Attention in *high-performance cognition* is goal-directed, selective, focused, and sustained

Benjamin Ultan Cowley (ben.cowley@helsinki.fi)
Faculty of Educational Sciences, University of Helsinki
Siltavuorenpenger 5a, Helsinki, 00014, Finland

Aila Kirjanen (aila.kirjanen@helsinki.fi)
Faculty of Educational Sciences, University of Helsinki

Abstract

We introduce the concept of high-performance cognition as a domain-general function of acquiring and performing cognitively demanding skills to a high level. We conduct a survey among academic experts to identify key attention categories of high-performance cognition: by independent consensus they highlight the importance of goal-directed attention. Selective, focused, and sustained attention are strongly associated at slightly less complete consensus. They qualify their ratings with free-text reflections. Our work offers a new framing for skilled performance and its underlying cognitive processes.

Keywords: learning, skill acquisition, Flow, expert performance, high-performance cognition, attention, expert survey

Introduction

Humans can learn to perform a wide range of different skills and understanding *how* new skills are learned and improved over time is of fundamental interest. When performance in skilled tasks reaches personally near-optimal levels, we become highly productive, intrinsically motivated, with attention finely tuned to the task at hand (Bejjanki et al., 2014) – as in, for example, e-sports, athletics, or surgery. This raises a vital question: how *universal* and *characteristic* are the cognitive processes subserving skilled performance?

We discuss a novel conceptualisation of the cognition underpinning skill acquisition and performance, which we term 'high-performance cognition' (HPC). We assume that HPC is *universal* in the sense that it comprises the same set of fundamental, domain-general cognitive processes - such as attention modulation, inference, emotion regulation, processing abstract relations - regardless of the specific skill being performed. And we assume that HPC is *characteristic* in the sense that it expresses differently across individuals, who differ in their propensity for phenomenal experience of HPC, their capacities in domain-specific faculties like spatial awareness or numerosity, and other factors.

In this paper we describe one plank in an overall program of research to characterise the domain-general cognitive processes of HPC. We start with attention and study the research question: *which categories of attention are thought to be most typical in HPC?* We conduct a brief review of attention literature and derive from this a set of attention categories, which are specific ways of conceiving of attention, such as 'goal-directed', or 'focused' vs 'divided'. We then survey 12 academic experts working in HPC-adjacent fields of study, illustrating by consensus which categories of attention they associate with HPC.

What is high-performance cognition?

Despite many lab studies on skill acquisition (Hardwick et al., 2019), we are far from understanding naturally-occurring HPC. This is due firstly to the complexity and incremental learning of real-life skills, which follow a power-law function indicating a decreasing rate of improvement with increased skill level, in contrast to the exponential curves which characterize lab tasks (Newell & Rosenbloom, 1993). Secondly, it is as yet unclear how subjective expectation from the cognitive model of one's own learning curve, plays a role (Palomäki et al., 2021). Thirdly, it is also challenging to identify occurence of genuine HPC experiences using standard lab measures such as self-report (Abuhamdeh, 2020). Fourthly, recent studies suggest a strong role for individual differences in HPC; e.g. deliberate practice accounts for less than half the variance in achievement at elite level (Hambrick et al., 2014); Flow propensity varies with personality (Ullén et al., 2012).

To acquire high-level skills in a complex, partially-predictable environment, humans must learn to efficiently *represent*, *reason about*, and *act on* that environment, via multiple cooperating cognitive processes to encode states and the structures that link them (Radulescu et al., 2019). Here, an *environment* is a set of relations and affordances, which is complex if it corresponds to Savage's (1961) *large world* idea (Binmore, 2017). Learning of structure and action for skill acquisition is a form of inferential intelligence, conceptually building on prior work in representation, reasoning, and reward (Foster, 2019; Rusanen et al., 2021). Such learning is driven by some as-yet unclear process of trial-and-error conditioning versus insight episodes (Gazzaniga, 2018, p208). This process might relate to the hypothesis that the brain uses cognitive maps, built up by trial-and-error structure learning, to perform insight-based generalisation (Whittington et al., 2022).

The embodied, enactive setting just described can give rise to HPC when we learn to *control* that setting to acquire skill: specifically, we learn to control the interaction with the environment, as suggested by theories of controlled perception (Friston et al., 2016; Mansell & Huddy, 2018; Rolfs et al., 2005). This has the specific meaning that individuals learn to control their own perception and action such that they opti-

In L. K. Samuelson, S. L. Frank, M. Toneva, A. Mackey, & E. Hazeltine (Eds.), *Proceedings of the 46th Annual Conference of the Cognitive Science Society.*

mise the information obtained by epistemic interactions, e.g. by playing probing moves in the early part of a game. In the domain of games, control pertains to the game outcome, i.e. to win or achieve high scores. Fig. 1 shows the process in brief: player X must learn how to set up traps by inferring multi-move structure, as opposed to just playing 'intuitive' moves to set up 3-in-a-row, that are easily blocked.

From this background, we give a working definition and explanation of HPC, with examples for clarity; survey participants saw a shorter 'orienting' description (see Methods):

HPC is goal-directed cognitive information processing which approaches locally-maximal efficiency, driven by a controlled oscillation between exploration and exploitation in the set of affordances, to generate locally-optimal performance.

HPC thus concerns the *way* a task is performed. Take, for example, cycling to work. The route is fixed so navigation is not demanding and performance is typically satisficing. However, consider a period of heavy construction work, which reroutes the cycle lanes, deforms the surface, and mixes cyclists with pedestrians. Consider changing seasonal weather conditions in a northerly climate. Under such conditions and with time pressure due to a work emergency, the cyclist must put forth considerable effort to meet all demands with high performance. The over-learned route navigation must be adapted on the fly. Constant vigilance is required for the rough or icy road surface and other traffic. Physical fatigue must be managed to prevent it affecting cognitive performance. The satisficing daily commute becomes somwhat closer to the demands of a trail-bike race: however, the performance is probably not at athlete level, hence is 'locally-optimal'.

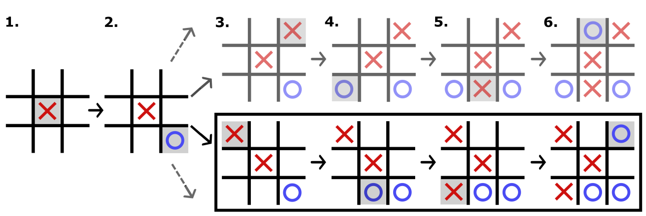

Figure 1: Learning of control via inference into task structure in TicTacToe: 2 (out of 4 possible) branches at move 3. **Top branch**: 'intuitive' moves try to line up 3-in-a-row, but are easily blocked. **Lower branch**: winning requires setting a trap (move 5); traps take 2 of one's own moves to set up (moves 3–5), thus requiring game-structure insight beyond the next move. **HPC example:** TicTacToe has very small number of branches at each move and attentive players will quite easily solve it to the equilibrium condition of forced draw. However, to 'optimally' learn perfect play (i.e. in fewest replays) requires a period of HPC, where gameboard information is tracked and extrapolated through all the decisive future moves, and separate move patterns are related to infer commonalities. With maximally-efficient task information processing, a learner can potentially achieve perfect play in as few as 10 games (Paul, 2020).

In summary: HPC must be goal-directed because there must be an objective against which to judge efficiency. What is being made efficient is resource-expenditure for task learning and performance. Learning is fundamental because, beyond the instantaneous experience, HPC integrates multiple scales across temporal and cognitive dimensions, as follows:

1. 100s-1000s hours; structured, learned activity (a sport, game, hobby, or professional task); Associated sub-skills

2. Hours/minutes; episodic activity, learning (a race; race track curves); Associated action plans/learning modules

3. Milliseconds; cognitive acts (perceiving, recalling, predicting, acting); Associated neural processes

HPC operates across these temporal scales via self-similar mechanisms. At the scale of actions, the instantaneous component of HPC involves the balance of activity (system+task) complexity with performance (memory+attention) complexity; simultaneous with the balance of task demands and time available. The time-dependent component of HPC is defined as cyclic exploration-exploitation within the space of possible actions; a learning process that leads to increased complexity of all kinds: representations, inferences, and actions. On the shorter two of the above time-scales, attention regulation is a vital component in HPC, thus motivating our study. 'Attention' is, however, a highly overloaded term with many definitions across several fields from psychology, neuroscience, and machine learning.

What is attention?

Everybody knows what attention is, but what is it? A vast body of work in many disciplines has studied attention. Pioneer of psychological attention research, William James, viewed attention as conscious selection. A cognitive view is that attention is the flexible control of limited computational resources (Lindsay, 2020). In predictive processing literature, attention has been described as "context or state-dependent optimization of the precision of prediction errors" (Brown et al., 2011). The empirical tradition from psychology and neuroscience, as led by figures such as Hermann von Helmholtz, studied the mind in its constituent domains. This leads to the view of attention as a categorical faculty which allocates limited neural processing resources across domains or modalities like time (e.g. sustained attention), perception (e.g. overt vs covert attention), locus (e.g. endogenous vs exogenous attention), level of analysis (e.g. feature vs object), spatial extent (e.g. focal vs global) and more. Although this categorical view may be limited and biased (Anderson, 2011), here we aim to use the categories in order to examine how *existing* literature and the authors thereof link the concepts of attention and HPC. Thus, we follow the *lexical hypothesis* to ask: which categories of attention are said to be related to HPC?

Methods

Categories of attention

The literature which reflects a categorical view of attention provides many terms to indicate the forms of attention studied. These terms are very often (but not always) dichotomous (Anderson, 2011) (a pattern which may reflect human bias towards dichotomisation rather than any natural kind). We conducted a narrative review of attention literature to obtain a 'foundation list' of such terms.

First, we began by collating 33 articles or book chapters with a primary focus on the theoretical structure or nature of attention. This search was non-systematic, directed by the first author, using multiple search terms across all relevant databases and stopping after broad coverage of the topic was achieved. These works are listed under References in a separate section termed *Seed bibliography*.

After reading these 33 works, we selected six to serve as the final basis of our term list, based on the criterion that they provided categories or a taxonomy of attention (Anderson, 2011; Buschman & Kastner, 2015; Chun et al., 2011; Knudsen, 2007; Krauzlis et al., 2014; Lindsay, 2020).

From these six works we extracted every term which was used as an adjective for attention, e.g. *selective attention*, resulting in 47 terms. We then refined this list by removing synonyms and terms for which we could find no definition, to obtain a final list of 36 commonly used attention terms, listed in Table 1.

To begin relating forms of attention to HPC, we surveyed academic experts studying topics adjacent to HPC, such as elite sports, games like chess and poker, and high skilled activities such as steep skiing.

Participants

We obtained a purposive sample of 12 participants (1 female, 11 male; 1 post-doctoral researcher, 7 senior researchers, 4 professors) who all meet the following criteria:

- hold at least a doctoral degree in psychology, cognitive science, or cognitive neuroscience (and thereby adjudged by the authors to have educational qualification to understand the attention terms listed)
- academic experts in HPC-adjacent topics
- publication record includes works relevant to attention in HPC (examples are listed under References in a separate section termed *Participants' publications*)

Survey

We developed a short survey to poll the opinion of this expert sample; respondents were instructed as follows:

> *You are asked to contribute your expert opinion to help identify the form of attention that best describes high performance cognition (HPC). A very simple description of HPC (strictly to help create common frame of reference) could be:*

Table 1: Attention terms derived by literature review.

Attention term	Antonym attention term
active	passive
auditory	
automatic	controlled
central	peripheral
conscious	non-conscious
executive	
exogenous	endogenous
focused	divided
goal-directed	
internal	external
local	global
multi-task	
object-based	feature-based
overt	covert
selective	
somatosensory	
spatial	temporal
stimulus-driven	
sustained	transient
top-down	bottom-up
visual	
voluntary	involuntary

> **[HPC is:] Performing, or learning to perform, a challenging dynamic cognitive task under uncertainty to a high level of skill**
>
> *To contribute to this expert opinion, you should have deep knowledge of one or two specific domains of human endeavour where you consider HPC to take place. Deep knowledge should entail (any or all of):*
>
> 1. *you have read extensive literature*
> 2. *you have observed practitioners*
> 3. *you have conducted experiments*
> 4. *you have phenomenal experience thereof*

To verify that participants had suitable background we requested them to cite support of the points 1–4 above. All had one or more relevant publications (as listed in their section of References), though their relevant publication count varied widely: some had tens of articles on their area of HPC research, whereas the least published participant had one. However, the latter had also worked as a professional analyst in the same area, and at least four had trained to perform their task of study to a very high level.

To help us understand participants' frame of reference, they were also asked to "*Describe a single scenario of HPC in your chosen domain...*" They were then asked to provide their own description of attention processes of HPC in their chosen domain, and directed to "*...focus on individual cognitive faculties, i.e. aim to take a reductionist approach.*"

Finally participants were asked to rate the 36 terms of attention from Table 1, on a three point scale ('*Not much*', '*Moderately much*', '*Very much*', scored 1 to 3) with fourth option 'No opinion' (scored as zero). Four additional terms – **inactive**, **uncontrolled**, **unfocused**, **unselective** – were included as so-called 'attention traps', to help assess the quality of responses. These terms were chosen because, alongside their valid counterparts – **active**, **controlled**, **focused**, **selective** – they *appear* to follow the dichotomy pattern identified by Anderson (2011). However they are logical negations rather than opposed kinds and so responses could be compared between, e.g. active and inactive, to detect a logical contradiction. These terms are also not used in the attention literature (to our knowledge) and make little sense in the HPC context. Responses to the scale were directed as follows:
"*How much does HPC involve the following attention terms: For example: how much does HPC involve SELECTIVE attention?*"

As a post-hoc reflection, participants were asked to "*Reflect on the terms given in the previous part, and note here whether the freetext description you wrote earlier reflects your term selections, or how does it differ?*"

Data gathering and analysis

The survey was emailed to 35 (9f, 26m) academics either known professionally to the first author, or recommended by one of those known. 12 responded, a 34% response rate. This data was collected from December 2021 until July 2023.

Using R (v4.3.2) platform for statistical computing (R Core Team, 2014), we analysed scale responses to the 36 attention terms (and four trap items) as follows:

1. attention trap items were converted to weights in (0..1] for each participant. The sum for each trap item and its valid pair (e.g. inactive/active) which were both scored at least 'Moderately much', was added to an overall sum. This sum was then normalised (scaled as the root-mean-square, added to one, and converted to recriprocal) by the equation: $f(x) = {}^{1}/(1+\sqrt{\frac{\sum_{i=1}^{n} x_i^2}{(n-1)}})$

2. the participants' scores for 36 attention terms were multiplied by the trap weights. Any resulting zero values were converted to NA so 'No opinion' scores do not contribute

3. the inverse coefficient of variation was computed for each term as per the equation below:
$\frac{\mu}{\sigma} = \frac{\frac{1}{n}\sum_{i=1}^{n} x_i}{\sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(x_i-\mu)^2}}$

Results

The weighted scores for attention terms are shown in Figure 2, categorised by whether they lie 2, 4, or 8 Median Absolute Deviations (MADs) from the median.

An illustrative subset of participants' qualitative responses are collated in Table 2 on the page below.

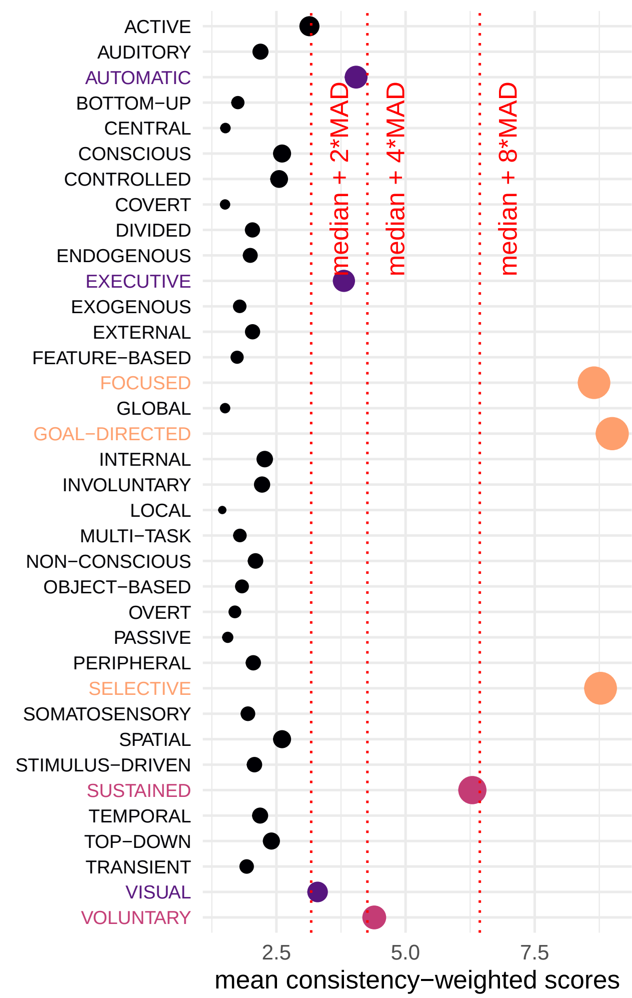

Figure 2: Attention terms scored by a custom formulation that accounts for attention traps and weights terms by consistency. Colours represent MAD levels above median. Point size is the weighted score itself, here used to aid visibility.

Discussion

Multiple existing theories have been proposed to explain phenomena similar or adjacent to HPC, for example: expert performance (Ericsson, 2006); Flow (or 'optimal experience') (Nakamura & Csikszentmihalyi, 2002); cognitive complexity in learning systems (Rauterberg, 1995); the 'neural efficiency hypothesis' (Bertollo et al., 2016). While all are valuable contributions, they have as their focus some domain that goes beyond the purely cognitive investigation of HPC, respectively: elite practitioners, psychology of happiness, human-computer interaction, or neuroscience. Meanwhile, recent work has aimed to renew certain seminal theories such as Flow or deliberate practice by re-examining their core tenets (Hambrick et al., 2020; Šimleša et al., 2018); illustrating a widely-held desire to supplement psychological theory with cognitive mechanistic explanans (Jalife et al., 2021).

Table 2: Participants' qualitative responses: one row per participant. Edited for grammar, spelling, and brevity

Hypothetical scenarios	Initial description of attention in HPC	Post-scale reflection
Thinking of the next move in a game of chess	Fully concentrating on the task at hand, which includes: trying to anticipate the other person's move(s); shifting focus from macro (e.g. position development) to micro (e.g. pawn at B2)	Even a single chess move involves a wide range of attentional processes (e.g. short- to long-term attention shifting). My responses to scale items may have differed by scenario, e.g. opening - midgame - endgame, etc
Making a race start in a racecar	Maintaining focus on both the external cues (starter or starting lights), and what one is doing/what the vehicle is doing	Difficult to judge the right contrast e.g. controlled vs. automatic is a different distinction than controlled vs. not controlled
A single poker gaming session (0.5-3 hours) with personally significant stakes and time pressure	The ability to crunch information, make +EV [positive expected value] decisions and handle variance mentally. Attention is needed [to] focus on relevant information (opponents' betting patterns, size of the pot, estimated probability of upcoming cards, physical tells, etc.), and keeping emotional control...attentive to emotional state	In poker, attention is a tool for focusing on how opponents' behavior or random [events] change the game state, and how that alters perceived goodness of potential moves. Such attention...will be overt, active, stimulus-drive and conscious. [The] mental control needed to remain calm under pressure and variance is a bit different...this [includes] terms such as 'internal'
Multitasking performance in Navy tasks	declarative knowledge; procedural knowledge; coordinated by fluid intelligence; psychomotor skill; motivation, goal orientation	quite similar, with some additional information - e.g., about conscious/unconscious, global/local
High accuracy, fast response times in computer tasks where subject should respond to unpredictable target and distractor stimuli	Optimal HPC requires: high vigilance (low mental fatigue); high working memory capacity; high executive/cognitive control (behaviour driven more by top-down than bottom-up processes); neural efficiency (minimal task-unrelated neural activity)	These [attention] terms...are relevant in HPC depending on task. Some [terms] overlap those mentioned earlier: attentional control (e.g., executive, top-down)
Striking a fast moving object such as a cricket ball or baseball	Processes for HPC are task specific...[not]...attention processes but relates to using the most important information from current environment and prior experiences to aid anticipation and decision-making to execute right responses under extreme time constraints	Many of the terms are very task dependent...even within the same domain. Some HPC domains require totally opposite attentional processes to others
Performing a BASE jump - or during [intense] skiing, mountainbiking	Intense, narrow focus of attention, the body is in high alert with increased heart rate and blood pressure...focused on the task at hand...[fewer] irrelevant tasks and thoughts. Non-relevant signals only semi-consciously attended. Some...describe this as 'going calm' before they exit...once the decision is taken there is only focus on performance	Conscious vs unconscious: Narrow attention under HPC and high stress may be conscious, but hard to recall. High-focus activities are object-based and bottom-up. Information collected is visual and auditory [yet] stimulus-responses may not be remembered. Highly selective but alert...often automatized. Intensity of attention ebbs and flows with challenge - transient. Internally-driven, but tied to relevant changes in external environment. Voluntary vs involuntary: often a battle of self-control.

However, aiming to rework existing theory risks self-sabotage, as novel ideas become bound to the existing frames. For example, it seems underappreciated how binding to Flow theory really is a commitment to the original author's conceptualisation, creating operationalisation challenges that bedevil empirical studies (Abuhamdeh, 2020). Thus, we argue for the investigation of HPC as a purely cognitive phenomenon, beginning with the questions from above: how universal and characteristic is it? In other words, what uniquely defines HPC episodes versus other experiences within an individual, and how does that vary between individuals?

Based on a survey of academic experts, we have described a conceptual link between HPC and categories of attention derived by literature review. This is intended to provide ground for further work by illustrating (A) the degree of consensus with respect to the categorical framing of attention in HPC, using the scale scores, and (B) the diversity of informed views on the same, using the free-text responses.

Regarding goal (A), we see a rather strong consensus as only nine terms are at or above the median plus 2×MAD threshold. Of these, **active**, **visual**, **executive**, **automatic**, and **voluntary** attention are all just below, within, or just above the range between two and four MADs. Beyond these, four terms are rated as '*very much*' involved in HPC by most or all respondents: **sustained** (10/12), **focused** (11/12), **selective** (11/12), and **goal-directed** (12/12) attention.

K-means clustering on 2, 3, and 4 centroids also consistently identifies these nine terms in two separate clusters. The number of clusters estimated by optimum average silhouette width is two, suggesting only the high-range subset as definitive; the mid-range subset should then be considered weakly linked to HPC based on this evidence. The objective degree of expert consensus is suggested by, for example, that the distribution of mean weighted scores (Figure 2) is rather long-tailed (kurtosis is 6.4), and that surprisal is rather high (Shannon entropy is 4.9 bits/3.4 nats).

In the mid-ranked subset, **visual** attention clearly reflects a bias in task modality from the sample. The four other terms seem complementary in that **automatic** seems in tension with **executive** and **voluntary** attention, in different ways. This was also reflected in the commentary related to extreme sports (last row, Table 2), where certain categories of attention were suggested to require management ("*often a battle of self-control*").

The four high-ranked terms point to a very particular mode of attention, focused to a goal-directed aim and selective of only relevant stimuli; most respondents say that this resource-intensive state is also sustained in HPC. Here, the combination of consensus terms is the informative part: low-performance cognition can certainly be goal-directed, but is unlikely to also require the other three modes of attention. Cycling slowly to work has a distinct goal, but attention is quite free to wander, divide, and be engaged transiently.

Some survey respondents reported that they prefer to view these as attentional *processes*. This is important to consider for developing HPC theory, which tracks cognitive system *state dynamics* through time. Time is fundamental to any learning system, which we consider HPC to be, yet there is a deficit of work integrating the state-like and temporal aspects of HPC-adjacent theories.

Limitations and future work

Our 'working definition' (see Intro) cannot be a complete or definitive description as that is both premature and out of scope. However, clarity of definition was missed by some survey respondents: "*To be honest I don't think this can be really be answered without at least a working definition provided. We don't really know what attention means still*". The HPC description we did give (see Methods) was as broad as possible to allow responses relevant to the academic experts' own work. Several respondents considered HPC to be strongly task and domain dependent; however, this was belied by their degree of agreement on a subset of terms.

The method of weighting the attention term scores is undefined when all scores are the same. In practice this was considered acceptable because such high agreement for a given term ('goal-directed') is of intrinsic interest. Ultimately, our statistical methods are intended to be indicative and our sample is not claimed to be anyhow representative.

Further studies will take the terms here reported and conduct systematic literature review to analyse their relationship to various forms of skilled, expert, and elite performance or ability. By this means, taking much larger samples of literature, we hope to establish a complementary view to our expert survey. We also aim to build up the sample size of experts.

In addition to surveys and reviews, empirical research programs studying Flow, learning, and expert performance are underway at the first author's group, seeking to identify evidence of how these phenomena relate to the predicted characteristics of HPC (Cowley et al., 2022; Cowley et al., 2020, 2019a, 2019b; Palomäki et al., 2020, 2021).

Conclusions

HPC is a little-studied topic within cognitive science, and using HPC to frame commonly-studied ideas from Flow, expert performance, and other areas raises many questions. Surveying other experts in the field for informed opinions on HPC's relevant synonyms, and relationship to the sometimes vaguely-defined terms of attention, will not shed much empirical light on these questions. What this work serves to do is to clarify what we mean when we think about HPC. This facilitates making testable empirical predictions, and supports building a theory of HPC in terms of, for example, free energy minimisation framework. The full program to examine HPC is extensive, yet with a piece-wise approach, it is tractable.

Acknowledgments

Thanks to Otto Lappi & Jussi Palomäki for early discussions on HPC. Funded by Research Council of Finland grant number 318913.

References

Abuhamdeh, S. (2020). Investigating the "Flow" Experience: Key Conceptual and Operational Issues. *Frontiers in Psychology*, *11*.

Anderson, B. (2011). There is no Such Thing as Attention. *Frontiers in Psychology*, *2*, 246.

Bejjanki, V. R., Zhang, R., Li, R., Pouget, A., Green, C. S., Lu, Z.-L., & Bavelier, D. (2014). Action video game play facilitates the development of better perceptual templates. *Proceedings of the National Academy of Sciences of the United States of America*, *111*(47), 16961–6.

Bertollo, M., di Fronso, S., Filho, E., Conforto, S., Schmid, M., Bortoli, L., Comani, S., & Robazza, C. (2016). Proficient brain for optimal performance: the MAP model perspective. *PeerJ*, *4*, e2082.

Binmore, K. (2017). On the Foundations of Decision Theory. *Homo Oeconomicus*, *34*(4), 259–273.

Brown, H., Friston, K., & Bestmann, S. (2011). Active Inference, Attention, and Motor Preparation. *Frontiers in Psychology*, *2*, 218.

Buschman, T. J., & Kastner, S. (2015). From Behavior to Neural Dynamics: An Integrated Theory of Attention. *Neuron*, *88*(1), 127–144.

Chun, M. M., Golomb, J. D., & Turk-Browne, N. B. (2011). A taxonomy of external and internal attention. *Annual Review of Psychology*, *62*, 73–101.

Cowley, B., Hellas, A., Ihantola, P., Leinonen, J., & Spape, M. Seeking Flow from Fine-Grained Log Data. In: In *44th International Conference on Software Engineering*. Software Engineering Education and Training (ICSE2022-SEET). Pittsburgh, USA: ACM, 2022, May 25–27.

Cowley, B. U., Dehais, F., Fairclough, S., Karran, A. J., Palomäki, J., & Lappi, O. (2020). Editorial: High Performance Cognition: Information-Processing in Complex Skills, Expert Performance, and Flow. *Frontiers in Psychology*, *11*.

Cowley, B. U., Palomäki, J., Tammi, T., Frantsi, R., Inkilä, V.-P., Lehtonen, N., Pölönen, P., Vepsäläinen, J., & Lappi, O. (2019a). Flow Experiences During Visuomotor Skill Acquisition Reflect Deviation From a Power-Law Learning Curve, but Not Overall Level of Skill. *Frontiers in Psychology*, *10*.

Cowley, B. U., Palomäki, J., Tammi, T., Frantsi, R., Inkilä, V.-P., Lehtonen, N., Pölönen, P., Vepsäläinen, J., & Lappi, O. (2019b). Flow Experiences During Visuomotor Skill Acquisition Reflect Deviation From a Power-Law Learning Curve, but Not Overall Level of Skill. *Frontiers in Psychology*, *10*.

Ericsson, K. A. The Influence of Experience and Deliberate Practice on the Development of Superior Expert Performance (K. A. Ericsson, N. Charness, P. J. Feltovich, & R. R. Hoffman, Eds.). In: *The cambridge handbook of expertise and expert performance* (K. A. Ericsson, N. Charness, P. J. Feltovich, & R. R. Hoffman, Eds.). Ed. by Ericsson, K. A., Charness, N., Feltovich, P. J., & Hoffman, R. R. Cambridge: Cambridge University Press, 2006, pp. 683–704.

Foster, J. M. (2019). *Integrating Analogical Similarity and Error-Driven Learning for Relational Concept Acquisition* [Doctoral]. University of Colorado.

Friston, K., FitzGerald, T., Rigoli, F., Schwartenbeck, P., O'Doherty, J., & Pezzulo, G. (2016). Active inference and learning. *Neuroscience & Biobehavioral Reviews*, *68*, 862–879.

Gazzaniga, M. (2018). *Psychological Science, 6th International Student Edition*. Norton.

Hambrick, D. Z., Altmann, E. M., Oswald, F. L., Meinz, E. J., Gobet, F., & Campitelli, G. (2014). Accounting for expert performance: The devil is in the details. *Intelligence*, *45*, 112–114.

Hambrick, D. Z., Macnamara, B. N., & Oswald, F. L. (2020). Is the Deliberate Practice View Defensible? A Review of Evidence and Discussion of Issues. *Frontiers in Psychology*, *11*.

Hardwick, R. M., Forrence, A. D., Krakauer, J. W., & Haith, A. M. (2019). Time-dependent competition between goal-directed and habitual response preparation. *Nature Human Behaviour*, *3*(12), 1252–1262.

Jalife, K., Harteveld, C., & Holmgøard, C. (2021). From Flow to Fuse: A Cognitive Perspective. *Proceedings of the ACM on Human-Computer Interaction*, *5*, 256:1–256:30.

Knudsen, E. I. (2007). Fundamental components of attention. *Annual Review of Neuroscience*, *30*, 57–78.

Krauzlis, R. J., Bollimunta, A., Arcizet, F., & Wang, L. (2014). Attention as an effect not a cause. *Trends in Cognitive Sciences*, *18*(9), 457–464.

Lindsay, G. W. (2020). Attention in Psychology, Neuroscience, and Machine Learning. *Frontiers in Computational Neuroscience*, *14*, 29.

Mansell, W., & Huddy, V. (2018). The Assessment and Modeling of Perceptual Control: A Transformation in Research Methodology to Address the Replication Crisis. *Review of General Psychology*, *22*(3), 305–320.

Nakamura, J., & Csikszentmihalyi, M. The concept of flow. (C. R. Snyder & S. J. Lopez, Eds.). In: *Handbook of positive psychology* (C. R. Snyder & S. J. Lopez, Eds.). Ed. by Snyder, C. R., & Lopez, S. J. New York (NY): Oxford University Press, 2002, pp. 89–105.

Newell, A., & Rosenbloom, P. S. Mechanisms of skill acquisition and the law of practice. In: In *The Soar papers (vol. 1): Research on integrated intelligence*. Cambridge, MA, USA: MIT Press, 1993, August 1, pp. 81–135. ISBN: 978-0-262-68071-4.

Palomäki, J., Laakasuo, M., Cowley, B. U., & Lappi, O. (2020). Poker as a Domain of Expertise. *Journal of expertise*, *3*(2), 66–87.

Palomäki, J., Tammi, T., Lehtonen, N., Seittenranta, N., Laakasuo, M., Abuhamdeh, S., Lappi, O., & Cowley, B. U. (2021). The link between flow and performance is moderated by task experience. *Computers in Human Behavior*, *124*, 106891.

Paul, A. J. (2020). Randomized fast no-loss expert system to play tic tac toe like a human. *Cognitive Computation and Systems*, *2*(4), 231–241.

R Core Team. (2014). *R: A Language and Environment for Statistical Computing*. R Foundation for Statistical Computing.

Radulescu, A., Niv, Y., & Ballard, I. (2019). Holistic Reinforcement Learning: The Role of Structure and Attention. *Trends in Cognitive Sciences*, *23*(4), 278–292.

Rauterberg, M. About a framework for information and information processing of learning systems. In: In *Ifip international working conference on information system concept*. Marburg, Germany: Chapman & Hall, 1995, 54–71.

Rolfs, M., Engbert, R., & Kliegl, R. (2005). Crossmodal coupling of oculomotor control and spatial attention in vision and audition. *Experimental Brain Research*, *166*(3-4), 427–439.

Rusanen, A.-M., Lappi, O., Kuokkanen, J., & Pekkanen, J. (2021). Action control, forward models and expected rewards: Representations in reinforcement learning. *Synthese*, *199*(5), 14017–14033.

Savage, L. J. (1961). The Foundations of Statistics Reconsidered. *Proceedings of the Fourth Berkeley Symposium on Mathematical Statistics and Probability, Volume 1: Contributions to the Theory of Statistics*, 575–586.

Šimleša, M., Guegan, J., Blanchard, E., Tarpin-Bernard, F., & Buisine, S. (2018). The Flow Engine Framework: A Cognitive Model of Optimal Human Experience. *European Journal of Psychology*, *14*(1).

Ullén, F., de Manzano, O., Almeida, R., Magnusson, P. K., Pedersen, N. L., Nakamura, J., Csikszentmihalyi, M., & Madison, G. (2012). Proneness for psychological flow in everyday life: Associations with personality and intelligence. *Personality and Individual Differences*, *52*, 167–172.

Whittington, J. C. R., McCaffary, D., Bakermans, J. J. W., & Behrens, T. E. J. (2022). How to build a cognitive map: Insights from models of the hippocampal formation. *arXiv:2202.01682 [cs, q-bio]*.

Seed bibliography

Amso, D., & Scerif, G. (2015). The attentive brain: Insights from developmental cognitive neuroscience. *Nature Reviews. Neuroscience*, *16*(10), 606–619.

Anderson, B. (2011). There is no Such Thing as Attention. *Frontiers in Psychology*, *2*, 246.

Brown, H., Friston, K., & Bestmann, S. (2011). Active Inference, Attention, and Motor Preparation. *Frontiers in Psychology*, *2*, 218.

Bundesen, C., Habekost, T., & Kyllingsbæk, S. (2011). A neural theory of visual attention and short-term memory (NTVA). *Neuropsychologia*, *49*(6), 1446–1457.

Buschman, T. J. (2015). Paying Attention to the Details of Attention. *Neuron*, *86*(5), 1111–1113.

Buschman, T. J., & Kastner, S. (2015). From Behavior to Neural Dynamics: An Integrated Theory of Attention. *Neuron*, *88*(1), 127–144.

Carrasco, M. (2011). Visual attention: The past 25 years. *Vision Research*, *51*(13), 1484–1525.

Chun, M. M., Golomb, J. D., & Turk-Browne, N. B. (2011). A taxonomy of external and internal attention. *Annual Review of Psychology*, *62*, 73–101.

Compton, R. J. (2003). The interface between emotion and attention: A review of evidence from psychology and neuroscience. *Behavioral and Cognitive Neuroscience Reviews*, *2*(2), 115–129.

Deco, G., & Rolls, E. T. (2005). Attention, short-term memory, and action selection: A unifying theory. *Progress in Neurobiology*, *76*(4), 236–256.

Fortenbaugh, F. C., DeGutis, J., & Esterman, M. (2017). Recent theoretical, neural, and clinical advances in sustained attention research. *Annals of the New York Academy of Sciences*, *1396*(1), 70–91.

Gottlieb, J., Oudeyer, P.-Y., Lopes, M., & Baranes, A. (2013). Information-seeking, curiosity, and attention: Computational and neural mechanisms. *Trends in cognitive sciences*, *17*(11), 585–93.

Helfrich, R. F., Fiebelkorn, I. C., Szczepanski, S. M., Lin, J. J., Parvizi, J., Knight, R. T., & Kastner, S. (2018). Neural Mechanisms of Sustained Attention Are Rhythmic. *Neuron*, *99*(4), 854–865.e5.

Hommel, B., Chapman, C. S., Cisek, P., Neyedli, H. F., Song, J.-H., & Welsh, T. N. (2019). No one knows what attention is. *Attention, Perception, & Psychophysics*, *81*(7), 2288–2303.

Joyce, A., & Hrin, S. (2015). Attention: An evolving construct. *Applied Neuropsychology. Child*, *4*(2), 80–88.

Kahneman, D. (1973). *Attention and effort*. Prentice-Hall.

Kaspar, K. (2013). What Guides Visual Overt Attention under Natural Conditions? Past and Future Research. *ISRN neuroscience*, *2013*, 868491.

Killeen, P. R., Tannock, R., & Sagvolden, T. The four causes of ADHD: A framework. In: In *Behavioral neuroscience of attention deficit hyperactivity disorder and its treatment*. Springer, 2011, pp. 391–425.

Knudsen, E. I. (2007). Fundamental components of attention. *Annual Review of Neuroscience*, *30*, 57–78.

Krauzlis, R. J., Bollimunta, A., Arcizet, F., & Wang, L. (2014). Attention as an effect not a cause. *Trends in Cognitive Sciences*, *18*(9), 457–464.

Kruschke, J. K. (2003). Attention in Learning. *Current Directions in Psychological Science*, *12*(5), 171–175.

Kujala, T., & Lappi, O. (2021). Inattention and Uncertainty in the Predictive Brain. *Frontiers in Neuroergonomics*, *2*, 28.

Langner, R., & Eickhoff, S. B. (2013). Sustaining attention to simple tasks: A meta-analytic review of the neural mechanisms of vigilant attention. *Psychological bulletin*, *139*(4), 870.

Lindsay, G. W. (2020). Attention in Psychology, Neuroscience, and Machine Learning. *Frontiers in Computational Neuroscience*, *14*, 29.

Luck, Woodman, & Vogel. (2000). Event-related potential studies of attention. *Trends in cognitive sciences*, *4*(11), 432–440.

McCarley, J. S., Wickens, C. D., Goh, J., & Horrey, W. J. (2002). A Computational Model of Attention/Situation Awareness. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, *46*(17), 1669–1673.

Niv, Y., Daniel, R., Geana, A., Gershman, S. J., Leong, Y. C., Radulescu, A., & Wilson, R. C. (2015). Reinforcement Learning in Multidimensional Environments Relies on Attention Mechanisms. *Journal of Neuroscience*, *35*(21), 8145–8157.

Panichello, M. F., & Buschman, T. J. (2021). Shared mechanisms underlie the control of working memory and attention. *Nature*, *592*(7855), 601–605.

Robertson, I. H., & O'Connell, R. Vigilant Attention (A. C. Nobre & J. T. Coull, Eds.). In: *Attention and Time* (A. C. Nobre & J. T. Coull, Eds.). Ed. by Nobre, A. C., & Coull, J. T. OUP Oxford, 2010, pp. 79–88.

Rosenberg, M. D., Finn, E. S., Scheinost, D., Constable, R. T., & Chun, M. M. (2017). Characterizing Attention with Predictive Network Models. *Trends in Cognitive Sciences*, *21*(4), 290–302.

Shalev, N., & van Ede, F. (2021). About time: Modelling dynamic voluntary attention. *Trends in Cognitive Sciences*, *25*(10), 821–822.

Tamber-Rosenau, B. J., & Marois, R. (2016). Central attention is serial, but midlevel and peripheral attention are parallel-A hypothesis. *Attention, Perception & Psychophysics*, *78*(7), 1874–1888.

Zalta, A., Petkoski, S., & Morillon, B. (2020). Natural rhythms of periodic temporal attention. *Nature Communications*, *11*(1), 1051.

Participant publications

Abuhamdeh, S., & Csikszentmihalyi, M. (2009). Intrinsic and Extrinsic Motivational Orientations in the Competitive Context: An Examination of Person-Situation Interactions. *Journal of Personality*, *77*(5), 1615–1635.

Cobb, N. M., Unnithan, V., & McRobert, A. P. (2018). The validity, objectivity, and reliability of a soccer-specific behaviour measurement tool. *Science and Medicine in Football*, *2*(3), 196–202.

Gallicchio, G., Cooke, A., & Ring, C. Eye quietness and quiet eye in expert and novice golf performance: An electrooculographic analysis. In: 14th World Congress of the International Society of Sport Psychology (ISSP). Seville, Spain: International Society of Sport Psychology, 2017, July. ISBN: 978-1-08-410914-8.

Gallicchio, G., Cooke, A., & Ring, C. (2016). Lower left temporal-frontal connectivity characterizes expert and accurate performance: High-alpha T7-Fz connectivity as a marker of conscious processing during movement. *Sport, Exercise, and Performance Psychology*, *5*(1), 14–24.

Grahn, H., Kujala, T., Silvennoinen, J., Leppänen, A., & Saariluoma, P. (2020). Expert Drivers' Prospective Thinking-Aloud to Enhance Automated Driving Technologies - Investigating Uncertainty and Anticipation in Traffic. *Accident Analysis & Prevention*, *146*, 105717.

Hambrick, D. Z., Altmann, E. M., Oswald, F. L., Meinz, E. J., Gobet, F., & Campitelli, G. (2014). Accounting for expert performance: The devil is in the details. *Intelligence*, *45*, 112–114.

Harris, D. J., Vine, S. J., & Wilson, M. R. Chapter 12 - Neurocognitive mechanisms of the flow state (M. R. Wilson, V. Walsh, & B. Parkin, Eds.). In: *Progress in Brain Research* (M. R. Wilson, V. Walsh, & B. Parkin, Eds.). Ed. by Wilson, M. R., Walsh, V., & Parkin, B. Vol. 234. Sport and the Brain: The Science of Preparing, Enduring and Winning, Part B. Elsevier, 2017, January 1, pp. 221–243.

Harris, D. J., Wilson, M. R., Crowe, E. M., & Vine, S. J. (2020). Examining the roles of working memory and visual attention in multiple object tracking expertise. *Cognitive Processing*, *21*(2), 209–222.

Hetland, A., & Vittersø, J. (2012). The feelings of extreme risk: Exploring emotional quality and variability in skydiving and BASE jumping. *Journal of Sport Behavior*, *35*(2), 154–180.

Hetland, A., Kjelstrup, E., Mittner, M., & Vittersø, J. (2019). The Thrill of Speedy Descents: A Pilot Study on Differences in Facially Expressed Online Emotions and Retrospective Measures of Emotions During a Downhill Mountain-Bike Descent. *Frontiers in Psychology*, *10*.

Hetland, A., Vittersø, J., Oscar Bø Wie, S., Kjelstrup, E., Mittner, M., & Dahl, T. I. (2018). Skiing and Thinking About It: Moment-to-Moment and Retrospective Analysis of Emotions in an Extreme Sport. *Frontiers in Psychology*, *9*.

Kujala, T., Mäkelä, J., Kotilainen, I., & Tokkonen, T. (2016). The Attentional Demand of Automobile Driving Revisited: Occlusion Distance as a Function of Task-Relevant Event Density in Realistic Driving Scenarios. *Human Factors*, *58*(1), 163–180.

Lappi, O. (2018). The Racer's Mind—How Core Perceptual-Cognitive Expertise Is Reflected in Deliberate Practice Procedures in Professional Motorsport. *Frontiers in Psychology*, *9*.

Lappi, O. (2022). Egocentric Chunking in the Predictive Brain: A Cognitive Basis of Expert Performance in High-Speed Sports. *Frontiers in Human Neuroscience*, *16*.

Palomäki, J., Laakasuo, M., Cowley, B. U., & Lappi, O. (2020). Poker as a Domain of Expertise. *Journal of expertise*, *3*(2), 66–87.

Palomäki, J., Laakasuo, M., & Salmela, M. (2014). Losing More by Losing It: Poker Experience, Sensitivity to Losses and Tilting Severity. *Journal of Gambling Studies*, *30*(1), 187–200.

Pfuhl, G., Tjelmeland, H., & Biegler, R. (2011). Precision and Reliability in Animal Navigation. *Bulletin of Mathematical Biology*, *73*(5), 951–977.

Runswick, O. R., Causer, J., Nakamoto, H., & Mann, D. L. Visual search behaviours in expert perceptual judgements. In: In *Anticipation and Decision Making in Sport*. Routledge, 2019. ISBN: 978-1-315-14627-0.

Runswick, O. R., Green, R., & North, J. S. (2020). The effects of skill-level and playing-position on the anticipation of ball-bounce in rugby union. *Human Movement Science*, *69*, 102544.

Ullén, F., Manzano, O., Theorell, T., & Harmat, L. The physiology of Effortless Attention: Correlates of State Flow and Flow Proneness. In: Bradford Books, 2010, pp. 205–218.