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1 Fast reconstruction of centre of mass and foot kinematics during a single-legged horizontal
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21 **Abstract**

22 Horizontal jumps are discrete, fast, over-ground movements requiring coordination of the
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25 assessment. In this paper, we describe a practical system which uses a single low-cost depth-
26 sensing camera and point-cloud processing (PCP) to capture feet and centre of mass (CoM)
27 kinematics. Fourteen participants performed 10 single-leg horizontal jumps for distance. Foot
28 displacement, CoM displacement, CoM peak velocity and CoM peak acceleration in the
29 anterior-posterior direction of movement were compared with a reference 15-segment criterion
30 model, captured concurrently using a nine-camera motion capture system (Vicon Motion
31 Systems, UK). Between-system Pearson's correlations were very-large to near-perfect ($n =$
32 140; foot displacement = 0.99, CoM displacement = 0.98, CoM peak velocity = 0.97, CoM
33 peak acceleration = 0.79), with mean biases being trivial–small (-0.13cm, 3.8cm, $0.03\text{m}\cdot\text{s}^{-1}$,
34 $0.42\text{ m}\cdot\text{s}^{-2}$, respectively) and typical errors being small for foot and CoM displacement (0.96
35 cm and 3.8 cm) and CoM peak velocity ($0.07\text{ m}\cdot\text{s}^{-1}$), and moderate for CoM peak acceleration
36 ($0.72\text{ m}\cdot\text{s}^{-2}$). Limits of agreement were -1.9cm to 2.0cm for foot displacement, -11.3cm to
37 3.6cm for CoM displacement, -0.17 to $0.12\text{m}\cdot\text{s}^{-1}$ for CoM peak velocity and -2.28 to $1.43\text{m}\cdot\text{s}^{-2}$
38 for CoM peak acceleration. The single camera system using PCP was able to capture foot and
39 CoM kinematics during horizontal jumps with acceptable precision. Further work to improve
40 estimates of CoM accelerations and validation across a wider range of populations are
41 warranted.

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87 There are several emerging technologies for the simultaneous measurement of foot and CoM
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102 To date, PCP has so far been restricted to the analysis of cyclical, slow and relatively stationary
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113 **Methods**

114 The study received ethical approval from The University of Sunderland's Ethics committee.
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119 *Depth sensor system:* A low-cost depth sensing camera (Kinect™ V2, Microsoft, USA) was
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134 *Criterion three-dimensional system:* The criterion method of quantifying foot and CoM
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136 Oxford, UK) at 100 Hz. Using a 19-segment plug-in gait model, markers were placed
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139 *Data processing:* The positional data from both systems were differentiated to yield
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142 data (not shown) as anchor points (20% and 55% of the cycles, respectively). The normalised
143 data were processed to yield outcome measures of jump performance, which were:
144 displacement of the feet (cm) defined the distance between the right and left toes at 20% and
145 55%, respectively; displacement of the CoM (cm) defined as the distance between 20% and
146 55%; peak velocity and acceleration defined as the highest positive velocity and acceleration
147 in the anterior-posterior direction throughout the cycle.

148 *Statistical Analysis:* Since our aims are to assess the agreement between two measurement
149 systems, rather than to examine any biological outcomes, data from all participants (n = 14)
150 and their trials (n = 10 pp) were treated as independent measures (i.e., n = 140 datapoints per
151 outcome measure). We used separate linear regressions (SPSS Version 24, IBM Corp.,
152 Armonk, NY, USA) to examine the criterion-related validity of the foot displacement and COM
153 kinematics. Criterion-derived values of the outcome measures were entered as separate
154 dependent variables and the corresponding PCP-derived values were entered as independent
155 variables. Relationship strength was quantified with Pearson's product moment correlation
156 coefficient (r), with the associated R^2 value (coefficient of determination) used to express the

157 proportion of explained variance. Additionally, the intraclass correlation coefficient was
158 calculated using a two-way mixed effects model ($ICC_{3,1}$), but these are not reported as values
159 were all within ± 0.0002 of the Pearson's r for displacement and velocity and ± 0.0274 for
160 accelerations. Typical errors ([TE], or standard errors of the estimate) were used to represent
161 unexplained (random) bias. The mean difference between PCP and the criterion was used to
162 represent systematic (mean) bias. Finally, Bland & Altman's 95% limits of agreement were
163 calculated by adding and subtracting 1.96 times the standard deviation of the difference (PCP–
164 criterion) in paired measurements (Bland and Altman, 1986).

165 Uncertainty in all estimates were expressed using 90% confidence limits (CL), calculated from
166 the t -distribution for mean differences, the z -distribution for (transformed) correlation
167 coefficients and the chi-squared distribution for SEE. We declared the magnitude of correlation
168 coefficients as small moderate, large, very large and near perfect based on standardized anchors
169 of 0.1, 0.3, 0.5, 0.7 and 0.9, respectively (Hopkins et al., 2009). To provide a real-world
170 interpretation of mean bias, we used 0.2, 0.6 and 1.2 of the pooled between-participant standard
171 deviation for each outcome metrics to represent small, moderate and large differences (Hopkins
172 et al., 2009). These thresholds were then halved to declare practical magnitudes of SEEs (Smith
173 & Hopkins, 2011). All analyses were performed in SPSS (Version 24, IBM Corp., Armonk,
174 NY, USA) and Microsoft Excel (Version 16.28, Microsoft, Redmond, WA, USA).

175 **Results**

176 The results of the validity analysis are shown in Table 1 and Figure 1c. The association (r)
177 between the systems for outcome measures were near perfect for foot displacement, CoM
178 displacement and peak velocity, and very large for peak acceleration. Mean biases were trivial
179 for total displacement ($\sim 3\%$) and peak velocity ($\sim 1.5\%$), and trivial-to-small for peak
180 acceleration ($\sim 1-7\%$) of the COM. The typical errors were small for foot displacement ($\sim 1\%$),
181 CoM displacement ($\sim 3\%$) and CoM peak velocity ($\sim 4\%$), and moderate for CoM peak
182 acceleration ($\sim 16\%$). The limits of agreement (Figure 1c) for foot displacement (-1.9cm to
183 2.0cm), CoM displacement (-11.3cm to 3.6cm), CoM peak velocity (-0.17 to 0.12m.s⁻¹) and
184 CoM peak acceleration (-2.28 to 1.43m.s⁻²).

185 **Discussion**

186 Biomechanical analysis of movement screening tests could play an important role in both
187 athletic and clinical settings. In these areas, expediency and validity are highly valued.
188 Following a ten-minute setup, the system was able run continuously to capture and display
189 outcome measures within 300ms of task completion. The novel PCP-based system developed
190 showed excellent concurrent validity with a 3D motion analysis system in tracking CoM and
191 feet simultaneously during a single-legged horizontal jump. Typical errors between the systems
192 in foot displacements were 0.94 cm ($< 1\%$) which are considered acceptable in field-testing
193 (McCubine et al., 2017). The errors in CoM displacement were 3.8 cm, being similar to other
194 practical measures used in gait research (3 cm, Yang and Pai, 2014; 4 cm Huntley et al., 2017)
195 but slightly larger than those from inertial suits (2.6 cm, Fasel et al., 2017). As with most areas
196 of biomechanics, an optimal trade-off may exist between accuracy, practicality, and cost
197 (Devetaka et al., 2019); this will depend largely on how accurate the system needs to be.
198 Accordingly, we provided a more practical (real-world) interpretation of our findings for this

199 task and found trivial mean biases for all outcome measures, with typical errors being trivial
200 for displacement, small for velocity and large for accelerations. Our data therefore suggest that,
201 although not perfect, both foot and CoM displacement can be quantified with acceptable
202 precision to detect small but worthwhile changes. However, velocities and accelerations may
203 need further work, and this may entail higher resolution, multiple cameras and/or higher
204 sampling frequency.

205 There are important limitations to this study. First, the current single camera was only able to
206 capture at 30Hz, a possible reason for the only moderate accuracy for the peak accelerations
207 (~16%). Further improvements such as higher sampling or multiple cameras may be required
208 to quantify acceleration-based CoM variables. Second, our sample was quite homogeneous in
209 terms of sex and training status; thus, the accuracy of the system may not be representative of
210 that in other populations. For example, highly trained (elite) athletes may produce faster
211 velocity and acceleration during jump tasks, and further examination of validity at these faster
212 speeds of capture would seem warranted. Third, and finally, we have not modelled all possible
213 performance outcomes related to the foot and CoM relationship: it is not known how these
214 errors propagate when other measures, such as dynamic balance (Hrysomallis, 2011), are
215 calculated.

216 **Conflict of interest statement**

217 At the time of this research, IS and MP were providing consultancy support to Pro Sport
218 Support Ltd—a company seeking the development and commercial sale of practical, marker-
219 based tracking systems for athletic movement screening. The novel PCP-based system for
220 assessing horizontal jumps forms part of an athlete assessment tool (AMAT Performance, Pro
221 Sport Support Ltd, UK) and is currently in use in football academies (Laas et al., 2020).

222 **Funding Sources**

223 The project received government funding from a Knowledge Transfer Partnership (Innovate
224 UK) to Pro Sport Support Ltd and Teesside University (KTP 009965).

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75 *Statistical Analysis:* Since our aims are to assess the agreement between two measurement
76 systems, rather than to examine any biological outcomes, data from all participants (n = 14)
77 and their trials (n = 10 pp) were treated as independent measures (i.e., n = 140 datapoints per
78 outcome measure). We used separate linear regressions (SPSS Version 24, IBM Corp.,
79 Armonk, NY, USA) to examine the criterion-related validity of the foot displacement and COM
80 kinematics. Criterion-derived values of the outcome measures were entered as separate
81 dependent variables and the corresponding PCP-derived values were entered as independent
82 variables. Relationship strength was quantified with Pearson's product moment correlation
83 coefficient (r), with the associated R^2 value (coefficient of determination) used to express the

84 proportion of explained variance. Additionally, the intraclass correlation coefficient was
85 calculated using a two-way mixed effects model ($ICC_{3,1}$), but these are not reported as values
86 were all within ± 0.0002 of the Pearson's r for displacement and velocity and ± 0.0274 for
87 accelerations. Typical errors ([TE], or standard errors of the estimate) were used to represent
88 unexplained (random) bias. The mean difference between PCP and the criterion was used to
89 represent systematic (mean) bias. Finally, Bland & Altman's 95% limits of agreement were
90 calculated by adding and subtracting 1.96 times the standard deviation of the difference (PCP–
91 criterion) in paired measurements (Bland and Altman, 1986).

92 Uncertainty in all estimates were expressed using 90% confidence limits (CL), calculated from
93 the t -distribution for mean differences, the z -distribution for (transformed) correlation
94 coefficients and the chi-squared distribution for SEE. We declared the magnitude of correlation
95 coefficients as small moderate, large, very large and near perfect based on standardized anchors
96 of 0.1, 0.3, 0.5, 0.7 and 0.9, respectively (Hopkins et al., 2009). To provide a real-world
97 interpretation of mean bias, we used 0.2, 0.6 and 1.2 of the pooled between-participant standard
98 deviation for each outcome metrics to represent small, moderate and large differences (Hopkins
99 et al., 2009). These thresholds were then halved to declare practical magnitudes of SEEs (Smith
100 & Hopkins, 2011). All analyses were performed in SPSS (Version 24, IBM Corp., Armonk,
101 NY, USA) and Microsoft Excel (Version 16.28, Microsoft, Redmond, WA, USA).

102 **Results**

103 The results of the validity analysis are shown in Table 1 and Figure 1c. The association (r)
104 between the systems for outcome measures were near perfect for foot displacement, CoM
105 displacement and peak velocity, and very large for peak acceleration. Mean biases were trivial
106 for total displacement ($\sim 3\%$) and peak velocity ($\sim 1.5\%$), and trivial-to-small for peak
107 acceleration ($\sim 1-7\%$) of the COM. The typical errors were small for foot displacement ($\sim 1\%$),
108 CoM displacement ($\sim 3\%$) and CoM peak velocity ($\sim 4\%$), and moderate for CoM peak
109 acceleration ($\sim 16\%$). The limits of agreement (Figure 1c) for foot displacement (-1.9cm to
110 2.0cm), CoM displacement (-11.3cm to 3.6cm), CoM peak velocity (-0.17 to 0.12m.s⁻¹) and
111 CoM peak acceleration (-2.28 to 1.43m.s⁻²).

112 **Discussion**

113 Biomechanical analysis of movement screening tests could play an important role in both
114 athletic and clinical settings. In these areas, expediency and validity are highly valued.
115 Following a ten-minute setup, the system was able run continuously to capture and display
116 outcome measures within 300ms of task completion. The novel PCP-based system developed
117 showed excellent concurrent validity with a 3D motion analysis system in tracking CoM and
118 feet simultaneously during a single-legged horizontal jump. Typical errors between the systems
119 in foot displacements were 0.94 cm ($< 1\%$) which are considered acceptable in field-testing
120 (McCubine et al., 2017). The errors in CoM displacement were 3.8 cm, being similar to other
121 practical measures used in gait research (3 cm, Yang and Pai, 2014; 4 cm Huntley et al., 2017)
122 but slightly larger than those from inertial suits (2.6 cm, Fasel et al., 2017). As with most areas
123 of biomechanics, an optimal trade-off may exist between accuracy, practicality, and cost
124 (Devetaka et al., 2019); this will depend largely on how accurate the system needs to be.
125 Accordingly, we provided a more practical (real-world) interpretation of our findings for this

126 task and found trivial mean biases for all outcome measures, with typical errors being trivial
127 for displacement, small for velocity and large for accelerations. Our data therefore suggest that,
128 although not perfect, both foot and CoM displacement can be quantified with acceptable
129 precision to detect small but worthwhile changes. However, velocities and accelerations may
130 need further work, and this may entail higher resolution, multiple cameras and/or higher
131 sampling frequency.

132 There are important limitations to this study. First, the current single camera was only able to
133 capture at 30Hz, a possible reason for the only moderate accuracy for the peak accelerations
134 (~16%). Further improvements such as higher sampling or multiple cameras may be required
135 to quantify acceleration-based CoM variables. Second, our sample was quite homogeneous in
136 terms of sex and training status; thus, the accuracy of the system may not be representative of
137 that in other populations. For example, highly trained (elite) athletes may produce faster
138 velocity and acceleration during jump tasks, and further examination of validity at these faster
139 speeds of capture would seem warranted. Third, and finally, we have not modelled all possible
140 performance outcomes related to the foot and CoM relationship: it is not known how these
141 errors propagate when other measures, such as dynamic balance (Hrysomallis, 2011), are
142 calculated.

143 **Conflict of interest statement**

144 At the time of this research, IS and MP were providing consultancy support to Pro Sport
145 Support Ltd—a company seeking the development and commercial sale of practical, marker-
146 based tracking systems for athletic movement screening. The novel PCP-based system for
147 assessing horizontal jumps forms part of an athlete assessment tool (AMAT Performance, Pro
148 Sport Support Ltd, UK) and is currently in use in football academies (Laas et al., 2020).

149 **Funding Sources**

150 The project received government funding from a Knowledge Transfer Partnership (Innovate
151 UK) to Pro Sport Support Ltd and Teesside University (KTP 009965).

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Figure Legends

Figure 1.

a) A schematic view of the movements of the skeleton during a single-legged jump (right to left). Note the AP displacements are accentuated for visual purposes. Between 0 to 10% the CoM moves laterally to above the position of the standing foot and the landing foot leaves the floor. During this initial period, there is flexion of the trunk, right hip, right knee and right ankle while the body created a shallow countermovement. At the same time, the athlete begins to shift the CoM anteriorly relative to the base of support thus creating anterior misalignment between the COM and base of support. The athlete then accelerate horizontally during the push-off (0-30%) during which time there is extension at the ankle, knee and hip. The peak height of the CoM occurs between 30 and 40% and for a short period (approximately 5% of the cycle) during which time the body is in free fall. The landing foot then hits the floor (approximately 60%) and the CoM is decelerated. The athlete attempts to control the CoM above the base of support provided by the landed foot and hold this position until the end of the trial. Failure to do so resulted in a retrieval after a 1min rest. The jumps were performed in the AP direction towards the camera.

b) Time-normalised kinematics from Vicon (blue) and PCP (yellow) (mean \pm SD) for the CoM in the AP direction (n= 1200) are shown. Overlapping regions of the standard deviations are shown in green. Note that all y-axes are scaled to span the range between maximal and minimal data points on the time-series.

c) Limits of agreements (Bland and Altman,1986) for the two systems ($\pm 1.96SD$) for foot displacement (i), CoM displacement (ii), CoM peak velocity (iii) and CoM peak acceleration (iv).

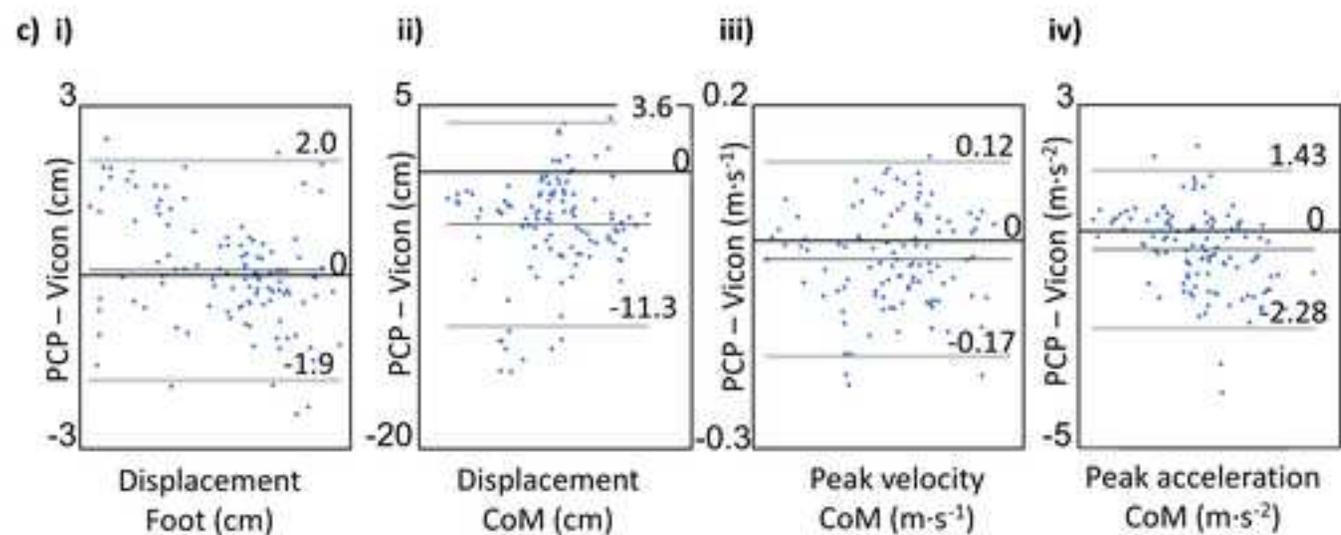
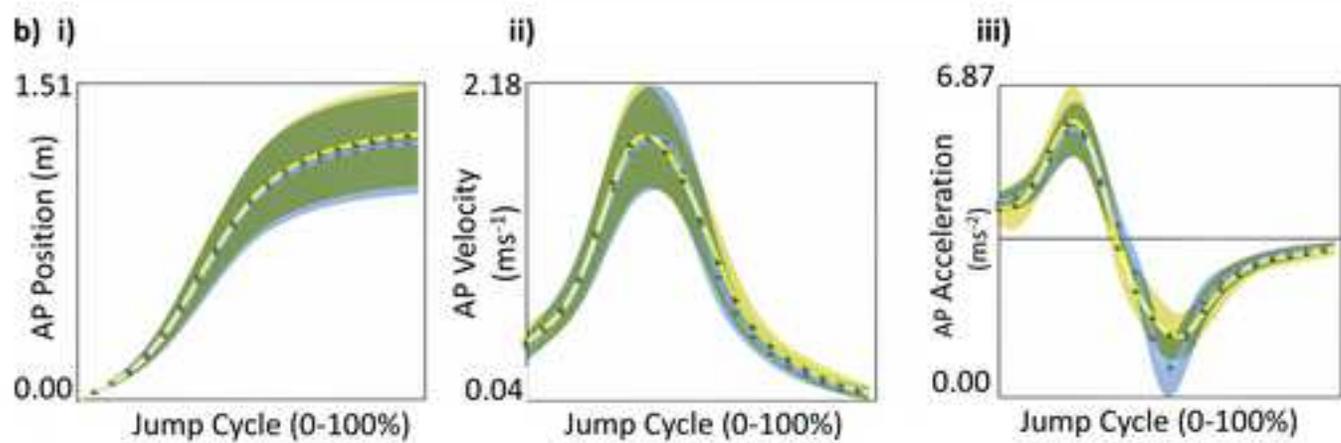
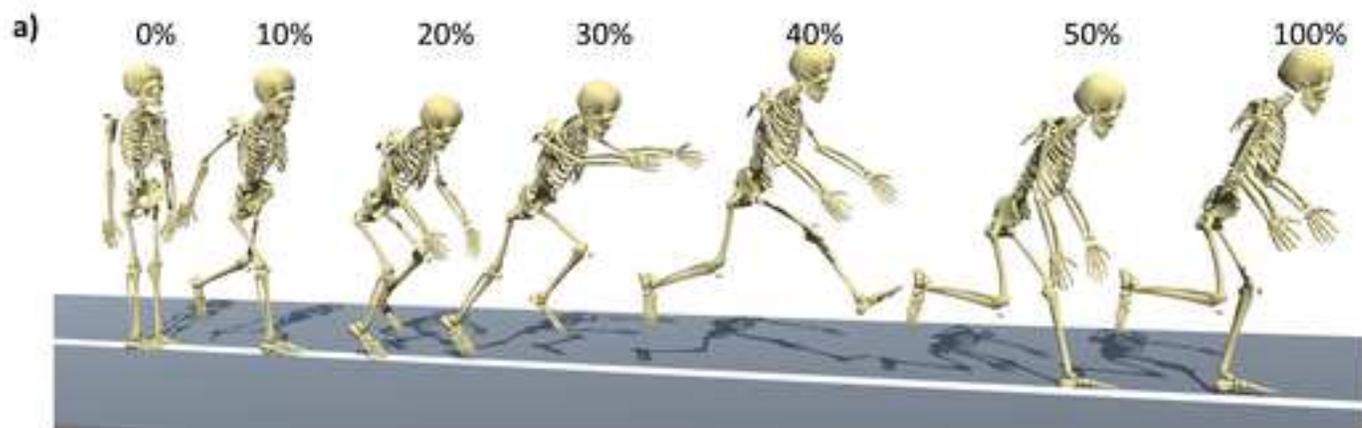


Table 1. Validity analysis between point-cloud processing (PCP) and criterion-derived estimates of jump performance during the single-leg jump

Outcome Measure	Performance* (mean \pm SD)	<i>r</i> (\pm90% CL)*	<i>R</i>²	Mean bias (\pm90% CL)	Typical Error (\times/\div90% CL)
Displacement Foot (cm)	140.5 \pm 27.2	0.999; \pm 0.0002	0.999	-0.07 (0.15)	0.92 (1.12)
Total displacement CoM (cm)	126.5 \pm 21.2	0.983; \pm 0.005	0.967	3.84 (0.6)	3.83 (1.12)
Peak velocity CoM (m·s ⁻¹)	1.84 \pm 0.30	0.973; \pm 0.009	0.946	0.03 (0.01)	0.07 (1.12)
Peak acceleration CoM (m·s ⁻²)	5.49 \pm 1.46	0.792; \pm 0.059	0.627	0.42 (0.15)	0.72 (1.12)

*from the PCP

CL, confidence limits.

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