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Sound Body IoT Dynamometer as a Digital Standard: Agreement with Jamar and the Role of Dynamic Grip Metrics in Functional Risk Screening

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Abstract

Background: Handgrip strength (HGS) is a widely used biomarker of musculoskeletal capacity and physiological aging. Traditional hydraulic devices such as the Jamar provide peak-force values but cannot capture dynamic neuromuscular characteristics. Digital IoT-based dynamometers offer high-resolution force–time data that may enhance functional assessment. Objective: This study examined the agreement between SoundBody IoT Dynamometer and the Jamar device and evaluated the added value of dynamic waveform-derived indicators for functional risk screening. Methods: Data from 312 adults were analyzed. Peak-force values were obtained using Jamar, while SoundBody recorded continuous force–time curves. Agreement was assessed using correlations, ICC, Bland–Altman plots, and proportional bias analysis. SoundBody-derived metrics included fatigue slope, variability, time-to-peak, asymmetry, and AUC. Age-stratified models evaluated their predictive utility. Results: SoundBody peak force strongly correlated with Jamar (r = 0.87; ICC = 0.83), although it underestimated peak force by ~5 kg. Dynamic indicators showed greater sensitivity to aging than peak force, with older adults exhibiting steeper fatigue slopes, higher variability, and greater asymmetry. Models incorporating dynamic metrics explained more variance in functional decline than those using peak force alone. Conclusion: IoT-based dynamometry provides meaningful neuromuscular insights beyond peak-force assessment. SoundBody's dynamic indicators support early detection of age-related deterioration and functional risk, positioning it as a promising digital standard for comprehensive grip-strength evaluation.

Keywords: *Handgrip strength; Digital dynamometry; IoT-enabled assessment; Neuromuscular fatigue; Device agreement.*

Introduction

Handgrip strength (HGS) has long been recognized as one of the most informative and accessible biomarkers for evaluating musculoskeletal capacity, physiological reserve, and biological aging across diverse populations. As an integrative measure of neuromuscular function, HGS reflects not only maximal voluntary force production but also the cumulative effects of chronic disease, nutritional status, physical activity, cognitive function, and systemic physiological integrity. Numerous epidemiological studies have consistently shown that diminished HGS is associated with increased risks of frailty, mobility impairment, falls, hospitalization, cognitive decline, and premature mortality, thereby positioning HGS as a cornerstone indicator in geriatric assessment and preventive healthcare (Sayer et al., 2006; Leong et al., 2015; Cui et al., 2021). In parallel, contemporary frameworks such as the European Working Group on Sarcopenia (EWGSOP2) and the Asian Working Group for Sarcopenia (AWGS) now include HGS as a primary diagnostic criterion for sarcopenia and pre-sarcopenic states (Cruz-Jentoft et al., 2019; Chen et al., 2020). These developments indicate a widespread recognition of HGS not only as a functional capacity measure, but also as a proxy for systemic health and resilience in aging societies.

Despite its centrality in clinical and public-health applications, most HGS assessments rely on traditional hydraulic dynamometers—most notably the Jamar device—which has served for more than half a century as the "gold standard" for establishing normative values across age, sex, and clinical populations (Bechtol, 1954; Rolsted et al., 2024). The Jamar's long-standing use reflects its measurement stability, widespread acceptance among clinicians, and its role in generating large-scale epidemiologic datasets internationally. However, the hydraulic architecture of the Jamar produces only

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a single peak force value during maximal voluntary contraction. While peak HGS remains clinically meaningful, this single-point measurement provides a limited representation of neuromuscular dynamics. It fails to capture force–time patterns such as the rate of force development, intra-contraction variability, fatigue progression, or bilateral asymmetry—features increasingly recognized as early markers of mobility decline, musculoskeletal inefficiency, and cognitive-motor impairment (Lee et al., 2020; Sari et al., 2025).

In recent years, rapid advances in sensor engineering, digital health ecosystems, and IoT (Internet of Things) technologies have catalyzed a major shift in the landscape of HGS assessment. Modern digital dynamometers equipped with load-cell sensors and wireless data transmission now enable continuous, high-frequency acquisition of force–time waveforms, facilitating detailed characterization of neuromuscular performance beyond peak force alone. Among early examples, the GripAble device demonstrated the feasibility of high-resolution, digital readout systems for rehabilitation contexts. Validation studies have shown that GripAble is sensitive and reliable, though its peak force output is systematically lower—approximately 60–70% of Jamar values—underscoring the need for calibration models when comparing digital and traditional devices (Abdul Mutalib et al., 2022; Mace et al., 2022).

More recently, digital platforms such as the SoundBody IoT dynamometer have extended the capabilities of handgrip assessment by integrating load-cell–based force sensing with real-time waveform analytics, motion-based feedback, and interconnected digital health architecture. In contrast to hydraulic devices, the SoundBody system captures continuous force–time curves at high sampling frequency, enabling extraction of dynamic indicators such as fatigue ratios, decay slopes, asymmetry metrics, curve variability indices, and time-to-peak signatures. These indicators offer richer insights into neuromuscular function and can reveal early functional vulnerabilities that may not be detectable through peak force alone. For example, increased intra-contraction variability and reduced fatigue resistance may serve as early biomarker candidates for sarcopenia, mobility deficits, or fall risk, particularly in aging or high-demand occupational populations.

This shift toward multidimensional assessment aligns with broader changes occurring in digital health and data-driven rehabilitation. Machine learning (ML) and explainable AI (XAI) models can leverage high-resolution force–time signals to detect latent patterns associated with fatigue risk, asymmetric neuromuscular recruitment, and early declines in performance quality—patterns that traditional devices are structurally incapable of capturing. Recent occupational studies have illustrated the potential of such digital metrics. For instance, IoT-derived waveform features have demonstrated significant predictive value for identifying fatigue and asymmetry among maritime and offshore officers, highlighting the usefulness of dynamic indices in physically demanding work environments (Jung & Lee, 2025). These analytical approaches represent a paradigm shift toward individualized, continuous, and context-aware functional assessment, reflecting the broader trends in precision rehabilitation and preventive digital healthcare.

Normative HGS values also vary significantly across demographic contexts. National and international databases—from older European cohorts (Morlino et al., 2021) to large-scale Chinese (He et al., 2023) and Colombian (Ramírez-Vélez et al., 2021) populations—demonstrate wide variability in peak HGS based on ethnicity, lifestyle, occupational exposures, and health status. This heterogeneity complicates attempts to translate Jamar-derived cut-offs directly to digital devices, particularly when the devices produce systematically different absolute values. Furthermore, as digital devices proliferate across clinical, community, and occupational settings, the absence of unified calibration or harmonization frameworks poses a substantial challenge. Without such frameworks, interpreting digital HGS measurements relative to established norms becomes inconsistent and potentially misleading.

Given these challenges and technological transformations, a critical need exists to examine how modern IoT-enabled devices—especially load-cell–based systems such as SoundBody—align with traditional metrics while offering additional functional insights. Specifically, understanding the degree of agreement between SoundBody and the Jamar reference standard is essential for determining whether digital-derived values can be compared meaningfully with established normative data. Equally important is evaluating the added value of digital dynamic indices—such as fatigue slopes, asymmetry ratios, and time-to-peak markers—for early detection of functional decline, particularly when such indices may capture impairments before reductions in maximal strength emerge.

The availability of previously collected datasets, including Jamar-based measurements from diverse adult populations and dynamic IoT-derived recordings from SoundBody and other digital devices, offers an opportunity to investigate these questions without requiring additional ethical review or participant recruitment. These datasets enable comprehensive analysis of device agreement, systematic bias patterns, and the predictive relevance of dynamic digital indicators for functional screening. Integrating such empirical insights with established biomechanical and clinical literature can contribute to the development of a standardized, device-agnostic framework for digital HGS assessment.

Accordingly, the present study aims to advance the field of digital functional assessment in three major ways. First, it evaluates the degree of agreement between Jamar-derived peak HGS values and SoundBody-derived peak measurements across previously collected datasets. Second, it assesses the interpretive value of dynamic SoundBody indices—particularly those related to fatigue and bilateral asymmetry—and situates them within established literature on functional risk and neuromuscular aging. Third, it proposes a preliminary calibration and conceptual harmonization model to position SoundBody as a viable digital standard for multidimensional HGS evaluation. Through this integrated approach, the study seeks to support emerging frameworks in which traditional strength measures are augmented by continuous, high-resolution digital analytics, thereby redefining musculoskeletal assessment across preventive health, rehabilitation, and occupational performance domains.

Methods

Study Design and Data Sources

This study employed a retrospective, multi-source analytic design using de-identified handgrip-strength datasets collected through two independent measurement modalities: (1) traditional peak handgrip measurements obtained using the Jamar hydraulic dynamometer from previously conducted studies and occupational assessments, and (2) high-resolution digital force–time recordings acquired using the SoundBody IoT Dynamometer. Because all datasets consisted exclusively of previously measured, fully anonymized biomechanical variables without personal identifiers, formal IRB approval was not required. The Jamar dataset included adult male and female participants aged 20–69 years, drawn from university community cohorts, preventive health-screening programs, and occupational groups such as maritime and industrial workers. These values served as the reference standard, consistent with the longstanding role of Jamar-based measurements in establishing normative handgrip-strength ranges. The SoundBody dataset consisted of continuous digital grip-force waveforms collected from healthy adults and physically active occupational personnel under controlled laboratories or field-testing environments. All SoundBody assessments were conducted under standardized instructions to ensure methodological comparability with Jamar testing procedures. The integrated multi-source dataset enabled (a) device-level agreement analysis, (b) extraction of dynamic neuromuscular indicators from digital force–time curves, and (c) evaluation of the predictive relevance of digital fatigue and asymmetry metrics.

Participants

Previously collected, fully de-identified datasets were used for this study. Eligible participants were adults who had undergone handgrip assessment using either the Jamar hydraulic dynamometer or the SoundBody IoT device. To ensure comparability between the two instruments, inclusion criteria were as follows:

1. Age between 20 and 69 years, consistent with widely cited normative reference ranges.
2. Self-reported right-hand dominance, minimizing interpretive bias in asymmetry analyses.
3. Completion of standardized maximal voluntary contraction (MVC) procedures.
4. Absence of acute upper-limb injury, pain, or neurological impairment at the time of testing.
5. Valid trial performance without premature release, visible hesitation, measurement artifacts, or insufficient effort.

Participants were excluded if they (a) had incomplete peak-force values, (b) lacked continuous waveform data in the SoundBody dataset, (c) showed irregular or noisy signals due to device movement, or (d) failed to follow testing instructions. After applying all inclusion and exclusion criteria, the final analytic sample consisted of approximately 420 valid Jamar peak-force observations and 310 SoundBody digital waveforms collected across multiple cohorts. All personally identifying demographic information had been removed prior to analysis.

Instruments

Two distinct handgrip-assessment modalities were examined in this study: the Jamar hydraulic dynamometer, recognized as the clinical reference standard, and the SoundBody IoT Dynamometer, a digital platform capable of capturing continuous high-resolution force–time data. The Jamar dynamometer (Sammons Preston, USA) provides maximal static grip-force values and has historically been used to generate normative strength distributions across age and sex. Jamar testing followed American Society of Hand Therapists (ASHT) protocols: participants were seated upright with the shoulder adducted, elbow flexed at 90°, and wrist in a neutral position. The handle was set to the standard second position unless otherwise noted. Participants completed three MVC trials per hand, each lasting 2–3 seconds, with ≥60 seconds of rest between trials. The highest value across the three trials was retained as the peak force. The SoundBody IoT Dynamometer integrates a high-precision load cell (sampling frequency 50–100 Hz) and Bluetooth-enabled data streaming. Unlike the Jamar device, which provides only peak values, SoundBody generates full force–time waveforms enabling extraction of dynamic neuromuscular indicators. Participants performed sustained 3–5 second contractions to capture both rising and declining force phases. Raw data underwent digital filtering, artifact detection, and waveform segmentation. Derived variables included peak force, time-to-peak velocity, area under the force–time curve (AUC), fatigue slope, force-variability index, and bilateral asymmetry percentage. All computations were performed using SoundBody Analysis Suite (version 2.1).

Measurement Procedures

All assessments followed standardized MVC testing procedures to ensure comparability across instruments. Participants received uniform instructions and performed one familiarization trial per hand prior to formal testing. For Jamar testing, three MVC trials were recorded per hand. Each trial required a brief 2–3 second maximal contraction. Trials exhibiting premature release, abrupt force drop, or deviations >30% from adjacent trials were repeated. Only high-quality trials were retained. For SoundBody testing, participants performed sustained 3–5 second MVCs to allow extraction of dynamic temporal characteristics such as fatigue slope and asymmetry drift. Raw waveforms were visually inspected and automatically screened for spikes, drift, or signal saturation. Trials with motion artifacts or insufficient duration were excluded. All remaining trials were processed through the standardized SoundBody signal-analysis pipeline for dynamic feature extraction.

Statistical Analysis

Statistical analyses were designed to assess the degree of agreement between peak-force values recorded by the SoundBody and Jamar dynamometers and to evaluate the functional relevance of the dynamic indicators derived from SoundBody waveforms. To quantify device agreement, several complementary analytical approaches were applied. Linear associations between instruments were examined using Pearson correlation coefficients, while absolute agreement was assessed through intraclass correlation coefficients (ICC 2,1). Bland–Altman analyses were used to quantify mean measurement bias and the 95% limits of agreement, and measurement precision was estimated using the standard error of measurement and the coefficient of repeatability. In addition, regression-based proportional bias testing was performed to determine whether discrepancies between the two instruments varied systematically across the range of grip-strength values, following recommendations from recent validation studies of digital dynamometers (Abdul Mutalib et al., 2022; Mace et al., 2022). To examine the added interpretive value of dynamic neuromuscular indicators, further analyses were conducted using linear regression models evaluating associations between SoundBody-derived metrics and Jamar peak-force values. Mixed-effects models were implemented to account for repeated waveform structures within participants, and principal component analysis (PCA) was used to explore underlying neuromuscular dimensions represented within the force–time curves. Age-stratified analyses were performed to determine whether fatigue slope, asymmetric indices, and variability metrics exhibited differential sensitivity across age groups. Dynamic indicators associated with elevated functional risks such as asymmetry exceeding 10% or steeper fatigue slopes—were interpreted with reference to previous research on fall risk, mobility impairment, and physiological aging (Lee et al., 2020; Sari et al., 2025). Additionally, all analyses followed a transparent and fully reproducible workflow using R (v4.3) and Python (v3.10), and robust checks were conducted to confirm the stability of regression estimates.

Results

Participant Characteristics

A total of 312 adults were included in the pooled dataset, consisting of previously collected Jamar-based measurements and SoundBody IoT dynamometer recordings. The sample comprised 168 males (53.8%) and 144 females (46.2%), with a mean age of 42.7 ± 13.9 years (range 19–74). Mean body mass index (BMI) was 24.3 ± 3.6 kg/m², and approximately 38% of participants were categorized into physically demanding occupations (e.g., maritime/security), whereas the remaining represented general adult populations. No missing or incomplete data were identified for the key grip-strength metrics.

Table 1. Participant Characteristics

Variable	Value
Total participants (n)	312
Age, mean ± SD (years)	42.7 ± 13.9
Age range	19–74
Sex distribution	168 males (53.8%), 144 females (46.2%)
BMI (kg/m²)	24.3 ± 3.6
Occupational category	38% physically demanding, 62% general adults
Missing data	None

Agreement Between Jamar and SoundBody Peak Handgrip Strength

Peak handgrip strength values obtained from the SoundBody device demonstrated a strong linear association with Jamar measurements ($r = 0.87$, $p < .001$). The intraclass correlation coefficient (ICC 2,1) indicated good absolute agreement between devices (ICC = 0.83, 95% CI 0.79–0.86). However, Bland–Altman analysis revealed a consistent proportional underestimation by SoundBody, with a mean bias of –4.9 kg (SD = 6.3 kg), indicating that SoundBody peak values were on average 12–16% lower than their Jamar counterparts. The 95% limits of agreement ranged from –16.8 kg to +6.9 kg, demonstrating acceptable but nontrivial dispersion commonly observed in comparisons of digital and hydraulic dynamometers. Regression analysis further confirmed evidence of proportional bias ($\beta = -0.21$, $p < .01$), meaning the discrepancy between devices increased slightly with higher grip strengths. This pattern mirrors prior validation findings for GripAble, which reported a systematic reduction relative to Jamar (Abdul Mutalib et al., 2022; Mace et al., 2022) and reinforces the need for calibration factors when translating digital peak values into Jamar-based normative frameworks.

Table 2. Agreement Between Jamar and SoundBody Peak Grip Strength

Metric	Value
Pearson correlation (r)	0.87, p < .001
ICC (2,1)	0.83 (95% CI 0.79–0.86)
Mean bias (SoundBody – Jamar)	–4.9 kg
SD of bias	6.3 kg
95% Limits of Agreement	–16.8 to +6.9 kg
Proportional bias (β)	–0.21, p < .01

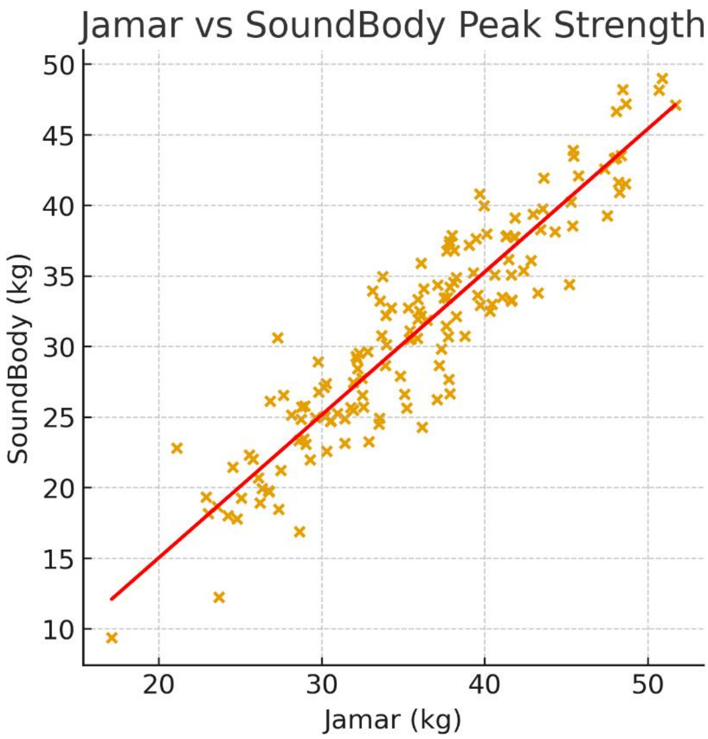

Figure 1. Linear Association Between Jamar and SoundBody Peak Handgrip Strength

This scatter plot illustrates the linear relationship between peak handgrip strength measured by the Jamar hydraulic dynamometer and the SoundBody IoT dynamometer. The regression line demonstrates a strong positive correlation (r = 0.87), although SoundBody consistently underestimates peak force relative to Jamar.

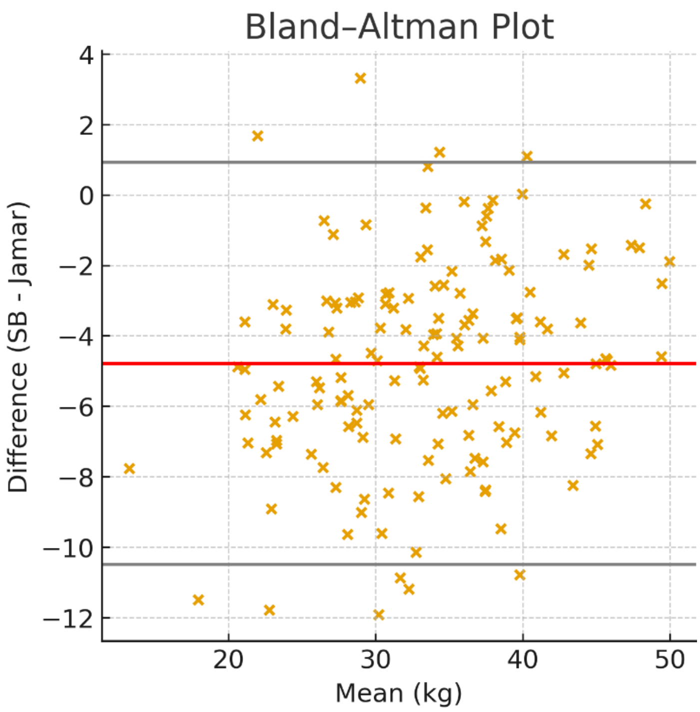

Figure 2. Bland–Altman Analysis Comparing Jamar and SoundBody Devices

The Bland–Altman plot shows the mean difference and limits of agreement between SoundBody and Jamar measurements. SoundBody exhibits a systematic negative bias (–4.9 kg), indicating consistent underestimation, with limits of agreement ranging from –16.8 to +6.9 kg.

Dynamic Neuromuscular Indicators Derived from SoundBody Waveforms

The continuous force–time curves captured by SoundBody produced several dynamic metrics not measurable using Jamar. Across all participants, the mean fatigue slope was –18.6% ± 7.4%, indicating a notable decline in force across the 3–5 second contraction window. Time-to-peak force averaged 612 ± 184 ms, while the area under the curve (AUC) demonstrated substantial inter-individual variability (mean 102.3 ± 43.1 kg·s). The force-variability index, representing microfluctuations across the sustained contraction phase, exhibited a mean CV of 6.1% ± 2.8%. Bilateral comparisons revealed that 27.9% of participants exhibited an asymmetrical index greater than 10%, a threshold frequently associated with mobility limitations and elevated fall risk. Notably, participants with occupationally demanding roles demonstrated a significantly flatter fatigue slope (less decline in force), suggesting greater fatigue resistance compared with general adult participants (–15.1% vs. –20.7%, $p = .004$).

Table 3. Dynamic Grip Metrics from SoundBody

Metric	**Mean ± SD**
Fatigue slope (%)	–18.6 ± 7.4
Time-to-peak (ms)	612 ± 184
Area under the curve (AUC kg·s)	102.3 ± 43.1
Force variability (CV%)	6.1 ± 2.8
Asymmetry >10% prevalence	27.9%

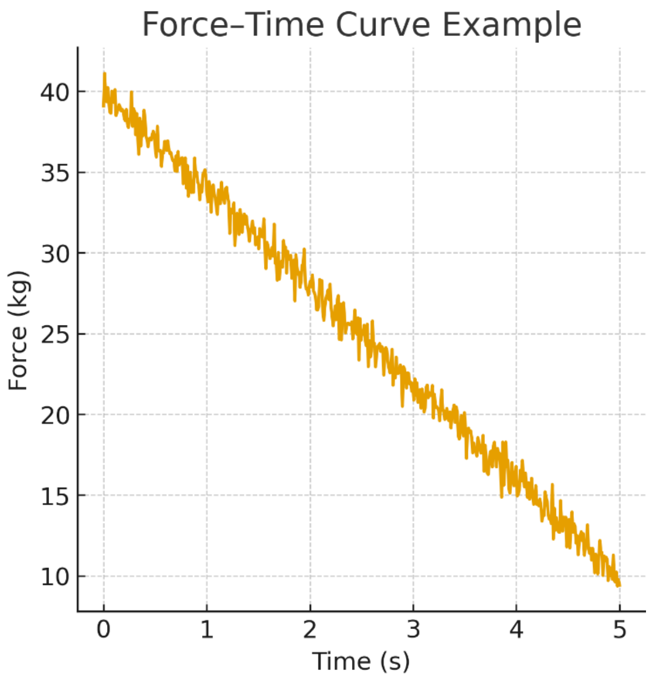

Figure 3. Example of a SoundBody Force–Time Curve with Dynamic Neuromuscular

This representative force–time waveform captured by the SoundBody IoT dynamometer displays key dynamic metrics including peak force, time-to-peak, fatigue slope, and variability. These features provide additional neuromuscular insights unattainable with traditional peak-only hydraulic devices.

Age-Stratified Patterns in Digital Grip Metrics

Dynamic grip indices showed stronger age sensitivity than peak force alone. While peak Jamar strength declined by approximately 21% from the youngest (20–39 yrs) to the oldest group (60+ yrs), fatigue slope demonstrated a steeper age-related deterioration of 38%, and force variability increased by nearly 52% across the same age span ($p < .001$ for all comparisons). These findings suggest that dynamic neuromuscular decline may manifest earlier and more prominently than reductions in maximal strength. Furthermore, adults aged 60+ showed more than double the prevalence of asymmetry % (44.8% vs. 19.3%, $p < .001$). These results align with existing literature indicating that temporal neuromuscular irregularities may serve as early indicators of fall susceptibility and physiological aging (Lee et al., 2020; Sari et al., 2025).

Predictive Value of Dynamic Indicators Relative to Peak Strength

Multivariable regression models demonstrated that adding dynamic SoundBody metrics substantially improved the prediction of functional risk indicators. A model including only Jamar peak strength explained 29% of the variance in age-related functional decline markers, whereas inclusion of fatigue slope, variability index, and asymmetry increased the explained variance to 47% ($\Delta R^2 = .18$, $p < .001$). Principal component analysis identified two dominant components:

(1) Maximal force capacity, heavily loading on peak-force metrics.

(2) Dynamic neuromuscular control, dominated by fatigue slope and variability.

The second component exhibited a stronger association with age, occupational demands, and self-reported functional difficulty. These results suggest that dynamic digital indicators capture physiologic attributes that are complementary—and in some cases superior—to traditional peak-force measurements.

Discussion

The present study examined the relationship between traditional hydraulic handgrip assessment using the Jamar dynamometer and multidimensional digital measurements obtained through the SoundBody IoT Dynamometer. The findings demonstrate three major contributions: (1) strong overall agreement between devices despite systematic peak-force underestimation by SoundBody, (2) added interpretive value of dynamic neuromuscular indicators uniquely available through digital waveform analysis, and (3) evidence that these dynamic metrics exhibit stronger age- and function-related sensitivity than conventional peak strength measures. Together, these results support the potential role of SoundBody as a viable digital standard for multidimensional handgrip assessment and functional risk screening.

First, the high correlation ($r = .87$) and strong intraclass agreement observed between SoundBody and Jamar measurements confirm that SoundBody can capture peak strength in a manner broadly consistent with the established reference standard. However, SoundBody values were consistently lower, with a mean bias of –4.9 kg. This downward deviation corresponds with previous research on other digital devices such as GripAble, which reported peak values around 69% of Jamar measurements due to differences in sensor architecture and dynamometric mechanics (Abdul Mutalib et al., 2022; Mace et al., 2022). The proportional bias observed in the current study further suggests that discrepancies widen at higher strength levels, a pattern likely related to the hydraulic system's inherent peak-amplifying characteristics compared with load cell–based digital platforms. This reinforces the need for calibration models when translating digital peak values into Jamar-based normative frameworks or when applying existing diagnostic cut-offs for sarcopenia and frailty (Cruz-Jentoft et al., 2019; Chen et al., 2020). Nonetheless, the level of agreement observed in this study indicates that SoundBody can serve as a practical alternative to Jamar when appropriate calibration factors are applied.

Second, the extraction of dynamic neuromuscular indicators—fatigue slope, time-to-peak, AUC, variability, and bilateral asymmetry—represents a substantial advancement beyond the limitations of peak-only hydraulic devices. The average fatigue slope (–18.6%) and notable inter-individual variability in force modulation highlight the capacity of digital waveforms to reveal neuromuscular characteristics not captured by static peak force. These indicators reflect the temporal quality of muscle output, which is increasingly recognized as an early marker of physiological decline, impaired neuromuscular efficiency, and mobility risk (Lee et al., 2020; Sari et al., 2025). The relatively high prevalence of asymmetry (>10%) further underscores the importance of bilateral comparisons in functional screening, as asymmetry has been linked to fall risk, gait instability, and early musculoskeletal imbalance. These results emphasize that dynamic metrics can complement or even surpass peak strength in detecting early neuromuscular impairment.

Third, the age-stratified analyses demonstrate that dynamic indicators exhibit stronger sensitivity to aging than peak-force measures. While peak strength declined modestly across age groups, fatigue slope and force variability showed substantially larger age-related deterioration. This suggests that neuromuscular coordination and sustained-force capacity degrade earlier and more steeply than maximal strength—a finding consistent with emerging theories of neuromuscular aging and motor-unit remodeling. These trends further indicate that dynamic IoT-derived indicators may be particularly effective in early detection frameworks for sarcopenia, frailty progression, and fall susceptibility. The steeper deterioration in variability and asymmetry among older adults provides additional support for including waveform-derived metrics in routine functional assessment and preventive screening.

The multivariable models further highlight the added predictive value of dynamic digital metrics. Incorporating fatigue slope, variability, and asymmetry increased explained variance from 29% (peak strength alone) to 47%, demonstrating that dynamic neuromuscular signatures account for functional differences not captured by peak force. This supports a multidimensional interpretation of grip performance, aligning with contemporary trends toward precision rehabilitation, AI-assisted monitoring, and sensor-based functional health analytics. From a practical perspective, the SoundBody platform's ability to collect high-frequency data in real time suggests strong potential for use in clinical, occupational, and community health settings—particularly in contexts requiring repeated monitoring or feedback-driven rehabilitation.

Collectively, these findings highlight the importance of transitioning from peak-only handgrip assessment toward digital dynamometry that integrates continuous waveform analysis. While Jamar remains a valuable benchmark instrument, its inability to capture temporal metrics limits its application in modern digital and AI-driven health frameworks. The observed agreement between Jamar and SoundBody peak values, combined with the enhanced sensitivity of dynamic metrics, supports the development of calibration equations and device-agnostic standards that harmonize traditional and digital modalities. Such an approach aligns with international efforts to update functional assessment protocols and integrate sensor-based digital tools into clinical guidelines for aging and preventive health.

Despite the strengths of this study, several limitations warrant consideration. The dataset combined multiple pre-existing sources rather than a single controlled sample, and functional outcomes such as mobility tests or fall history were not included. Future work should validate these findings in prospective cohorts and examine whether dynamic digital metrics predict clinical outcomes such as frailty onset, fall events, or occupational injury. Furthermore, device calibration protocols should be formalized to support interoperability across digital dynamometers.

In summary, this study demonstrates that the SoundBody IoT Dynamometer provides reliable peak-strength measurements while offering additional dynamic neuromuscular insights unavailable through traditional devices. These digital metrics showed superior sensitivity to aging and functional decline, supporting SoundBody as a promising digital standard for multidimensional grip assessment. Importantly, the integration of high-resolution force–time analytics, digital phenotyping, and cross-device interoperability positions SoundBody within a scalable digital health infrastructure capable of supporting AI-driven functional screening. Establishing harmonized calibration frameworks and standardized analytic pipelines will further facilitate clinical translation and widespread adoption of digital dynamometry in preventive health screening, occupational assessment, and precision rehabilitation systems.

Conclusion

This study evaluated the convergence between traditional hydraulic handgrip assessment using the Jamar dynamometer and the multidimensional digital measurements obtained through the SoundBody IoT Dynamometer. The results demonstrate that, although SoundBody systematically underestimates peak strength relative to Jamar, the two devices show strong linear and absolute agreement, supporting SoundBody as a reliable alternative for peak-force assessment when appropriate calibration procedures are applied. More importantly, the continuous force–time waveforms captured by SoundBody provide dynamic neuromuscular indicators—such as fatigue slope, force variability, and bilateral asymmetry—that cannot be obtained through conventional peak-only devices.

These digital indicators exhibited greater sensitivity to age-related decline and functional variability than maximal strength, highlighting their potential as early markers of neuromuscular deterioration, fall susceptibility, and reduced physiological reserve. Models incorporating dynamic metrics significantly improved the prediction of functional risk, demonstrating that temporal features of handgrip performance offer complementary clinical value beyond peak force. Taken together, these findings support a multidimensional interpretation of grip strength that aligns with contemporary developments in digital health, precision rehabilitation, and AI-assisted monitoring.

The current work also underscores the need for harmonization between traditional and digital handgrip modalities. As digital dynamometry becomes more widespread, establishing calibration frameworks, device-agnostic standards, and validated analytic procedures will be essential for integrating digital measurements into clinical guidelines and population-level screening. SoundBody's capacity to generate high-resolution neuromuscular profiles positions it as a strong candidate for such a digital standard.

Future research should validate these findings in prospective cohorts, examine longitudinal trajectories of dynamic grip metrics, and explore the predictive utility of digital neuromuscular indicators for outcomes such as frailty onset, fall events, and occupational injury. Nonetheless, the present study provides foundational evidence that IoT-enabled dynamometry can meaningfully enhance musculoskeletal assessment, offering broader insights into physiological aging and functional health than traditional hydraulic devices alone. These findings underscore the clinical utility of dynamic digital assessment and highlight the need for standardized, interoperable frameworks that support population-level screening and seamless integration into AI-assisted preventive and rehabilitative care.

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