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BASIC RESEARCH

Prediction of Polyethylene Wear Rates from Gait Biomechanics and Implant Positioning in Total Hip Replacement

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Abstract

Background Patient-specific gait and surgical variables are known to play an important role in wear of total hip replacements (THR). However a rigorous model, capable of predicting wear rate based on a comprehensive set of subject-specific gait and component-positioning variables, has to our knowledge, not been reported.

Questions/purpose (1) Are there any differences between patients with high, moderate, and low wear rate in terms of gait and/or positioning variables? (2) Can we design a model to predict the wear rate based on gait and positioning variables? (3) Which group of wear factors (gait or positioning) contributes more to the wear rate?

Patients and Methods Data on patients undergoing primary unilateral THR who performed a postoperative gait test were screened for inclusion. We included patients with a 28-mm metal head and a hip cup made of noncrosslinked polyethylene (GUR 415 and 1050) from a single manufacturer (Zimmer, Inc). To calculate wear rates from radiographs, inclusion called for patients with a series of standing radiographs taken more than 1 year after surgery. Further, exclusion criteria were established to obtain reasonably reliable and homogeneous wear readings. Seventy-three (83% of included) patients met all criteria, and the final dataset consisted of 43 males and 30 females, 69 ± 10 years old, with a BMI of 27.3 ± 4.7 kg/m^2. Wear rates of these patients were determined based on the relative displacement of the femoral head with regard to the cup using a validated computer-assisted X-ray wear-analysis suite. Three groups with low (< 0.1 mm/year), moderate (0.1 to 0.2 mm/year), and high (> 0.2 mm/year) wear were established. Wear prediction followed a two-step process: (1) linear discriminant analysis to estimate the level of wear (low, moderate, or high), and (2) multiple linear and nonlinear regression modeling to predict the exact wear rate from gait and implant-positioning variables for each level of wear.

Results There were no group differences for positioning and gait suggesting that wear differences are caused by a combination of wear factors rather than single variables. The linear discriminant analysis model correctly predicted the level of wear in 80% of patients with low wear, 87% of subjects with moderate wear, and 73% of subjects with high wear based on a combination of gait and positioning variables. For every wear level, multiple linear and nonlinear regression showed strong associations between gait

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Each author certifies that his or her institution approved or waived approval for the human protocol for this investigation and that all investigations were conducted in conformity with ethical principles of research.
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biomechanics, implant positioning, and wear rate, with the nonlinear model having a higher prediction accuracy. Flexion-extension ROM and hip moments in the sagittal and transverse planes explained 42% to 60% of wear rate while positioning factors, (such as cup medialization and cup inclination angle) explained only 10% to 33%.

Conclusion Patient-specific wear rates are associated with patients' gait patterns. Gait pattern has a greater influence on wear than component positioning for traditional metal-on-polyethylene bearings.

Clinical Relevance The consideration of individual gait bears potential to further reduce implant wear in THR. In the future, a predictive wear model may identify individual, modifiable wear factors for modern materials.

Introduction

In many patients, a total hip replacement (THR) does not last for a lifetime and revision surgery is becoming more common [29]. For traditional THR that used non-crosslinked polyethylene liners, loosening and/or osteolysis account for nearly 30% of all performed revisions [9]. With the introduction of crosslinked polyethylene, the wear rate has been greatly reduced even in the young active population [22]; however, at this time it is unclear if the loosening or lysis problem has been solved or just has been delayed to the second or third decade of the lifetime of the prosthesis. Therefore, it makes sense to further investigate the factors governing wear in the hopes of keeping them under control.

Many factors contribute to polyethylene wear, including implant design variables (geometric features and material properties) [1, 2, 23, 28, 31, 36], surgical variables (implantation method and component positioning) [15, 16], and patient factors [10, 14, 39]. Regarding patient factors, gait and motion patterns have been shown to affect the hip contact force, one of the variables that influences polyethylene wear [20, 21]. Two studies showed that the inclusion of patient-specific factors in hip-wear simulation yielded to clinically relevant wear results [27, 30]. However, it is not possible to comprehensively account for large interpatient variability in gait and implant positioning in simulators owing to machine time and costs. Therefore, computational models such as finite element analyses have been used to model the influence of gait cycle [32], implant orientation [18, 19, 44], and joint loading parameters [17, 34]. Despite these previous efforts, a predictive wear model, based on a comprehensive set of patient-specific gait and component-positioning variables, is not available. Further, from a technical viewpoint, most predictive models rely on multiple linear regression modeling which does not fully accommodate the existing nonlinearities of the complex interactions between wear factors and wear rate.

Using repository data of patients who had THR, we therefore asked the following questions: (1) Are there any differences between patients who had THR with high, moderate, and low wear rate in terms of gait and/or positioning variables? (2) Using statistical models, such as regression models, can we predict the wear rate based on gait and positioning variables? (3) Which group of wear factors (gait or positioning) contributes more to the wear rate?

Patients and Methods

Patients

All patients who had THR who had performed a gait test and were listed in the institutional review board-approved data repository at the Motion Analysis Lab at Rush University Medical Center were reviewed. All patients provided written consent for inclusion. Patients with unilateral hip arthroplasty and with one or more gait trials 10 months or more after surgery (to ascertain recovery from surgery) and a minimum of 3 years of clinical followup (that needed to be available and documented in the orthopaedic tissue, implant, and information repository) qualified for inclusion. Two senior surgeons (JOG and AGR) performed the majority of the procedures (> 90%) and used a posterior and an anterolateral approach, respectively. To control for the most important design and material variables for THR wear between head and cup, inclusion was further restricted to patients with a 28-mm cobalt-chromium metal ball and a liner made of non-crosslinked polyethylene (GUR 415 and 1050) that was housed in a fiber mesh titanium cup (Zimmer, Inc, Warsaw, IN, USA). While all cups were cementless and shared a similar design philosophy, various cemented and cementless stems were used (Table 1). Finally, to calculate a meaningful wear rate (defined as head penetration into the polyethylene liner with time), inclusion called for patients with at least two AP view standing radiographs, taken at least 1 year apart with the first radiograph taken after the bedding-in phase 1 year or more after surgery. This led to the immediate inclusion of 88 patients from the repository.

Exclusion criteria were established to obtain reasonably reliable and homogeneous wear readings: (1) patients with a negative wear rate (implying material gain or growth which is physically impossible), (2) patients with wear readings for which the interobserver correlation coefficient (ICC) was less than 0.90, and (3) patients with extreme outliers of wear (ie, more than three times the interquartile range from the rest of the wear readings) as identified from

Table 1. Final patient dataset for analysis

Patient number	Gender	Age (years)	BMI (kg/m^2)	Side	Stem	Cup	Polyethylene	Surgeon/approach	Time in situ (years)	Number of radiographs
1	F	67	23	R	Mark II	Mark II	GUR 4150	1/Posterior	9	6
2	M	70	35.1	L	Harris Precoat (†)	HG II	GUR 4150	1/Posterior	11	8
5	F	58	22	R	Cementless Anatomic	HG II	GUR 4150	1/Posterior	12	8
8	M	64	30.8	L	Mark II	Mark II	GUR 4150	1/Posterior	17	9
9	F	66	22.4	L	Mark II	Mark II	GUR 4150	1/Posterior	17	5
10	M	50	27	L	Cementless Anatomic	HG II	GUR 4150	1/Posterior	9	5
12	M	66	28	R	Epoch®	Trilogy®	GUR 1050	1/Posterior	6	6
13	M	58	29.2	L	Epoch®	Trilogy®	GUR 1050	1/Posterior	4	5
14	M	63	26.9	R	Cementless Anatomic	HG II	GUR 4150	1/Posterior	11	8
19	F	64	32.6	R	VerSys® FullCoat	Trilogy®	GUR 1050	2/Anterolateral	6	4
21	F	51	24.4	L	Multilock™	HG I	GUR 4150	1/Posterior	12	10
23	F	63	31	R	Cementless Anatomic	HG II	GUR 4150	1/Posterior	5	5
24	M	66	23.4	L	Multilock™	HG I	GUR 4150	2/Anterolateral	17	7
27	M	55	24.4	R	Multilock™	HG I	GUR 4150	1/Posterior	13	8
30	M	45	28.5	L	Multilock™	HG I	GUR 4150	2/Anterolateral	6	6
31	M	63	31.8	L	Multilock™	HG I	GUR 4150	2/Anterolateral	5	6
32	F	70	30.9	L	Harris Precoat (†)	HG II	GUR 4150	2/Anterolateral	2	3
33	M	38	18.2	L	Cementless Anatomic	HG II	GUR 4150	1/Posterior	10	7
35	M	64	21.7	R	Multilock™	HG I	GUR 4150	1/Posterior	2	2
36	M	76	23.6	R	Harris Precoat (†)	Trilogy®	GUR 1050	2/Anterolateral	3	3
37	F	72	24.1	R	Harris Precoat (†)	HG I	GUR 4150	3/Unknown	7	3
38	F	51	33.2	L	Multilock™	HG II	GUR 4150	1/Posterior	12	6
39	F	58	24	L	Multilock™	HG I	GUR 4150	1/Posterior	14	7
40	F	68	28.8	R	Harris Precoat (†)	HG II	GUR 4150	1/Posterior	13	6
43	F	63	25.7	L	Multilock™	HG I	GUR 4150	2/Anterolateral	13	6
45	M	67	28.7	R	Cemented Anatomic (†)	Trilogy®	GUR 1050	1/Posterior	6	5
46	M	33	21.7	R	Cementless Anatomic	HG II	GUR 4150	2/Anterolateral	1	2
47	F	66	23.9	L	IOWA	HG II	GUR 4150	1/Posterior	7	6
48	M	71	23	L	VerSys® Cemented (†)	Trilogy®	GUR 1050	2/Anterolateral	3	2
49	F	50	38.1	L	VerSys® FullCoat	HG II	GUR 4150	1/Posterior	6	8
50	M	74	30.9	L	Cemented Anatomic (†)	Trilogy®	GUR 1050	1/Posterior	2	3
51	M	64	30.2	R	Multilock™	HG I	GUR 4150	1/Posterior	14	8
54	M	74	32.5	R	Harris Precoat (†)	HG I	GUR 4150	2/Anterolateral	11	6
56	M	61	25.3	L	Harris Precoat (†)	HG I	GUR 4150	2/Anterolateral	4	5
57	F	64	24.5	R	IOWA	HG II	GUR 4150	1/Posterior	8	5

Table 1. continued

Patient number	Gender	Age (years)	BMI (kg/m²)	Side	Stem	Cup	Polyethylene	Surgeon/ approach	Time in situ (years)	Number of radiographs
58	F	56	26.1	R	Cementless Anatomic	HG II	GUR 4150	3/Unknown	6	6
59	F	38	35.3	R	Cementless Anatomic	Trilogy®	GUR 1050	1/Posterior	6	7
60	F	57	20.5	R	Multilock™	HG I	GUR 4150	1/Posterior	15	4
61	F	62	23.1	L	Multilock™	HG I	GUR 4150	1/Posterior	14	8
62	M	68	31.4	R	Multilock™	HG I	GUR 4150	4/Unknown	14	7
63	F	72	28.1	R	Mark II	Mark II	GUR 4150	1/Posterior	15	6
64	M	50	25.3	L	VerSys® FullCoat	Trilogy®	GUR 1050	2/Anterolateral	2	3
65	F	58	27.4	R	Cementless Anatomic	HG II	GUR 4150	1/Posterior	6	6
66	M	68	28.6	L	Harris Precoat (†)	HG I	GUR 4150	1/Posterior	6	6
70	M	70	28.6	L	Cemented Anatomic (†)	Trilogy®	GUR 1050	1/Posterior	4	5
71	F	56	27.8	L	Multilock™	HG I	GUR 4150	2/Anterolateral	10	5
72	M	51	37.3	L	Cementless Anatomic	Trilogy®	GUR 1050	5/Unknown	3	2
74	M	65	25.9	R	Multilock™	HG I	GUR 4150	2/Anterolateral	11	6
75	M	74	32.3	L	VerSys® Cemented (†)	Trilogy®	GUR 1050	2/Anterolateral	1	2
78	F	61	27.1	R	Cementless Anatomic	HG II	GUR 4150	1/Posterior	10	7
79	M	69	23.9	R	Multilock™	HG I	GUR 4150	1/Posterior	16	6
82	M	73	36.6	R	Harris Precoat (†)	Trilogy®	GUR 1050	2/Anterolateral	2	3
83	M	70	28.2	L	Harris Precoat (†)	HG II	GUR 4150	1/Posterior	9	6
86	F	57	32.1	R	Cementless Anatomic	HG II	GUR 4150	1/Posterior	2	3
87	M	54	37.6	R	Multilock™	HG I	GUR 4150	1/Posterior	6	4
88	M	65	25.1	R	Cementless Anatomic	Trilogy®	GUR 1050	1/Posterior	6	6
89	F	70	19.8	R	Mark II	Mark II	GUR 4150	1/Posterior	15	8
90	F	64	24.9	R	Harris Precoat (†)	HG II	GUR 4150	2/Anterolateral	8	5
92	F	56	40.4	R	VerSys® FullCoat	Trilogy®	GUR 1050	2/Anterolateral	2	2
93	M	93	23	R	AML®*	HG I	GUR 4150	1/Posterior	6	5
95	M	37	24.5	R	Multilock™	HG I	GUR 4150	1/Posterior	9	6
98	F	61	26.6	R	Multilock™	HG I	GUR 4150	1/Posterior	15	5
102	M	73	29.6	L	Mark II	Mark II	GUR 4150	1/Posterior	14	8
103	M	58	29.6	L	Cementless Anatomic	HG II	GUR 4150	1/Posterior	10	9
104	M	57	25.9	L	VerSys® FullCoat	Trilogy®	GUR 1050	2/Anterolateral	1	2
106	F	67	22	L	Harris Precoat (†)	HG II	GUR 4150	1/Posterior	8	5
108	M	41	24.6	R	Cementless Anatomic	HG II	GUR 4150	1/Posterior	11	7
109	M	61	26.1	L	Multilock™	HG I	GUR 4150	1/Posterior	17	5
111	M	47	25.9	L	AML®*	HG I	GUR 4150	1/Posterior	10	5
112	M	74	24.3	R	Harris Precoat (†)	HG I	GUR 4150	1/Posterior	5	6

Table 1. continued

Patient number	Gender	Age (years)	BMI (kg/m^2)	Side	Stem	Cup	Polyethylene	Surgeon/ approach	Time in situ (years)	Number of radiographs
115	F	64	19.7	R	Mark II	Mark II	GUR 4150	1/Posterior	4	4
117	M	77	21.6	L	Harris Precoat (†)	HG I	GUR 4150	1/Posterior	5	4
119	M	57	28	L	Cementless Anatomic	Trilogy®	GUR 1050	1/Posterior	4	4

All implanted components are from Zimmer, Inc (Warsaw, IN, USA) unless marked with *; all cups were implanted cementless, cemented stems are indicated with a (†). All GUR 4150 liners were gamma sterilized and packaged in air. All GUR 1050 liners were gamma sterilized in inert atmosphere and packaged in nitrogen; Surgeon 1 (JOG) used a posterior approach, while Surgeon 2 (AGR) used an anterolateral approach; F/M = female/male; R/L = right/left; (†) = cemented; *DePuy (Warsaw, IN, USA).

box plots (SPSS Version 15.0; SPSS Inc, Chicago, IL, USA). These criteria led to the exclusion of 15 patients: four patients were excluded owing to negative wear readings, nine were excluded owing to low ICC wear readings (0.2–0.77), and two were excluded owing to wear readings classified as outliers (68 and 97 mm/year). This left 73 patients (83% of the included) for analysis: 43 males and 30 females, 69 ± 10 years old, and BMI of 27.3 ± 4.7 kg/m^2. These patients had their implants 10 to 123 months (average, 37 ± 31 months) in situ and had two to 10 radiographs acquired every 9 to 20 months during followups (Table 1).

Gait Analysis

Gait data had been collected from 1990 through 2004 using a four-camera motion-capture system with passive markers (120 frames per second) (Qualisys, Gothenburg, Sweden) and a multicomponent force plate (Bertec Corporation, Colombus, OH, USA) for measurement of ground reaction forces. A total of six retroreflective markers were placed on the lateral aspect of the iliac crest, superior aspect of the greater trochanter, mid-point of the lateral joint line of the knee, lateral malleolus, head of the fifth metatarsal, and the lateral aspect of the calcaneus. Patients were required to be pain free at the date of the gait test. During gait analysis patients walked at three self-selected speeds of "normal", "slow", and "fast" with multiple trials collected at each speed. The trial with median speed was chosen as the most representative from the patients' self-selected "normal speed" trials.

To calculate external forces and moments, the lower extremities were modeled as a collection of three rigid links (thigh, shank, and foot). This link model assumed that no axial rotation occurred about the long axes of the segments. The hip center was assumed to be at a point 2.5 cm below the mid-point of a line that runs from the anterior superior iliac crest to the pubic tubercle [3]. The inertial properties for each segment were lumped at its mass center and were used in the calculations for the external moments. Inverse dynamics was used to calculate the external moments in all three dimensions about the hip centers [3]. The external moments included the moment about the joint center created by the ground reaction force and inertial forces of the body segments. The external moments were transformed into a local coordinate system aligned with the femur. A total of seven gait variables (Table 2) were extracted for each patient that were considered for further analysis: hip range of motion (HROM), maximum hip flexion moment (HMXFLEX), maximum hip extension moment (HMXEXT), maximum hip adduction moment (HMYADD), maximum hip abduction moment (HMYABD), maximum hip internal rotation moment (HMZINT), and maximum hip external rotation moment (HMZEXT).

Table 2. Summary of wear factor abbreviations and descriptions

Wear factor and abbreviation	Description
Gait variable	
HROM	Sagittal hip range of motion
HMXFLEX	Maximum hip flexion moment
HMXEXT	Maximum hip extension moment
HMYADD	Maximum hip adduction moment
HMZINT	Maximum hip internal rotation moment
HMZEXT	Maximum hip external rotation moment
Component positioning	
C-INCL	Cup inclination
C-ANTE	Cup anteversion
C-MED	Cup medialization
V-SET	Vertical offset
H-SET	Horizontal offset
ABD-L	Abductor lever arm

Wear Analysis

A computer-assisted technique (Hip Analysis Suite; UChicagoTech, Chicago, IL, USA) was used to determine the relative, linear displacement ("penetration") of the metal ball into the polyethylene liner from digital radiographs. The measured penetration correlates with material removal (wear) from the polyethylene liner, as previously described and validated by Martell and Berdia [33] and Berzins et al. [11]. Standard AP radiographs with the patient in a standing position were obtained from the repository for all included patients. The radiographic films were converted to digital format using a flatbed scanner (Vision Ten Inc, Carlstadt, NJ, USA). Typically, during the first year after surgery, embedding of the articulating components takes place. Therefore, it is likely that the actual wear rate is masked. For this reason, only radiographs after the first year of surgery were chosen. Moreover, because wear rates, determined from shorter implant duration times, may tend to be higher, the association between wear rate and the length of followup (time in situ) was investigated using a linear regression model. Ideally, several (minimum two) radiographs were available to determine the wear rate using a linear regression model. Two observers (PPAE and DB) independently measured the wear rate using the Hip Analysis Suite. Only subjects with ICCs of the wear readings greater than 0.90 were included in the study. There were nine patients for whom the ICC was less than 0.9 (range, 0.50–0.75). These patients were excluded from the study.

Component Positioning

Vertical joint-center position was measured as the superoinferior distance between the center of the head and the interteardrop line of the pelvis while the horizontal position was measured as the mediolateral distance between the center of the head and the teardrop. A line connecting the most-lateral aspect of the greater trochanter and Charnley's origin of the abductors (defined at a location 2.5 cm medial and 2.5 cm superior to the inferior portion of the anterior superior iliac spine) was drawn to represent the line of action of the abductor muscles [12]. A line perpendicular to this line was drawn through the center of the femoral heads to represent the abductor lever arm (ABD-L) (Fig. 1A). The contralateral hip center was identified computationally using the Hip Analysis Suite by a three-point click on the native femoral head.

The horizontal offset (H-SET) was defined as the mediolateral distance between the center of the head and the anatomic axis of the femur [25] (Fig. 1A). Vertical offset (V-SET) was identified by drawing a line through the center of the head and perpendicularly on the femoral implant axis. The offset is the perpendicular distance between the center of the head and the implant axis (Fig. 1B). Cup medialization (C-MED) was measured as the distance between the medial wall of the acetabulum and the center of the cup (Fig. 1A). The cup anteversion (C-ANTE) was estimated as the angle formed by the long axis of the cup component and the line connecting the top point of the ellipse and the endpoint of the long axis (Fig. 1C). Cup inclination (C-INCL) was defined as the angle between the longitudinal axis of the patient and the radiographic projection of the acetabular axis, that is, perpendicular to the major axis of the cup projection [42] (Fig. 1D). All measurements were expressed in degrees and millimeters after correction for magnification.

Wear Predictive Model

Before proposing the wear predictive model, and to avoid inclusion of redundant variables, potential collinearity among gait variables and among positioning variables was investigated using the variance inflation factor (VIF) as the investigative tool. Each of the seven gait variables (or six positioning variables) was considered as the output of a linear regression model and all other remaining gait variables (or remaining positioning variables) served as predictors. Only gait variables (or positioning variables) for which all other gait (or positioning) variables yielded a VIF less than 2.5 were considered independent and entered in the wear predictive model.

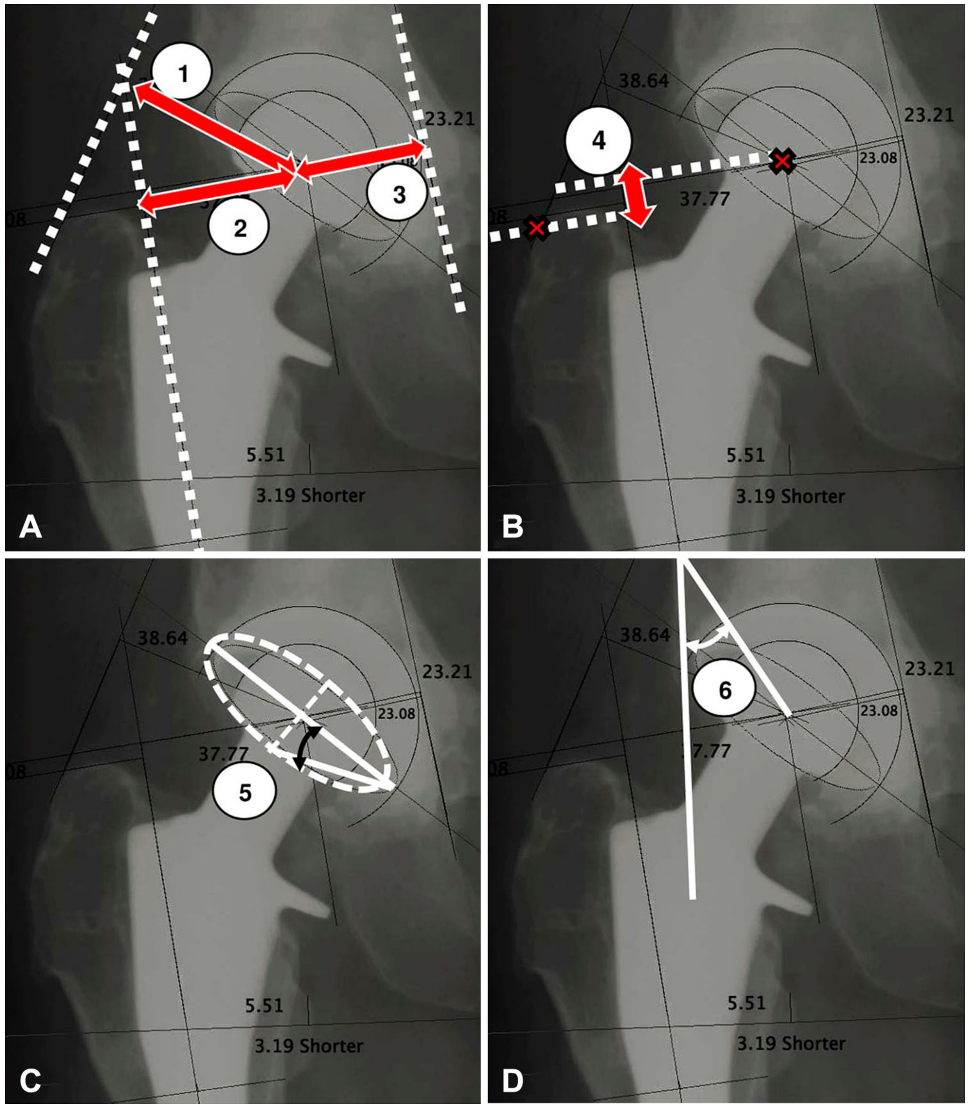

Fig. 1A–D Component positioning factors consisted of the **(A)** abductor lever arm (1), horizontal offset (2), and cup medialization (3), **(B)** vertical offset (4), **(C)** cup anteversion (5), and **(D)** cup inclination (6).

The proposed predictive model consisted of two parts: (1) predicting the level of wear rate (high, moderate, or low) using a linear classifier (ie, linear discriminant analysis (LDA) [35]) and (2) predicting the amount of wear rate using a multiple linear regression (MLR) and/or nonlinear regression in form of an artificial neural network (ANN) model. The level of wear rate was considered "low" when the linear wear rate was less than 0.1 mm per year; "moderate" when the linear wear rate was more than 0.1 mm per year and less than 0.2 mm per year; and "high" when the linear rate was greater than 0.2 mm per year. This classification criterion was obtained from a study in which noncrosslinked UHMWPE wear less than 0.1 mm per year was considered "low" and a wear rate greater than 0.2 mm per year was associated with osteolysis and subsequent component loosening [41]. Using these criteria, our 73 patients with THRs were divided in three groups: 25 patients with low-wear rate (wear rate, 0.06 $\pm$ 0.02 mm/year; age, 63.7 $\pm$ 7.8 years; BMI, 27.3 $\pm$ 4.3 kg/m^2), 29 patients with moderate-wear rate (wear rate, 0.15 $\pm$ 0.03 mm/year; age, 60.4 $\pm$ 10.7 years; BMI, 26.5 $\pm$ 4.7 kg/m^2); and 19 patients with high-wear rate (wear rate, 0.27 $\pm$ 0.04 mm/year; age, 58.3 $\pm$ 9.8 years; BMI, 28.6 $\pm$ 5.1 kg/m^2) (Table 3).

The LDA model consisted of three classification rules; one rule per wear group (low, moderate, and high wear). Each rule was a linear combination of the wear factors and calculated a membership score for each patient. Patients then were assigned to the wear group whose classification rule led to the highest membership score. To establish this classifier, patients were randomly divided into two subsets: 80% of the patients were used to establish the classification rules and the remaining 20% of patients were used to test whether the classifier could correctly classify new patients (test dataset). The classification accuracy of the LDA model was defined as the number of correctly classified patients divided by the number of total test patients. To achieve a 95% CI about the classification accuracy, the training and testing procedures were iterated until all

Table 3. Demographic description of three classes (mean ± SD)

Group	Number of patients	Age (years)	Height (m)	BMI (kg/m^2)	Speed (m/second)	Linear wear rate (mm/year)
Low wear	25	63.7 ± 7.8	1.7 ± 0.07	27.3 ± 4.3	1.1 ± 0.1	0.06 ± 0.02
Moderate wear	29	60.4 ± 10.7	1.7 ± 0.08	26.5 ± 4.7	1.1 ± 0.1	0.1 ± 0.03
High wear	19	58.3 ± 9.8	1.7 ± 0.08	28.6 ± 5.1	1.1 ± 0.2	0.3 ± 0.04

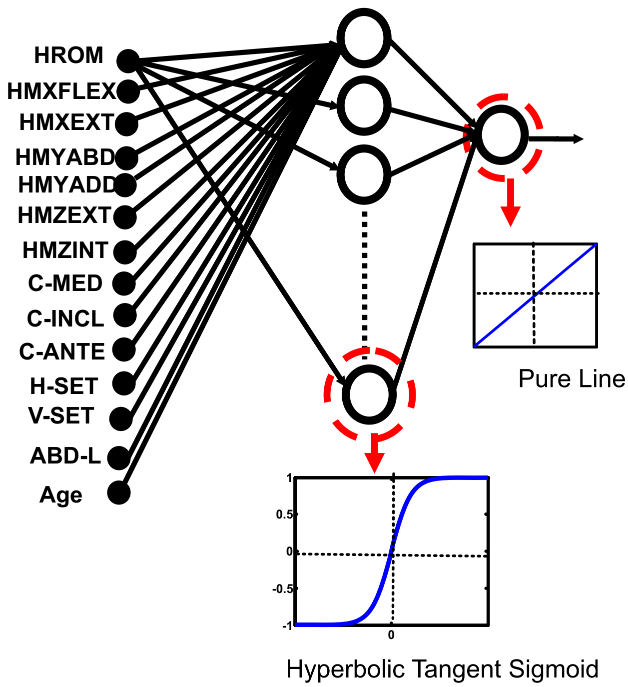

Fig. 2 The proposed three-layer artificial neural network had 14 input nodes including hip range of motion (HROM), hip flexion moment (HMXFLEX), hip extension moment (HMXEXT), hip abduction moment (HMYABD), hip adduction moment (HMYADD), hip hip external rotation (HMZEXT), internal rotation (HMZINT), cup medialization (C-MED), cup inclination (C-INCL), cup anteversion (C-ANTE), horizontal offset (H-SET), vertical offset (V-SET), abductor lever arm (ABD-L), and subject age (Age).

participants were used as test data. The classification accuracy then was averaged over all the iterations.

Once classified, the wear rate of each patient was predicted using MLR and ANN models. Considering that the level of patient activity plays a central role in wear of the polyethylene liner, and age has been shown to be a surrogate of patient activity [37], age was included as a factor, together with gait and positioning variables. For the MLR, the relationship between wear factors (that is, age, seven gait variables, and six positioning variables) and wear rate was modeled by fitting a linear equation to the observations of each wear group:

$$\text{Wear rate} = \alpha_1 \times x_1 + \alpha_2 \times x_2 + \alpha_3 \times x_3 + \cdots + \alpha_{14} \times x_{14} + \beta$$

Where x_1 to x_{14} represent the wear factors (age, gait, and component-positioning variables), α_1 to α_{14} represent regression coefficients, and β is the intercept of the model. Wear factors were entered in the regression model using a backward-selection approach to reassure the exclusion of redundant variables. As previously reported [8], two cases per predictor variable are adequate for estimation of regression coefficients, standard errors, and CIs in MLR modeling, a condition which was just met in this study. The prediction ability of the constructed models then was tested by the leave-one-out cross-validation technique [40]. The cross-validation procedure was repeated until each patient was used as the test subject in his or her corresponding wear group.

ANN can be considered a nonlinear regression model that can model the relationship between the independent variables (predictors) and dependent variable in an analogous fashion to linear regression [4–7, 38]. The most-featured difference between linear regression and ANN is that the latter splits a complex nonlinear relationship into several piecewise approximations, where each approximation is generated as a nonlinear function of predictors (instead of a simple linear combination of predictors as in linear regression). ANN was used to predict the wear rate from the 14 inputs (same variables as above) for each wear class. The proposed ANN structure consisted of processor units (neurons) organized in layered arrangements. In each layer, neurons were related to the neurons of the next layer via weights (Fig. 2). Each input node was related to each mid-level neuron (called hidden neurons) via input weights. Thus, a weighted combination of all input parameters was fed into each hidden neuron where a nonlinear function (*func*), a hyperbolic tangent sigmoid, determined the wear-rate output of the hidden neuron (representing a nonlinear regression). A pure line function at each output then was used to combine all the piecewise nonlinear regressions produced by the hidden neurons. Using the above ANN structure, the linear wear rate was modeled as:

$$\text{Wear rate} = \alpha_1 \times y_1 + \alpha_2 \times y_2 + \alpha_3 \times y_3 + \cdots + \alpha_n \times y_n + \beta \quad n = \text{number of hidden neurons}$$

Where:

$$y_i = \mathit{func}(x_1,\ x_2,\ x_3, \ldots + \ x_{14}) + \eta_i \quad 1 < i < n$$

Where y_1 to y_n are the outputs from hidden neurons, β is the intercept related to the ANN output, and η_i is the intercept related to each hidden neuron and x_1 to x_{14}

Table 4. Comparison of component positioning among three wear groups

Variable	Group 1	Group 2	Mean difference	Standard error	95% CI	p Value	Bonferroni p value
C-INCL	Low	Moderate	−2.77	1.83	−6.42 to 0.87	0.134	1.000
	Low	High	−0.71	2.04	−4.78 to 3.36	0.729	1.000
	High	Moderate	−2.07	1.98	−6.01 to 1.88	0.300	1.000
C-ANTE	Low	Moderate	−2.99	1.85	−6.68 to 0.70	0.110	1.000
	Low	High	−0.93	2.06	−5.04 to 3.18	0.654	1.000
	High	Moderate	−2.06	2.00	−6.05 to 1.93	0.306	1.000
H-SET	Low	Moderate	1.31	2.21	−3.19 to 5.81	0.558	1.000
	Low	High	−3.21	2.47	−8.22 to 1.81	0.203	1.000
	High	Moderate	4.52	2.14	0.16–8.87	0.042	0.764
V-SET	Low	Moderate	0.61	1.33	−2.04 to 3.26	0.648	1.000
	Low	High	3.27	1.48	0.31–6.22	0.031	0.551
	High	Moderate	−2.66	1.42	−5.49 to 0.18	0.066	1.000
C-MED	Low	Moderate	−0.65	1.22	−3.10 to 1.79	0.596	1.000
	Low	High	1.02	1.37	−1.71 to 3.74	0.458	1.000
	High	Moderate	−1.67	1.32	−4.31 to 0.97	0.211	1.000
ABD-L	Low	Moderate	0.78	2.21	−3.73 to 5.29	0.726	1.000
	Low	High	−0.25	2.45	−5.26 to 4.76	0.919	1.000
	High	Moderate	1.03	2.12	−3.31 to 5.37	0.631	1.000

C-INCL = cup inclination; C-ANTE = cup anteversion; V-SET = vertical offset; C-MED = cup medialization; ABD-L = abductor lever arm.

represent the wear factors (age, gait, and component-positioning variables). A gradient-descent back-propagation algorithm with adaptive learning rate was used to train the ANN. A class-specific ANN was assigned to each wear group (low, moderate, and high). In each wear group, patients were randomly divided in three subgroups: 70% of the patients were used to train the ANN (that is, adjust the weights and biases), 15% were used to validate the trained ANN, and the remaining 15% were used to challenge the trained ANN with new patients and investigate the generalizability of the trained ANN. The prediction accuracy of the trained ANN then was evaluated by comparing ANN estimations versus radiograph-based readings using normalized-root-mean-square error (NRMSE %) and Pearson correlation coefficients. To achieve a 95% CI for prediction accuracy, the training and testing procedures were iterated for 100 times, as suggested by Iyer and Rhinehart [24]. The prediction accuracy of the ANN then was averaged over all the iterations. The ANN structures were established using Neural Network Toolbox™ (MathWorks®, Natick, MA, USA).

Statistical Analysis

Statistical analysis was conducted using SPSS Version 15.0. Demographic characteristics of participants (age, height, body weight) and all other variables of interest (wear rate, gait, and positioning factors) were compared among patients with high, moderate, and low wear using one-way ANOVA with a significance level of $p = 0.05$ and Bonferroni-adjusted post hoc tests. Before the analysis, the presence of outliers was checked using boxplots. The normality of the data and homogeneity of variances also were tested using the Shapiro-Wilk and Levene's tests respectively to assure reliability of the ANOVA. To assure the homogeneity of patient groups in terms of other wear covariates that were not the main focus of this study, the distribution of implant design, polyethylene material, and surgical approach across wear groups was investigated using Chi-square analysis.

Results

Differences Among Patients By Wear Rate

There were no group differences in terms of component positioning (Table 4) and gait (Table 5). This suggested that wear differences might be caused by a combination of wear factors rather than by individual variables. Noteworthy, all the VIF computations were less than 2.5. Of all 72 investigated variable combinations, the VIF was less than 2.0 in 86% and 93% of the patients for positioning and gait variables, respectively. We therefore concluded that the predictor variables are only weakly correlated with each other and multicollinearity is not of concern. Regarding output, a weak

Table 5. Comparison of gait biomechanics among three wear groups

	Group 1	Group 2	Mean difference	Standard error	95% CI	p Value	Bonferroni p value
Speed	Low	Moderate	−0.025	0.048	−0.120 to 0.070	0.604	1.000
	Low	High	0.029	0.053	−0.076 to 0.135	0.581	1.000
	High	Moderate	−0.054	0.051	−0.157 to 0.048	0.296	1.000
HROM	Low	Moderate	−0.84	1.70	−4.22 to 2.55	0.624	1.000
	Low	High	−1.45	1.89	−5.23 to 2.32	0.446	1.000
	High	Moderate	0.62	1.84	−3.05 to 4.28	0.738	1.000
HMXFLEX	Low	Moderate	−0.28	0.58	−1.43 to 0.88	0.635	1.000
	Low	High	0.43	0.65	−0.86 to 1.71	0.511	1.000
	High	Moderate	−0.70	0.63	−1.95 to 0.55	0.266	1.000
HMXEXT	Low	Moderate	0.12	0.30	−0.466 to 0.713	0.678	1.000
	Low	High	−0.07	0.33	−0.729 to 0.585	0.828	1.000
	High	Moderate	0.20	0.32	−0.442 to 0.833	0.544	1.000
HMYADD	Low	Moderate	0.12	0.31	−0.489 to 0.729	0.695	1.000
	Low	High	0.16	0.34	−0.519 to 0.839	0.640	1.000
	High	Moderate	−0.04	0.33	−0.698 to 0.619	0.905	1.000
HMYABD	Low	Moderate	−0.33	0.20	−0.74 to 0.08	0.109	1.000
	Low	High	−0.11	0.23	−0.57 to 0.34	0.624	1.000
	High	Moderate	−0.22	0.22	−0.66 to 0.22	0.324	1.000
HMZINT	Low	Moderate	0.06	0.07	−0.0733 to 0.2010	0.357	1.000
	Low	High	0.07	0.08	−0.0802 to 0.2257	0.346	1.000
	High	Moderate	−0.01	0.07	−0.1573 to 0.1394	0.905	1.000
HMZEXT	Low	Moderate	0.02	0.08	−0.147 to 0.187	0.816	1.000
	Low	High	0.05	0.09	−0.135 to 0.237	0.585	1.000
	High	Moderate	−0.03	0.09	−0.212 to 0.149	0.728	1.000

HROM = sagittal hip range of motion; HMXFLEX = maximum hip flexion moment; HMXEXT = maximum hip extension moment; HMYADD = maximum hip adduction moment; HMYABD = maximum hip abduction moment; HMZINT = maximum hip internal rotation moment; HMZEXT = maximum hip external rotation moment.

association between wear rate and time in situ was found (adjusted $R^2 = 0.09$) (Fig. 3). Regarding secondary variables, there were no statistical differences in terms of implant design or polyethylene among the three wear groups. However, 'surgeon' (or surgical approach) showed a difference: Surgeon 2 (who used an anterolateral approach) had a larger number of patients in the high-wear group compared with Surgeon 1 (who used a posterior approach) (Table 6). No group differences were found in demographic characteristics such as age, height, and weight (Table 7).

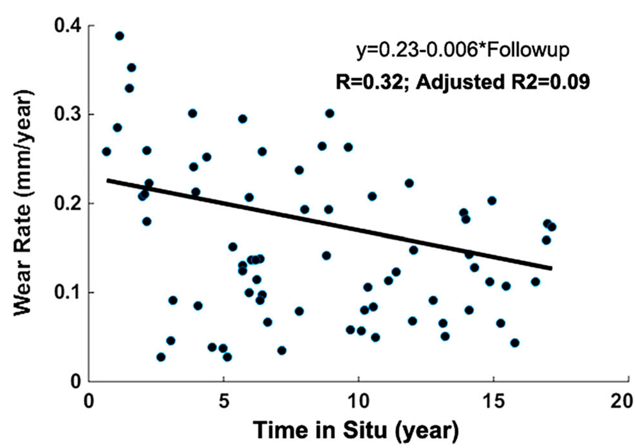

Fig. 3 The association between time in situ and wear rate represented a weak correlation (adjusted $R^2 = 0.09$).

Can We Predict Wear Rate Using Gait and Positioning Variables?

The level of wear rate (high, moderate, low) was predictable based on wear factors (gait and positioning variables) using the following classification rules:

Table 6. Chi-square distribution of cup, stem, polyethylene, and surgical approach among the three wear groups

Variable	Wear group			p Value
	High	Low	Moderate	
Cup				
HG I	3	11	13	
HG II	6	9	7	
Mark II	2	1	4	0.124
Trilogy®	8	4	5	
Stem				
Cemented	5	7	3	
Cementless	14	18	26	0.215
Polyethylene				
GUR 1050	8	4	5	
GUR 4150	11	21	24	0.917
Surgical approach				
Anterolateral	12	6	1	
Posterior	17	17	26	0.002

$$\begin{aligned}\text{Membership-of-high-wear-group} &= 1.2 \times (\text{C-INCL}) + 1.6 \times (\text{C-MED}) + 2.4 \\ &\quad \times (\text{HMXFLEX}) - 0.4 \times (\text{HMXEXT}) + 8.7 \\ &\quad \times (\text{HMYADD}) + 8.6 \times (\text{HMYABD}) - 24.9 \\ &\quad \times (\text{HMZINT}) - 19.9 \times (\text{HMZEXT}) - 69.8\end{aligned}$$

Each subject then was assigned to the wear group with the highest membership value. Eighty percent of patients with low wear rate, 87% with moderate wear rate, and 73% with high wear rate were correctly classified (Table 8). This part of the wear prediction model (LDA) will allow assignment of any future patient to the appropriate wear class without prior knowledge of wear rate. Once subjects were classified according to wear, the MLR (Fig. 4) and ANN (Fig. 5) were able to successfully predict wear rate from wear factors (age, gait, and implant positioning). The MLR-based predictive model consisted of the following three equations:

MLR models:

$$\text{Wear rate} = \begin{cases} = -0.27 * \text{Age} + 0.22 * \text{HROM} - 0.22 * \text{HMXEXT} + 0.6 * \text{HMYABD} - 0.33 * \text{HMZINT} - 0.24 * \text{HMZEXT} & \text{For low-wear group} \\ = 0.13 * \text{Age} + 0.55 * (\text{ABD-L}) - 0.38 * \text{HROM} + 0.47 * \text{HMXFLEX} - 0.45 * \text{HMYABD} & \text{For moderate-wear group} \\ = -0.54 * \text{C-MED} - 0.55 * \text{HMYADD} + 0.38 * \text{HMZINT} + 0.40 * \text{H-SET} - 0.4 * \text{C-INCL} & \text{For high-wear group} \end{cases}$$

ANN-based predictive model consisted of the three following equations:

$$\text{Wear rate} = \begin{cases} = 0.050 \times \mathit{func}(\text{Age}) + 0.15 \times \mathit{func}(\text{HMXFLEX}) - 0.17 \times \mathit{func}(\text{HMYABD}) + 0.19 \times \mathit{func}(\text{HMZINT}) - 0.21 \times \mathit{func}(\text{HMZEXT}) + 0.25 \times \mathit{func}(\text{HROM}) \quad \text{For low-wear group} \\ = 0.0030 \times \mathit{func}(\text{Age}) + 0.32 \times \mathit{func}(\text{ABD-L}) + 0.35 \times \mathit{func}(\text{HROM}) + 0.27 \times \mathit{func}(\text{HMXFLEX}) + 0.32 \times \mathit{func}(\text{HMXEXT}) - 0.24 \times (\text{HMYADD}) - 0.18 \times \mathit{func}(\text{HMYABD}) \\ \quad +0.17 \times \mathit{func}(\text{HMZINT}) - 0.15 \times \mathit{func}(\text{HMZEXT}) \quad \text{For moderate-wear group} \\ = -0.35 \times \mathit{func}(\text{C-INCL}) - 0.40 \times \mathit{func}(\text{C-MED}) \\ \quad + 0.32 \times \mathit{func}(\text{H-SET}) - 0.08 \times \mathit{func}(\text{V-SET}) + 0.32 \times \mathit{func}(\text{HROM}) + 0.14 \times \mathit{func}(\text{HMXFLEX}) + 0.15 \times \mathit{func}(\text{HMXEXT}) \\ \quad - 0.27 \times \mathit{func}(\text{HMYADD}) - 0.21 \times \mathit{func}(\text{HMYABD}) + 0.25 \times \mathit{func}(\text{HMZINT}) - 0.16 \times \mathit{func}(\text{HMZEXT}) \quad \text{For high-wear group} \end{cases}$$

$$\begin{aligned}\text{Membership-of-low-wear-group} &= 1.1 \times (\text{C-INCL}) + 1.8 \times (\text{C-MED}) + 2.5 \\ &\quad \times (\text{HMXFLEX}) - 1.2 \times (\text{HMXEXT}) + 8.5 \\ &\quad \times (\text{HMYADD}) + 6.8 \times (\text{HMYABD}) - 21.6 \\ &\quad \times (\text{HMZINT}) - 15.0 \times (\text{HMZEXT}) - 68.7\end{aligned}$$

$$\begin{aligned}\text{Membership-of-moderate-wear-group} &= 1.4 \times (\text{C-INCL}) + 1.9 \times (\text{C-MED}) + 2.8 \\ &\quad \times (\text{HMXFLEX}) - 2.4 \times (\text{HMXEXT}) + 10.1 \\ &\quad \times (\text{HMYADD}) + 10.6 \times (\text{HMYABD}) - 29.7 \\ &\quad \times (\text{HMZINT}) - 20.2 \times (\text{HMZEXT}) - 85.4\end{aligned}$$

In which "*func*" refers to tangent sigmoid function modeling the nonlinearity aspects of the interaction between wear factors and wear.

The ANN model provided higher prediction accuracy when compared with the actual wear data. For patients with low- and moderate-wear rates, the average prediction errors of the ANN model were NRMSE 8% and 11% respectively, while those of the MLR model were NRMSE 27% and 54%. Thus, ANN outperformed the MLR model which became even more evident when the wear of the high-wear group was predicted. For patients with a high wear rate, the ANN predicted wear with an average prediction error of NRMSE 14%, while the prediction error for the MLR model was NRMSE 43%.

Table 7. Comparison of patient demographics and wear rates among three wear groups

Variable	Group 1	Group 2	Mean difference	Standard error	95% CI	p Value	Bonferroni p value
Age (years)	Low	Moderate	3.27	2.62	−1.96 to 8.50	0.217	1.000
	Low	High	5.36	2.92	−0.47 to 11.20	0.071	0.851
	High	Moderate	−2.10	2.84	−7.76 to 3.56	0.462	1.000
Height (m)	Low	Moderate	−0.035	0.023	−0.082 to 0.011	0.137	1.000
	Low	High	−0.033	0.026	−0.085 to 0.019	0.214	1.000
	High	Moderate	−0.002	0.025	−0.053 to 0.048	0.922	1.000
Weight (N)	Low	Moderate	−36.3	43.6	−123 to 51	0.408	1.000
	Low	High	−84.0	48.6	−181 to 13	0.088	1.000
	High	Moderate	47.7	47.1	−46 to 142	0.315	1.000
Linear wear rate (mm/year)	Low	Moderate	−0.088	0.010	−0.11 to −0.07	0.000	0.000
	Low	High	−0.207	0.0	−0.23 to −0.19	0.000	0.000
	High	Moderate	0.119	0.0	0.10–0.14	0.000	0.000

Table 8. Comparison between the actual wear level (determined based on radiography followups) and the predicted wear level (from LDA technique)

Actual wear level	Estimated wear level			% correctly classified
	Low	Moderate	High	
Low	20	2	3	80%
Moderate	1	25	3	86%
High	2	2	15	79%

Twenty of 25 patients with low wear rate were correctly classified as "low-wear"; 25 of 29 with moderate wear rate were correctly classified as "moderate wear"; 15 of 19 with high wear rate were correctly classified as high wear.

Does Gait or Positioning Contribute More to Wear Rate?

Gait was found to have a greater influence on the wear rate than surgical positioning variables. In both predictive models (ANN and MLR), gait variables explained between 42% to 60% of wear rate while positioning factors only explained between 10% to 33% of the wear rate. It seemed that positioning variables became more important in patients with high wear rate. For example, in patients with high-wear rate cup medialization and cup inclination angle emerged as part of the predictive models.

Discussion

Wear, a major barrier for implant longevity, has been greatly reduced with the introduction of crosslinked polyethylene. However, at present it is unknown if the problem of wear has been completely resolved or just has been delayed to a later time in the lifetime of the prosthesis. Therefore, it makes sense to further investigate the factors governing wear in the hopes of better understanding (and perhaps being able to influence) those factors. Patient-specific variables, such as gait or implant positioning, play an important role in wear. However, before this report, to our knowledge, no study with a rigorous model capable of predicting wear rate based on these variables has been published. Therefore, in the current study, we developed a predictive wear model based on subject-specific gait and implant-positioning variables. Our predictive model showed that (1) cup medialization and inclination angle plus three-dimensional hip moments can predict the level of wear rate (low, moderate, or high); (2) hip moments are more important than positioning factors (as they emerged with a higher contribution in the predictive models); (3) cup-positioning variables, such as medialization and inclination angle, become more important in the presence of high wear rates.

This study had several limitations. Perhaps the most important limitation was that patient activity was not included in the model. It is known from wear simulators that polyethylene wear increases linearly with cycles [13]. It has been shown that patient steps throughout the day play a critical role in the wear of polyethylene, and it as been postulated that "wear is a function of use not time" [43]. In

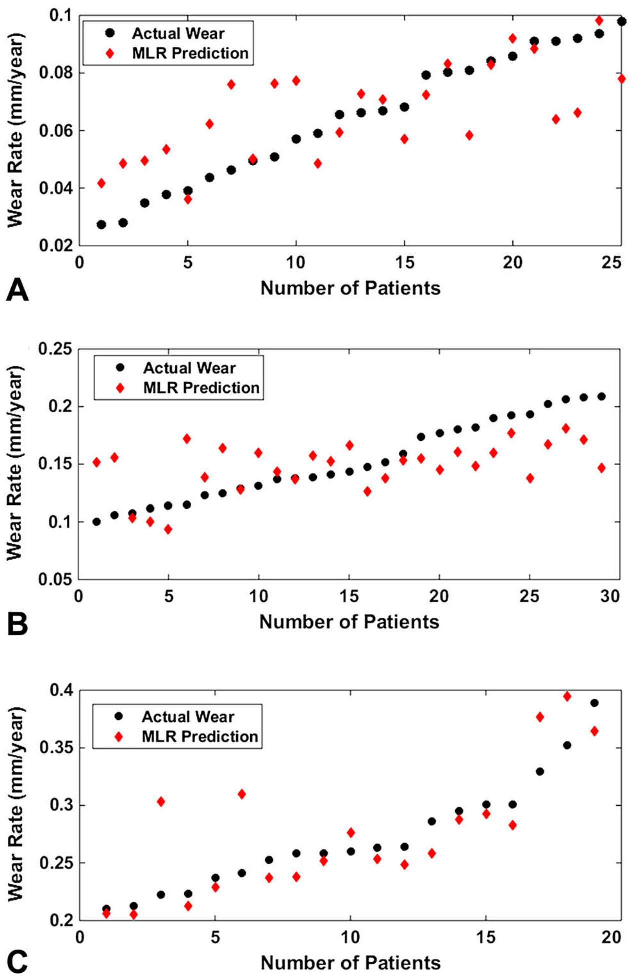

Fig. 4A–C Class-specific linear regression predictions of linear wear rate compared with radiographic wear assessment for patients with **(A)** low wear, **(B)** moderate wear, and **(C)** high wear are shown. MLR = multiple linear regression.

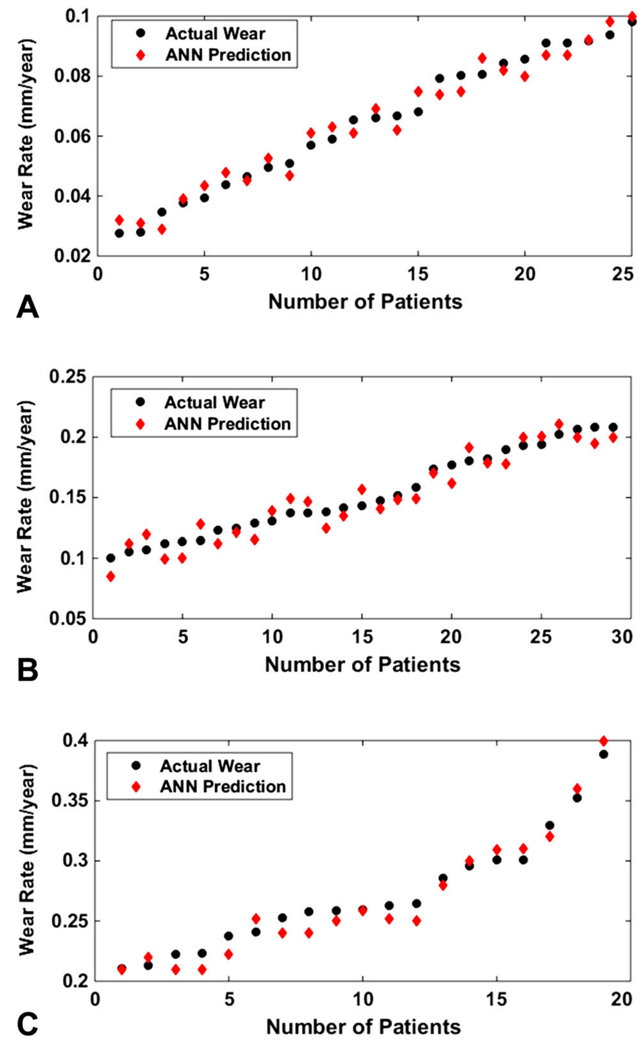

Fig. 5A–C Class-specific artificial neural network (ANN) predictions of linear wear rate compared with radiographic wear assessment for patients with **(A)** low wear, **(B)** moderate wear, and **(C)** high wear are shown.

the current study, the number of daily performed steps was unknown, as were the specific activities. We therefore used age as a surrogate for steps per day [37] in the analyses. We found that age was dropped from most regression models, and if present, entered as a nonsignificant variable. Since the meta-regression by Naal and Impellizzeri [37] showed a relatively strong relation between age and steps per day, we propose that the patient's gait pattern is indicative of his or her activity pattern, a hypothesis that needs to be verified in the future.

In terms of other limitations, we note that our study design allowed statistical associations to be drawn in the hopes of increasing prediction accuracy; however, no mechanisms and causes can be provided. However, it is interesting that gait pattern (together with positioning) is such a strong predictor for wear rate. In addition, the patients in this series all received THRs without cross-linked polyethylene (either GUR 415 or 1050). Generalizing our findings to newer materials should be done with caution as the influence and ranking of the wear factors may vary depending on implant material and design. However, the methodology (a two-step wear-predictive model consisting of a linear classifier and a regression model) is equally applicable to other types of implant design and material. Moreover, wear is a function of other variables such as implant design, material, and surgical approach that are not part of our proposed model. We attempted to control the potential influence of these variables by choosing patients with similar implant design and material. There were no statistical differences in terms of implant design or polyethylene type among the three wear groups, but 'surgeon' emerged as a potential confounder. Surgeon 2 had a larger number of patients in the high-wear group compared with Surgeon 1. Although this might be related to surgical approach, we believe it is a case-distribution issue in that Surgeon 2 may have worked on more-complex cases. Unfortunately, this retrospective study does not allow a more-definite conclusion. Future studies on a larger patient population with a heterogeneous distribution of implant design and surgical technique may consider these variables as additional predictors.

In addition, patients underwent only one gait test that was conducted 1 year after surgery, whereas radiographic followups continued for several years after surgery. Patients' gait may have changed with time as a function of age, rehabilitation, or weight gain or loss, that is not accounted for in this study. Further, the hip center has been assumed to be at a point 2.5 cm below the mid-point of a line that runs from the anterior superior iliac crest to the pubic tubercle. We did not compare this preassumed location versus hip centers calculated from the radiographs. However, Kirkwood at al. [26] reported that this hip center leads to the least error in the hip moment calculation (0.4 Nm/kg in the frontal plane, 0.07 Nm/kg in the sagittal plane, and 0.03 Nm/kg in the transverse plane). Ten of our patients had only two radiographs each; therefore, the quality of these wear-rate calculations may have suffered. Two observers independently measured the wear rate, and only patients with an ICC greater than 0.90 were included. This makes the inclusion of reading errors unlikely, but cannot account for inferior radiographs in the first place. Moreover, two patients with wear rates between 0.4 and 1.0 mm per year (0.68 and 0.97 mm/year) were excluded from our study. These two patients were not removed because of having a high wear rate but because their wear rate was more than three times the interquartile range from the rest of the data and caused a prediction gap in the dataset. Ignoring these outliers would have affected the prediction accuracy of the MLR and ANN. For example, the accuracy of the ANN would have been reduced by 10%. For these prediction models it is necessary to have a sufficient number of patients to uniformly cover the whole data range. In the future the model could be expanded to include extreme wear.

Historically, gait pattern has not been implicated as a wear factor of polyethylene in THR, but for the first time, to our knowledge, we document this relationship. Despite the availability of newer materials that seem to marginalize the wear problem, the observed relationship is of more than academic value. A patient's gait pattern provides information beyond loading of the hip during walking and should be considered a potential (mechanical) biomarker. In addition, the interdependence between component positioning and gait in the wear outcome is clinically relevant. Thus, to minimize wear, the ideal placement of implant components should be determined from the individual gait pattern. In the future, with the availability of modern technology (such as inertial measurement units), gait analysis will become a more-widespread and accessible tool in hospitals. Therefore, a patient's gait pattern should become part of the clinical evaluation for THR. A predictive wear model then might identify individual wear factors, which are modifiable, either during surgery with the appropriate component placement or after surgery through gait retraining.

Our predictive wear model consists of two steps: (1) LDA to estimate the level of wear (low, moderate, or high) from gait and implant-positioning parameters, and (2) ANN (or MLR) to further estimate the contribution of wear factors and the exact wear value. Before designing such a two-step predictive model, we attempted to design a one-step wear-predictive model that consisted of only one regression model (ANN or MLR). The models could predict the wear rate with an average accuracy of 65% for ANN and 32% for MLR. The low prediction accuracy may be related to two reasons: (1) there is no reasonable relationship between input and output and (2) the statistical model is only incompletely trained. In our case, we believe the latter is true, because the limited number of patients (73) and high interpatient variability of wear rates (range, 0.001–0.4) prevented meaningful training of a one-step ANN model. In addition, for the two-step model herein, a priori knowledge of a patient's wear class is not required and knowledge of gait and implant-positioning variables are sufficient.

Our predictive model showed that patient-specific wear rates are associated with the patients' gait patterns. Gait was found to have a greater influence on the wear rate than surgical positioning variables, which suggests that gait analysis should become part of the clinical evaluation process for THR. We believe that the consideration of individual gait bears potential to further reduce implant wear. In the future, a predictive wear model might identify individual wear factors that could be modified during surgery or after surgery through gait retraining. Although the findings are based on traditional polyethylene, the concept is applicable to modern materials.

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