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Original article

Implementation and learning curve of an advanced imageless navigation system in total hip arthroplasty

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ABSTRACT

Background: Understanding the learning curve for technology-assisted total hip arthroplasty (THA) is critical for healthcare systems investing in robotic platforms and for ensuring patient safety during the learning phase. The aim of this study was to define the learning curve of operative time metrics, postoperative precision in limb length discrepancy (LLD) and offset discrepancy, and computer system complications during implementation of an advanced navigation system implemented with dynamic spinopelvic parameters.
Hypothesis: We hypothesized that surgeons adopting TA-THA would demonstrate progressive gains in operative efficiency, reaching proficiency within a quantifiable case volume identifiable through statistical analysis.
Patients and methods: We reviewed consecutive patients who underwent primary THA performed using the RI.HIP NAVIGATION system (Smith & Nephew), combined with preoperative planning based on spinopelvic parameters through the MODELER software (Smith & Nephew), at a single institution between 2023 and 2024. Adults aged ≥18 years treated for hip osteoarthritis or femoral head osteonecrosis were included. Data on skin-to-skin and computer-assisted system time and limb length discrepancy and offset discrepancy were collected. Primary outcomes were learning curves for operative time metrics and case volume required for proficiency. Secondary outcomes were associations between surgical precision metrics and surgeon experience. Statistical analyses included segmented regression, CUSUM analysis, rolling window analysis, and multivariable linear regression.
Results: 111 consecutive cases were analyzed for time-based metrics; 109 cases (98.2%) had complete femoral measurement data. CUSUM analysis identified initial proficiency at case 15 for computer registration time and case 17 for overall surgery time, with sustained proficiency achieved at case 38 and case 43, respectively. After sustained proficiency achievement, computer registration time improved 21.3% (19.7 vs 15.5 min, $P < 0.001$) and overall surgery time improved 8.2% (86.0 vs 78.9 min, $P < 0.001$). Both LLD precision (R-squared = 0.6, $P < 0.001$) and offset precision (R-squared = 0.3, $P < 0.001$) improved significantly over time. Computer system bugs accelerated learning through significant case number interactions ($\beta = -0.49$ min per case, $P < 0.001$).
Discussion: Proficiency in advanced navigation THA requires 15–17 cases, substantially exceeding previously reported thresholds and challenging current proficiency assessment methodologies.
Level of evidence: III.

1. Introduction

Technology-assisted systems in adult hip reconstruction surgery require surgeons to develop new technical skills and adapt established surgical workflows to achieve optimal outcomes [1–3].

Technology-assisted total hip arthroplasty (TA-THA) has become increasingly common due to its potential for improved acetabular cup positioning, better reproducibility of femoral component placement, and fewer positioning outliers compared to conventional techniques [4–10]. However, technology adds complexity to THA, requiring mastery of system-specific protocols, software navigation, and modified surgical techniques that may differ from traditional approaches [11–13].

TA-THA represents an important advancement in precision surgery, but the learning curve for these systems remains poorly defined [14]. Understanding the learning curve for TA-THA is important for several

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reasons. Healthcare systems investing in robotic platforms need to understand the case volume required for proficiency to justify these investments. Patient safety requires clear identification of the learning phase, during which operative times may be longer and technical errors of the system and imprecisions in component restoration may be more frequent, although technology-assisted systems have demonstrated favourable safety and efficacy profiles in both hip and knee arthroplasty [15–17]. As TA-THA adoption increases, particularly in high-volume centres, evidence-based guidelines are needed for surgeon training, credentialing, and minimum case requirements [18,19]. Without established proficiency benchmarks, institutions risk extended learning periods that compromise both cost-effectiveness and patient care.

We hypothesized that surgeons adopting TA-THA would demonstrate progressive gains in operative efficiency, reaching proficiency within a quantifiable case volume identifiable through statistical analysis.

The aim of this study was to define the learning curve of operative time metrics, postoperative precision in limb length discrepancy (LLD) and offset discrepancy, and the computer system bugs that occurred during the case series.

2. Material and methods

2.1. Patients

Data from consecutive patients undergoing primary TA-THA using the RI.HIP NAVIGATION system (Smith & Nephew plc, Pittsburgh, USA) with the same preoperative planning software RI.HIP MODELER (Smith&Nephew) at our institution between 2023 and 2024 were reviewed. We included patients aged 18 or older treated for hip osteoarthritis (ICD-9 715.95) or femoral head osteonecrosis (ICD-9 733.42). No further eligibility criteria were applied. The study was conducted according to the STROBE guidelines [20].

2.2. Surgical protocol

All THAs were performed by one single high-volume adult hip reconstruction surgeon (>200 primary THAs per year) with previous experience in hip computer-assisted and robotic-assisted surgery. Components included POLAR stems, OXINIUM femoral heads, and R3 acetabular systems (all Smith & Nephew) for all cases. No dual mobility constructs were used in this series. Primary fixation was cementless, with femoral cemented components reserved for cases of severe osteoporosis or patients over 80 years of age.

THAs were performed using the imageless RI.HIP NAVIGATION system (Smith&Nephew). The RI.HIP NAVIGATION system is an imageless, optical-tracking platform that relies on preoperative weightbearing pelvis X-rays acquired with the KingMark device (Brainlab Munich, Germany). Patient-specific guidance is achieved by registering anatomical landmarks intraoperatively, including the bilateral anterior superior iliac spines and the acetabular fossa, with a navigated pointer and by three tracking reference devices through an infrared camera, including a T-shaped pelvic reference array, fixed to the iliac crest of the operated side with two percutaneous Schanz pins; a pinless distal femoral baseplate, fixed to the anterolateral distal thigh used as an intermittent reference; and a cortical screw placed in the most lateral part of the greater trochanter (Fig. 1).

With the patient in supine position, the procedure begins with the registration of anatomical landmarks and tracking devices. After femoral neck resection and dislocation of the femoral head, the acetabular fossa is registered.

During the acetabular phase, the RI.HIP NAVIGATION system provides real-time guidance referenced to the Anterior Pelvic Plane (APP), defined intraoperatively by the anterior superior iliac spines and the acetabular landmarks, and the patient's individual pelvic tilt measured on the preoperative supine radiograph. Acetabular reaming is performed

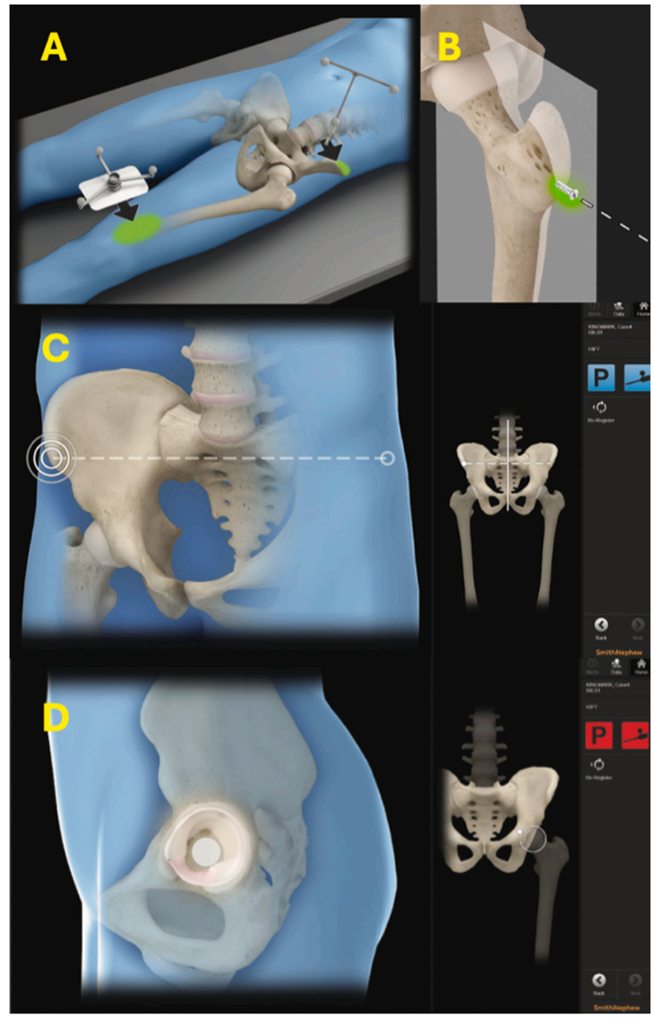

Fig. 1. Anatomical landmarks and reference arrays of the RI.HIP NAVIGATION system. (A) A T-shaped pelvic reference array is fixed to the iliac crest of the operated side with two percutaneous Schanz pins and a pinless distal femoral baseplate is fixed to the anterolateral distal thigh used as an intermittent reference. (B) A cortical screw placed in the most lateral part of the greater trochanter. Anatomical landmarks are registered intraoperatively, including the bilateral anterior superior iliac spines (C) and the acetabular fossa (D).

free-hand, without navigation control, according to standard surgical technique and preoperative planning of cup size and depth. Once the acetabulum is reamed to the planned size, the navigated impactor is recognized by the optical camera. The surgeon adjusts inclination and anteversion to the patient-specific targets defined preoperatively with the RI.HIP MODELER, and the cup is impacted under continuous navigation feedback. Final cup orientation is recorded and verified after impaction.

Cup positioning was based on personalised preoperative spinopelvic parameters using the RI.HIP MODELER software (Smith&Nephew) (Fig. 2). The RI.HIP MODELER is an iOS application that accesses the simulation database generated by LifeMOD™. By accessing the spinopelvic mobility of the patients, hip kinematics and distance to implant impingement are calculated for multiple daily-life activities, given a set of implant specifications. This preoperative planning tool guides surgeons in determining the optimal parameters for cup inclination, anteversion, polyethylene lip presence and positioning reducing the risk of dislocation and impingement during common hip motions in everyday activities, such as squatting, bending, and hyperextension. The RI.HIP MODELER (Smith&Nephew) provides detailed assessments for every combination of cup, stem, and polyethylene positioning, enabling

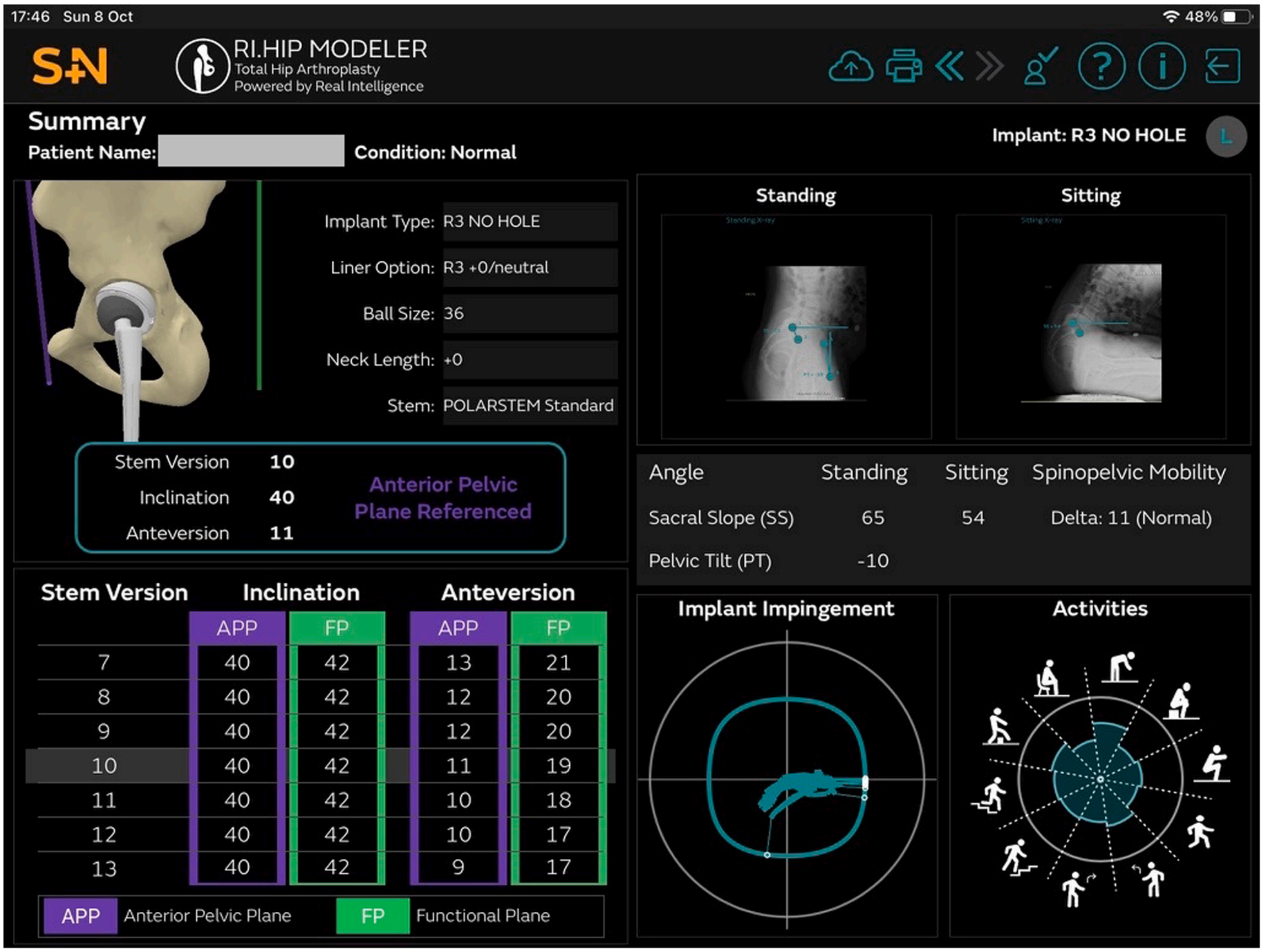

Fig. 2. RI.HIP Modeler preoperative report for personalized acetabular cup orientation planning based on dynamic sitting-to-standing lumbar spine radiograph.

surgeons to make informed decisions tailored to each patient's unique spinopelvic condition [21–24]. The surgical approach adopted was the anterior-based muscle-sparing (ABMS) for every case with patient positioned supine [25].

2.3. Data collection and outcome measures

Data collection included baselines and surgical data including surgery date, age (years), gender, BMI (Kg/m^2), fixation, total surgical operative time (skin-to-skin - min), computer system time (min), intraoperative radiographic check time (min), cementation time (min), wound closure time (min), postoperative LLD (mm), postoperative offset discrepancy compared to the contralateral unaffected hip (mm), and any bugs or errors of the imageless navigation platform intraoperatively occurred.

Computer system time was defined as cumulative time from initial anatomical landmark registration to final implant position verification, including time for any re-registration procedures or system restarts. Technical complications were classified into two categories: computer system bugs (operational technical events requiring re-registration: femoral array displacement, ASIS recording failures, iliac crest pin mobilization, and acetabular registration errors) and system crashes (complete software failures requiring system restart). In cases

of system crashes, computer time included both pre-crash and post-restart periods. Cases where crashes occurred after femoral neck resection were included for time-based and acetabular analyses but excluded from femoral measurement analyses (LLD and offset) as femoral re-registration was not possible after neck resection.

The preoperative planning time was used for preoperative planning and templating with RI.HIP MODELER. LLD was measured as the vertical distance between the bilateral acetabular teardrop line and the line connecting the most prominent point of each lesser trochanter on the bilateral femurs [26]. The offset discrepancy was the difference between the affected and contralateral hip, measured between the pubic symphysis and the long axis of the femoral shaft [27]. LLD and hip offset were measured by a single orthopaedic resident using postoperative weight-bearing AP pelvis X-Rays. The measurements were obtained using TraumaCad software (Brainlab, Munich, Germany).

The primary outcomes were the characterisation of the learning curves for the operative time metrics (total operative time, navigation system time, and preoperative planning time) and the determination of case volume required to achieve proficiency. The secondary outcomes were the associations between surgical precision metrics (LLD and offset discrepancy) and both time metrics and sequential case number (surgeon experience).

2.4. Data analyses

Descriptive statistics included means, medians, ranges, and interquartile ranges for continuous variables, and frequencies and percentages for categorical variables. Missing data analysis assessed the distribution and the pattern of missingness. Time-based metrics were analysed using segmented regression with automatic breakpoint detection to identify distinct learning phases. When no significant breakpoints were detected, linear regression was used to characterize continuous improvement patterns. LLD and offset discrepancy were analysed using

10-case sliding windows that moved incrementally through the series, generating rolling means and standard deviations for each window; two linear regression models were fitted for each accuracy metric to test whether systematic bias and measurement consistency changed with surgical experience: rolling mean for bias trend analysis and rolling standard deviation for precision trend analysis. Cumulative summation (CUSUM) analysis was performed to identify specific proficiency milestones within the learning curve, complementing the linear regression analysis. For each case, performance was classified as 'success' when the observed time was below or equal to the target and as 'failure' when it exceeded the target; the CUSUM curve was then constructed by sequentially summing negative increments for successes and positive increments for failures. Two detection methods were employed to provide robust proficiency milestone identification: slope-based method, which identified the point after three consecutive positive CUSUM slopes occurred; and (2) consistency method, which identified the point after five consecutive cases below target performance occurred. The slope-based method to detected proficiency, while consistency detected sustained proficiency. Target performance was defined as the mean of final 20 cases, representing optimal performance level. Multivariable linear regression with hierarchical model building was performed to identify factors influencing all outcome metrics (time-based and accuracy metrics) beyond baseline learning effects. Four nested models were constructed by sequentially adding: (1) case number only, (2) patient factors (BMI, gender), (3) technical factors (fixation type and system bugs), and (4) case number interactions. Model selection used F-tests for nested comparisons ($\alpha = 0.05$). Statistical analysis was performed using RStudio version 2024.12 with significance set at $P < 0.05$.

3. Results

A total of 112 consecutive advanced imageless navigation total hip arthroplasty cases were performed. One case with system crash after acetabular preparation was excluded due to inability to complete the navigation protocol, resulting in 111 cases included in the time-based learning curve analysis (Fig. 3).

System complications occurred in 8 cases (7.2%). Those occurring before femoral neck resection allowed complete procedure restart without measurement compromise; those occurring after femoral neck resection precluded femoral re-registration and required exclusion from LLD and offset analyses while maintaining valid acetabular measurements. System complications included femoral array displacement (n = 3), ASIS recording failures (n = 2), iliac crest pin mobilization (n = 1), and acetabular registration errors (n = 2). Thus, missing data on LLD and offset was recorded in two cases (1.8%), both involving acetabular registration errors that occurred after femoral neck resection, precluding femoral re-registration. Descriptive statistics for patient characteristics and operative metrics are provided in Table 1.

3.1. Learning curves analysis

The learning curve analysis demonstrated linear improvement for preoperative planning time (*R-squared* = 0.4, $\beta = -0.1$ min/case, $P < 0.001$), navigation system time (*R-squared* = 0.1, $\beta = -0.06$ min/case, $P < 0.001$), and overall surgery time, (*R-squared* = 0.136, $\beta = -0.1$ min/case, $P < 0.001$) (Fig. 4). The absence of distinct breakpoints in all time metrics indicates that learning was continuous rather than occurring in discrete phases, though CUSUM analysis identified specific proficiency milestones within this continuous trajectory. CUSUM analysis identified objective proficiency thresholds (Table 2), complementing the regression analysis (Fig. 5).

Different components of the navigation procedure demonstrated varying learning curve durations:

navigation registration proficiency by case 15, surgery time by case 17, and preoperative planning by case 90.

LLD analysis revealed no systematic bias change over time (R-squared = 0.006, $\beta = -0.002$, $P = 0.441$; Table 3, Fig. 6), with values remaining centred around zero throughout the series. This indicates that the navigation system maintained neutral leg length restoration from the earliest cases without systematic under- or over-correction. However, LLD precision showed highly improvement over time (*R-squared* = 0.6, $\beta = -0.03$, $P < 0.001$), demonstrating substantial reduction in measurement variability with experience. The precision improvement suggests that while mean LLD was consistently at target, the surgeon's ability to consistently achieve this target improved markedly with experience. Offset discrepancy demonstrated systematic bias change over time (*R-squared* = 0.1, $\beta = -0.008$, $P = 0.001$; Table 3, Fig. 6), indicating a progressive shift in mean offset restoration as the

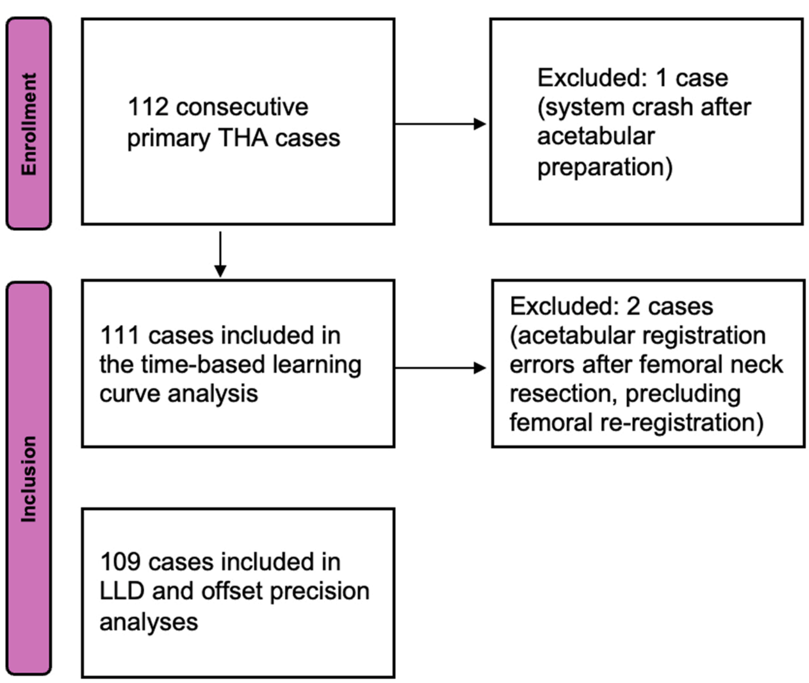

Fig. 3. Flowchart of the included population.

Table 1
Descriptive statistics of the included population.

Variable	Mean	Median	SD	Min	Max	Q1	Q3	IQR
Female sex [n(%)]	60.0	(54.0)						
Age (y)	68.8	68.0	9.5	47.0	90.0	61.0	76.0	15.0
BMI (Kg/m^2)	26.8	27.0	4.9	16.5	41.6	23.6	29.4	5.8
Hip osteoarthritis [n(%)]	103	(93%)						
Femoral head osteonecrosis [n(%)]	8	(7%)						
Uncemented fixation	93.0	0.8						
Preoperative planning time	29.5	30.0	9.6	15.0	60.0	20.0	35.0	15.0
Computer system time	17.0	16.0	6.3	7.0	40.0	13.0	20.0	7.0
Overall surgery time	81.8	80.0	12.4	55.0	120.0	75.0	90.0	15.0
Cementation time	1.6	0.0	3.7	0.0	10.0	0.0	0.0	0.0
Intraoperative radiographic check time	5.5	5.0	2.8	0.0	16.0	4.0	7.0	3.0
Wound closure time	18.1	19.0	3.7	9.0	24.0	15.0	21.0	6.0
Limb length discrepancy	0.1	0.0	2.2	−8.0	10.0	0.0	0.0	0.0
Offset discrepancy	0.3	0.0	2.8	−10.0	16.0	0.0	1.0	1.0

SD = Standard Deviation; Min = Minimum; Max = Maximum; Q1 = First Quartile; Q3 = Third Quartile; IQR = Interquartile Range; y = years; BMI = Body Mass Index; Kg/m2 = Kilograms per meter squared.

Fig. 4. Learning curves for time-based metrics showing steady and decreasing times.

surgeon gained experience. Offset precision also showed improvement (*R-squared* = 0.3, $\beta = -0.03$, $P < 0.001$), with reduced variability in offset measurements across the learning curve. Both the bias correction and precision improvement suggest that offset restoration, unlike LLD, required a learning period to optimize both accuracy and consistency.

3.2. Factors influencing learning curves

Multivariable analysis revealed distinctly different learning patterns between computer registration time and total surgery time (Table 4 and Table 5).

Computer registration demonstrated significant main effects were observed for BMI (+0.5 min/unit, *SE* = 0.2, $P = 0.01$; 95% *CI*: 0.1 to 0.9) and computer system bugs (+12.4 min, *SE* = 3.1, $P < 0.001$; 95% *CI*: 6.09–18.7). Significant case number interactions indicated non-uniform learning across patient and technical subgroups. The BMI × -case number interaction ($\beta = -0.01$, *SE* = 0.0, $P = 0.04$; 95% *CI*: −0.02 to −0.00) demonstrated accelerated learning for higher BMI patients—while these patients required more time initially, they showed faster improvement rates with increasing experience. The computer system bugs × case number interaction ($\beta = -0.4$, *SE* = 0.10, $P < 0.001$; 95% *CI*: −0.6 to −0.2) showed that cases involving system bugs led faster improvement per subsequent case.

Total surgery time also exhibited significant interaction effects (*R-squared* = 0.2, $P = 0.02$). The interaction model provided significantly better fit than simpler models ($F = 2.9$, $P = 0.02$ compared to the technical factors model). A bugs × case number interaction was found ($\beta = -0.6$, *SE* = 0.21, $P = 0.003$; 95% *CI*: −1.07 to −0.2), indicating that surgeons demonstrated accelerated learning following technical computer system complications.

Both LLD (*R-squared* = 0.01, $P = 0.82$) and offset discrepancy (*R-squared* = 0.01, $P = 0.236$) had no variables reaching statistical significance, indicating that accuracy was maintained consistently throughout the learning curve without improvement or deterioration.

All models satisfied standard regression assumptions including linearity, independence, homoscedasticity, and normality of residuals.

Table 2
CUSUM Analysis showing proficiency milestones and performance improvements.

Metric	Target Performance (min)	Proficiency Milestone (Case #)	Consistent proficiency Milestone (Case #)	Learning Phases	Pre-Proficiency Mean ± SD (min)	Post-Proficiency Mean ± SD (min)	Absolute Improvement (min)	Relative Improvement (%)	Precision Improvement (% reduction in SD)
Computer Registration Time	15.1	15	38	Cases 1–14 (Early Learning) Cases 15–37 (Proficiency) Cases 38+ (Consolidation)	19.7 ± 8.6	15.5 ± 3.9	4.2	21.3	54.6
Total Surgery Time	79.4	17	43	Cases 1–16 (Early Learning) Cases 17–42 (Proficiency) Cases 43+ (Consolidation)	86.0 ± 15.1	78.9 ± 9.3	7.0	8.2	38.3
Preoperative Planning Time	21.5	90	100	Cases 1–89 (Early Learning) Cases 90–99 (Proficiency) Cases 100+ (Consolidation)	30.6 ± 9.4	20.0 ± 4.2	10.6	34.8	54.9

CUSUM = Cumulative Sum; min = minutes; SD = Standard Deviation; # = number.
Proficiency Detection Method: Proficiency method: slope-based method detected represents sustained proficiency; Consistent proficiency method: 5 consecutive cases below target performance represents sustained proficiency; Target Performance: defined as mean of final 20 cases, representing optimal performance level.

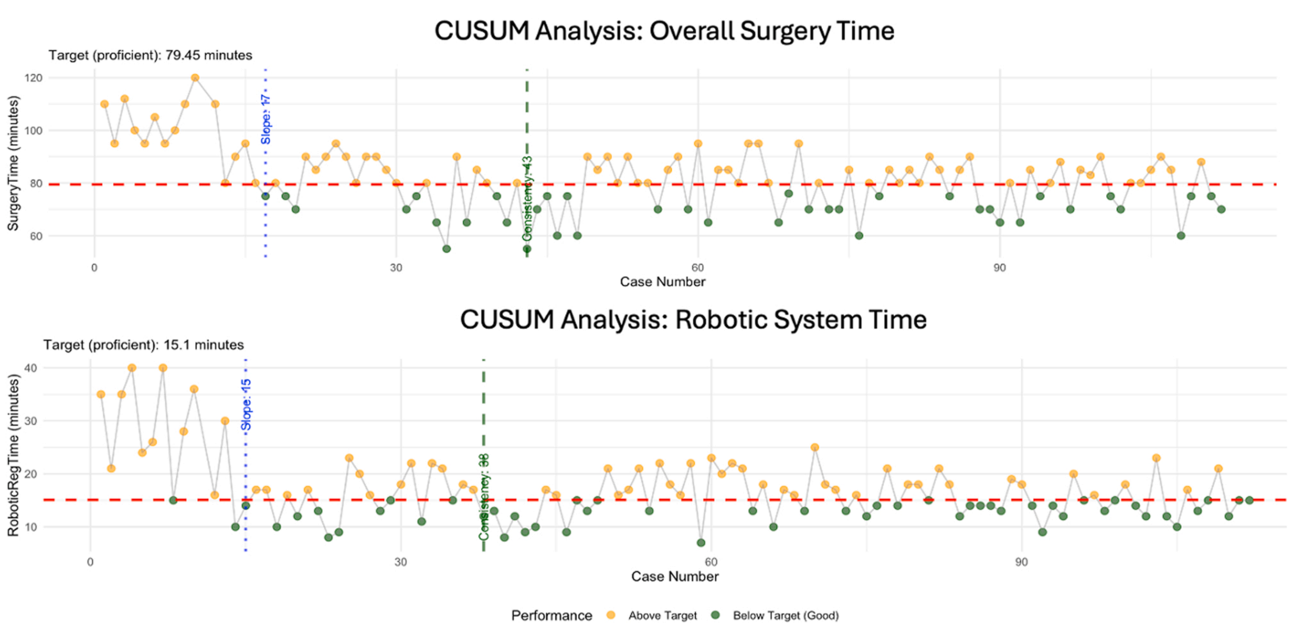

Fig. 5. CUSUM analysis for overall surgery time and computer system time showing threshold for proficiency based on two methods: slope and consistency.

Table 3
Rolling windows analysis showing learning curves in precision metrics for limb length discrepancy and offset discrepancy.

Metric	Component	R-squared	P-value	Significance	Interpretation
Limb length discrepancy	Mean (Bias)	0.006	0.441	Not significant	No systematic bias change over time
	SD (Precision)	0.6	<0.001	Highly significant	**Precision improved significantly**
Offset discrepancy	Mean (Bias)	0.1	0.001	Significant	**Systematic bias change detected**
	SD (Precision)	0.3	<0.001	Highly significant	**Precision improved significantly**

4. Discussion

The most significant findings of this study demonstrated that TA-THA using the RI.HIP NAVIGATION system exhibited measurable learning curves with objective proficiency at case 15 for computer registration time and case 17 for overall surgery time. Precision metrics showed distinct patterns: LLD precision improved substantially while maintaining centred bias around zero, indicating enhanced consistency without systematic error. Conversely, offset discrepancy demonstrated both precision improvement and systematic bias improvement, suggesting that offset measurement presented greater technical complexity and required focused attention during the surgical learning curve. The

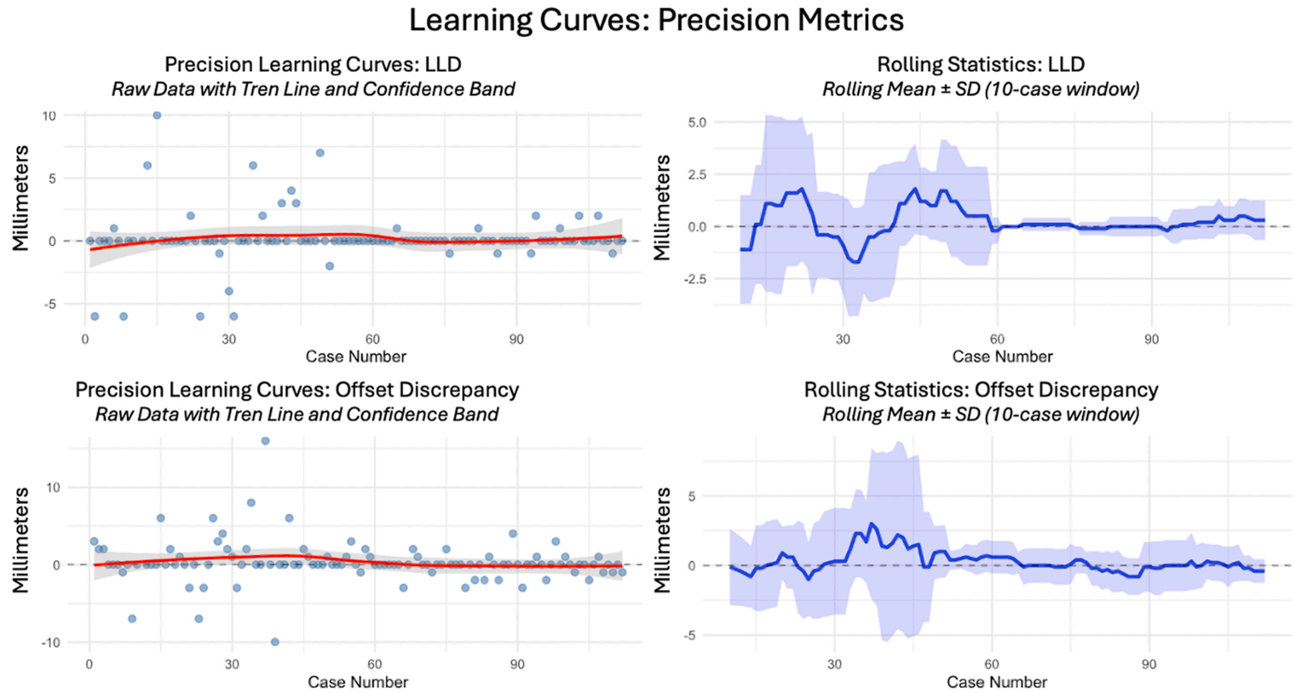

Fig. 6. Learning curves for the LLD and offset discrepancy precision.

Table 4
Hierarchical model comparison for learning curve outcomes.

Outcome Variable	Model	R-squared	Adjusted R-squared	F-statistic	P-value	Model Comparison	F-test	P-value
Computer Registration Time								
	Base (Case Number)	0.1	0.1	14.9	<0.001*	–	–	–
	+ Patient Factors	0.1	0.1	–	–	vs Base	1.6	0.206
	+ Technical Factors	0.1	0.1	–	–	vs Patient	0.1	0.891
	+ Interactions	**0.3**	**0.2**	–	–	**vs Technical**	**7.1**	**<0.001***
Total Surgery Time								
	Base (Case Number)	0.1	0.1	17.1	<0.001*	–	–	–
	+ Patient Factors	0.1	0.1	–	–	vs Base	0.9	0.396
	+ Technical Factors	0.1	0.1	–	–	vs Patient	1.2	0.284
	+ Interactions	**0.2**	**0.1**	–	–	**vs Technical**	**2.9**	**0.023***
Leg Length Discrepancy								
	Base (Case Number)	**0**	**−0.01**	**0.05**	**0.82**	–	–	–
	+ Patient Factors	0.05	0.02	–	–	vs Base	2.5	0.082
	+ Technical Factors	0.06	0.01	–	–	vs Patient	0.7	0.491
	+ Interactions	0.1	0.03	–	–	vs Technical	1.4	0.233
Offset Discrepancy								
	Base (Case Number)	**0.01**	**0**	**1.4**	**0.236**	–	–	–
	+ Patient Factors	0.04	0.01	–	–	vs Base	1.3	0.277
	+ Technical Factors	0.04	−0.01	–	–	vs Patient	0.2	0.795
	+ Interactions	0.05	−0.03	–	–	vs Technical	0.3	0.837

Notes: Bold text indicates the selected best model for each outcome based on nested F-tests ($\alpha = 0.05$). * indicates $p < 0.05$.
Patient factors: BMI, Gender Technical factors: Fixation type, Computer system bugs Interactions: Case number × (BMI, Gender, Fixation, Bugs).

finding that these improvements occurred independent of patient factors suggests that skill acquisition is primarily experience-driven rather than case-selection dependent, supporting broader application of technology without restriction to patient or surgery technical factors selection during the learning phase.

The RI.HIP NAVIGATION system does not reference the contralateral hip and does not propose a default null target; it reports leg length and offset variations relative to the pre-resection position of the operated hip, while the restoration target is defined preoperatively for each patient through templating with the RI.HIP MODELER. The preoperative plan was followed without intentional deviation in all cases, and postoperative LLD and offset discrepancy, measured radiographically against the contralateral hip, were used as the outcome measures. Within this framework, the observed precision improvement does not reflect a change in the surgeon's confidence in the system, but rather the progressive refinement of the technical steps that determine the agreement between intraoperative and postoperative measurements.

One potential explanation for the reduced precision in offset discrepancy involved the computer system's excessive rotational tolerance during final offset verification and registration. Intraoperatively, the computer system calculated offset as the absolute difference between pre-femoral neck resection measurements and post-final component positioning in the ipsilateral hip. Offset measurement was determined through triangulation of three key reference points: the distal femoral array (positioned mid-thigh anteriorly), which evaluated distal femoral condylar rotation relative to neck anteversion; the proximal femoral pin, positioned at the most lateral part of the greater trochanter in line with the femoral neck; and the iliac crest arrays. Notably, offset is influenced

Table 5
Detailed regression coefficients of the significant models from Table 4 for both computer registration time and total surgery time.

Variable	Coefficient (β)	SE	t-value	P-value	95% CI	Clinical Interpretation
Computer Registration Time (Interaction Model, R-squared = 0.34, P < 0.001)						
Main Effects						
Intercept	6.8	6.2	1.0	0.277	−5.5 to 19.1	–
Case Number	0.1	0.0	1.3	0.198	−0.06 to 0.3	No independent baseline effect when interactions present
BMI (kg/m^2)	0.5	0.2	2.4	0.017*	0.1 to 0.9	Each BMI unit adds 0.51 min
Gender (Male)	−1.4	2.5	−0.5	0.573	−6.4 to 3.5	No gender effect
Fixation (Uncemented)	−4.2	4.7	−0.8	0.374	−13.5 to 5.1	No fixation effect
Computer Bugs (Yes)	12.4	3.1	3.9	<0.001*	6.0 to 18.7	Bugs add 12.4 min initially
Interaction Effects						
Case × BMI	−0.01	0	−2.0	0.044*	−0.02 to −0.00	Higher BMI → faster learning
Case × Gender	0	0.04	0.1	0.924	−0.08 to 0.08	No gender learning difference
Case × Fixation	0.05	0.06	0.7	0.434	−0.07 to 0.1	No fixation learning difference
Case × Bugs	−0.49	0.1	−4.9	<0.001*	−0.6 to −0.2	0.49 min faster learning per case after bugs
Total Surgery Time (Interaction Model, R-squared = 0.26, P = 0.023)						
Main Effects						
Intercept	92.90	12.9	7.2	<0.001*	67.2 to 118.6	Baseline surgery time
Case Number	−0.32	0.1	−1.6	0.102	−0.7 to 0.06	Marginal baseline learning
BMI (kg/m^2)	0.01	0.4	0.03	0.978	−0.8 to 0.8	No BMI effect
Gender (Male)	−6.68	5.2	−1.2	0.207	−17.1 to 3.7	No gender effect
Fixation (Uncemented)	−4.51	9.7	−0.4	0.645	−23.8 to 14.8	No fixation effect
Computer Bugs (Yes)	12.10	6.5	1.8	0.069	−0.9 to 25.1	Marginal bug effect (+12.1 min)
Interaction Effects						
Case × BMI	0	0.01	0.7	0.459	−0.02 to 0.02	No BMI learning difference
Case × Gender	0.1	0.08	1.2	0.207	−0.06 to 0.2	No gender learning difference
Case × Fixation	0.07	0.12	0.5	0.575	−0.1 to 0.3	No fixation learning difference
Case × Bugs	−0.65	0.21	−3.0	0.003*	−1.07 to −0.2	0.65 min faster learning per case after bugs

β = Beta coefficient; SE = Standard Error; CI = Confidence Interval; BMI = Body Mass Index; kg/m^2 = Kilograms per meter squared; min = minutes.
Notes: * indicates p < 0.05.

by femoral anteversion [26,28–31], which is directly affected by femoral rotation [30,32–34]. For accurate offset assessment, the computer system required the surgeon to restore the limb to the precise pre-resection anteversion and rotational position during final registration. This enabled accurate calculation of the absolute difference between pre-resection and post-implant positioning. However, the system's excessive rotational tolerance during this critical verification phase may have compromised measurement accuracy, potentially explaining the observed systematic bias in offset measurements. Another potential explanation may be due to the femoral pin, based on where it's positioned, whether slightly more anterior or posterior to the most lateral part of the greater trochanter. Femoral pin positioning can determine a difference in offset when the patient's new leg rotation is given by the combined version (Fig. 7).

The current CUSUM-derived proficiency thresholds aligned the 12–17 cases consistently reported in the robotic THA learning curve literature. Previous studies using similar CUSUM methodology identified proficiency at 13 cases for the MAKO robotic system [35], 12 cases for fluoroscopy-based robotic platforms [36], 17 cases for seven-axis robotic systems [37], and 13 cases for alternative robotic platforms [38]. One novelty of the current study was the introduction of an additional, complementary, and more clinically meaningful threshold for sustained and consistent proficiency defined using 5 consecutive cases below target performance. This also highlighted how methodological choice fundamentally influences proficiency determination and the clinical implications of such assessments. Previous studies relied exclusively on basic slope-deflection detection, identifying the point where the slope changes from positive to negative [35–38]. The results from the current temporal learning curve analysis demonstrated 21.5% improvement in computer registration time and 6.6% improvement in overall surgery time after proficiency achievement, aligning with the 6−35 minute operative time reductions reported across multiple robotic platforms [14,36,38]. Additionally, our leg length and offset restoration analysis revealed systematic improvements in measurement consistency over time, a finding not captured in previous studies. While Buchan et al. [36], Tian et al. [37], and Sun et al. [38] found no differences in LLD between learning and proficiency phases, their analyses examined only mean values rather than measurement precision. These observations align with a recent scoping review of robotic THA learning curves [39] and with granular analyses of operative time across robotic platforms [40], while earlier work first characterised the learning curve of robotic-assisted THA [41].

Another novelty was the introduction of interaction models in the learning curves analysis. Computer system bugs in the first 50 cases and high patient BMI initially prolonged computer registration time but accelerated the learning trajectory through their interaction with sequential case number. While technical complications disrupted workflow, this was offset by improved efficiency in later cases, possibly through problem-solving skills and contingency strategies developed during early troubleshooting. These findings may suggest that managed exposure to technical challenges during initial training may facilitate skill acquisition, though causality would require further investigation.

Previous comparative studies demonstrated that robotic cases achieved superior radiographic accuracy compared to manual techniques despite longer operative times during the learning phase. Schwartz et al. [42] reported that only high-volume surgeons (>51 cases annually) demonstrated early learning curves, while low and medium-volume surgeons showed no improvement through 20 and 63 cases, respectively. Our single-surgeon design eliminated inter-operator variability while providing sufficient case volume to detect genuine proficiency achievement, addressing the volume-dependent learning effects previously identified in multi-surgeon studies.

This study also provided the first comprehensive learning curve analysis of the RI.HIP NAVIGATION system in a pilot centre implementation, offering initial insights into the technical and educational aspects of this technology platform's adoption.

The current findings will likely influence clinical practice in several important ways. Healthcare systems can now use evidence-based case volume requirements (approximately 40 cases) for technology-assisted THA credentialing rather than arbitrary institutional policies. The identification of computer registration time as an intraoperative quality indicator provides surgeons with real-time feedback—prolonged registration times should prompt careful reassessment of planning parameters before component positioning. Training programs can structure

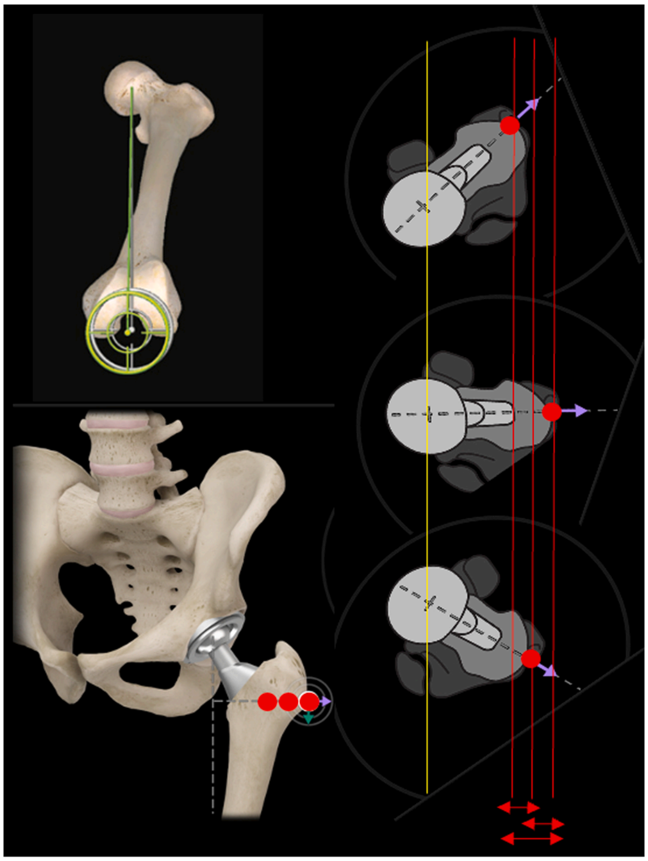

Fig. 7. This figure illustrates the intraoperative measurement system used in RI.HIP NAVIGATION advanced imageless navigation system for offset calculation and verification. The precision of offset measurement depends critically on the accurate alignment of all three reference arrays, particularly during final verification when the surgeon must restore the limb to match the pre-operative rotational position. The tolerance zones around these targeting arrays directly impact measurement accuracy, with excessive rotational tolerance potentially contributing to systematic bias in offset calculations. Left Panel. The anatomical view shows the pelvis and proximal femur following implantation. Three red tracking points are visible, representing the anatomical landmarks used for offset measurement in the coronal plane by the system. Right Panel. The image shows the corresponding representation of the same anatomical landmarks in the axial plane. If the femur is malrotated, offset can change related to the malrotation. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

mentorship and supervision protocols around the identified learning phases. Interestingly, the counterintuitive finding that system bugs accelerate learning may suggest that complications, errors, and obstacles serve as catalysts for surgical proficiency.

The single-centre, single-surgeon design limits generalizability to other institutions and surgeons with different baseline technical skills or training backgrounds. The absence of long-term clinical outcomes and complications data prevents assessment of whether technical proficiency translates to improved patient safety and clinical results. The lack of a concurrent control group performing conventional THA limits conclusions about the relative advantages of technology assistance and whether the observed learning curves represent system-specific skill acquisition or general surgical experience effects. Additionally, the study did not account for potential confounding factors such as case complexity evolution over time or changes in surgical team composition that might influence learning trajectories.

Dedicated prospective comparative studies, incorporating cost-effectiveness analyses that account for operative time, sensor and hardware costs, training investments, and long-term clinical outcomes, will be necessary to quantify the economic implications of this technology compared to conventional THA.

5. Conclusion

Proficiency in technology-assisted total hip arthroplasty required 15–17 cases for competency and 38–43 cases for consolidated proficiency, establishing evidence-based thresholds for surgeon credentialing and training programs. Precision in limb length and offset restoration continued improving beyond time-efficiency plateaus, while technical system complications during early implementation paradoxically accelerated subsequent learning trajectories, suggesting that problem-solving experiences may enhance surgical skill acquisition.

Authors' contributions

The study was conceptualized by RC and MI. Surgical procedures involved in the investigation were performed by MI. Data collection and curation were performed by MM and DS. Data analysis was performed by FL. The first draft of the manuscript was written by FL and CC, and all authors commented on subsequent versions of the manuscript. All authors edited and approved the final manuscript.

Ethical approval

This observational study was conducted in accordance with the principles of the Declaration of Helsinki. Under local regulations and institutional policy, formal ethical committee approval was not required for this study as it involved retrospective analysis of anonymized clinical data collected during routine standard-of-care procedures without any experimental interventions or modifications to clinical practice. All data were handled in compliance with the European General Data Protection Regulation (GDPR, 2016/679). Data were collected and analysed in accordance with institutional privacy regulations.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used ChatGPT-4o (Open AI) to improve language clarity and grammar. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the final content.

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Declaration of competing interest

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