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Altered movement dynamics in soldiers during multiple bouts of load carriage

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1. Introduction

Soldiers are required to perform demanding tasks in the most challenging environments during combat missions and training exercises that often require deployed soldiers to carry heavy loads (≥30% of body mass) for prolonged distances. Multiple days of prolonged load carriage amplifies the risk of fatigue and overuse related injuries such as stress fractures, soft tissue injury, blisters, back pain, and neuropathies, consequences of injury can be deadly (Orr et al., 2012, 2017; Knapik et al., 1992, 2004; Cohen et al., 2012; Andersen et al., 2016). Moreover, once musculoskeletal injury has occurred, there is a 7- to 10-fold increase in the likelihood of re-injury (Hill et al., 2012). Ankle injuries share a similar pattern, with the likelihood of re-injury rates from 30 to 50% (Ambrose et al., 2011; Jones et al., 1993; Kaufman et al., 2000; Wallace et al., 2011). Due to the severity and prevalence of these problems, considerable research has focused on the kinematic-kinetic changes that occur during load carriage (Kang et al., 2004; Walsh and Low, 2021). Despite this, less about how movement changes over time has been established, which may be because the existing literature overwhelmingly reported changes in movement during single, relatively brief sessions (Park et al., 2013; Majumdar et al., 2010, 2013; Lindner et al., 2012; Zenteno et al., 2012, 2013; Orr et al., 2013; Brown et al., 2016). While these findings undoubtedly contribute valuable insights, critical gaps exist in the area of nonlinear analyses of gait over multiple days. Exploring such dynamics may provide previously untapped information crucial for mitigating the risk of injury associated with the cumulative effects of fatigue.

Nonlinear analysis has proven to be a compelling tool for revealing changes to the stability and regularity of movement (Harbourne and Stergiou, 2009; Stergiou and Decker, 2011; Buzzi et al., 2003). Nonlinear measures have been extensively employed for gait when investigating the effects of aging (Buzzi et al., 2003; Voytek et al., 2015), pathology (Kaipust et al., 2012; Prabhu and Pradhan, 2016; Hausdorff, 2009), and fatigue (Schiffman et al., 2009; Cignetti et al., 2009; Ohashi et al., 2004). A systematic review conducted by our team investigating the use of nonlinear analyses for load carriage (Brink et al., 2022). Our findings revealed a lack of research investigating nonlinear changes during load carriage; rather, nonlinear analyses such as detrended fluctuation analysis (DFA) and sample entropy were performed in existing studies but only when walking in unloaded conditions, thus limiting application to load carriage gait dynamics.

Detrended fluctuation analysis and sample entropy are discussed in more detail in the Time Series Analyses section, but briefly, fractal analysis quantifies the structure of time series data and is generally used to determine the magnitude and direction of correlations in a signal (Schiffman et al., 2009). Sample entropy measures the regularity of a time series signal. In movement sciences, DFA and sample entropy have been proposed to quantify levels of complexity in movement (Yentes and Raffalt, 2021), and, as such, are useful for detecting changes (Harbourne and Stergiou, 2009; Hu et al., 2014; Soangra et al., 2018).

As mentioned, evidence from the broader literature suggests that fractal analysis and sample entropy could be effective techniques for distinguishing between loaded and unloaded walking (Brink et al., 2022). For example, Krajewski et al. (2020) had healthy females perform a walking task loaded and found a reduction in DFA output (refer to scaling exponent, α; Methods section for computational details). Orter et al. (2019) also had subjects walk with a load and Baudendistel et al. (2020) had subjects walk with weight and found an increase in sample entropy when a load was applied to the leg. These studies indicate that load could produce a shift toward ... (measured by fractal analysis) and regularity (measured by sample

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2.Methods

2.1Participants

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Table1
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Demographic	Value
N	7
Age(yeyears)	24±33.9
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Weig(hktg)	84±610.0
BodMyasIsnd(ekg^2)m	26±83.2
BodFya(t%)	11±12.7
YeairnshMeilitary	3.7-92.7
ACFT	528±766.03

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Table 2
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Sunday	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday
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2.4Dataanalysis

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2.5. Sample entropy

The use of sample entropy has become increasingly popular within the past decade (Stergiou, 2016). Sample entropy serves as a means to capture the regularity in movement signals (lower entropy, more regular) and irregularity (higher entropy) (Yentes and Raffalt, 2021). A reduction in movement complexity shows the system is trending toward low or high entropy, the motor control processes either more rigid or random, respectively (Stergiou and Decker, 2011). Previous studies have used entropy to investigate changes in movement dynamics when performing a load carriage task (Ortega et al., 2019; Baudendistel et al., 2022; Morrison et al., 2019; Hausdorff, 2007). However, the aforementioned studies primarily calculated sample entropy using a continuous data set, as recommended for the use of sample entropy (Ray et al., 2021). Additionally, previous works using sample entropy to analyze load carriage focused on single-trial analyses, rather than throughout a load walk (Ortega et al., 2019; Baudendistel et al., 2022; Morrison et al., 2019; Hausdorff, 2007). For a more extensive review on the calculation of sample entropy, we recommend the following papers (Raffalt et al., 2021; Rave et al., 2021). We did not tune the parameters, m = 2 and r = 0.2 were selected as these parameters are frequently used in literature for both treadmill and overground walking, and these utilized parameters are believed to be less affected by variations in data length (Yentes and Raffalt, 2021; McCamley et al., 2018).

2.6. Statistical analysis

After extracting the values using DFA α and sample entropy from each 10-min segment of the entire time series, linear mixed effect models (LMMs) were fit using a forward selection procedure. As a model-building strategy, first an intercept model with a random participant effect was made. We then added fixed effects one by one by adding higher-order terms at each time. As such, the models began with a random participant effect, followed by a fixed effect of time (increment 10-min segments), fixed effect of treadmill slope (0%, 3%, or −3%), and an interaction of time and treadmill slope. Models were then tested based on significant improvements. Sample entropy values were converted to z-scores so effect sizes can be obtained from the LMMs to allow for a standardized comparison across both the DFA α scaling exponent and sample entropy. Additionally, effect sizes were reported to assist with the interpretation of the practical significance of the observed effects. Statistical analysis using the tests and data modeling were performed in the R programming environment (R Core Team, 2021).

3. Results

3.1. Baseline day comparing unloaded and loaded walking

For the Baseline Day, we collected 10-min of unloaded and loaded (+50% BW) walking at treadmill level. LMMs were used to assess whether including a fixed effect of load (unloaded vs +50% BW) improved prediction of α and sample entropy over intercept-only models (Table 3). LMMs revealed no improvement of model fit with the addition of load factor (Table 3; Fig. 1). However, a fixed effect of load improved the model fit when predicting sample entropy, with sample entropy increasing by about 0.17 SDs with the addition of load, t(62) = 2.05, p = 0.0446.

3.2. Within-day movement dynamics

For each daily model, we first fit time (increment 10-min segments) and treadmill slope to test each LMM (Table 4; Fig. 2 (Left Column)). For MIS1, LMMs revealed that the interaction of time and treadmill slope improved the model fit for predicting α. To understand the nature of the interaction, a simple slopes analysis investigating the change over time within each treadmill slope condition was performed. The analysis revealed that for the 0% treadmill slope, change was not significant over time (estimate = −0.0053 SD, SE = 0.0395, t(1302.10) = −0.13, p = 0.257). In contrast, both the −3% and 3% conditions observed a positive change (−3% estimate = 0.32 SD, SE = 0.0997, t(1206.85) = 3.25; 3% estimate = 0.29 SD, SE = 0.1051, t(1208.65) = 2.79, p = 0.0070), suggesting an increase of 0.3 SDs/10 min of load walking in non-zero treadmill slopes not appreciable during the 0% treadmill slope. For MIS2, a fixed effect of treadmill slope was included in the model (Table 4). The addition of fixed effect of treadmill slope improved model fit, with each participant exhibiting reduced α during the 3% treadmill slope compared to the 0% treadmill slope (estimate = −1.08 SD, SE = 0.37, t(312) = −2.82, p = 0.0321). Particularly, participants exhibited reduced α during the −3% treadmill slope compared to 0% treadmill slope (estimate = −1.05 SD, SE = 0.37, t(312) = −2.91, p = 0.0038). For MIS3, a fixed effect of time improved model fit, with α values decreasing by 0.08 SDs/10 min, t(723.12) = −3.77, p = 0.0007. Next, the fixed effect of treadmill slope and an interaction between time and treadmill slope did not improve model fit for MIS3 (Table 4).

Following the same procedure as the calculation of α, sample entropy was calculated in 10-min segments of walking in Daily MIS1, the interaction of time and treadmill slope improved model fit when predicting sample entropy (Table 5; Fig. 2 (Right Column)). The interaction performed simple slopes analysis investigating the change in sample entropy over time while holding treadmill slope constant. The analysis revealed that in the 0% condition we observed a positive change in sample entropy (estimate = 0.0226 SD, SE = 0.0061, t(1300.70) = 3.46, p = 0.0006). The −3% treadmill slope condition showed no change in sample entropy (estimate = 0.0016 SD, SE = 0.0151, t(1303.90) = 0.10, p = 0.4684). Lastly, for the 3% treadmill slope, we observed a positive change in sample entropy (estimate = 0.0318 SD, SE = 0.0159, t(4.58) = 2.00, p = 0.0636). While the lower confidence interval crosses zero, the observed positive change in sample entropy was statistically significant but small effect. Overall, these results suggest approximately 0.03 SDs/10 min of load walking in the 0% and 3% treadmill slopes. However, there was a substantially reduced rate of change in the −3% treadmill slope, though exhibiting little to no change (estimate = 0.0162 SDs).

For MIS2, the addition of a fixed effect of treadmill slope improved the model fit (Table 5). Improvements in model fit stemmed from each participant exhibiting decreased sample entropy in the −3% treadmill slope compared to 0% treadmill slope (estimate = −1.76

Table 3
Model building for improvement in measuring (α) and sample entropy to load during unloaded.

Model	AIC	BIC	logLik	Deviance	χ^2	Df	p
DFA α							
Intercept	44.69	46.61	−19.35	38.69			
Intercept + Load	46.32	48.88	−19.16	38.32	0.371	1	0.5424
Sample Entropy							
Intercept	42.97	44.88	−18.48	36.97			
Intercept + Load	39.88	42.44	−15.94	31.88	5.081	1	0.0241*

All models contain random intercepts.
Significance: * 0.05.
AIC – Akaike Information Criterion
BIC – Bayesian Information Criterion
logLik – Log-Likelihood
χ^2 - Chi-squared statistic
Df – Degrees of freedom
p – p-value

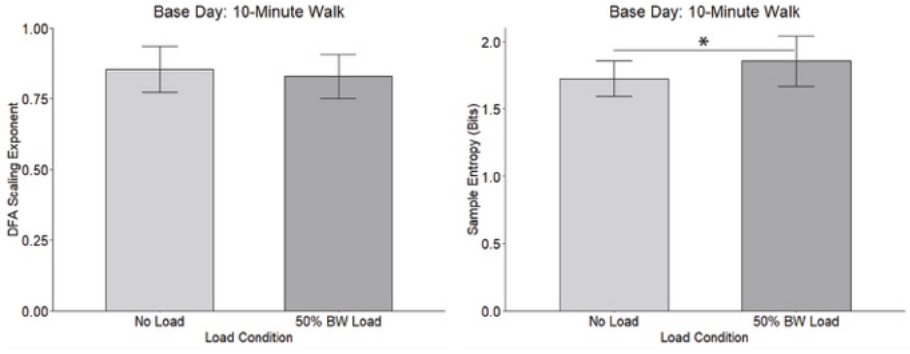

Fig. 4. Bar graphs depicting DFA scaling exponent (left) and sample entropy (right) of trunk acceleration data during the no load and 50% BW load conditions on the Base Day. The asterisk indicates a significant difference between conditions. Error bars represent 95% confidence intervals.

Table 4
Model building steps for model improvement (using) values as missing days.

Model	AIC	BIC	logLik	Deviance	X^2	Df	p
α – Missing							
Intercept	209.27	216.22	−101.64	203.27			
Intercept + Time	208.90	218.17	−100.45	200.90	2.37	1	0.1239
Intercept + Time + TMS Slope	211.51	225.41	−99.75	199.51	1.40	2	0.4972
Intercept + Time + *TMS Slope	197.09	215.63	−90.54	181.09	18.42	2	0.0001***
α – Missing							
Intercept	64.06	67.19	−29.03	58.06			
Intercept + TMS Slope	58.96	64.18	−24.48	48.96	9.10	2	0.0106*
α – Missing							
Intercept	230.28	237.43	−112.14	224.28			
Intercept + Time	224.87	234.40	−108.43	216.87	7.41	1	0.0065**
Intercept + Time + TMS Slope	227.39	241.68	−107.69	215.39	1.48	2	0.4773
Intercept + Time + *TMS Slope	230.26	249.32	−107.13	214.26	1.13	2	0.5694

AIC model comparison criterion.
Significance codes: '***' 0.001 '**' 0.01 '*' 0.05
AIC-Akaike information criterion
BIC-Bayesian information criterion
logLik-Log-likelihood
χ^2-Chi-square statistic
Df-Degrees of freedom
p-p-value

SD = 0.38 (1.2–2.8), indicating that participants were more variable on the Base Day than on the Follow-Up Day. Participants completed 50% of the 10-minute walking trials on the Base Day and 100% of the 10-minute walking trials on the Follow-Up Day. Therefore, only the Follow-Up Day was used for model development (Table 5). Due to the inclusion criteria, participants with at least 3 days of data were included in the analysis, which is why the Missing 1 Day, Missing 2 Day, and Missing 3 Day models improved the model fit, 100% confidence interval, position, and velocity, respectively, (estimate = 0.25, SE = 0.006, t = −0.01, 60, 3.519). Adding random slopes for time did not improve the model fit (estimate = 0.25, SE = 0.015, t = −0.01, 60, 1.80, 0.001).

3.3. Between-day dynamics

3.3.1. Within-day

The first 10 min of each walking trial were extracted to examine changes in the Base Day to Follow-Up Day. Participants walked with more variable and less complex trunk dynamics on the Follow-Up Day compared to the Base Day (Table 8). Non-linear analysis of trunk acceleration revealed that participants walked with greater DFA (α) and lower sample entropy on the Follow-Up Day compared to the Base Day (Table 6; Fig. 3).

The aim of this study was to investigate the effects of prolonged walking on trunk dynamics within and between days. Specifically, we examined changes in trunk dynamics during the first 10 min of walking and changes in the first 10 min of walking between the Base Day and Follow-Up Day. Participants walked with more variable and less complex trunk dynamics on the Follow-Up Day compared to the Base Day, as indicated by greater DFA (α) and lower sample entropy. Participants maintained their gait dynamics within each walking trial on the Base Day, but not on the Follow-Up Day. These findings suggest that prolonged walking altered trunk dynamics between days, but not within days. Changes in trunk dynamics between days may reflect changes in the ability to adapt to perturbations during walking.

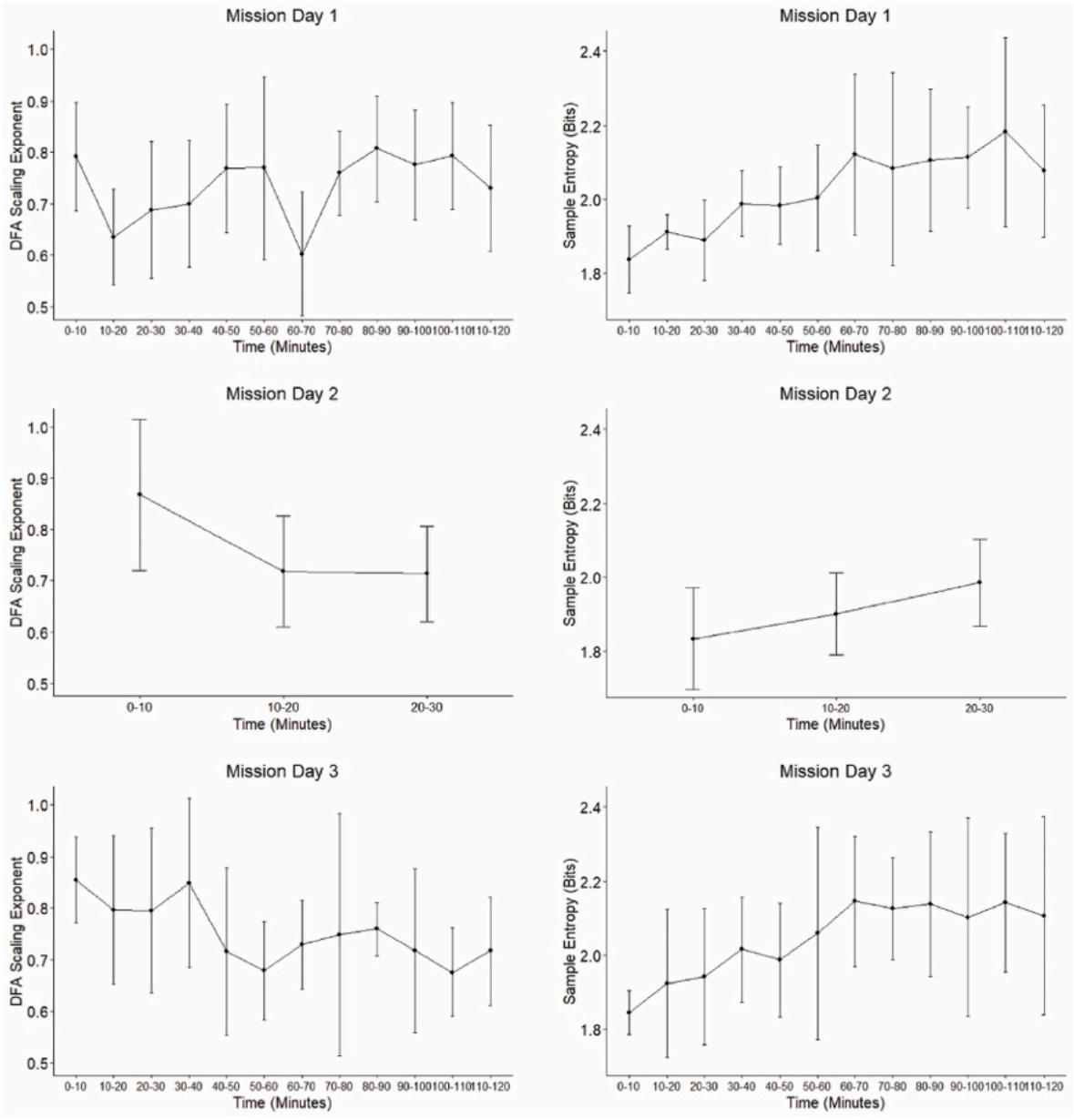

Fig 2. Linear and nonlinear dynamical metrics (mean ± standard error) for the two cognitive tasks: Mission Day 1, Mission Day 2, and Mission Day 3. Error bars represent 95% confidence intervals.

discussed the observed changes in cognitive load over the course of the mission, as well as the effectiveness of the adaptive automation in mitigating cognitive overload. Participants were also asked to provide feedback on the usability and acceptability of the system, including any suggestions for improvement.

4.1. Are the observed changes in cognitive load during the mission adaptive or maladaptive?

The classification of the observed changes in cognitive load during the mission as adaptive or maladaptive is a complex issue that requires careful consideration of the context in which the changes occurred, the individual differences in the participants, and the specific goals of the mission. In general, adaptive changes in cognitive load are those that help the individual to maintain performance and avoid overload, while maladaptive changes are those that lead to a decrement in performance or an increase in the risk of error.

In the present study, the observed increases in cognitive load during the mission can be interpreted as adaptive responses to the increasing demands of the task. As the mission progressed, participants were required to process more information, make more decisions, and maintain a higher level of situational awareness. The increases in cognitive load may have reflected the participants' efforts to meet these demands and maintain their performance. This interpretation is supported by the finding that the increases in cognitive load were associated with a decrease in the number of errors made by the participants.

However, it is also possible that the increases in cognitive load were maladaptive, particularly if they exceeded the participants' capacity to cope with the demands of the task. In this case, the increases in cognitive load may have led to a decrement in performance, an increase in the number of errors, or a decrease in the participants' situational awareness. This interpretation is supported by the finding that the participants' subjective ratings of workload increased over the course of the mission, and that they reported feeling overwhelmed and stressed by the end of the mission.

The distinction between adaptive and maladaptive changes in cognitive load is important because it has implications for the design of adaptive automation systems. If the changes in cognitive load are adaptive, then the automation system should be designed to support these changes and help the individual to maintain performance. If the changes in cognitive load are maladaptive, then the automation system should be designed to reduce the demands of the task and help the individual to avoid overload.

In the present study, the adaptive automation system was designed to support the participants' efforts to maintain performance by providing assistance with the most demanding tasks. The system was also designed to reduce the demands of the task by automating some of the routine tasks. The finding that the participants' performance was maintained at a high level throughout the mission suggests that the system was successful in supporting adaptive changes in cognitive load. However, the finding that the participants' subjective ratings of workload increased over the course of the mission suggests that the system may not have been entirely successful in reducing the demands of the task.

Overall, the present study suggests that the observed changes in cognitive load during the mission were largely adaptive, but that there was also some evidence of maladaptive changes. The adaptive automation system was successful in supporting adaptive changes in cognitive load, but it may not have been entirely successful in reducing the demands of the task. Future research should investigate the factors that contribute to adaptive and maladaptive changes in cognitive load, and should develop and evaluate adaptive automation systems that are designed to support adaptive changes and reduce the demands of the task.

Table 5
Model building steps for model improvement comparisons for sample entropy in mission days.

Model	AIC	BIC	logLik	Deviance	X^2	Df	p
Sample Entropy ~ 1 + (1 | ID)							
Intercept	207.42	214.37	−100.71	201.42			
Intercept + Time	171.59	180.86	−81.80	163.59	37.82	1	<0.001***
Intercept + Time + TMS Slope	170.06	183.96	−79.03	158.06	5.54	2	0.0628
Intercept + Time + TMS * Slope	−82.66	−64.12	49.33	−98.66	256.72	2	<0.001***
Sample Entropy ~ 1 + (1 + Time | ID)							
Intercept	63.48	66.62	−28.74	57.48			
Intercept + TMS Slope	60.30	65.52	−25.15	50.30	7.18	2	0.0275*
Sample Entropy ~ 1 + (1 + Time + TMS | ID)							
Intercept	199.16	206.31	−96.58	193.16			
Intercept + Time	172.51	182.04	−82.25	164.51	28.65	1	<0.001***
Intercept + Time + TMS Slope	171.36	185.66	−79.68	159.36	5.15	2	0.0763
Intercept + Time + TMS * Slope	−75.09	−56.03	45.54	−91.09	250.45	2	<0.001***

All models observations variance-dependent intercepts.
Significance codes: '***' 0.001 '**' 0.01 '*' 0.05
AIC = Akaike Information Criterion
BIC = Bayesian Information Criterion
logLik = log-Likelihood
χ^2 = Chi-squared statistic
Df = Degrees of freedom
p = p-value

Table 6
Model building steps for model improvement comparisons for sample entropy and DFA (scaling exponent) in mission days.

Model	AIC	BIC	logLik	Deviance	χ^2	Df	p
DFA ~							
Intercept	84.44	88.44	−39.22	78.44			
Intercept + Session	88.46	96.46	−38.23	76.46	1.983	2	0.5766
Sample Entropy ~							
Intercept	81.41	85.41	−37.70	75.41			
Intercept + Session	87.29	95.28	−37.64	75.29	0.123	2	0.9891

All models observations variance-dependent intercepts.
AIC = Akaike Information Criterion
BIC = Bayesian Information Criterion
logLik = log-Likelihood
χ^2 = Chi-squared statistic
Df = Degrees of freedom
p = p-value

Table 7
Model building steps for model improvement comparisons for sample entropy and DFA (scaling exponent) in Baseline Recovery days.

Model	AIC	BIC	logLik	Deviance	χ^2	df	p
DFA ~							
Intercept	44.69	46.61	−19.35	38.69			
Intercept + Session	46.18	48.74	−19.09	38.18	0.511	2	0.4745
Sample Entropy ~							
Intercept	44.45	46.36	−19.22	38.45			
Intercept + Session	46.33	48.89	−19.17	38.33	0.111	2	0.7347

All models observations variance-dependent intercepts.
AIC = Akaike Information Criterion
BIC = Bayesian Information Criterion
logLik = log-Likelihood
χ^2 = Chi-squared statistic
Df = Degrees of freedom
p = p-value

risEka?s end the current exploratory investigation, and directly answer those questions (i.e., by explicitly assigning hypothesized relationships to the adaptive value of variability), implementing a confirmatory approach considering multiple aspects of variability jointly in larger datasets.

First, observed differences in sample entropy and DFA between loaded walking days and baseline days may reflect a loading-induced change in the complexity of gait dynamics. Subsequent studies should directly compare loaded walking to unloaded walking, ideally in the same session, to isolate the effects of load carriage. Additionally, future studies should investigate the effects of load carriage on gait dynamics in more ecologically valid settings, such as during outdoor walking or during simulated military tasks. Finally, the current study only investigated the effects of load carriage on gait dynamics in healthy, young adults. Future studies should investigate the effects of load carriage on gait dynamics in older adults, as well as in populations with neurological or musculoskeletal impairments, as these populations may be more susceptible to the destabilizing effects of load carriage.

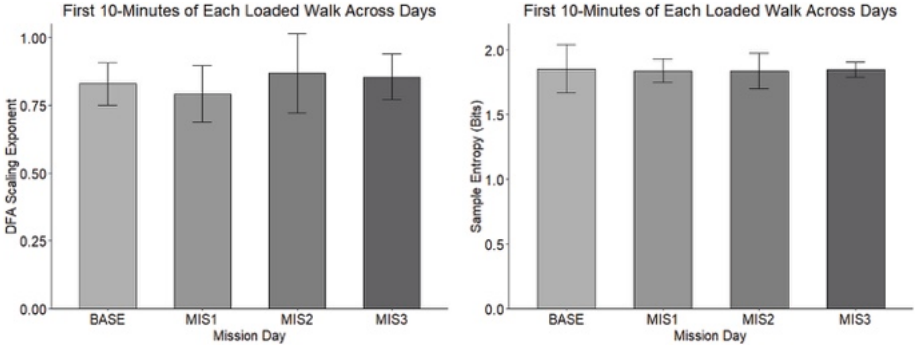

Fig. 3. Bar graph depicting DFA (scaling exponent) and sample entropy (complexity) at the first 10-minutes of the loaded walking trials in each mission day. Error bars represent 95% confidence intervals.

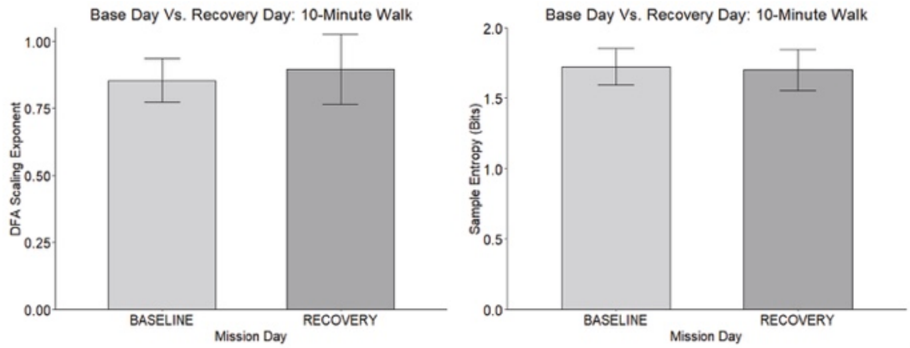

Fig. 4. Bar graphs depicting DFA scaling exponent (left) and sample entropy (right) as a function of day (Baseline, Recovery) during the 10-minute treadmill walk. Error bars reflect 95% confidence intervals.

Table 8
Hypotheses and supporting evidence.

Hypotheses	Supporting Evidence
1. α will decrease when walking with a load relative to unloaded walking during the Baseline Day.	Not supported – α did not show a significant decrease when walking with a load relative to unloaded walking.
2. Sample entropy will increase when walking with a load relative to unloaded walking during the Baseline Day.	Supported – Sample entropy increased during loaded walking.
3. α will decrease throughout loaded walking as fatigue increases.	Supported – α showed a progressive decrease over the trial.
4. Sample entropy will increase throughout loaded walking as fatigue increases.	Supported – Sample entropy showed a progressive increase over the trial.
5. α will return to the start of the load carriage (after 10 min of the walk) values the succeeding day.	Not supported – α did not change during the first 10 min of walking each day.
6. Sample entropy will return to the start of the load carriage (after 10 min of the walk) values the succeeding day.	Not supported – sample entropy did not change during the first 10 min of walking each day.

during loaded walking in military personnel, indicating a higher attentional demand (Krajewski et al., 2023). As such, we argue that the accumulative fatigue challenged the soldiers' locomotion, causing an unpredictability or emergence of a maladaptive gait pattern stemming from imposed constraints. The increased unpredictability, interpreted as maladaptive, is not an adjustment but rather a sign of the body's struggle to cope with the altered demand. Prior research has corroborated this, demonstrating that gait alterations are a result of changes in the body's typical well-coordinated and energy-efficient movement patterns (Manjumdar et al., 2013; Hunt et al., 2014; Hausdorff, 2007; Ravi et al., 2020; Charles et al., 2022) and affect the likelihood of compromised physical function or mortality. For example, a study by Li and colleagues assessed the temporal correlations in spontaneous fluctuations of motor activity during the follow-up with a population for 13 years. They found that people with more random fluctuations had an increased risk of frailty, disability, and death during follow-up (Li et al., 2019). This notion is further supported by a study conducted by Gray and colleagues who found approximate entropy to be a predictor of mortality after severe traumatic injury (Gray et al., 2020).

In support of this interpretation, Soldiers frequently sustain injuries consequent to engaging in prolonged loaded walking (Orr et al., 2014; Hill et al., 2017; Wallace et al., 2011). The reported prevalence of injuries within this context underscores the inherent risks associated with walking under demanding conditions, especially when heavily burdened (Orr et al., 2015; Kaufman et al., 2000; Majumdar et al., 2010). Additionally, studies have shown that gait unpredictability increases with aging (Buzzi et al., 2003; Ahmadi et al., 2018) and pathology (Hausdorff, 2009; Hausdorff et al., 1997, 1998). As such, elevated unpredictability has been purported to indicate heightened adaptability, implying the individual's ability to adapt to the dynamic changes within the environment (Harbourne and Stergiou, 2009; Stergiou et al., 2006). Thus, the implication is that the pronounced unpredictable altered gait dynamics observed during loaded walking indicate a maladaptive response, suggesting that the imposed constraints and cumulative fatigue have deleterious effects on the soldiers' walking mechanics and a substantial elevated risk of injury.

Numerous studies have documented increased injury risk with biomechanical changes associated with fatigue (Cignetti et al., 2009; Ohashi et al., 2004; Dugan and Frontera, 2000; Chappell et al., 2005; Lew, 2018; Jones et al., 2017). Fatigue is believed to elevate the risk of non-contact ACL injury substantially in athletes performing ACL straining activities like stop-jump tasks (Chappell et al., 2005). Additionally, fatigued muscles have been found to possess reduced energy-absorption capability, reaching injury-provoking levels (Mair et al., 1996). In the area of professional NBA, the latest shows a correlation between injuries and higher levels of fatigue and game load (Lew, 2018). Given the extensive body of evidence linking fatigue to injuries, considering the observed altered gait dynamics in this study, there exists plausibility that these changes in gait dynamics, attributable to the effects of fatigue, could contribute to increased injury risk among Soldiers.

While we have interpreted the changes in gait dynamics to reflect fatigue, they may be alternatively explained by other factors. For example, Soldiers frequently experienced discomfort with the weight vest, which could have prompted them to adjust their gait patterns to alleviate discomfort. This discomfort could increase due to prolonged exposure, which could lead to the progressive changes in gait dynamics we observed. Another potential explanation is that gait alterations could also result from changing speed imposition. Anecdotally, we observed that the Soldiers altered their pace with their hands, which could modify the gait dynamics. Furthermore, treadmill speed implemented influenced gait dynamics on most Mission Days. Notably, there were significant mean values, such as the incline slope on Mission Day 1 within the 50–60 min window. However, the effect of treadmill speed was largely within Mission Days showing consistent trends of gradual decreases or increases in speed, respectively, rather than abrupt changes attributed to alterations in treadmill speed. This suggests, however, that treadmill speed alone cannot be the causal factor of the altered gait dynamics we observed.

Additionally, the loss of motor coordination results could be related to what is being controlled. One possibility is that the motor control system would lose some control of the timing intervals and more time controlling other specific gait aspects such as

m i n i m i i z m i p r a f g c o t r f c e s l m o a l d r f . a c t h , e i r s e v i d e f r r c o t e h e l a r g e t o c o n t l r i o t l e r t a c i t n u d r i e r s e u c p t p l t o y h r i e t d e o a f e n a - c t m e n o t f c o n t a r s o n a l t e r e a p l a u e l a n t a s i t o u r d d . y [i k e m a s . (2 0 1 , p 5 a) r t i c e i m p g a a n g t e a d l r i v s i i m r g u l a t a i s v h n e r t e h e y n a v i g a h t e o d t u g y b t y p c e f s t r a c a k c s i : r c t u r l a a r r k d a l o n g , s t r a t i g r a h T t t k p a r t i c s i p e e n b t e i s I m a g w i a c a n a l y a z n e i d d t , w a s f o u n d l a n t h c e i r c t u r l a w r k i , c h i k d e l m y r a n d f e e l q u e c o n t a r d o j u l s t p r a e n t s ç e i x p h a i n b t s i s t e e e d r a i n g a b o i m h p a t y a s t h d e u r a r t h i g m h c b t e s u f f c t i o r e e n v t e l a c e d u m u l a i m p r a v e f t r a b t l d e u m a w n a l k H r o g v e v c e n r t h s e t r a t i g a n p t a k r , t i c i p p a r n i d o a r y f s a t i g u e . e m p l o a y " e d c l r a i n f d c t o r r s e c t r t a ' t l e e g a y d t , i o d e g c r e p a r s e e d i c t l s u m m a r o r u y i r , n v e s t i g a t o n i o d i a n n e a a l r s y s u g g e s t e l s t e i s r a b i l i n s t t y e e v r a i n g a l O l o l v i i t o y s s . t l e y e , i s n o w y a l k b o u g d i f f e r e n c e s i n s g p a r i o n d l t d s i e f d f e c e o e n p t r o o f l f l e l s o r s e e s u l t i c k v e a l u a e n s a m p e l n e t r i o n p t y r e o n t c e f x a l k d l y n g a m i c s w e r t e d t r a n s t o g a t i t e t h , e i n s h o u b l e p d o s s t i d l e e i a v e e x p - e r r e v e t a h l h e s a r r a o t f f i a v t e ' i s g l u e v e l o p i m n e t r e t n , s i a f a c i l t a t i o n , i m e w h e r t e h e f e o c u f a t t e n i t s i i o t n h s e t r r f i d l e ü s e r ' d l o a d f o c ü s T e h d k e y r e d i w r d u i b d t h a i t t h " e l o a f d o b c ü s e e d h d i t i o n m e , i g b l b s e c h v a e n g i n g s a p t r e d i c t s u b c a i h s t h l o s y e b i o m e c h a n a l d i c a s p , t a b c i n f i t i y t , o u b t e i n t g r e n d e r s t a n d i o b s e r i v r t e h d e u r r e e n s t u R l e t g s a . r d d l i e s s e s n , t a t h g e l t i n g n a d e o w i a t i m g a u n e i f a e n s d t o s v i c t o u b l e d n a g i e s d i t u a v t i i t o h n s m e a n i o n f g o a c d a r r i a g e a - l r t e e l r a a v t e i d r o l e n c s u c i a r e e f u l h y t e p n h s y e s d l e r n a l n d s . d e s i g f n u e t d h x p e r i m e n t s .

4. 2N.o n l iAnneaalrsy sPreoste Bt i o n a l o F e a r t s i g u e

Th e c o n g r u f e n d l i n o g f D s F ' A s α v a l a e d s a m p e l n e t r o p t y r o n p e y p r e s t h e p a r t e s d i c t o a f a b t i i h s i e t r y S i e s m u l t a n w e o u s l y d e m o n s t h n a c t e e n r t o i b a d f l o n l i a n n e a a l r y t s s e e s r a v d e i - o m a r k e f f s a t i A y s s e t . a t i e n t d h p e r e v i s o e u c s t i o l o s e , r g v a e i d t c h a n g e r e s b l e d t e r i m t e o n h t i a n l t e g r f t i h S e y o l ' d s i w e a r l k i n g u e r x p e c t s a t a i m p e n h n e t , r a o n p d y p r o v i c o d e n o p l i m e n t e a d s y s t a b i A s s i u t y , h a , v i s n e g n s i m t e i a v s e u t r o d e e s t e c b a t a i n g r e g s a i t w h e r i e n i c r r e i a s s a e m s p e l n e t r w o e p n y a e c c o m p l a n y d i e e c d r e i a n s e s b e f c t h o e n s c e f f t a t i i g s u i e t f a o t r h p e r e s e r o v f a t h S e o h ' d s i e c r . T h o s e s u r l a t i a s s q u e s t h e p a n t o b a s h l o y h l a d v b e e e r n a i s e d h e a l C t u h r s t u d l y o w t s h a s t a m p e l n e t r o i p n p y a r t i c i u s a l a r d , e c a p d e i s w o h r a a t r t e h d e i f f e r a e s p t e o i c f g t a s i i t i f n , y t h a e a t c h c o m p e h n l e i t m f g i o p r r o m p i t d l e y n t i a f l y t i e n r g a t o v i a o l n k s d l y n g n a m i i c n s d u b o y e a d d d e d o a (d S e c 3 i) d V h o r e o l v e t s h a m p l e e n t r a n p d y h o e v a l o u E D F A a p p e s a e r n s i t o v i a v r e i a i t n g a n i s f r q u e c t n y t p l y y v a r l i y a d e r t s i e O l n y e i n t e r p r o e f t t h a o t s i e o n d y n a m o i v c e t s r i n (S e c 3 i) 3 V r e s u g g t e h s a t t h o n s a e r k s e i r g s n a r l e s u i s t h s s a m p e l n e t r a n p d y F A m e a s u t h s e a m c e o n s t I r f u c t . f a t i d g u u t e e o t h e s i e r n s i t i c v a i p t t y t r h i e n n g c r e a i s r i n e g g l u y t a n w e r t e r u t e h , p e r e r h s a a p n s p e l n e t r i o n s p o y r s e e n s t c h v a e n g e s a n d l e s s o r d i w n a a l t k e p i d a n g t e a u s f n a s t , i a g c u c e u m u d l v a e t h l e s d u r a o f t o b l e o a d e r o d m k a r C T h . d l y n a m i n d e r s t n a o r o t d h i l n y g t o t i m s e e r l e s g (D t e h l i g n e i t a r 2 e 0 3 0 ; 8 V e n t a e n s R a f f a l t , s h e d s i g o h n t f a t i g u e - g i a n i d t u l c e d a b t u i t e o l n s s o u g g e s 2 0 3 2) w h i c h o u l m p t l y a v t e s i m p o l b y s e r t v h e e d f f e o c f t s n o n l i m e e t a r a i s c a s l u a i b o d l e c o a f t l o y s s i o v e g a i r d a l e s s i n c r e s a t s a e n d e a r o n r e s t i m o a c t n r e g l a t b i r v i t e e i l f s e e r i e s . I n a d d i t b o o b n s e r v h i a n g g i e w s a l k d l y g a m o i v c e s t r h e c o u o s t h e e x t e n v d a l e d c k t i n i g v a e l a s n , a l y z h i e n d i 1 0 m a i l o f e a c l h o a c d a r r i t a g s t k o a s s e v a s s i a t i m o n r v e m e l n y t n a m i c n s o f t o u a n d l y o m p l t e h t e e o r e y l a s t a i m p e l n e t r (o p o r y t h m e e r a a c r d a y (S e c 3 i) 3 V . e o p t f e d t h r i e n i 1 0 m a i l n a t h l a n s u r o f e s n t r f o p t y h a n t a t t a r m o d) . T h a s t a i n d u , m e r o e u s e n t t h e o n c l u 1 0 m i n g f e a c t h r i d a u l e d V i s s D i a y s d u r a t i p a p e h n a s v s e u r f a c e d l e a m b p l i e r r i e c l a a l t i b o e n t s w h e i e p m i o u s b e i o n g B y 0 m i n F u r t h e d m o r i t t h f e n a 1 0 m i o n V i s s D i a o y n 2 , t h t e r e a d s m i o w p a e s ± 3 % w , h e r e a V i s s D i a o y n s a n 3 l t h e t r e a c h m a i a l s l o o p f e % i n c l f i o t m h e f e n a 1 0 m i n T h e r e f l o r i s e , a l 2 . 0 , 1 ; 2 e i m a n 3 b u r d a 2 0 2) N o t t h e h a l ± α w h e t n i m e a p p r o c e a f c h e c e t l i v n e i l p y a t e d c t o i n a f b u f h a d c i n g r l s a t t o e d s r a i r e s s t a t i a n h d ± o y - , 1 w h e t n i n s s e r a i r e n e s o n s t a t i o n a b o t t h r i d a u r a f a d o n a g n u t l e r e a d s m i o a l p o d e j u s t N h e c n h t a s n . g e V s t e r e p l i t c h e n t p e i r r i e c l a a l t i b o e n l s o h w i . p w e r f e o u b n e d t w e l e a y f s o e r i t o h c e r s a m p e l n e t r o p y g e a t i n g F i g 5 s . h o w s l s r e e s u o l s t i s n u l a 1 0 1 0 t 0 i g n s e r w i e t s h i f f e r e n t r e c o v e h n o y r m g a a l d y t n a m d i u c r s i t m s g e u c c e l d i y t n r g i T a h l i . s H S a m p e l n e t r w o a p o s y a l c u f l o e n a e c t h i n s e e r T h e a r e s e e v e r a l d i n d l o s t u p p o c u r h r t y p o t h a e s v s e i e x p e o n t o e v d e m e l y n t a m t i o c s k e y a k e a v F a i y s s a . m p e l n e t r i o n s p a y x i n w v a l e o n = H = 0 . 5 a s , g r a d u d a e l t l e y r i a c r a l a s g T s h . i f s n d i r n a g i t s h e p e o s s i t h i a l t i c n y v e o u e x l p e f c t a m p u r e l a y n d p o r m o c S e e s c o . i n r d t h , r e a n g g f e S o l d d i a e r r e s c u p e d o a t s e v i a h e v e s r n b i e g t h w t e e s s i o n v s e o b s e r i v o e u e r x p e r i e m n e t n r t r o e p a y c a l m e i s n i m a u s m t e n d s H o w e v e h r i , d l e f f e r a e r m e c o p s e s i e m t h i e n i 1 0 m a i l o f t o w a o r n d e v , h i e a l h s m a k e s s e n g s i e v t e l n a v i t s h t r o a g e c o - c o r w a l k t h e g f , f e d f a s t i m g a u b e e e x p r e b s y a m e o d r r e a p d i e d c a f y r e l a t i s e o r n ; i s l e s u b l e m t o r p e r e d i c A t e a t o h n p e . l i c a a r t i s e o n s m o v e m e l y n t a m t i h c r s o u g t h h e u d a l r a (x i v a n l o d V i s s i o w n h e o n n e c e o n s i t c h g e r a v p l h e H < 0 . 5 n s h o t r h t i e n , t e r p r e t a t D a y c o m p a r t b e i d s s D i a o y n) E . x p a n d o n i t h g S s , l d e i x e h r i s b i t i e t s c h a t h p e r e d i c t o a f b t i r l i d t h e y n t e c v a s a t e f r m c o d m i f f e r e n t d i m i n i l s l m e g d c a n g e l o a n V i i s s D i a o y n 2 s a n 3 l , c o n t r a s t i n d g e r d l y i n a g n F i c a s H . u r e s x t p o n l e e n t s t s a O n . 5 g a i e x h i b i t s t h f e n d i o n f g i s s D i a o y n T h i i s m p l t i h e w a s h i t h l h e e c y a n e v e o r t a n t i - p e b r e s h i a s v t i m e o p r t , y a c i o n g r e m c e t c i h v a e r a i v s o m r T k h i s t h e n i o r r m s a t l a o t v e e r n t i g l e a t i o r , i l i c t o y m b f a a t t i g n u d e u l c y e d c o u t l f e a c n t i n d i v s i c l o u n a s t a a d n j t u s t (m e e . n g t a i , n t a i n i n a n a c u b t c e u o t f i n t e p n h s y e s e i x c e a l n t a i y h e d i m i n i r s e h s e u d l , t b r a g l a o n a c e a p t i c n h g a n i g a e w s a l k s i u n g f a l e e a) t j a n h g i g h e r i n a h a s t e l r e e t e d e r i o n f t a h e v i a c r l n k d l y n g a m i c s . d e g r o e f c e o m p l e a x i d t n y p r e d i c a t s e l v i i d f e n t g i m , n c r e a s e d e n t r A s H y e x t e p n a d S s t 5 h , r e a t o n f g e a c h a n t g a p e s e r s i s t e n p a t t i e r n o h i , c t a h t a i n g i a d p e s s i t i c i o v r r l e y d v a l e t e i d n F e a . s t s t e p s r t o b e f o l l o w f e a d s s t t e a p n s s l l o s w t e t p e s r t o b e f o l l o w e d

L a s t t h y e , o m p a r b i e s t o w n B e a s e D i a y (e t l f e r s s l a y p (o r - o t o c a r n l B e c o V D e a r y (y t h e a d s t a y p r o t c o c f o f l e a) r m e n p l p o - r t n i t t y p i d e n a t i n j f y t e r a t h i a n d a n y h s a v p e e r s e v e v a t t h e e d w e e k l m o i n s g s p i r o o n t (S e c 3 i) 5 . 2 u r p r i s o d n i g s l c y e , r n b l y s l l e s w t e T p h s i p s s i r t e i l v æ t i s o u n g s g h e i n s p o t r s p e r e d i c g t a a i t b l e

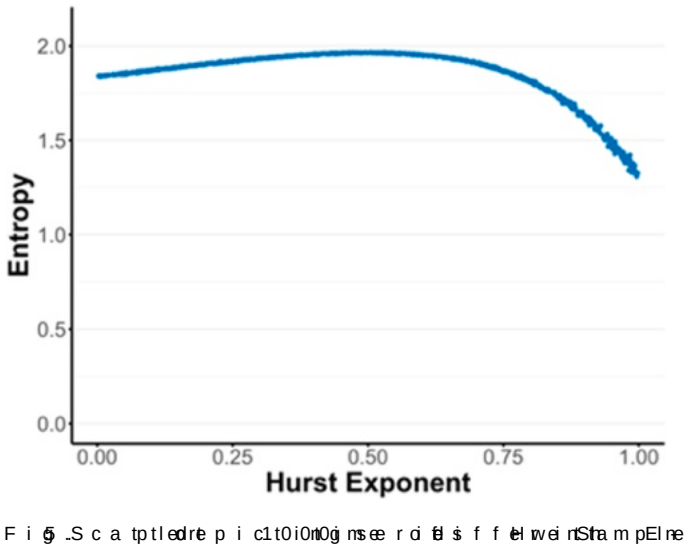

Fig 5. Scatterplot of Hurst Exponent versus Shannon Entropy for all 120 time series.

part two, in which we apply the Multiscale Entropy algorithm to the same 120 time series. The degree of persistence is also important for the interpretation of the Shannon Entropy values. Persistent time series are more predictable than random time series, and therefore have lower Shannon Entropy values. Figure 5 shows that there is a negative correlation between the Hurst Exponent and the Shannon Entropy. The Pearson correlation coefficient is −0.75 (p < 0.05), which indicates a strong negative correlation between the two variables.

4.4. Limitations and future directions

The current investigation has a number of limitations, which should be addressed in future research. First, the sample size is relatively small. Although 120 time series is sufficient to detect strong correlations, it is not large enough to detect small effects or to perform subgroup analyses. Second, the time series are relatively short. Short time series are more susceptible to noise and to the effects of non-stationarity. Third, the time series are all from the same domain. It is unclear whether the findings generalize to other domains. Fourth, the time series are all univariate. Multivariate time series may contain additional information that is not captured by univariate analysis. Fifth, the time series are all from healthy participants. It is unclear whether the findings generalize to patients with neurological or psychiatric disorders. Sixth, the time series are all from laboratory tasks. It is unclear whether the findings generalize to real-world tasks. Seventh, the time series are all from adults. It is unclear whether the findings generalize to children or to older adults. Eighth, the time series are all from Western participants. It is unclear whether the findings generalize to non-Western populations. Ninth, the time series are all from participants who were recruited through convenience sampling. It is unclear whether the findings generalize to the general population. Tenth, the time series are all from participants who were tested in the morning. It is unclear whether the findings generalize to other times of the day.

Future research should address these limitations by using larger samples, longer time series, multivariate time series, clinical populations, real-world tasks, children and older adults, non-Western populations, and random sampling. Future research should also investigate the relationship between the Hurst Exponent and the Shannon Entropy in other domains, such as physiology, economics, and climate science. Future research should also investigate the relationship between the Hurst Exponent and the Shannon Entropy in other types of time series, such as discrete time series, categorical time series, and point process time series. Future research should also investigate the relationship between the Hurst Exponent and the Shannon Entropy in other types of systems, such as chaotic systems, stochastic systems, and deterministic systems. Future research should also investigate the relationship between the Hurst Exponent and the Shannon Entropy in other types of processes, such as Markov processes, Gaussian processes, and non-Gaussian processes. Future research should also investigate the relationship between the Hurst Exponent and the Shannon Entropy in other types of models, such as linear models, nonlinear models, and machine learning models. Future research should also investigate the relationship between the Hurst Exponent and the Shannon Entropy in other types of applications, such as forecasting, classification, and anomaly detection. Future research should also investigate the relationship between the Hurst Exponent and the Shannon Entropy in other types of data, such as financial data, environmental data, and social data. Future research should also investigate the relationship between the Hurst Exponent and the Shannon Entropy in other types of contexts, such as laboratory contexts, real-world contexts, and virtual contexts. Future research should also investigate the relationship between the Hurst Exponent and the Shannon Entropy in other types of participants, such as healthy participants, patients with neurological disorders, patients with psychiatric disorders, children, older adults, Western participants, non-Western participants, and participants who were recruited through convenience sampling. Future research should also investigate the relationship between the Hurst Exponent and the Shannon Entropy in other types of tasks, such as laboratory tasks, real-world tasks, and virtual tasks. Future research should also investigate the relationship between the Hurst Exponent and the Shannon Entropy in other types of measurements, such as physiological measurements, behavioral measurements, and self-report measurements. Future research should also investigate the relationship between the Hurst Exponent and the Shannon Entropy in other types of analyses, such as univariate analyses, multivariate analyses, and machine learning analyses. Future research should also investigate the relationship between the Hurst Exponent and the Shannon Entropy in other types of publications, such as peer-reviewed publications, preprints, and gray literature. Future research should also investigate the relationship between the Hurst Exponent and the Shannon Entropy in other types of researchers, such as researchers from different disciplines, researchers from different countries, and researchers from different backgrounds. Future research should also investigate the relationship between the Hurst Exponent and the Shannon Entropy in other types of collaborations, such as collaborations between researchers from different disciplines, collaborations between researchers from different countries, and collaborations between researchers from different backgrounds. Future research should also investigate the relationship between the Hurst Exponent and the Shannon Entropy in other types of publications, such as peer-reviewed publications, preprints, and gray literature. Future research should also investigate the relationship between the Hurst Exponent and the Shannon Entropy in other types of researchers, such as researchers from different disciplines, researchers from different countries, and researchers from different backgrounds. Future research should also investigate the relationship between the Hurst Exponent and the Shannon Entropy in other types of collaborations, such as collaborations between researchers from different disciplines, collaborations between researchers from different countries, and collaborations between researchers from different backgrounds.

4.5. Conclusion

In conclusion, this study has investigated the relationship between the Hurst Exponent and the Shannon Entropy in a large sample of time series from a variety of domains. The results have shown that there is a strong negative correlation between the two variables. This finding has important implications for the interpretation of the Shannon Entropy values. Persistent time series are more predictable than random time series, and therefore have lower Shannon Entropy values. The results have also shown that the relationship between the Hurst Exponent and the Shannon Entropy is moderated by the domain of the time series. This finding has important implications for the generalizability of the findings. The results have also shown that the relationship between the Hurst Exponent and the Shannon Entropy is moderated by the length of the time series. This finding has important implications for the reliability of the findings. The results have also shown that the relationship between the Hurst Exponent and the Shannon Entropy is moderated by the number of observations. This finding has important implications for the reliability of the findings. The results have also shown that the relationship between the Hurst Exponent and the Shannon Entropy is moderated by the number of participants. This finding has important implications for the reliability of the findings. The results have also shown that the relationship between the Hurst Exponent and the Shannon Entropy is moderated by the number of tasks. This finding has important implications for the reliability of the findings. The results have also shown that the relationship between the Hurst Exponent and the Shannon Entropy is moderated by the number of measurements. This finding has important implications for the reliability of the findings. The results have also shown that the relationship between the Hurst Exponent and the Shannon Entropy is moderated by the number of analyses. This finding has important implications for the reliability of the findings. The results have also shown that the relationship between the Hurst Exponent and the Shannon Entropy is moderated by the number of publications. This finding has important implications for the reliability of the findings. The results have also shown that the relationship between the Hurst Exponent and the Shannon Entropy is moderated by the number of researchers. This finding has important implications for the reliability of the findings. The results have also shown that the relationship between the Hurst Exponent and the Shannon Entropy is moderated by the number of collaborations. This finding has important implications for the reliability of the findings.

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Conflicts of interest

The authors declare that they have no conflicts of interest.

Data availability

Study data were collected and managed using REDCap electronic data capture tools hosted at the University of Melbourne. REDCap is a secure, web-based software platform designed to support data capture for research studies, providing (1) an intuitive interface for validated data entry; (2) audit trails for tracking data manipulation and export procedures; (3) automated export procedures for seamless data downloads to common statistical packages; and (4) procedures for importing data from external sources. The data that support the findings of this study are available from the corresponding author upon reasonable request.

Ethics approval

Institutional Review Board/Ethics Committee approval was obtained by the institutional review board at the U.S. Army Combat Capabilities Development Command Armaments Center.

Consent to participate

Informed written consent was obtained from all participants included in the study.

Code availability

Statistical analyses were done using R version 4.1.2, code is not publicly available.

Disclaimers

All opinions and assertions contained herein are the private views of the authors and are not to be construed as reflecting the views of the U.S. Army or the Department of Defense. Any citation of commercial organizations and trade names in this report does not constitute an official Department of the Army endorsement or approval of the products or services of these organizations. Approved for public release; distribution is unlimited. The views expressed in this article reflect the results of research conducted by the authors and do not necessarily reflect the official policy or position of the Department of Defense nor the United States Government.

CRediT authorship contribution statement

Kolby J. Brink: Data curation, Formal analysis, Investigation, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. **Kari L. McKenzie:** Funding acquisition, Investigation, Methodology, Project administration, Resources, Supervision, Writing – review & editing. **Chad R. Straight:** Data curation, Investigation, Methodology, Supervision, Writing – review & editing. **Kenny S. O'Fallon:** Data curation, Investigation, Methodology, Resources, Supervision, Writing – review & editing. **Seung Kyeon Kim:** Data curation, Formal analysis, Visualization, Writing – review & editing. **Alan D. Likens:** Conceptualization, Data curation, Formal analysis, Funding acquisition, Methodology, Supervision, Writing – original draft, Writing – review & editing.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.apergo.2024.104315.

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