Multifractal Mice: Operationalising Dimensions of Readiness-to-hand via a Feature of Hand Movement

Daniel Bennett
Anne Roudaut
Oussama Metatla
daniel.bennett@aalto.fi
roudauta@gmail.com
o.metatla@bristol.ac.uk
University of Bristol
UK

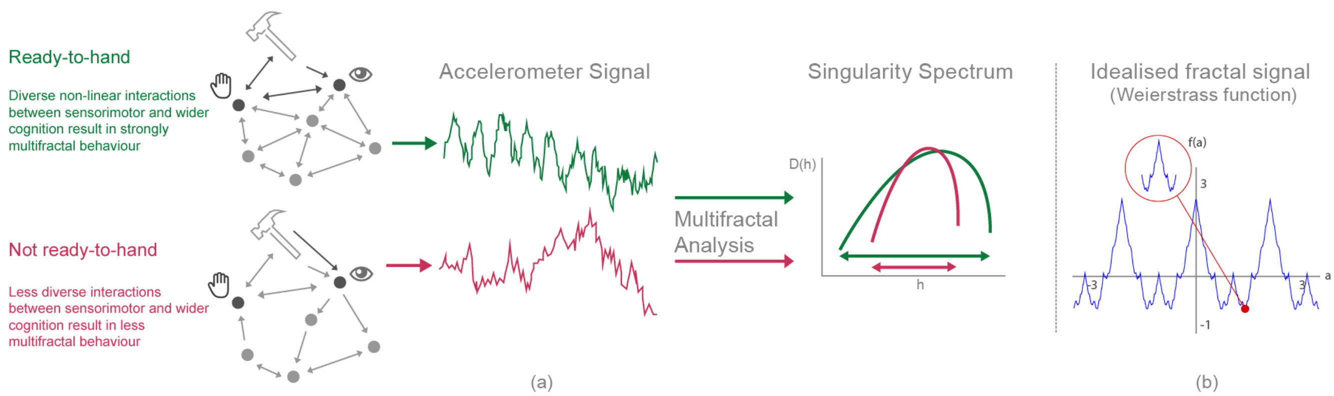

Figure 1: Connecting readiness-to-hand to changes in complexity and multifractality. 1a: Multifractal dynamics emerge when cognitive structures organise to use a tool, for some task, in a context sensitive and flexible way. Strength of multifractality can be quantified by the width of the multifractal "singularity spectrum" - a metric analysed from recordings of movement. (see *2.4.1*). 1b: self-similarity in an idealised monofractal signal

ABSTRACT

The philosophical construct *readiness-to-hand* describes focused, intuitive, tool use, and has been linked to tool-embodiment and immersion. The construct has been influential in HCI and design for decades, but researchers currently lack appropriate measures and tools to investigate it empirically. To support such empirical work we investigate the possibility of operationalising readiness-to-hand in measurements of multfractality in movement, building on recent work in cognitive science. We conduct two experiments (N=44, N=30) investigating multifractality in mouse movements during a computer game, replicating prior results and contributing new findings. Our results show that multifractality correlates with dimensions associated with readiness-to-hand, including skill and task-engagement, during tool breakdown, task learning and normal play. We describe future possibilities for the application of these methods in HCI, supporting such work by sharing scripts and data (https://osf.io/2hm9u/), and introducing a new data-driven approach to parameter selection.

CCS CONCEPTS

• **Human-centered computing → Empirical studies in HCI**; *Laboratory experiments.*

KEYWORDS

readiness to hand, embodiment, phenomenology, cognitive science, complex systems, engagement, user experience

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1 INTRODUCTION

Almost all interaction with technology involves a degree of physical movement - from full body interaction in VR, to finer movements in mouse and keyboard use. This marks a continuity between digital

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technology and more traditional, physical tools which has been drawn upon by HCI researchers and designers pursuing intuitive, natural, and transparent interactions.

One idea that HCI has borrowed from theories of conventional tool use is the distinction between two modes of technology engagement: "*ready-to-hand*" and "*present-at-hand*" (which for convenience we can refer to together as the account of "readiness-to-hand"). "Ready-to-hand" describes engaged, skilful, fluid, tool use experience, in which the user pays little conscious attention to the technology. In this condition, the technology becomes "transparent" or invisible to the user, not drawing conscious attention, and even feeling like part of the body. "Present-at-hand" engagement, by contrast, involves a detached, reflective attitude to the technology in which the user perceives the technology as a separate object with determinate properties [28, 92, 95, 99]. This account can be illustrated nicely via the example of pen use. For most adults a pen is a very familiar tool, and during writing it will "disappear" from awareness as we focus on the writing task at hand. That is: the pen becomes *ready-to-hand* for us. If the pen begins to function badly, however (perhaps by spilling too much ink or drying up), then it will draw our attention and become obtrusive. In this case the pen will be less "ready-to-hand" and may even become fully "present-to-hand": the task will recede into the background, and the pen itself will draw our attention. We will now attend to the pen with an observing, perhaps reflective and problem-solving attitude.

For HCI researchers much of the appeal of this account lies in its suggestion that users will move between two particular modes of engagement in a more-or-less predictable way; and that this movement will be tied to the task's demands, to the user's experience, and to the tool's adequacy. Moreover the account suggests that different experiences, needs, and patterns of attention, will arise in these different cases, and suggests that systems might respond more or less adequately to this [10]. Accordingly, in HCI, ready-to-hand use has been associated with engaged, natural and "fluid" technology use [2, 28, 68, 81, 92], with the sense the tool is "part of us" [9], and with locus of attention [2, 3, 81]. 'Present-at-hand' and 'unready-to-hand' modes of engagement have been associated with "breakdowns" in fluid interaction, and with lack of skill or familiarity [10, 81, 95]; but also with useful and valuable behaviours such as reflection and analysis [15, 34, 66, 96] problem solving [34, 96, 99], and conscious awareness of the tool's properties [2, 3, 29, 81, 96].

Discussing this account in an *Interactions* article, Bird argued for the need to operationalise (define the measurement of a phenomenon that is not itself directly measurable) the concept of readiness-to-hand [10]. He suggested that operationalisation can help connect theory to practice, and allow researchers to test design ideas and interaction variables for their ability to support phenomenally transparent interaction. This could support empirical work to to refine understandings of readiness-to-hand in interaction, understand the role it plays in engagement, and help us understand how to support users in inhabiting and transitioning between what appear to be important phases and modes of interaction.

Since the publication of Bird's article, there have been attempts to operationalise readiness-to-hand, at least in some of its aspects. Alzayat et al. developed an approach to inferring readiness-to-hand by measuring user awareness of tool-properties [2, 3], an approach which was found to be useful in measuring sense-of-immersion during tool breakdown. Bergström et al., evaluated a measure of *tool-extension* which addressed the sense that the tool becomes "part of us", and which they related to readiness-to-hand, [9]. However these approaches leave important gaps to be filled. Readiness-to-hand is a complex, multidimensional phenomenon, which takes in not only visual attention, and tool-extension, but also other dimensions including skill, familiarity and engagement [95], which are not addressed in this work. Further both approaches rely on secondary tasks which might be expected to be distracting to the user: something which might be considered problematic when observing experiences of focused tool use and immersion.

In this paper, we evaluate a new approach to operationalising readiness-to-hand in technology use, by measuring *multifractality* in movement. This dispenses with the need for distracting secondary tasks, and only requires the recording and analysis of task-directed hand movement. Multifractality is a measure of dynamical complexity in movement which can be informative about coordination structures in systems, including in human behaviour. It has been observed in a wide range of skilled, tool-using behaviours [8, 71], and has been shown to correlate with at least some patterns of behaviour associated with readiness-to-hand, during tool breakdown [26, 27]. Since this prior work provides a theoretical account of how behavioural and experiential dimensions of readiness-to-hand arise, it supports the formation and testing of further hypotheses about the phenomenon. However, as with the other approaches discussed above, prior work has only addressed some of the dimensions and conditions which are associated with readiness-to-hand, and which have been important in HCI research. This paper addresses this gap by articulating and testing new hypotheses about ready-to-hand technology use, based on existing theories and prior empirical results We develop two experiments (N=44, N=30) on mouse use in a computer game, and develop approaches to multifractal analysis which support good hypothesis testing in future work in HCI. The main contributions of our work are as follow:

(1) We conduct a replication of previous findings that multifractality correlates with shifts in attention when the tool malfunctions, while addressing important gaps in that previous work.
(2) We articulate further implications of the account linking multifractality to readiness-to-hand, developing and testing new hypotheses around multifractality and tool-familiarity and engagement. These findings provide new evidence for the theoretical account linking readiness-to-hand to multifractality and focus on aspects of readiness-to-hand which are important in HCI. We find that
    - multifractality increases both as users become more familiar with the tool
    - multifractality is higher during a more engaging version of a game, than during a less engaging version.
(3) We develop a tuning method for multifractal analysis algorithms which supports good hypothesis testing practice around the technique.
(4) To support future use of multifractal analysis in HCI, we share all the scripts and data used in our analysis via an Open Science Framework repository[1].

[1] https://osf.io/2hm9u/

Our work marks an early step toward operationalising readiness-to-hand for HCI research. It supports further theory-building [43] work around readiness-to-hand, and provides a measure which can be seamlessly incorporated into interaction scenarios without requiring the user to perform separate and distracting measurement tasks. Since multifractality has been observed in a wide range of skilled behaviours, it seems likely that its usefulness in HCI will generalise beyond mouse use and into other interaction modalities. As in other first efforts to bring methodologies from the cognitive sciences to bear on user experience concepts in HCI [17], it is natural that open questions must be addressed, and further validation work completed before the approach can be applied more generally. As we end with extensive discussion of limitations and open questions, and suggest routes forward for future research.

2 BACKGROUND

2.1 Readiness-to-hand in HCI

Readiness-to-hand is an influential concept for understanding technology use [15, 28, 34, 92, 99]. In HCI it has been related to experiences of fluidity, immersion, "good feel" [3, 59, 68], reflectiveness, and creativity, [16, 22], and has been used as a basis for analytical methods and measures of user experience [2, 3, 68]. In its original formulation, in the thought of Heidegger, readiness-to-hand appears as part of an enquiry into the nature of being, and describes our most fundamental mode of engaging with an artefact [22, 26, 29, 52, 96]. HCI researchers have naturally taken a more pragmatic approach, treating the account as a description of tool-use experience to guide design.

According to accounts in philosophy [29, 42, 96] and HCI [28, 99], a technology becomes ready-to-hand when it being used by an adequately skilled person for some task, and when the technology itself is both adequate and reliable for the task. When a technology is ready-to-hand in this way it withdraws from attention or becomes 'transparent': we 'act through' the technology, with our focus on the task. [26, 27, 96]. In such circumstances the tool may even come to feel like an extension of ourselves, as when a trusted tennis racket feels like "part of our arm" [9, 59, 96], and some accounts in HCI have emphasised that we will feel immersed in the task [3, 87] (though this is not a *necessary* feature in the main philosophical accounts of readiness-to-hand [29, 42, 95]). There can be various reasons why a tool might not be experienced as ready-to-hand. The most commonly discussed reason for this is tool malfunction or "breakdown", but other reasons may include lack of skill or familiarity with tool and task, and a mismatch between tool, user skill, and some aspect of the task [15, 22, 42, 95]. In these cases, where the tool is said to be 'unready-to-hand' or in more severe cases 'present-at-hand', it becomes obtrusive and the sense of transparency and integration disappears. However this condition is not pictured as wholly bad, and has its own role. It is suggested that we become more vividly conscious of the tool as a separate object, with determinate properties, and we move into a more abstract, observing mindset, which can support creativity and more reflective, problem-solving engagement [10, 15, 99]. It is suggested by some accounts that movement between these modes is necessary for learning and effective adaptation [29, 96]. Much of HCI's interest in readiness-to-hand has focused on cases of breakdown [2, 3, 28, 99], but accounts in HCI and elsewhere point to other reasons why a tool may not be ready-to-hand. We may not yet have acquired sufficient skill or familiarity with the tool, or the task and tool may be (or become) badly matched

Recently, HCI researchers have suggested there is value in operationalising the account of readiness-to-hand: to support the testing of design ideas and interaction variables, and understand how they support phenomenally transparent interaction and the sense of immersion and reflective engagement [2, 10]. These ideas follow a precedent, established in philosophy and the cognitive sciences, of treating accounts of readiness-to-hand as descriptions of behaviour and experience, within which it is possible to identify particular dimensions of experience and behaviour [24, 26, 52, 58, 95]. These dimensions may include locus of awareness [2, 26, 97]; adequacy of skill [22, 29, 96], and engagement with task [29, 95])

To date, however, only two short lines of research in HCI have pursued such an approach. First, over two papers, Alzayat et al. developed a measure of readiness-to-hand to help understand "immersion" and "naturalness" in VR and tangible interaction [2, 3] — an approach which is broadly in line with a previous suggestion made by Bird [10]. This approach focuses on the way the tool "withdraws" from awareness when it is ready-to-hand, measured via the user's ability to identify changes in the presentation of a tool. These results show that measured changes in awareness correlate both with both standard measures of engagement and presence, and with performance on task. This work focuses only on the functioning of the tool: other variables which may affect readiness-to-hand, such as the effect of greater or lesser familiarity with the tool and task, are not considered. In addition, the approach to measurement of readiness-to-hand relies on secondary tasks and pauses in interaction. We suggest these distractions from the task may make the approach difficult to incorporate into many interaction scenarios, and might be considered problematic more generally for a measure which aims to measure fluid, immersive engagement with technology. Second, Bergström et al. investigate a measure [9] which they suggest captures another dimension of readiness-to-hand: "tool-embodiment" - the degree to which a tool is incorporated into cognition and seems in some ways a part of us. This is measured via reaction times to congruent and in-congruent stimuli, displayed at various points on the tool. Their results show differences in tool-embodiment related to the realism of the tool representation, and whether the user's relationship to the tool is either active or passive. They do not relate their measure to conditions of tool breakdown, familiarity with the tool, nor measures of user-engagement and immersion; and they do not measure shifts in user attention. As in the work by Alzayat et al., the reliance of this approach on a secondary task may be considered distracting when understanding certain aspects of readiness-to-hand.

Outside of HCI, Dotov et al. take a quantitative approach to the study of readiness-to-hand based on multifractal signatures in movement of the hand wielding the tool. They find that a these signatures diminishes when the tool malfunctions, and they find that this change correlates with changes in a measure of attention [26] similar to that used by Alzayat et al.. Unlike the approaches discussed above, this approach is potentially unobtrusive to interaction, relying only on measurement of existing behaviour, which we suggest makes it highly appropriate for the non-disruptive study of user experience and behaviour in HCI. In addition, the grounding of the approach in a large body of theoretical and empirical work linking multifractality to skilled behaviour seems likely to support theory building and further extension of the approach.

Based on these advantages, our own work in this paper builds on Dotov et al.'s approach, replicating previous findings, drawing new hypotheses from the underlying theoretical model and testing these hypotheses. As such, following a discussion of the related issue of task engagement, we discuss this work at greater length below (sec. 2.3.1).

2.2 Task-Engagement

Readiness-to-hand overlaps with the construct of task-engagement, though the two are distinct. To summarise this relationship: readiness-to-hand assumes a certain level of engagement with a task [96], and while very *high* engagement may not be a necessary property of all ready-to-hand tool use, researchers often associate readiness-to-hand with high engagement [88, 93], and with related concepts such as immersion [3, 87] and flow-states [12, 81]. The constructs remain importantly distinct since readiness-to-hand clearly emphasises properties which are not essential to task-engagement: these include the phenomenal 'transparency' of the technology, and changes in cognition between involved, and abstracting, reflective modes.

Doherty & Doherty note a multitude of perspectives on engagement in HCI, from "macro" views which include "socio-structural, and temporal factors", to "micro" views which are limited particular task contexts, and which deal only with "the nature and distribution of conscious focus" [23]. It is common to distinguish between three kinds of engagement: emotional, behavioural, and cognitive. Of these, cognitive engagement, which focuses on awareness, attention, challenge, focus, and conscious effort [23], best captures task-engagement as discussed in this paper.

In HCI, the most common approaches to measuring and understanding cognitive engagement are what Doherty & Doherty call subjectivity-oriented. Examples of this include for example Csikszentmihalyi's Flow theory [23, 32], the Flow State Scale (FSS) questionnaires [48], and the User Engagement Scale (UES) [74]. Of these scales FSS and UES have subscales dealing with task-focused, cognitive, engagement - a kind of engagement which seems particularly relevant to the construct of readiness to hand. In FSS this is "concentration-on-task-at-hand", and in UES "focused-attention", which itself draws on flow theory, with a focus on concentration, absorption, and temporal dissociation [74].

Recent work has indirectly suggested a potential association between engagement and fractality and multifractality, relating fractal properties to constructs which can be related to engagement, including performance on task [60, 71], and immersion [62]. In our second experiment we investigate the connection to task-engagement more directly, pointing to the potential value of multifractality among what Doherty & Doherty's categorise as psycho-physiological, "objectivity oriented" measures of engagement. Psycho-physiological approaches approximate notions of engagement via observable features, and thus may lack richness and specificity of description by comparison to subjective report. But at the same time, psycho-physiological approaches are more easily applied within tasks, and less disruptive to experience [23]. Engagement has previously been inferred via eye-tracking, Electrocardiography (ECG), heat flux (HF), and electroencephalography (EEG) — techniques which often require users to wear specialised equipment, potentially creating a barrier to deployment. By contrast, multifractal approaches need not require specialist equipment.

2.3 Multifractality, Human Behaviour, and Readiness-to-Hand

Here we discuss the theory and empirical work which links multifractality in tool-control to readiness-to-hand. We introduce the background to this research: the theory that multifractality in movement arises from a particular kind of behavioural control structure, which supports effective, flexible adaptation to circumstances. We then discuss the empirical work relating this to readiness-to-hand. We begin with a fairly black-boxed account of multifractality, allowing us to focus on the theory relating it to behaviour, but at the end of the section we give more detail on the concept of multifractality in signals, and how this can be analysed.

2.3.1 Multifractality in Skilled Behaviour. A large and growing body of work in cognitive and human movement science focuses on signatures of multifractal variation in human behaviour, and the information these can provide about underlying structures of behavioural control [45, 56, 79]. Specifically, higher levels of multifractality have been associated with effective, responsive adaptation to the task context [8, 26, 60, 70, 71]. Multifractality quantifies non-linear dynamical complexity in a signal, and indicates the presence of non-linear, multi-scale interactions in the source system's behaviour [56]. The so-called *strength* of multifractality in a signal (detailed below) indicates the strength and diversity of interactions, across multiple scales, which play a role in the system's behaviour [56].

There is a growing body of evidence that multifractality in task-directed movement varies in response to changes in the task's demands and constraints. These variations in multifractality in behaviour (which, as noted, provide information about non-linear interactions in a system) are taken to indicate differences in the way the underlying neural and neuromotor pathways and physiology have coordinated themselves in response to these demands and constraints [55]. Perhaps the clearest illustration of this account comes via recent work on eye gaze. For example Stan et al. investigated multifractality in eye-gaze during both perception-action tasks and perception-only tasks, involving no hand movement. They found stronger multifractal signatures in perception-action tasks, which they regarded as evidence of the way skilled perception-action performance emerges out of non-linear coordination between sensory and motor control pathways [85]. Other recent work on eye gaze has argued that the presence of multifractality in eye movements is informative about underlying cognitive processes, and suggests that eye-gaze behaviour should be treated as emergent from non-linear interactions between sub-processes [5]. Similar arguments have been made for a range of other movement phenomena related to both cognitive and sensorimotor tasks [8, 54, 60, 71, 91]

Much of the work in this area has focused on effective, responsive adaptation to the task context [8, 26, 60, 70, 71] – what might, in plainer language, be called "skilled performance" – and the role played in it by multifractal dynamics. It is theorised that multifractal patterns are connected to this kind of skilled performance due to their mathematical association with "critical" or "metastable" states. These states have been shown to arise in the neuromotor system and in wider human behaviour [1], and are argued to support flexible and adaptive behaviour [45, 53, 90]. A system is said to be metastable when it is poised at a critical transition point which allows it to make rapid qualitative change into one of multiple behavioural states [1]. It is argued that such metastable states in the neuromotor system and body [1], promote effective behavioural transitions when people are confronted by novelty, or by the need to adapt responsively to the changing moment-by-moment demands of a task [1, 45, 60, 90]. The neuromotor and physiological structure of the human behavioural system is argued to be modulated by the constraints and dynamics of the task-context, thereby being organised into a task-specific state which supports appropriate adaptation to the specific context [90].

The association between Multifractality and metastability or criticality in behaviour comes via a specific kind of organisational structure: the multiplicative cascade [45, 56]. In a multiplicative cascade many simultaneously occurring processes (e.g. cognitive and physiological) constrain and modulate one-another, such that processes at longer time-scales both affect, and are affected by, those at shorter and shorter time-scales in a cascading manner [56, 60]. Multifractality arises from these structures and provides evidence for them [47, 56]. Multifractality and cascade structures have been associated with effective adaptive skill in a range of behaviours. In eye-gaze, visual search is more efficient when eye movements exhibit fractal properties [86]. In the crafting of stone and glass beads, greater multifractality was observed in the hand movements of more skilled crafters, and predicted the ability to adapt to unfamiliar materials [71]. Finally, in a card-sorting task designed to elicit executive function, significantly different trajectories in multifractality over time were observed depending on whether the card sorting task needed to be inferred during sorting, or whether the rule was given at the start and merely executed [6, 7].

2.3.2 Multifractality and Readiness-to-Hand. Over three papers, Dotov and colleagues built on the account described above to develop and test hypotheses relating multifractality to the phenomenon of readiness-to-hand [26, 27, 70]. To recapitulate that account: it proposes that context-adaptive, skilled tool use is grounded in multiplicative cascade structures in behavioural control, and that these structures are partly established and maintained via bodily, sensorimotor coupling to task-context [1, 73, 90, 94]. Dotov et al. hypothesise that ready-to-hand experience is grounded in an adaptive sensorimotor coupling to the tool and task, and that this supports adaptive skilled performance by maintaining the neuromotor system in a flexible, metastable state [26, 27, 70]. Since it is well established that attention is a limited resource, and that allocation of attention affects performance on tasks [41, 84], they hypothesise that such reorganisation will de-prioritise visual attention in favour of sensorimotor coupling and fast adaptation, and that it is this which underlies the experience of "seeing through" the tool, to the task [27]. Following the discussion above, this tool-coupled, ready-to-hand, state is expected to result in stronger multifractal patterns in movement [26, 27, 70].

By contrast, the breakdown in tool use is theorised to involve interruption of the user's sensorimotor coupling to the tool and task which previously helped maintains the task-specific, adaptive coupling. The state is expected to have less strongly multifractal signatures [26, 27, 70]. They argue that such behavioural states, less tightly coupled to task constraints, are conducive to more reflective, conscious, characteristically cognitive activities. This is in line with past evidence that tasks requiring more cognitive attitude, such as decision making, display reduced fractal properties [38].

These hypotheses were supported by the results of four experiments on mouse use in a computer game (a methodology which we adapt for our own experiment, and which is discussed in detail below). These results showed that multifractal signatures in movement of the mouse hand were higher during normal game-play, and reduced when they simulated a malfunction in the mouse's control of the game cursor. They found that during malfunction the participants visual awareness of the game increased, and cognitive load increased.

2.3.3 Limitations in Dotov et al's approach for HCI. We believe this account offers a promising way of operationalising readiness-to-hand for HCI. It offers a principled account of the mechanisms which underly ready-to-hand behaviour from which further hypotheses can be drawn, and it is grounded in a property of behaviour - task-directed movement - which is easy to measure without interrupting or altering an interaction. Further to this, multifractality has been demonstrated in a wide range of skilled movement types, including keyboard use [60] and movement in VR [79] pointing to the potential to extend the approach to readiness-to-hand to a wide range of interaction modalities. However, while there is a great deal of work on multifractality in skilled performance [55, 56, 71] relatively little of this has addressed the association between readiness-to-hand and multifractality [26, 27, 70], and there remain limitations, and a range of open questions for HCI. In extant work on readiness-to-hand and multifractality:

(1) Awareness of other visual properties in the environment other than the tool were not measured. As such the methodology cannot distinguish a shift in attention towards the tool from a more general increase in visual awareness. Stronger evidence is required to strongly establish multifractality with a shift in attention towards the tool. In HCI research with its focus on interface design, precision around the direction of the user's attention is likely to be particularly important.
(2) Dotov et al. do not perform an important analytical technique which allows the ruling out of spurious contributions to the multifractal spectrum. Confirmatory evidence from *Surrogate Analysis* (discussed in detail below) is now considered essential [45, 47, 56] for validating that multifractal spectra provide evidence for the cascade structures which Dotov et al.'s account centres on [26, 27, 70]
(3) Extant work focuses exclusively on tool breakdown — only one of the scenarios which may affect readiness-to-hand. The work does not address the association between readiness-to-hand and familiarity with the tool and task [26, 27, 70] which has been considered important in accounts in philosophy and HCI [10, 22, 29, 31, 42, 95]. Nor does it address the association

between readiness-to-hand and engagement or immersion in activity, which has also been important in HCI [3, 87]

In this paper we build on Dotov et al.'s theoretical account and methodology. We draw out further implications of the underlying account, articulating a likely association between multifractality and previously unstudied dimensions of readiness-to-hand. We replicate Dotov et al.'s breakdown experiment, addressing the methodological limitations outlined above, then develop and test novel hypotheses investigating the association between multifractality and other dimensions of readiness-to-hand.

2.4 Multifractal fundamentals

Multifractality was developed in the study of fluid mechanics, to understand the role of non-linear, multi-scale, interactions in turbulence. It has subsequently been applied in different domains (e.g. geology, physiology, individual human behaviour [49, 54]). In these cases, multifractal signatures are taken to indicate the degree to which a system's behaviour emerges from complex interactions between sub-components, and the multi-scale diversity of these interactions.

Multifractality extends the concept of the fractal, which can be described as "a shape made of parts similar to the whole"[63]. When we "zoom in" on a fractal form, observing it at progressively finer scales of measurement, we find that the structure at each finer scale contains nested versions of the same structure which we observed at coarser scales (see fig.1b). In signals (multi)fractal scaling implies both nesting and scale dependency in the waveform: measurements of variance in the signal will depend on the temporal scale over which they are measured, and long-range correlation patterns will be observed. Long range correlations imply history in processes: they imply that an observation made at one point in the signal will be related to future observations [60].

If a signal's fractal structure is uniform, we can describe these scaling behaviours with a single scaling exponent α. In a *multi*fractal signal however this scaling structure in the variance of the signal will itself vary – over time and over scales – making a single scaling exponent insufficient. Multifractal scaling is thus captured by a so-called *singularity spectrum* $D(h)$: the set of exponents, $h_1, h_2, ...h_n$, and accompanying dimensions, $Dh_1, Dh_2, ...Dh_n$, which characterise the distribution of variance in the signal over time and over scales of analysis. As this spectrum narrows, tending towards a single exponent value, the signal will increasingly approximate monofractality. As the spectrum widens, with a larger range of exponents required to capture scaling, we can say that the signal becomes more strongly multifractal. [49, 56]

2.4.1 Overview of Multifractal Analysis. There are various methods for estimating the multifractal singularity spectrum of a signal. These methods have different properties, and some are suited to particular signal types [49]. In cognitive science, human movement science, and physiology, one of two methods is commonly used. Either Wavelet Transform Modulus Maxima (WTMM - an approach based on the wavelet transform, analogous to box-counting methods for analysing fractal shapes), or Multifractal Detrended Fluctuation Analysis (MDFA - an approach based on detrending the time-series and then analysing variance) [47, 56]. In this paper we use the former since it is robust to non-stationaries which can be found in accelerometer signals [26]. A schematic representation of WTMM is shown in fig.2, and a technical overview can be found in our supplementary materials. Detailed treatments of WTMM and other multifractal analysis methods can be found in [47, 51] or in a descriptive "tutorial" style [56]. Several implementations of each algorithm are available either as software or as worked examples [39, 46, 50, 82].

We noted above that autocorrelation was an important feature of fractality in signals. This takes on a particular methodological importance in multifractal analysis, since contributions to the singularity spectrum from these autocorrelation patterns in the signal are the strongest evidence of multi-scale, non-linear interactions in the underlying system [45, 47]. Empirical singularity spectra may also be affected by other, linear and static features of the signal such as larger hand movements (increased variance), or faster hand movements (a shift in the Fourier spectrum) [56], and these do not provide evidence for the underlying nonlinear interactions which are important to our account. This is addressed by a technique called surrogate analysis which quantifies the contributions of linear and non-linear components to the singularity spectrum. In this approach, for each signal captured, a large number (N>30) of "surrogates" are generated using by applying an Iterated Amplitude Adjusted Fourier Transform process to the original [83]. This process imposes random phase shifts on frequency bands in the signal, destroying autocorrelation patterns without affecting its linear features – the Fourier spectrum and probability density function. Confirmatory surrogate analysis can be used to provide further evidence that results reflect variations in interactivity in the control system, rather than static features of behaviour such as changes in speed.

3 EXPERIMENT 1: TOOL FAMILIARITY AND BREAKDOWN

3.1 Overview and Purpose

In line with calls for HCI to follow more general scientific practice in first replicating, and then extending existing results [98], our first experiment (N=44) replicates and then extends prior work on the relationship between multifractality and readiness-to-hand. The experiment replicateswork by Dotov et al.[26, 27], which found an association between multifractality and readiness-to-hand during tool breakdown (H1 and H2). It also tests a new hypothesis (H3) relating multifractality to skill and familiarity.

3.2 Hypotheses

- H1. In line with accounts of ready-to-hand tool use, users whose tool malfunctions (the "breakdown" group) will show an increase in visual awareness, centred on the tool, when compared to a control group whose tool continues to function well.
- H2. This tool breakdown and shift in attention will be accompanied by weaker signatures of multifractality in hand movement.
- H3 Since skill and familiarity are considered pre-requisites of ready-to-hand engagement, multifractality should increase as users become more familiar with the tool: When confronted with a novel task and given the chance to practice it

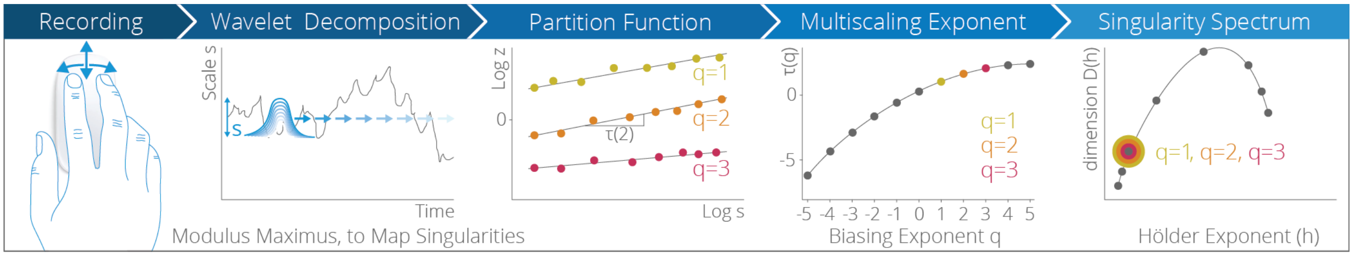

Figure 2: Overview of the Wavelet Transform Modulus maximus analysis process.

over a number of trials, multifractal signatures will become stronger.

3.2.1 *Rationale.* It is helpful to begin by articulating the theoretical account which grounds these hypotheses, before articulating the motivation for replication and extension. Dotov et al.'s account Ready-to-hand tool use [26, 27, 70], directly grounds H1 and H2, which we replicate here. Their account suggests that readiness-to-hand emerges when effective, active, sensorimotor coupling to the tool supports the maintenance of a task-specific and adaptive state in the user. This sensorimotor coupling temporarily incorporates the tool into behavioural control, supported by so-called cascade structures across the user's neuro-physiology, which allow the user to quickly move between a range of behaviours relevant to the moment-by-moment adaptive control of the task [60]. These cascade structures are known to result in strongly multifractal signatures. Hence Dotov et al. predicted that (H2) ready-to-hand tool use would be accompanied by stronger multifractal signatures [26, 27, 70]. They argue that when the tool is ready-to-hand, conscious attentional resources (which are known to be limited [41, 84]) are de-prioritised in favour of supporting the more immediate sensorimotor coupling described above. They suggest this grounds the experience of seeing-through the tool, rather than perceiving it, and will result in poorer ability to report on visual tool-properties (H1). Completing the account it is argued that non-ready-to-hand modes (unready-to-hand and present-at-hand) arise when the active sensorimotor coupling described above is disrupted or otherwise not strong. The malfunction of the tool changes the dynamics of the task into something unfamiliar and perhaps unpredictable. Since the user does not (yet) have the resources to adapt smoothly to these new dynamics, the prior sensorimotor coupling to the tool and task, and the cascade structures which support it, collapse. In their place a more cognitive, reflective state emerges, and attentional resources, which are now useful for diagnosis and problem-solving, are no longer de-prioritised. The tool again becomes an object of attention and conscious perception (H1).

We replicate and provide stronger evidence for these hypotheses, responding to gaps in previous work, which we outlined in section 2.3.3. In short evidence in previous work is not sufficient to distinguish a shift in attention towards the tool from a general increase in attention [26, 27], and further confirmatory analysis is required to provide evidence that the multifractal spectra observed follow from the theorised cascade structures, rather than other possible sources. We discuss below how our new methodology addresses these issues.

We also develop a third hypothesis H3, to the best of our knowledge articulated and tested for the first time in this paper. Accounts of ready-to-hand tool emphasise that the user must have sufficient familiarity and skill with the tool and task, to support smooth-coping [22, 29, 95]. We know from everyday experience that for even moderately skilful tasks, familiarity and skill must be acquired over time. As such, if ready-to-hand tool use does depend upon the ability to maintain cascade structures in cognition which support sensorimotor-coupling to the task environment then we would expect the ability to maintain these structures to increase with practice and familiarity. This predicts that multifractal signatures, which are evidence of such cascade structures, will become stronger the longer the user has spent with the task (H3). If this effect were not observed this might suggest problems with the underlying theoretical model.

Beyond providing further evidence for the underlying theoretical account, we suggest that skill and familiarity are particularly relevant to HCI. Full breakdown is relatively rare, but users often meet new tools and unfamiliar task contexts. This may be particularly relevant in education and training contexts.

3.3 Experimental Task

In this first experiment users are split into two conditions: breakdown, or control. They play a modified version of the game task developed by Dotov et al. for six trials (t1-6) while we capture the movement of their mouse-hand with an accelerometer. The first five trials are learning trials. In the breakdown group, in the second half of the sixth and final trial (t6b), a malfunction is simulated by introducing noise between the mouse and the cursor. No such perturbation is applied to the control group. After the final trial we conduct an attention test, focused on visual aspects of the game.

We use a variant of Dotov et al's "sheep herding" game [26, 27]. Here the participant moves an on-screen cursor with a mouse, to "herd" three "sheep" objects. They must keep the sheep close to the centre of the screen for the duration of the task and prevent them from touching a boundary at the edge of the field. The sheep move as a loose group, away from the cursor. The further the cursor is from the group's spatial centroid, the quicker they move, and the harder they are to control. To ensure presenting an effective challenge to the user, and avoid entering a stable condition where user input is not required, a small amount of noise is added to the sheep movement. The game can be intentionally "broken" in order to elicit a change in readiness-to-hand. Breakdown is implemented by disrupting the relationship between mouse and cursor movement

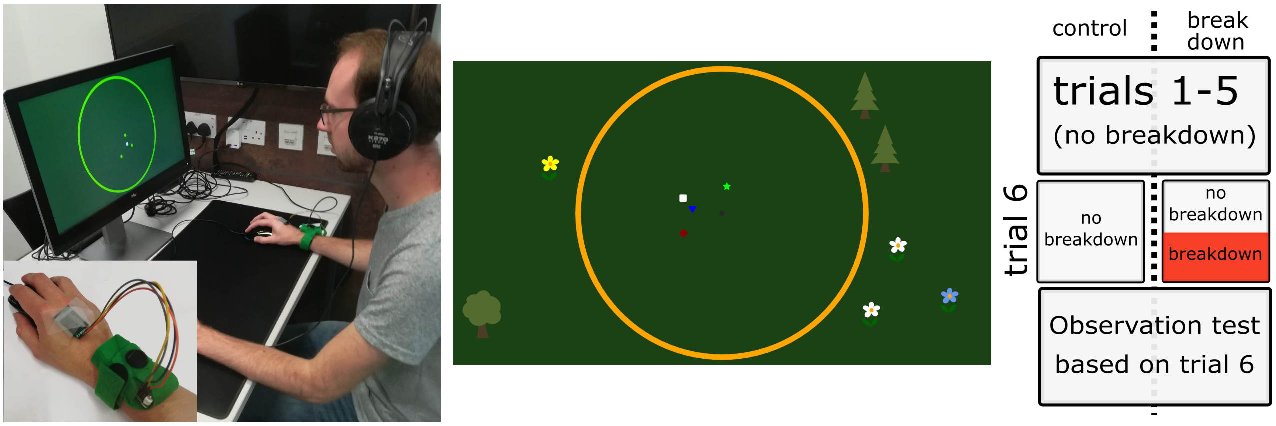

Figure 3: L: Experimental setup, with closeup showing attachment of the accelerometer (inset) Mid: experiment 1 game screen. Cursor: white square, sheep: red, green, blue. R: experiment 1 process

to produce a "sticky mouse" effect. During breakdown, the cursor is frozen at randomly determined intervals, for randomly determined periods. Timescale ranges for this freezing were arrived at by user-testing, aiming to disrupt skilled coping with the game and present an authentic appearance of breakage.

3.3.1 Observing change in visual awareness. A defining property of ready-to-hand tool use is the lack of conscious attention to properties of the tool, compared to non-ready-to-hand states where this conscious attention increases, for example during breakdown. We follow established precedent in both HCI [2, 3, 10] and cognitive science [26, 27, 70], in measuring visual awareness of tool properties as a marker of ready-to-hand and non-ready-to-hand modes of tool use. To support this, each game object (sheep, cursor, arena boundary) is presented in unique combination of colour and shape, (e.g. a yellow square, a white star, a green triangle, a blue diamond, etc.). After the final trial participants filled a questionnaire about the colours and shapes of elements. As previous work [2, 3, 26, 27], a greater number of correct answers would indicate greater attention to visual properties of the tool – characteristic of non ready-to-hand states. Our methodology moves beyond previous work by not only measuring awareness of task-relevant objects, but also measuring awareness of task-irrelevant scenery objects (trees and flowers - see fig3). By separately measuring attention to tool and non-tool elements, we are able to observe whether any change in measured attention focuses specifically on the tool, as predicted by accounts of readiness-to-hand, or reflects a more generalised change in awareness. This was motivated by the idea that understanding locus of attention is important for interface design and UX research in HCI.

3.4 Equipment & Environment

The game was implemented in C++. The user's movement was measured with an accelerometer-logger: a polulu minumu-9 IMU and rasberry pi zero, running logging software we developed in C++ on realtime raspbian to ensure accurate timing. This logged at 250hz and 16bit/G resolution. The raspberry pi was attached to the arm and the IMU taped to the back of the hand using micropore tape, aligned as closely as possible to the axes of the mouse. An accelerometer was used following Dotov et al.'s approach [26, 27, 70], since the signal is technically appropriate due to its stationarity and spectral bandwidth, and theoretically appropriate since the acceleration signal is the closest measure to the control forces which act on the hand during mouse interaction. Participants sat at a standard office desk, with a 24" monitor. They used a Logitech G300s gaming mouse, on a high quality mouse mat, and wore headphones, playing low-level white noise, to minimise distraction. All data, and software can be found at our Open Science Framework repository[2]

3.5 Protocol

Participants (N=44, 14 female, 30 male, 18+, recruited from student population via posters) played the game in one of two conditions - "control" or "breakdown" - 22 in each condition. 50 participants were recruited in total, but 4 were lost to hardware failure, 1 due to a power cut, and 1 participant was excluded due to colourblindness. Each participant played the game 6 times (t1-6), 5 "training" trials and one "breakdown" trial, for 70 seconds each time. In t1-5 the game performed normally. In t6 the tool was "broken" for the "breakdown" group only, by randomly freezing the cursor (see 3.3). Breakdown began 35 seconds in, and continued to the end, dividing the trial into two 35 second blocks (t6a and t6b). Participants were not told to expect breakdown. They were also told they would play 7, not 6, trials in order to avoid any performance or expectation effect on the final trial, and no distinction was made between the status of the trials.

At the end of the trials participants answered a questionnaire about visual features of the game during t6 (see *Experimental Task*). This allowed measurement of differences in attention to tool, between the breakdown and control groups. In order to distinguish attention-to-tool from a more general increase in visual attention, the questionnaire included questions about both task-relevant "tool" elements, and task-irrelevant "scenery" elements - trees and flowers. These trees and flowers were placed in the four corners of the screen

[2]https://osf.io/2hm9u/

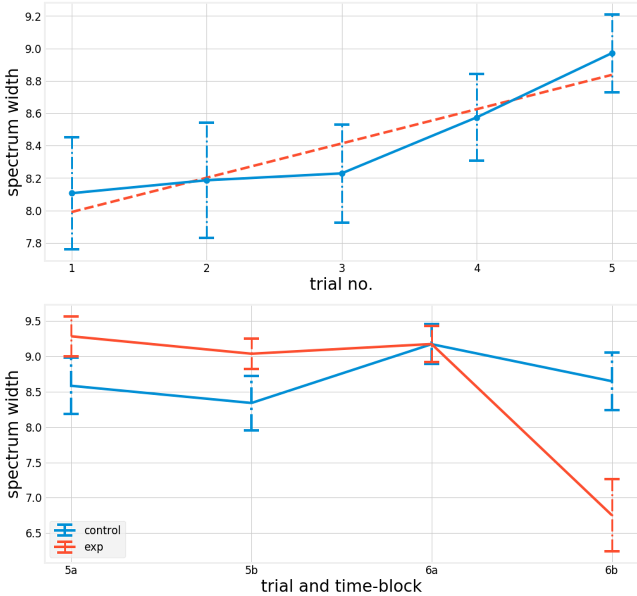

Figure 4: experiment1. spectral widths for learning (above), and breakdown (below)

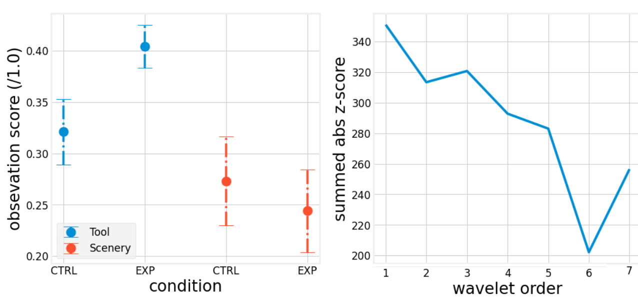

Figure 5: experiment1. left: scores on the observation questionnaires (out of possible 1.0) right: Z-scores for surrogate analysis, wavelet orders 1-7. Our selection criterion is to maximise the z-score which quantifies the difference in multifractality between the original data and the population of artificial surrogates of those datasets. This indicates the degree to which parameters minimise spurious linear contributions to the multifractal measure

around the field of play. Two varieties of tree and three colours of flower were used (fig.3). "Scenery" questions concerned the number of trees and flowers in each corner of the screen, along with their colour or type. To avoid any learning effect, relevant visual features of the game ("scenery" and "tool") were randomised during t1-5, but consistent for all participants in t6. The visual elements shown in t6 did not overlap in colour or shape with those shown in previous trials.

3.6 Ethics

All experiments were submitted in advance to the university ethics committee for approval. Since the experiment involved deception. This necessitated a more rigorous approval process, the giving of consent both before and after the experiment, and a debrief process, explaining the deception.

3.7 Analysis Method

Our analysis comprises 3 stages. We describe these stages and provide a working description below. More technical details of some aspects are provided in our supplementary materials (analysis code and data at our osf repository).

(1) Initial signal processing to prepare data for analysis
(2) Data driven selection of parameters for multifractal analysis, grounded in surrogate analysis.
(3) Multifractal analysis: calculation of the singularity spectrum of the signal using WTMM, and specifically the "width" of this spectrum

3.7.1 Data Preparation. Multifractal analysis techniques take a one dimensional data input, and it is common to analyse a single dimension of activity, even manipulating data into this format where necessary (e.g. [6, 18, 19, 26, 60]). Theoretically any dimension measured from a system which exhibits multifractal dynamics should reflect the multifractal dynamics of the system - as demonstrated in Takens' theorem [44]. In this case, we observed that users playing the game did not preference one dimension over the other, so ranges of motion and variance were similar on either axis, providing similar data resolution. We thus followed Dotov et al in using data from the X axis of the accelerometer [27].

Before processing our signal, DC offset was removed by subtracting the signal's mean, to remove effect of gravity on an inclined accelerometer axis. Signal was low-pass filtered at 15hz, as hand movements occur below 12hz [36]. Data were then integrated since preliminary Detrended Fluctuation Analysis revealed negative Hurst exponents (see [39]).

3.7.2 Overview of Multifractal analysis. The singularity spectrum for hand movement was calculated using physionet's implementation of WTMM [40] (see *2.4.1*). We used the "width" of this spectrum - the difference between its smallest and largest exponents (2.4.1) - to indicate multifractality. WTMM is a commonly used methods of multifractal analysis in the behavioural science literature, and was used by Dotov et al. [26, 70]. Like them we analyse hand movement data from an accelerometer, and WTMM is robust to non-stationaries which can arise in accelerometer recording [26]. Parameters for multifractal analusis were selected using an empirical approach described below (section 3.7.4), but since this approach builds on the *surrogate analysis* methodology, we first introduce that methodology first.

3.7.3 Surrogate analysis. In line with best practice [30, 45] we subjected our data to confirmatory surrogate analysis. As noted in 2.4.1, this provides evidence that the estimated singularity spectrum reflects multifractal behaviour and is not significantly influenced by other, linear, factors. In our experiments the linear factors we wish to rule out include changes in movement behaviour such as larger hand movements (increased variance), or faster hand movements (a shift in the Fourier spectrum) [56]. The singularity spectrum of the original signal was compared to that of a population of processed copies, or "surrogates" of that data. In these surrogates, temporal-correlations between time-scales (characteristic of multifractal behaviour) are disrupted by an Iterated Amplitude Adjusted Fourier Transform, or IAAFT [83]. The IAAFT does not affect probability density function or Fourier spectrum of the signal (affected by e.g. speed, amplitude and jerkiness in hand-movement). If the width of the singularity spectrum of the original signal sits outside the 95% probability interval of the singularity spectra in the surrogate population, then these features can be judged to make an insignificant contribution and the observed spectrum attributed to multifractal behaviour. If enough of the sample meets this criterion then this provides evidence that the analysed spectra reflect nonlinear interactions which provide evidence for multiplicative cascade structures, and that the influence of other factors is small.

3.7.4 Parameter Selection for Multifractal Analysis. Multifractal analysis relies on the selection of analysis parameters,

but discussion of this selection is largely passed over in empirical work making the approach less accessible than it could be. To support future work in HCI we expose the details of this process.

Two parameters of analysis can significantly affect results. As seen in section 2.4.1, multifractal analysis quantifies variation over multiple scales of analysis. The parameter q determines range of these scales and must be large enough to capture the phenomenon at all relevant scales. For this parameter we followed prior work by using $-5 < q < 5$ - considered adequate for physiological data [25, 30, 39]. The second parameter is the choice of "mother wavelet". This is a finite function repeatedly scaled, and convolved with the signal in WTMM, in order to measure fluctuations at different scales of analysis (see [4]). The order of the wavelet determines the orders of polynomial trends in the data which are rejected. In biological time series, system dynamics appear as residual variability around contingent environmental trends. By rejecting these trends the results of analysis focus on variability which captures system dynamics. [19, 76]. This choice of order can thus affect the degree to which true multifractal behaviour is captured, and the degree to which spurious contributions to the result are rejected. But in a particular set of empirical data it is difficult to determine the correct order of trends in advance, and the literature lacks techniques for making this selection [49]. As such we developed a data-grounded approach to wavelet selection. Which builds on the surrogate analysis described above (3.7).

While we expect this approach to result in close-to-optimal parameter selection, the aim is not (as in e.g. machine learning) to find the optimal value which most effectively separates experimental conditions. Rather the aim to allow specification of the analysis approach ahead of analysis, in a principled and theoretically grounded way, thereby supporting good hypothesis testing practice.

We begin by stating the rationale for the our parameter selection approach: In MFA, our goal is to quantify multifractality in the measured system. Thus our goals in selecting parameters are: 1) to maximise the degree to which the analysis captures multifractality, and 2) to minimise spurious contributions, from sources other than multifractal behaviour. The surrogate analysis described in the previous section provides a way of addressing the second of these, by quantifying the influence of spurious contributions. It compares the original data, to "surrogate" data in which temporal correlations between frequency bands have been disrupted, but in which the "spurious" factors remain, so that a larger difference, means a smaller contribution from spurious features. We can thus use surrogate analysis to identify which parameters minimise spurious contributions most effectively: applying this surrogate analysis repeatedly using different parameters, and selecting the parameters which maximise difference between original and surrogates.

We evaluated the use of Gaussian wavelets of orders 1-7 since these are commonly used for physiological data [26, 40], though our approach can be applied to any set of candidate wavelets. Having established these candidates, we evaluated each using our algorithm. For each candidate wavelet we conducted a surrogate analysis of the entire dataset using the wavelet, finally selecting the wavelet where surrogate analysis showed least evidence of spurious linear contributions to the singularity spectra. The surrogate analysis for a single data item proceeds as follows.

(1) Generate $N = 30$ surrogates from the original data using a python implementation of the Iterated Amplitude Adjusted Fourier Transform algorithm (IAAFT) [64]
(2) Calculate the singularity spectrum for the original and each of the N surrogates using WTMM and the current candidate wavelet
(3) Calculate the widths of the spectra (difference between smallest and largest exponents - see refMF) for both the original w_o and each of the surrogates w_s
(4) Calculate the z-score of w_o within the population of w_s, and take the absolute value of this z-score.

This process was repeated for every item in the dataset, summing the absolute z-scores across the dataset to give a fitness score for the wavelet. This in turn was repeated for each candidate wavelet, and the wavelet with the largest z-score was chosen.

3.8 Results

Our wavelet selection method showed that the 1st order Gaussian wavelet gave the greatest differentiation between original and surrogates (91% of samples outside the 95% confidence interval), indicating that it best minimised the contribution of linear features such as speed and variance in hand-movement, and that the multifractal spectra would be likely to reflect nonlinear contributions, characteristic of multiplicative cascades [45]. The 3rd order Gaussian wavelet ranked second (83% outside the 95% confidence interval) (fig.5). We thus use the 1st order analysis when drawing conclusions, but present results for the 3rd order too.

Breakdown: Per H1, we observed a shift in attention, toward task-relevant elements of the game during breakdown. Participants in the breakdown condition correctly identified more details of the task-relevant objects ($t(43) = 2.19, p = .02$). There was no difference between the groups for non task-relevant objects ($t(43) = -0.49, p = .31$). Per H2. widths of singularity spectra in the breakdown group were significantly lower than in the control group (Wavelet order 1: $t(43) = 2.9 p = .003$). Within the breakdown group, widths were significantly lower during the breakdown block 6b, than in the equivalent period during the previous trial, 5b ($t(21) = 4.4, p < .001$). On a 3rd order analysis these results would not have been significant ($t(43) = 1.4, p = .087$ and $t(21) = 1.1, p = .13$ respectively).

Familiarity and Learning: Per H3., we observed an increase in spectral width during learning. This was significant on analysis at wavelet order 1 and would have been significant also at 3. We did not see strong correlation for spectrum width with respect to trial no at population level (Order 1: $r(43) = .03, p = .14$; Order 3: $r = .04p = .14$) indicating a lack of evidence for consistent trial-to-trial increases over the five trials. However, by the last training trial t5 spectral widths were significantly wider than at the beginning, during t1. (Order 1: $t(43) = 2.46p = .009$; Order 3: $t(43) = 2.51, p = .008$).

Summary: These results show correlations between multifractality and three dimensions associated with readiness-to-hand: familiarity with tool, locus of attention, and tool breakdown. We replicated the previously observed result that shifts in attention to the tool were accompanied by wider multifractal spectra [26], providing stronger evidence (via surrogate analysis) that these changes in spectra reflect non-linear interactions in the control system (rather than other static factors of analysis such as speed of movement, or variance). We also found evidence for a new hypothesis: that multifractal signatures would be stronger when the participant was more familiar with the tool and task.

4 EXPERIMENT 2: ENGAGINGNESS OF THE TASK

4.1 Overview and Purpose

Our second experiment (N=30) tests two new hypotheses associating multifractality with engagement, responding to patterns observed in our first experiment, and the association between readiness-to-hand and engagement. When reviewing results we noticed that multifractality was slightly lower in the second half of each trial, even where there was no malfunction. We hypothesised that this result might be due to waning engagement over time, since we found that it required considerable concentration to remain engaged with the task and perform well. We found theoretical and empirical support to pursue this association in previous literature.

As discussed above, multifractality provides evidence for the coordination of behavioural resources in cascade structures, which have been associated with flexibility and adaptation to circumstances [6, 60]. Wider multifractal signatures are taken to indicate that a wider range of behavioural resources are coordinated [56, 60]. Researchers have drawn connections between this account of resource coordination, and accounts of *executive function* — a psychological construct which describes the control and coordination of cognitive resources towards consistently maintained goals [6], and which can be undermined by sustained performance [11, 21, 75, 89]. While previous work has not tested the association between engagement or fatigue and multifractal signatures, there is evidence that multifractal signatures are affected by tasks which place higher demands on executive function [6, 7, 57].

We therefore predicted that sustained engagement on a challenging task like the sheep game, would result in lower multifractal signatures in task-directed movement (H1 below). This would be due to a slightly reduced ability to coordinate behavioural resources and thereby maintain the sensorimotor coupling, which Dotov et al. suggest supports performance on the task [26, 27, 27]. It is also known that more engaging tasks better support executive function, while less engaging tasks result in lower executive function and mind-wandering [21]. Based on this and the aforementioned association between multifractality and executive function, we hypothesised that a more engaging task would result in stronger multifractal signatures in task-directed movement (H2 below), due to the stronger motivation to engage and effectively coordinate resources.

4.2 Hypotheses

H1. Multifractal signatures will be stronger in the group playing the "engaging" game.
H2. Multifractal signatures will be stronger in the 2nd half of each trial than in the 1st.

4.3 The "Engaging" Sheep Game

To test these hypotheses, we created a version of the sheep game which supported engagement by providing continuous ability-calibrated challenge and informational feedback on progress. The kinds of engagement which seem most relevant to readiness-to-hand, are cognitive - focus-on-task and cognitive effort (see 2.2). We therefore focused on these dimensions of engagement. We drew on sub-dimensions of Flow theory and other accounts of cognitive engagement to adapt the game. We did not aim to measure flow-states specifically, but followed previous authors in drawing on sub-dimensions of flow which were relevant to cognitive engagement [72]. We redesigned the task to match challenge to the user's ability, since there is evidence that this supports task focus and effort [69]. We also provided clear informational feedback on performance, since this has been shown to increase engagement [23].

The challenge of the task was adapted to player ability via a simple mechanism: A variable controlling difficulty continually increased for as long as the sheep did not touch the edge of the field. On touching the border, the difficulty was decreased by a fixed amount, and *immunity* was granted for 1 second. During immunity the difficulty could not be reduced again, giving players a chance to recover. The difficulty variable affected two game parameters: the rate at which the sheep flee from the cursor, and the noise which is added to the movement of the sheep. To increase investment and to keep the level of difficulty well adapted to the player, this progression in difficulty level carried over from game to game - players started each game on the average difficulty level they reached in the previous game. The first game began at a nominal difficulty level of 0. To further increase sense of investment, and engagement, simple informational feedback on the current difficulty level was provided via the colour of the game elements, which was tied to the difficulty parameter. The colour slowly and smoothly interpolated between four fixed colours: green at the easiest level, then yellow, red, and finally white. This scheme was designed to provide clear information without being distracting, and was explained to users at the start of the game.

In the control version of the game, difficulty was fixed at zero throughout, and game elements remained green. There was thus no difficulty adaptation, and no feedback on performance. Since this experiment did not include an observation task, game elements were presented in a single colour and shape. The sheep objects were all circles, and the cursor was a square. To help distinguish the cursor, this was coloured a fixed white in both conditions.

After informal piloting to arrive at appropriate parameters, we performed a short study to confirm the effect of these adaptations. 12 participants each played both versions of the game engaging (A) and control (B), twice each. Half of the participants played two games of A, for 2 minutes each, then two games of B for the same time. For the other half this order was reversed. After completing both sessions for one version of the game, participants completed a questionnaire comprising three questions, answered on a 5 point Likert scale. *1) I was completely focused on the task at hand, 2) I felt motivated to keep engaging with the task. 3) I put a great deal of effort into performing the task.*

The first question was taken from the short Flow State Scale questionnaire (SFSS) [48]. The SFSS consists of 9 questions each addressing one sub-dimension of flow. We did not aim to measure flow states as such, and our hypotheses did not concern dimensions of flow such as autotelic experience. Instead we focused on one sub-dimension of the SFSS: "concentration on task", which captures cognitive engagement [23, 48]. There is precedent for drawing on sub-dimensions of flow, for example the development of the Focused Attention construct in the UES scale [74].

The second and third questions were formulated for the experiment, to capture continuing motivation, and level of cognitive effort. Scores on this questionnaire were significantly higher for the more engaging version of the game ($t(11) = 4.81, p < .001$ (paired)).

4.4 Protocol

30 Participants (10 female, 20 male, 18+, recruited from student population via posters) played this game 4 times for 2 minutes each. The longer play time per game was designed to maximise any effect of sustained performance on multifractality over the course of each trial. The same equipment and environment was used as in the first game.

4.5 Results

As in the first experiment, the surrogate analysis showed that the 1st order Gaussian wavelet resulted in the greatest differentiation between original and surrogates (91% outside the 95% confidence) indicating that this wavelet minimised the contribution of linear features such as speed and variance in hand-movement. This statistic in addition gives confidence that the effect of these linear features in the results is low, and so the results can be taken as reflective of differences in nonlinear behaviour, characteristic of multiplicative cascades [45]. This was followed by the 3rd order (87% of samples outside the 95% confidence interval) . As such we draw our conclusions from the 1st order analysis.

The hypotheses were supported by the results using 1st order wavelet, and would have been supported by a 3rd order analysis also. Per H1 we observed that spectral width was significantly higher for participants playing the engaging game than for those playing the non-engaging game (Order 1: $t(29) = 4.07, p < .001$; Order 3: $t(29) = 3.72, p < .001$). Per H2 both groups' widths in the first

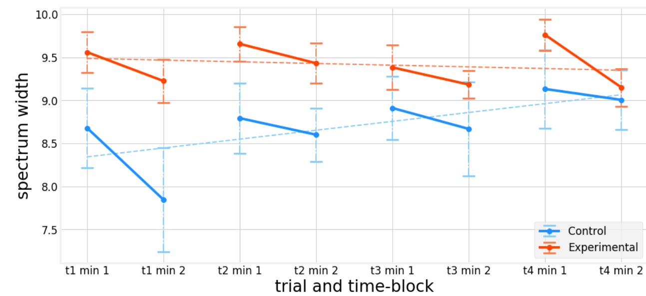

Figure 6: Experiment 2: Spectral widths during first and second minute of each game

minute of each trial were higher than those in the second minute (Order 1: $t(119) = 2.76p = .003$; Order 3: $t(119) = 2.39p = .009$).

Summary: Our second experiment indicate that the multifractal singularity spectra correlated with another dimension associated with readiness-to-hand: task engagement. The singularity spectrum was significantly higher when participants performed a more engaging task, and higher in the first half of each session, than the second - which might be attributed to waning interest, or to fatigue from sustained performance.

5 DISCUSSION

Readiness-to-hand has been an important concept in HCI and design theory, and researchers in HCI have pointed to the value of operationalising the concept to support the testing of design ideas and interaction variables, and to help integrate design practice and theory around the concept [10]. The two experiments presented in this paper take the first steps towards developing an operationalisation of readiness-to-hand for HCI, drawn from research in cognitive science and human movement science. In the sections below we discuss the key results from these experiments, their implications for future research, design, and theory-building around readiness-to-hand in HCI; and the questions which need to be addressed on the way to developing applications and methodologies around this operationalisation.

5.1 Key Findings and Contributions

We first summarize the key contributions of our results and then give a situating discussion of these contributions.

(1) In experiment one we articulate and test a new hypothesis linking multifractality to readiness-to-hand. Our results show that multifractality in hand movement increases as the user becomes more familiar with the task. These results provide evidence that changes in multifractal-signatures associated with readiness-to-hand do not rely on the specific conditions of breakdown. We suggest this is important to HCI since full breakdown is a less common scenario in everyday technology use, than the process of becoming familiar with a new technology.
(2) In experiment two we articulate and test another new hypothesis: multifractality will be stronger during a more engaging task. While reduced *mono*fractality has previously

been observed when users must carry out very trivial almost skill-free tasks [61], we demonstrate the effect during a skilful game, and our results shows the potential to discriminate levels of engagement between two fairly engaging tasks, pointing to opportunities for real-world use. Further, by observing the effect in *multi*fractal signatures we provide stronger evidence for the underlying theory linking core dimensions of readiness-to-hand to cascade dynamics

(3) In experiment two we also provide evidence for another, related, new, hypothesis — that multifractality will diminish over the course of a somewhat extended, challenging, task. Again, to our knowledge, this result has not previously been observed, and we suggest it points to the potential for future work to investigate whether multifractal spectra carry information about fatigue.

(4) Finally, the results in experiment one replicate, and address gaps in, previous work. They replicate the observation that multifractality correlates with a shift in locus-of-attention during tool breakdown, while addressing gaps in evidence in previous work. We provide stronger evidence that the user's locus-of-attention shifts towards the tool, and (via the use of surrogate analysis), stronger evidence that the observed multifractality is due to changes in interactivity between the component processes underlying behaviour.

In addition to these empirical contributions, the work we have presented also makes methodological contributions to support future use of MFA in HCI. We provide analysis scripts and data at our OSF page, and describe a new methodology for selecting parameters of analysis in MFA, which can help guide analysis in new interaction modalities, and support good hypothesis-testing practices around multifractal analysis (3.7.4).

5.1.1 Breakdown. :

In line with recognised good practice [98], we first replicated previous results which related readiness-to-hand to multifractality during breakdown before extending them. These replications do not simply repeat previous work, but adapt methodologies to address gaps in previous evidence. Consistent with previous results [26] we observed that when the tool functioned well for the task at hand, the movement of the hand was more multifractal, and the user's attention was not focused on the tool (as indicated by low recall scores on a test of visual awareness). When the tool became inadequate for the task due to a simulated malfunction in cursor control, movement became less multifractal, and attention on the tool increased. Participants showed higher recall scores on a test of visual awareness of interface objects, and no change in recall scores for task-irrelevant objects in the same interface. Our results provide evidence that changes in multifractality during breakdown correlate with a shift in attention specifically towards the tool, as described in accounts of readiness-to-hand. Previous work only measured attention to task-related objects [26], making it uncertain whether the observed effect was grounded in a shift in attention towards the tool, or simply a general increase in attention. Precision in this matter was motivated by the assumption that the location of user attention is of particular interest in UX research and interface design.

We also move beyond previous findings in two further ways: First, our results show that the change in multifractality during breakdown occurs in the absence of a distracting counting task[26] which seems likely to affect the ability to engage and "smoothly cope" with the task as described in canonical accounts of readiness-to-hand. Second, our methodology provides stronger evidence that the analysed multifractal spectra derive from the cascade dynamics which have previously been argued to ground the observed effect [26, 27]. Multifractal spectra can also be affected by linear features of the signal which need not reflect cascade dynamics in the measured system - Fourier spectra and probability density functions. Surrogate analysis (which was not carried out in work by Dotov et al. [26, 27] provides confirmatory evidence that the observed spectra are not significantly affected by these linear features. As such it is increasingly considered best practice in multifractal analysis [45, 56].

These results point to future possibilities for using multifractal measures in system design. Further work is required to extend these results into other scenarios or subtler forms of breakdown. However the unobtrusive nature of the measure – requiring only the capture of task-directed movement – suggests there is future potential in developing this line of research. Multifractal analysis might be used to infer users' locus of attention during game play, in VR environments and with tangible gadgets. They also point to the possibility of using multifractal analysis to identify situations where the user's 'grip' on an interaction situation is diminishing: breakdown need not be restricted to tool malfunction. The account we extend suggests that any circumstances which result in the user failing to maintain an effective sensorimotor and behavioural coupling to the task environment may result in reduced multifractal signatures.

5.1.2 Learning, and Familiarity with Technologies.

Accounts of readiness-to-hand in philosophy [29, 96] and HCI [22] emphasise "skilled coping" - adequate familiarity with tool and task - as a pre-requisite of ready-to-hand tool use. Despite this, previous work on empirical approaches to readiness-to-hand had not addressed this issue. Our first experiment addressed this gap, testing the hypothesis that multifractal signatures in movement will increase with familiarity. Though this hypothesis had not previously been articulated or tested, we argue that it is an implication of the existing theory linking readiness-to-hand to multifractal signatures and provides further evidence for that account. Dotov et al. argued that ready-to-hand modes of engagement arise when neuromotor resources are organised into cascade structures which support adaptive behaviour, via task-specific, sensorimotor coupling to the task. It seems clear that the ability to maintain such states, should be learned over time, and accounts of readiness-to-hand emphasise the need to acquire skill and familiarity with the tool [22, 95]. It follows that, since multifractality is a signature of such adaptive behavioural structures, we should expect multifractality in task-directed movement to increase over time, as the user familiarises themselves with the tool and task. Our first experiment tested and found evidence to support this new hypothesis. Multifractal signatures were significantly higher in the 5th trial, after the user had gained experience with the tool and task, than in the first.

This result addresses a gap in previous efforts to operationalise readiness-to-hand. Previous measures in HCI have focused on the effect of tool deficiencies and breakdown [2, 3], lack of realism [9]), or the difference between passive and active engagement [9]. While such issues are important and relevant, it is arguably more common and useful to observe changes in user's familiarity with an adequately functioning tool, during active use. Finally, this result points to the possibility of applying multifractal analysis in skill training applications, in line with recent calls to apply multifractal measures and associated theories in physical therapy, based on evidence that multifractal signatures predict the generalisation of learned movement behaviours and adaptability in skill [14].

5.1.3 Engagement with task . In our second experiment we observed that hand movements of players were significantly more multifractal in the more engaging game, than in the less engaging game. Engagement is a core dimension of readiness-to-hand, and while specifically *high* engagement is not *necessary* in readiness-to-hand (2.2), accounts in HCI have often stressed the connection to high-engagement, focus, and immersion [2, 3, 88, 93].

Previous work has connected multifractal patterns with executive function [6], which points to the possibility that multifractality signatures may predict the related construct of engagement. However, the association between fractal signatures and engagement has only been investigated in *mono*fractal signatures, and only when comparing tasks which require no cognitive engagement, to tasks which are only minimally engaging [61]. Our experiment is the first work to our knowledge to investigate the association between multifractality and engagement during realistically challenging and engaging tasks. This is important for HCI where these measures must be useful in realistically challenging and engaging tasks, and where they must be able to identify changes in engagingness due to relatively small differences in user feedback and task calibration.

The results of the same experiment also confirmed our hypothesis that multifractality would diminish over the course of each session of play. This result is again consistent with a link between multifractality and engagement. However, we suggest that this result offers at least two possible interpretations: it could follow from lower ability to engage due to sustained performance and fatigue, or from disengagement due to boredom, or low arousal. The theoretical model we build upon suggests that multifractality follows from behavioural coordination [26, 45, 56], and both fatigue and boredom are consistent with the reduced ability to coordinate behavioural resources towards the performance of a task [21]. Our preferred interpretation is that the effect is more likely due to fatigue than boredom: the same effect is clearly observable in both conditions, and since we observed that participants in the "engaging" task were highly motivated, and seemed to engage strongly right to the end of the task. However, our experimental design does not allow us to clearly distinguish fatigue from disengagement due to boredom, so future work will be required to understand this. The relationship between fatigue and multifractality has not, to the best of our knowledge, been investigated and this seems to us a fruitful direction for future work in HCI and cognitive ergonomics.

One final observation in the second experiment warrants some discussion. In the non-engaging condition there seems to be an increase in multifractality over the course of the trials,in line with the results of the learning phase in the first experiment. However, we were surprised not to observe such a pattern in the "engaging" group. Overall our results suggest that the metastable states of behavioural coordination which are argued by Dotov et al. to give rise to both multifractality and ready-to-hand experience [26], are supported by both engagement and learning. It may be that high engagement is effective in encouraging the earlier attainment of such states as the user learns the task. This is supported by the similar levels of multifractality observed between the groups by the final trial. Whether similar patterns are observed in different tasks is an interesting question for future research. But further to this, it is worth noting that this increasing multifractality over trials coexists with a diminishing multifractality within each trial. It may be that that three forces are at work across this experiment: level of engagement between conditions, learning effect over the course of the trials, and fatigue due to sustained performance during the course of each trial. It is also possible that this effect is an artefact of the methodology - that the anticipation of the end of the trial changes user behaviour or engagement in some way. This could be addressed by observing longer trials in which gradients in multifractality in the middle of the task could be isolated from any such end-effect. Such work might coexist with qualitative methods, perhaps making use of phenomenological interview techniques [65, 77], or other user experience approaches to further the understanding of the relationship of these measures to experiential dimensions of readiness to hand.

5.2 Practical Considerations

Data capture for MFA is less disruptive to interaction than previous approaches in HCI, and easier to incorporate into existing interaction situations. It does not rely on secondary measurement tasks which may interrupt performance on the primary task, and alter level of engagement and perhaps focus of attention, and only requires commonly available input devices. Our study applies MFA to recordings from accelerometers, which are now commonly available in consumer technologies. Below, we note it may be possible in future to collect this data directly through the mouse. In other studies data from video object tracking [71], and even the keyboard [60], have been used as sources. All of this makes MFA cheap and discrete to deploy, even in existing systems, and it opens up the potential to measure readiness-to-hand outside the lab, both for studies "in-the-wild", and for incorporation into everyday technologies, allowing systems to react to user requirements more effectively. In the right circumstances it may be possible to use only the sensors already incorporated in the system, for example recording mouse or accelerometer input directly, or using motion detection tools such as leap motion and video motion analysis [71, 79]. This could result in lower barriers to acceptance, since no unfamiliar peripherals are required. Finally, the approach seems likely to fit into a wide range of interaction situations. While this paper evaluates multifractality in mouse use, previous research makes it clear that the same approach can be applied to many other circumstances which are quite mechanically different: examples include steering a car [61], sports training [35], and writing an essay at a keyboard [61].

5.3 Operationalising Readiness-to-hand in Multifractality

Readiness-to-hand is an important theoretical construct in HCI. It gathers together a complex of experiential and behavioural dimensions relevant to HCI, and predicts that these dimensions will vary together in a more or less reliable and predictable way, in response to particular conditions. It thus seems natural to frame some of the account in terms of hypotheses and design implications. For example: accounts of readiness-to-hand suggest that the user's attention will be distributed differently under different conditions of technology use, at different levels of engagement. When the user is deeply engaged in performing a task they are less likely to notice visual elements at the control interface, and perhaps sounds which are associated with the normal functioning of that interface. But when this "smooth coping" with the task is interrupted - either the task changes, or the user realises their strategy is ineffective, or the tool proves ineffective - then this pattern of attention will change, and these features of the interface may become more noticeable. If this turns out to be a reliable phenomenon during interaction, then it suggests certain approaches to design: we might, for example, vary interface layouts for different phases of interaction, use different notification strategies. This is one example, and the account of readiness-to-hand raises many others, pointing to the value of operationalising the concept in order to explore these possibilities empirically [10]. For some recent interpreters, readiness-to-hand implies predictions about a user's sensitivity to relevant affordances [80, 96]. Some accounts, including the theoretical model we build, suggest ready-to-hand tool use involves the functional incorporation of the tool into cognition [9, 27], and some point to implications of this functional incorporation for the user's perceived ability to act in space [9, 20].

Our work here is only an early step towards an empirical approach to readiness-to-hand in HCI. We develop and test hypotheses drawn from an account of how core behaviours associated with readiness-to-hand arise from control structures, and our results provide further evidence for that account. While we have noted that the account of multifractality in movement and cognition is well developed, the account connecting it to readiness-to-hand is newer. As such further work is required to develop and test the account, clarifying that multifractal signatures predict behaviours associated with readiness-to-hand in a stable and consistent way across the core dimensions which have been found useful to HCI, and across multiple interaction modalities and scenarios. We give specific examples of the future work required in the key contributions above, and in the limitations below. By developing the account and addressing its open questions, there is potential to deepen and clarify our understanding of readiness-to-hand. Previous HCI research indicates that an empirical approach to readiness-to-hand can ultimately help us understand intuitive interactions, and the way users integrate technologies into behaviour and experience [10], opportunitites to understand the patterns by which users become familiar with technologies and appropriate them [15] and to understand the ways in which breakdowns affect user experience [2, 10, 99]. We suggest they can also help us understand the relationship between readiness-to-hand and adjacent constructs such as flow [12, 37], attentional blindness [2], peripersonal space [9].

5.4 Limitations and future work

As an early step towards operationalising readiness-to-hand for HCI, this work naturally comes with limitations, and opportunities for future research. First, our experiments focus on one particular game. This may raise concerns that peculiarities of the task and manipulations create sources of error which influence the measure of multifractality - for example by directly influencing the user's movement amplitude, or speed. However, it is worth noting that, not only were our hypotheses supported through quite different manipulations, including when the only manipulation was time (experiment 3, H2) but also that our analysis procedure follows standard practice in using surrogate analysis to rule out exactly this kind of error [45, 56]. Surrogate analysis provides stronger evidence that the observed multifractal spectra are due to cascade structures in behaviour and not due to linear factors (e.g. amplitude, speed).

It is also worth noting that many previous studies have related multifractality (and fractality - see 2.3.1 for discussion of how these relate) to closely related phenomena. For example (multi)fractality has been associated with engagement in steering [61], skill in crafting with a hammer [71], immersion in the experience of drawing [62], and quality of essays during typing [60]. The mechanical diversity of these tasks, and the connection to dimensions of readiness-to-hand provide further evidence for the likely transfer of our results beyond the particularities of our task. However, future work should test this, exploring more ecologically valid tasks in various interaction modalities. This may include a focus on multifractal variations in subtler forms of "breakdown" than occurred in our experiments: due for example to disengagement and mind-wandering, user-confusion, and occlusion of relevant information for action.

Awareness of the tool is an core dimension of readiness-to-hand and might be expected to be predicted by multifractality not only over conditions of breakdown, but also over changes in familiarity and engagement. We did not test this in our experiments on skill and engagement, since they focused on continuous engagement with a task, and we felt this engagement could be disrupted by observation tasks. Future work should address this limitation, finding imaginative approaches to testing whether more skilled players and users are less attentive to the visual properties of the game or tool, as might be expected from the account. The results of this work could be useful for understanding information display in different modes and phases of interaction, for example in the design of alerts and information for experienced users. It is perhaps particularly relevant in safety critical applications.

There also remains a need to further investigate the relationship between multifractality and first person experience. In this work we only establish an association with the engagingness of the task. Future work might deploy qualitative and quantitative measures to more precisely understand the relationship to the experience of engagement. One direction may be to investigate the relationship of multifractality and other constructs which have been related to readiness to hand. Our measure of attention is already quite close to the measure Alzayat et al. associated with presence and tool-embodiment [2, 3], differing primarily in its focus on the observation of persisting properties rather than change. It thus seems likely that we measure the same phenomenon, though there is value in testing the association of multifractal measures with their

Shift of Locus of Attention Index, and with measures of presence and tool-embodiment in VR. Future researchers may also investigate the relationship between multifractality and experiences of of tool-extension and peripersonal space, which have been considered valuable in HCI and linked to experience of immersion and perception of ability to act in space [9]. In the work of Dotov et al. [26, 27] and others [33] multifractality in tool use was treated as evidence of the tool's incorporation into cognition, but to date no work has attempted to link multifractality in movement with reaction time measures of tool-extension, and peripersonal space [9].

Turning to practical issues: since our work focused on grounding evidence associating readiness-to-hand and multifractality, it has been left to future to test the applicability of the approach recordings of direct mouse input, and other common input methods. This task is non-trivial since mouse drivers use nonlinear transfer functions to translate physical movement into screen movement [13], and high time-precision in recording movement is difficult to achieve in modern, multi-threaded operating systems [78].

Future work may also address potential real-time applications, drawing on e.g. "epoching" approaches used to investigate patterns in multifractal variation over time [6, 7, 71]). These patterns may be used alongside other features of behaviour and machine learning algorithms to identify phases and transitions in interaction behaviour and experience. One challenge here will be to understand the signal length required to identify patterns and discriminate between behaviours (since signal length will be an obvious limiting factor on the responsiveness of the system).

Finally it is worth addressing limits on how multifractality might be expected to relate to the philosophical construct of readiness-to-hand. We do not claim that philosophical accounts of readiness-to-hand can, even in principle, be *reduced* to multifractality in the behavioural system, or any other simple measurable feature. In particular, we do not suggest that variations in multifractality in movement capture accounts of readiness-to-hand in their full richness, complexity and philosophical implications. We follow prior HCI researchers [2, 3, 9], cognitive scientists [24, 26, 58], and some philosophers [52, 58, 96] in approaching accounts of readiness-to-hand as descriptions of a behavioural and experiential phenomenon, bracketing out the contribution to ontology and their association with Heidegger's wider critique of technology [22]. We follow previous work [2, 26, 29, 97] in identifying in accounts of readiness-to-hand, particular dimensions of behaviour and experience, and descriptions of how, and in response to which conditions, they are expected to vary. The specific dimensions we focus on are drawn from previous work: locus of attention [2, 26, 97]; prior achievement of adequate skill [22, 29, 96], and task engagement [29, 95]). We do not claim these dimensions are exhaustive of the construct of readiness-to-hand, but we do feel they form a useful core of the concept as it is approached in HCI. In addition to addressing empirical limitations discussed above, future work might return to Heidegger [42], Merleau-Ponty [67] and later commentators [29, 58, 95, 97], to further clarify the boundaries of the construct, and develop new hypotheses.

6 CONCLUSION

We present an approach to operationalising readiness-to-hand in a qualitative measure based on Multifractal Analysis (MFA), and grounded in a large empirical and theoretical literature on the organisation of movement control in skilled performance. Our work contributes to the growing effort to develop quantitative approaches to the understanding of readiness-to-hand and related phenomena of interaction - phenomena to which past research has mostly taken a subjective approach. We move beyond previous empirical approaches to readiness-to-hand both in terms of the dimensions measured, convenience, portability, and unobtrusiveness of the technique. As such we suggest that the approach we describe marks a significant milestone in this strand of research. We support further research in this area by collating existing tutorials, mathematical treatments, libraries and other resources on MFA. We describe a new approach to parameter tuning, and provide all our data and analysis scripts for others to build upon at an Open Science Framework page. This also contains a step-by-step technical description of how we calculated multifractality using Wavelet Transform Modulus Maximum (WTMM). We think our work has considerable scope in HCI, opening up a new and more systematic approach to the construct of readiness-to-hand. Our paper focuses on application of MFA to questions in HCI, and on pointing to opportunities for MFA to enrich our understanding of interaction. We hope this will help researchers to develop and test hypotheses about readiness-to-hand, and support the development of interfaces which react dynamically to behavioural and experiential aspects of more-or-less ready-to-hand interaction.

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