixation or arthroplasty with pain, infection, implant failure, non-union or a need for hardware removal, while the original operative documentation was incomplete or unavailable. In such circumstances, senior surgeons could review radiographs, recognize the implant system and identify the screwdriver, extraction bolt, clamp, reamer or other equipment required for safe removal. This experience-based knowledge was clinically valuable but dependent on individuals and difficult to transfer across institutions and generations. The challenge has grown as proprietary implant systems and surgical techniques have proliferated. Permanent identification of surgical implants predates modern barcode and RFID systems. By the mid-1960s, individually identified implanted medical devices are clearly documented; although non-orthopedic, a Selloff-Cutter prosthetic heart valve made circa 1966 carries serial number 534A [1]. Historical orthopedic implants likewise demonstrate direct permanent marking; an Austin Moore-type hip prosthesis preserved by the Science Museum Group bears serial number 6940-0-470 and the engraving 'LAHYW' [2]. By 1986, permanent identification was sufficiently established in orthopedics for ASTM F983-86 to describe it as common practice and to recommend, where implant size permitted, marking the manufacturer, material, catalogue or model number and serial or lot number [3,4]. These stamped and engraved identifiers formed an important bridge between memory-based visual recognition and later machine-readable systems such as barcodes, Data Matrix codes, RFID and contemporary digital identification.

Persistence of the Problem: Contemporary Evidence

The burden of implant identification has not been eliminated by electronic records or modern implant databases. In a 2012 American Association of Hip and Knee Surgeons member survey (published 2014), approximately 87% of respondents reported using three or more methods to identify failed implants before revision surgery [5]. The median surgeon spent 20 minutes on identification, while supporting staff spent 30 minutes; approximately 10% of implants could not be identified preoperatively using available methods [5]. Subsequent national modelling suggested that the cumulative burden of implant identification could increase as revision volumes rise [6]. The problem is not simply recognizing an implant on an image; its identity also needs to remain available throughout the life of the device. Orthopedic implants may remain in situ for many years, during which the treatment of surgeons, hospitals and product generations may all change. In practical terms, an

identification system should help answer four basic questions: What is the implant? What is its model and size? When was it implanted? Is it affected by a recall or safety alert?

Review Approach

This article is a narrative, technology-focused review rather than a systematic review. It synthesizes selected clinical, engineering, regulatory and standards literature relevant to orthopedic implant and instrument identification; no formal systematic-search or meta-analytic methodology is claimed. Literature was identified through targeted searches of PubMed and of regulatory and standards websites, supplemented by reference tracing, with the most recent search conducted in October 2026. The search was not exhaustive, and the selection of sources reflects the authors' judgement. Search concepts included orthopedic implant identification, surgical-instrument identification and traceability, Unique Device Identification (UDI), Data Matrix and direct part marking, RFID, NFC, implant databases, artificial intelligence, radiographic implant recognition and smart implants. Priority was given to orthopedic clinical studies, external or multicenter validation where available, primary regulatory or standards sources, and foundational engineering studies directly relevant to implant or instrument identification. Non-orthopedic sources were used selectively where they provided foundational historical, regulatory or technical context. The aim is practical comparison rather than exhaustive coverage of every published study.

Existing Identification and Tagging Technologies

Paper Labels, Implant Stickers and Linear Barcodes

Manufacturer packaging labels and duplicate adhesive implant stickers have long been used to preserve implant information in operative records. In a study of patients undergoing revision total hip or knee arthroplasty, Electricwala and colleagues assessed the availability and accuracy of primary operative notes and implant stickers and found that implant documentation was frequently unavailable or incomplete [7]. This illustrates an important limitation of record-dependent identification: implant information may not be reliably available when a patient later presents for revision surgery [7]. Barcode technology brought machine-readable identification into healthcare, with hospital applications appearing in the early 1980s and healthcare-specific barcode standards developing during that decade [8,9]. On implant packaging, scanning reduces reliance on manual transcription and allows device information to pass directly into electronic systems. This has also supported automated implant capture in orthopedic registries. In a single-institution study within the Irish National Orthopedic Register, barcode-based capture was more complete and accurate than legacy manual recording [10]. Paper labels, implant stickers and linear barcodes therefore mark the transition from handwritten or manually entered implant information to

standardized machine-readable traceability.

Unique Device Identification (UDI)

In 2013, the U.S. Food and Drug Administration established the Unique Device Identification system [11]. Under the UDI framework, devices carry identifiers in human-readable and machine-readable forms, and device information is submitted to the Global Unique Device Identification Database (GUDID) [11,12]. A UDI comprises a Device Identifier (DI), which identifies the labeler and the specific version or model of a device, and, when applicable, Production Identifier (PI) elements such as lot or batch number, serial number, manufacture date and expiration date [12]. In practical terms, the DI identifies the product, whereas PI elements distinguish the specific production unit or batch [12]. An important regulatory distinction is that FDA direct-marking requirements apply to devices intended to be used more than once and reprocessed before each use, subject to specified exceptions [13]. This is particularly relevant to reusable surgical instruments. For permanent implants, the UDI is typically carried on the label and packaging at the time of implantation; engraved or stamped manufacturer markings on the implant itself (for example, those described in ASTM F983 [3,4]) may identify the manufacturer, model or lot but do not necessarily encode a complete UDI. Wilson and colleagues linked the potential value of UDI to the practical problem of implant identification before revision hip and knee arthroplasty [5,6]. Subsequent implementation work has shown how UDI can link clinical documentation, supply-chain data, electronic health records, registries and post-market surveillance systems [14-17]. Full realization of that potential still depends on consistent capture and interoperable systems across institutions.

Data Matrix Codes and Direct Part Marking

Two-dimensional Data Matrix codes are well suited to small surfaces. GS1 guidance describes Data Matrix as a machine-readable carrier used for healthcare identification and supports direct part marking methods such as laser etching and dot-peen marking where appropriate [18]. This is particularly relevant to reusable surgical instruments because their packaging is discarded after opening, whereas instruments such as screwdrivers, drill guides, depth gauges, reduction clamps and reamers may remain in service for years. Clinical studies of direct Data Matrix marking reusable surgical instruments show both its practical value and its durability challenges. Rioblanco and colleagues compared laser and micro percussion markings over 250 sterilization cycles. Laser marks initially had better visibility but developed corrosion early, whereas micro percussion marks were less prone to corrosion but had lower initial contrast [19]. Guinier Pinault and colleagues later showed that reader setup also matters systematic optimization of reader parameters reduced instrument-reading time by 81%, making individual instrument traceability more practical within the sterilization workflow [20]. These findings show that a durable code alone is not enough; the marking method and the scanning system both need to be validated under repeated reprocessing

conditions.

Direct part marking moves traceability from the tray to the individual instrument. A durable machine-readable identity can allow an instrument to be followed through cleaning, inspection, assembly, sterilization, storage, use and eventual retirement. When linked with UDI data, persistent identifiers can also contribute to post-market safety surveillance [21,22]. UDI barcode systems have been reported for management of individual surgical instruments [23]. Readability, however, varies with code size, surface curvature and finish, marking quality and scanning conditions. For that reason, direct marking should be tested in the actual processing and clinical environment in which it will be used.

QR Codes, NFC and RFID: Optical and Wireless Identification

QR Code is a standardized two-dimensional barcode symbology defined by ISO/IEC 18004 [24]. Its ability to encode machine-readable information in a compact optical symbol makes it a potential link to digital device information. However, evidence for QR-code-based orthopedic implant identification remains limited; applications such as patient-held implant records, technical information or manufacturer communications should therefore be regarded as potential uses rather than established clinical practice. NFC is a standards-based short-range contactless technology designed for close-proximity interactions; current NFC Forum specifications support contactless connections at centimeters-scale range [25]. In principle, NFC could provide convenient access to device information without optical scanning. Its role in routine orthopaedic implant identification, however, remains less established than the implant-embedded RFID and transcutaneous near-field communication prototypes discussed below. Unlike optical codes, RFID tags can be read without direct line of sight, an advantage also reported in intraoperative instrument-tracking studies [26]. In orthopedics, however, two uses need to be kept separate: identification of an implanted device and tracking of reusable surgical instruments. Their engineering requirements and levels of clinical maturity are different.

Implant-Embedded Passive RFID: The Ortho-tag Prototype

One early orthopaedic example is the University of Pittsburgh Ortho-tag concept. The prototype used a passive tag designed for attachment to an orthopaedic implant and a reader that powered and interrogated the tag using Transcutaneous Near-Field Communication (TNFC). The system was developed to provide a unique implant identifier linked to relevant information [27]. It should be interpreted as translational engineering work rather than evidence of routine clinical adoption.

Wireless identification from inside the body is technically difficult. Tissue and metal can interfere with electromagnetic communication, and passive implanted systems have no

internal power source. Pittsburgh investigators explored several approaches, including TNFC, volume conduction and capacitive coupling. A 2013 IEEE report described a UHF Gen 2 RFID system designed for transcutaneous operation with orthopaedic implants [28]. These studies are best regarded as proof-of-concept and translational engineering, not evidence of routine clinical use. Their value lies in addressing a simple but persistent question—how can an implant still be identified once it is inside the body?—while also demonstrating the communication problems created by tissue and metal.

RFID for Surgical Instrument Tracking

RFID-based surgical-instrument tracking has progressed beyond laboratory-only evaluation. Kusuda and colleagues reported 27 months of experience using RFID-tagged surgical instruments for management, tray preparation and recording instrument-use history [29]. Subsequent operating-room evaluation showed that RFID-tagged instruments could be detected, although detection performance was affected by practical limitations including electromagnetic interference [30]. RFID can

provide not only instrument identity but also objective utilisation data. Hill and colleagues reported an automated intraoperative instrument-tracking system with near-perfect agreement with human observation and used the resulting data to enable a supply reduction of 50.8% in breast and orthopaedic surgery [26]. In a surgical-oncology pilot study, Olivere and colleagues reported that RFID-based intraoperative instrument tracking was a feasible, data-driven method for tray reduction [31]. This has an operational consequence. Surgical instruments may be unpacked, counted, cleaned, inspected, repackaged and sterilised even when they are rarely or never used. Studies of tray optimisation in total joint arthroplasty and other major orthopaedic procedures have shown reductions in instrument burden, processing requirements and associated costs [32,33]. Tagging can therefore support workflow redesign, not merely location tracking.

Comparative Overview of Identification Approaches

These technologies solve different clinical and operational problems, so a single ranking would be misleading (Table 1).

Table 1: Provides a practical side-by-side comparison of their main uses, requirements, maturity and limitations.

Technology	Primary use	Line of sight	Through tissue	Maturity in orthopedics	Key limitations
Visual / memory + records	Legacy implants	Yes	N/A	Established	Dependent on experience; records often incomplete
Paper labels / stickers / linear barcodes	Implant packaging & records	Yes	No	Established	Lost or incomplete documentation common
UDI (DI + PI)	Standardized device identity	Yes (label)	No	Established regulatory framework	Requires consistent capture & interoperable systems
Data Matrix / direct part marking	Reusable instruments	Yes	No	Operationally evaluated	Sterilization durability; reader optimization needed
QR / NFC	Potential info access	Yes / short range	Limited	Emerging / limited evidence	Not established for routine implant ID
Implant-embedded RFID / TNFC	In-body implant ID	No	Designed for	Investigational	Tissue & metal interference; not routine
RFID instrument tracking	Reusable instruments & trays	No	N/A	Operationally evaluated	EMI; infrastructure & cost
AI radiographic recognition	Legacy / unknown implants	Yes (image)	N/A	Externally validated in selected classes	Dataset-specific; limited trauma coverage; needs external validation

Artificial Intelligence-Based Implant Recognition

Legacy Implant Identification

Modern tagging systems do not solve the problem of older implants. Many patients still carry devices inserted before standardized UDI processes, and the original records may be incomplete or missing. Implant databases can help identify products [34], while radiographs may show useful features such as overall geometry, manufacturer markings, collar design, surface coating and stem-tip shape. AI builds on this visual approach by using the radiographic appearance itself as a pattern for device recognition.

Reported Performance in Development Studies

Studies in hip and knee arthroplasty have reported high classification accuracy in selected datasets. Patel and colleagues developed a deep-learning algorithm to identify 12 hip and knee implant models. On a balanced unseen dataset of 180 radiographs, the final network achieved 98.9% accuracy (178/180) and 100% top three accuracy (180/180), outperforming the five specialists evaluated in the study (median accuracy 76.1% [137/180]; best accuracy 85.6% [154/180]; both $P < .001$) [35]. Karnuta and colleagues reported 99.0% accuracy for nine knee arthroplasty implant models in an external test set [36] and 99.6% accuracy for 18 femoral implant models in a separate external test set [37]. These findings demonstrate technical feasibility, but the reported values are study-specific and should not be interpreted as universal performance across implants, institutions or imaging conditions.

External Validation and Multicenter Studies

External validation is important because implant prevalence, radiographic technique and patient populations vary between institutions. In a multicenter knee-arthroplasty study, the model achieved 97.4% accuracy, 89.2% sensitivity and 99.0% specificity in an external test set of 744 anteroposterior radiographs, with a reported mean classification time of 0.02 seconds per image [38]. A separate study across three academic referral Centres and 13 surgeons reported 97.9% accuracy for eight hip implant models in an external test set [39]. Klimt and colleagues reported accuracy, sensitivity and specificity above 95% for identification of total hip and knee arthroplasty designs from plain radiographs [40]. In shoulder arthroplasty, Geng and colleagues reported overall accuracy of 93.9% across 10 anatomic and reverse shoulder implant types [41], while Yang and colleagues evaluated eight reverse shoulder arthroplasty brands with uncertainty quantification [42]. A single accuracy figure does not fully describe model performance. Depending on the study, useful measures include sensitivity, specificity, positive and negative predictive values, F1 score, area under the receiver-operating-characteristic curve, and measures of uncertainty or coverage. Results also need to be read in light of the implant classes included, class balance, dataset construction, radiographic views, internal versus external testing and the reference standard. Performance figures from different studies should therefore not be treated as directly interchangeable.

Practical Considerations and Remaining Gaps

For clinical practice, identifying the implant is only the first step. A more useful system would identify a likely device and then lead the surgeon to verify manufacturer information, compatible components, extraction instructions and the local availability of the required revision instruments. AI is therefore better viewed as one recognition step within a wider traceability workflow, rather than as a replacement for verified implant records. Generalizability across institutions is best assessed through multicenter external validation [38,39], and shoulder arthroplasty studies illustrate that validation is joint- and implant-specific [41,42]. Uncertainty reporting, as incorporated in recent shoulder implant identification work, may help flag predictions that require human verification [42]. Important gaps remain for prospective and external validation. These include class imbalance, differences in real-world implant prevalence, non-standard radiographic projections, image quality, overlapping hardware and variation in acquisition techniques between institutions. Most published models have been trained on defined sets of arthroplasty implants. Rare, legacy and region-specific devices—and particularly trauma implants such as plates, nails, locking mechanisms and discontinued systems—may fall outside those classes. Because these are closed-set classifiers trained on predefined implant classes, an unfamiliar or out-of-distribution implant may still be assigned to one of the available classes rather than recognised as unknown. Performance should also be reassessed as implant libraries change and new designs enter use [37,42]. Clinical systems should therefore include calibrated confidence or uncertainty thresholds, an option to abstain, and human verification when a case is unfamiliar or confidence is low. Prospective studies should also ask whether AI-assisted identification improves clinically relevant outcomes, including time to instrument readiness and avoidance of procedure delay or abandonment.

Trauma and Legacy Implant Recognition

Published AI implant-identification studies have concentrated largely on arthroplasty. Trauma surgery presents a different identification challenge because surgeons may encounter multiple generations of plates and intramedullary nails, varying locking mechanisms, cannulated screws, proprietary drive interfaces, extraction threads and discontinued systems. Similar-appearing implants from different manufacturers may require different removal instrumentation. One useful long-term goal would be a curated international radiographic and technical database covering both historical and current trauma implants. Representative images could be linked to the manufacturer, product line, catalogue information, screw interfaces, removal threads, compatible instruments and archived surgical techniques. This is proposed as a research priority rather than an existing clinical system; standardised implant databases have already shown feasibility in arthroplasty registries [34]. Until broader coverage is available, surgeons will still need a combination of AI tools, manufacturer databases and local institutional knowledge.

Sensor-Enabled and Smart Implant Technologies

Identification and tracking tell us what a device is and where it is. Sensor-enabled smart implants add a different question: how is the implant functioning? These devices have been studied for measurement of load, strain, pressure, temperature, motion and other biomechanical or biological variables. They are included here because they extend implant identification into connected monitoring. Smart and sensor-based orthopaedic technologies have been described across arthroplasty, trauma, spine surgery, fracture healing, infection surveillance and rehabilitation [43,44]. Spine-specific applications include instrumented rods, cages and related sensor-enabled constructs [45], while smart knee systems have incorporated measurements such as force, pressure, gait kinematics and temperature [46]. The evidence base is heterogeneous and ranges from instrumented research implants and preclinical systems to a small number of clinically available smart knee technologies [43–46]. Reported challenges include power and telemetry constraints, long-term durability, validation of sensor outputs against clinically meaningful endpoints, regulatory requirements, cybersecurity and cost [43–45]. For knee arthroplasty, Kelmer and colleagues reviewed smart implants capable of measuring variables such as forces, pressure, gait kinematics and temperature and emphasized that the field remains at an early stage despite the availability of first-generation clinical systems [46]. In spine surgery, systematic reviews have described instrumented rods, cages and other sensor-enabled constructs while emphasising the need to link measured signals to validated clinical outcomes [45]. A broader orthopaedic review described sensor applications in arthroplasty, trauma, spine, infection monitoring and rehabilitation [44]. These distinct bodies of literature should not be treated as interchangeable. The concept is not new. Burny and colleagues described the design and fabrication of smart orthopaedic implants in 2000 [47], and Sell had reviewed instrumented implants even earlier [48]. Clinical adoption has nevertheless been slow because of technical, regulatory and economic barriers. In this sense, smart implants extend rather than replace identification: a conventional tag tells us what the device is, while a connected implant may also report how it is functioning.

Practical Limitations of Current Tagging Technologies

Technical and System Challenges

Legacy implants: Many patients still have implants that pre-date UDI and may have incomplete or unavailable institutional records. Consequently, image-based and AI-assisted identification

is likely to remain relevant where documentary identification is unavailable. **System fragmentation:** Manufacturers, hospitals, registries and information-system vendors do not yet operate within a single universally adopted interoperable framework. UDI implementation studies describe organisational, workflow and information-technology barriers to consistent integration across health systems [14–17]. **Technical constraints:** Direct markings must withstand repeated cleaning, handling and sterilisation while remaining readable [19,20]. Electronic tags must likewise tolerate the intended processing environment without compromising instrument function. RFID performance can also be affected by electromagnetic interference and the operating-room environment [30].

Economic and Workflow Factors

RFID implementation requires more than purchasing tags. Readers, software, infrastructure and changes to workflow all need to be considered. UDI implementation similarly depends on coordination between clinical documentation, supply-chain processes and information systems [14–17]. These technologies should therefore be assessed in the workflow in which they will operate, rather than assumed to remove manual work. Connected systems also require attention to cybersecurity, privacy and data governance according to the architecture and the type of data handled.

Artificial Intelligence Limitations

The principal limitations of AI-based recognition (dataset bias, absent trauma and legacy implants, closed-set behaviour, variable radiographic quality, and the need for external and prospective validation and periodic reassessment) are discussed in Section 3.4. In practice, AI outputs should be treated as decision support and verified against authoritative product information.

Resource and Access Considerations

The resources needed for each technology also matter, especially where infrastructure or staff support is limited. RFID, EHR-integrated and cloud-dependent approaches should be judged against the connectivity, technical support and workflow available in the intended setting. Where that infrastructure is not practical, simpler approaches such as direct part marking, locally stored databases or optical codes may be worth evaluating. They should not, however, be assumed to be equivalent substitutes without local validation. International standardization should take these differences in implementation capacity into account (Figure 1).

1. Review operative records and prior documentation	2. Capture UDI, packaging label or direct mark when available	3. Search verified implant database or manufacturer information	4. Use radiographic / AI- assisted recognition if identity remains uncertain	5. Verify predicted identity against authoritative product information	6. Confirm compatible revision or removal instruments before surgery
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Note*: This is intentionally a hybrid workflow. Documentary and machine-readable sources are used first when they are available; image-based recognition is most useful for legacy or undocumented implants, and any proposed identity should be verified before operative planning.

Figure 1: Practical workflow for orthopedic implant identification before revision or removal surgery.

Conclusions

Orthopaedic implant and surgical-instrument identification now span several technology groups: visual recognition and documentation, linear barcodes, UDI, Data Matrix and direct part marking, QR codes, NFC, implant-embedded passive RFID prototypes, RFID-based instrument tracking and AI-assisted radiographic recognition. Sensor-enabled smart implants extend this continuum beyond identification into functional monitoring. The available approaches address different problems and have reached different levels of maturity. Optical codes and direct marking provide machine-readable identity; UDI standardizes the underlying data model; RFID has been used both in experimental transcutaneous implant identification and in clinically evaluated perioperative instrument tracking; and AI can help when documentary identification is missing. No single method solves both the legacy-implant problem and the instrument-lifecycle problem. For that reason, an application-specific combination of methods is more realistic than a universal solution. In current practice, the most workable approach is a hybrid one: use documentary records and machine-readable identifiers when they exist, and image-based or AI-assisted recognition when they do not. Further progress will depend on interoperable systems, better coverage of trauma implants, external validation of AI tools, and careful local assessment of cost and workflow before technical capability can translate into reliable clinical benefit.

Conflicts of Interests

None.

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