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SEEKING AFTER THE GLITTER OF INTELLIGENCE IN THE BASE METAL OF COMPUTING: THE SCOPE AND LIMITS OF COMPUTATIONAL MODELS IN RESEARCHING COGNITIVE PHENOMENA

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ABSTRACT

Computational modelling has a rich history of successful use in researching cognitive phenomena. Its discoveries and applications do not seem to be stopping, yet with the rise of contemporary cognitive science paradigms, its scope and limits have been consistently put into the spotlight. The article reveals the scope of computational modelling by revealing its important role in progressing cognitive science research and helping cause important paradigm shifts as well as being useful at many levels of analysis. The limits are revealed to be some that are not easily solvable, if at all, mostly as they are not dependant on technological advancements. There are two main obstacles for computational modelling of cognitive phenomena: research bias, which manifests through the necessary presence of the designer's epistemological position as well as ideas on the mind and thus unavoidably being included in the model; and autonomy, the impenetrable basic element of living nature, which seems to make living organisms self-determine and thus create their own meaning in the world, something that seems to be unmodellable due to the designer always inputting her own meanings into the model and onto the modelled agents, which has been dubbed the PacMan Syndrome. Computational modelling is discussed in the light of these shortcomings, especially what it means to model living nature.

KEY WORDS

cognitive science paradigms, computational modelling, history of cognitive science, PacMan Syndrome, research bias

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INTRODUCTION

Terry Winograd, a computer scientist, mostly known for his work on natural language processing in his SHRDLU program in the 1960s and 1970s [1], became rather quickly disillusioned when he started researching the mind using artificial intelligence (AI) half a decade ago. "Seekers after the glitter of intelligence are misguided in trying to cast it in the base metal of computing," Winograd expressed his scepticism in his acclaimed paper "Thinking Machines: Can there be? Are we?" [2; p.217]. In it, he argues that computer models that are used for researching cognitive phenomena are limited to investigating and exhibiting only a particular kind of intelligence, "one that can usefully be likened to bureaucracy" [2; p.198]. This particular kind of intelligence, the only one computational modelling (CM) and AI are supposed handle, has two bases. This kind of intelligence covers everything that can be represented as a search problem, as some AI researchers say that everything in AI is a search problem [3]. Therefore, if it is a search problem, if it really is a search problem – and few things in life really are search problems for natural cognition – CM and AI can be used to research and replicate it. What is more – a lot more, since this seems to be deeply problematic and wholly unsolvable – is that search problem solving is only meaningful to humans. This is not disconnected from the second basis, which seems to be equally unsolvable. Since researchers in cognitive science usually (even if unknowingly) subscribe to one cognitive science paradigm or another, they have different ideas about cognition and how it works. These more oft than not epistemological presuppositions have their way of creeping into the models and simulations, stay there and manifest in influencing the research and its results profoundly. Removing researchers' bias and presuppositions is impossible as long as there are cognitive science paradigms.

However, CM has historically proven to be a powerful tool for researching cognitive phenomena. The limits of this scope are still debated on, especially in direct relation to natural cognition, but if anything, CM has produced impressing results. It has been one of the, if not the main catalyst for radical progress in cognitive science, whether through its virtues or through its faults, its positive results or its failures. A look through the history of cognitive science and the role of CM in the paradigm shifts is paramount to understanding the scope (and some limits) of CM. First, an overview of cognitive CM and its methods is given, with a few listed examples of how CM helped researchers in understanding cognitive phenomena at different levels of analysis. Second, an overview of the role of CM in paradigm shifts in cognitive science is presented.

THE ROLE OF COMPUTATIONAL MODELLING IN COGNITIVE SCIENCE AND ITS HISTORY

This section overviews how computational modelling can be and has been used in cognitive science. The overview looks at CM's use at different levels of analysis as well as its role in different cognitive science paradigms and their shifts. The role of CM in cognitive science's progress and paradigm shifts is especially important. Its recount is meant to show how certain ideas about the mind limited research on cognitive phenomena, and CM's use helped explore new ideas to fuel progress in how the mind is viewed.

There are numerous domains of phenomena CM can be used in for research. To showcase this wide scope, one example from each level of analysis, arguably pertaining to cognitive science, will be listed (see Table 1): from "the sociological level, the psychological level, the componential level, and the physiological level" [4; p.14].

Table 1. Hierarchy of four levels of analysis, from [4; p.12].

Level	Object of analysis	Type of analysis	Computational model
1	inter-agent processes	social/cultural	collections of agents
2	agents	psychological	individual agents
3	intra-agent processes	componential	modular construction of agents
4	substrates	physiological	biological realisation of modules

Computational research on the sociological level, which includes collective behaviour, group cognition, inter-agent processes and agent-environment interaction, is mostly concerned with emergent phenomena from interactions. Recently, CM of pedestrian behaviour has been successful in determining individual behaviour from emergent properties of crowding. Moussaïd, Helbing and Theraulaz found that “guided by visual information, namely the distance of obstructions in candidate lines of sight, pedestrians apply two simple cognitive procedures to adapt their walking speeds and directions” [5; p.6884]. Their model predicts “individual trajectories and collective patterns of motion in good quantitative agreement with a large variety of empirical and experimental data”, “the emergence of self-organization phenomena, such as the spontaneous formation of unidirectional lanes or stop-and-go waves” and that “the combination of pedestrian heuristics with body collisions generates crowd turbulence at extreme densities” [5; p.6884]. They assert that their model gives insight into spontaneous human behaviour in dynamic systems with many agents, and this insight has already been accepted in the circles of research on human crowd motion [6].

Computational research on the psychological level, which includes individual behaviour, mental states, emotion, perception, action, concepts, development, learning and so on, has been investigated with CM of child development. The endeavour has been largely successful in accounting for and giving insights into developmental processes. One of the big questions in this area is whether development and learning are distinct processes. Sun [4] summarises computational insights on this, which have become important components of contemporary child development theories in psychology [7]:

> “Using constructive learning models also resolves the ‘paradox of development’: It was argued that if learning was done by proposing and testing hypotheses, it was not possible to learn anything that could not already be represented. This argument becomes irrelevant in light of constructive learning models where learning mechanisms that construct representations are separate from the representation of domain-specific knowledge. […] [C]omputational modeling suggests that development is functionally distinct from learning” [4; p.20].

Computational research on the componential level, which includes intra-agent processes or cognitive architectures, produced a number of architectures, such as CLARION, ACT-R and Soar, which succeeded in various cognitive domains. CLARION has been indispensable in developing a comprehensive theory on skill learning. Sun [4] explains CLARION’s role in understanding skill learning:

> “At a theoretical level, this work explicates the interaction between implicit and explicit cognitive processes in skill learning […]. It highlights the interaction between the two types of processes and its various effects on learning […]. At an empirical level, a model centered on such an interaction constructed based on CLARION was used to account for data in a variety of task domains […]. The model was able to explain data in these task domains, shedding light on some apparently contradictory findings […]” [4; pp.20-21].

Sun argues that CLARION “helped to achieve a level of theoretical integration and explanation beyond the previous theorizing” [4; p.21].

Computational research on the physiological level, which includes biological substrates, is mostly applied in the discipline of computational neuroscience. One inspiring example of the use of neuroscientific CM is understanding how blind people perceive after being implemented with technological artefacts. Fine and Boynton [8] use “a computational model of axon fibre trajectories developed using traced nerve fibre bundle trajectories extracted from fundus photographs of 55 human subjects” [8; p.4] to understand “distortions of the perceptual experience” [8; p.1]. Gained insights about visual perception in blind people from this research has been used in developing better sight restoration technologies [9].

The examples on CM usage in studying cognitive phenomena at different levels of analysis show clear contribution to knowledge on cognition, thereby exhibiting CM’s wide scope. To understand it in context, CM research that fuelled paradigm change in cognitive science will be discussed. Again, specific examples will be listed for showcasing. The paradigm changes that occurred in cognitive science shifted core epistemological presuppositions and ideas about the mind and cognition, removing some limits older paradigms unwittingly imposed onto research. Consecutive paradigms therefore trod the path to new knowledge, as new research was able to be produced on previously unsolvable obstacles.

Three paradigm shifts can be discerned in cognitive science and its history, each with its own scientific tool, in no coincidence belonging to computational methodology (see Figure 1): cognitivism [10] with symbolic information processing, connectionism [11] with artificial neural networks and embodied-embedded-enactive approaches [12] with mobile robots [13].

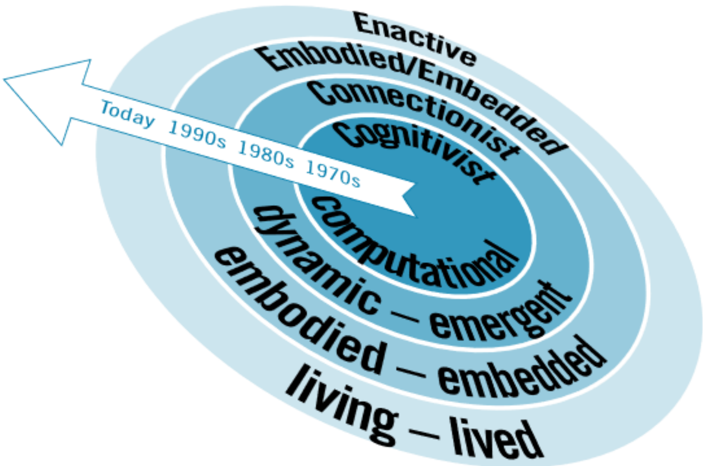

Figure 1. Illustration of one interpretation of the evolution of paradigms in cognitive science, from [13; p.76].

The first paradigm, the paradigm that gave birth to cognitive science, is cognitivism, which claims that cognition is computation with arbitrary symbols which represent the world [10]. Cognitivism can be said to have started with one important insight. This insight can be traced back to the Pythagorean school, which tried to describe reality with abstract descriptions – e.g., they figured out a “harmonious relationship between strings on an instrument which have certain simple mathematical relationships to each other (e.g. if one string is precisely double the length of another, its pitch is an octave lower)” [14; p.14]. The insight that parts of the world can be usefully represented by manipulation of arbitrary symbols has found home in thinking about mind and cognition as well, mostly due to many (initial) successes in applying this insight. The most well-known example may be a computer model of a chess player, which was first created by D. Prinz (Turing’s colleague) in 1951. Progress in the modelling of a chess player, which was supposed to represent higher cognitive functions such as abstract thinking, escalated very quickly, pinnacled by IBM's Deep Blue 1996 winning against the then greatest chess player, G. Kasparov. Computational models of cognitive phenomena that showed results, like the artificial chess player, signalled to cognitive science researchers that natural cognition is computational as well.

However, cognitivist CM has had a lot of issues due to its ideas on how cognition works. One stark example is when dealing with large domains, where the number and complexity of rules are too high to model top-down, computational models are unable to output desirable behaviours. A shift in focus was needed for solving problems such as generalisation. Rumelhart and McClelland [15] were able to predict past tense forms of English verbs, a feat previously unsolved, when they dealt with computations not in the sequential, centralised, top-down and symbolic way, but rather in a parallel, distributed and bottom-up way:

> "The task is interesting because although most of the verbs in English (the regular verbs) form the past tense by adding the suffix '-ed', many of the most frequently verbs are irregular ('is' / 'was', 'come' / 'came', 'go' / 'went'). The net was first trained on a set containing a large number of irregular verbs, and later on a set of 460 verbs containing mostly regulars. The net learned the past tenses of the 460 verbs in about 200 rounds of training, and it generalized fairly well to verbs not in the training set [11; §.11]".

The researchers managed to solve the task using artificial neural networks, and the design and successful application of this method itself was influential in a paradigm shift that produced a new set of fundamental and epistemological ideas on cognition as an emergent phenomenon from a network of distributed, interconnected basic elements [11]. However, many researchers, such as Varela [12], felt that connectionism was still too focused on the brain, as connectionism classified it as the sole source of cognition, and everything, including the world – in the form of representations – was crammed in it. Opposition[1] to such views thought that the connectionist account of cognition was incomplete, and consequently could not completely explain how organisms perceive and act in the world so elegantly, effectively and efficiently.

The roboticist R. Brooks, who used CM to explore cognition, was part of the opposition. Brooks "pointed out that the bulk of evolution had been spent getting organisms to the stage where they had useful sensory and motor systems; phenomena such as tool use, agriculture, literature, and calculus represent only the most recent few 'seconds' in the evolutionary clock" [16; p.20]. He therefore focused his efforts "on the hard job of building systems which have sound basic sensorimotor capacities" [16; p.20], which were until his time in the 1980s still an unattainable goal for artificial design. Brooks' idea was that sensorimotor abilities and the organism's direct interaction with the world were crucial to understanding and unlocking the mystery of cognition, and that thinking about the latter as if it is building complex representations of the world in the central cognition unit (the brain), is wrong. These ideas were later applied to many phenomena thought to be in the domain of higher cognition, such as mental imagery [17]. This was a fairly obscure view in mainstream cognitive science circles, but a growing movement started to champion such ideas in that same time (although not all came to the same conclusions, neither furthered the cause by using computational methods [12]). Brooks demonstrated the value of his ideas on cognition by building a robot that could act intelligently in his laboratory by moving and performing simple tasks [18], a feat not achieved before. The relatively simple, multi-layered subsumption architecture was key for the robot to demonstrate Brooks' notion that "the world is its own best model" [19; p.15].

Such computational works played a role in spawning a new way of thinking about cognition in terms of its relationship with the world. The embodied-embedded-enactive view sees cognition as situated (cognition does not deal with abstract descriptions, but rather the world here and now), embodied (bodies non-trivially constitute cognition) and emergent (a central concept of connectionism as well, but here cognition is seen as emerging from the brain-body-environment triad). The organism supposedly enacts its world, constructs it. The role of CM is unclear in this last, yet no less central bit of the paradigm. The many problems, rather than solutions, in using CM in researching cognition seem to have had a much bigger, if not an essential role in paving the way towards the paradigm shift itself, as they strengthened the idea that the mind is not working as a computer is [12]. There are some emerging areas of investigation, very close to the enactive part of the paradigm, that use CM in their studying of how cognition constructs the world, such as predictive processing [20]. However, their impact, scope and limits are, as of yet, unclear.

UNDERSTANDING THE LIMITS TO THE SCOPE OF COMPUTER MODELLING IN COGNITIVE SCIENCE

Despite the important role of CM in cognitive science, there seem to be significant limits to its use – and most are not well understood at all. The necessary consequence of not understanding the limits of CM is that its scope and reach in researching cognitive phenomena are ambiguous as well. Two issues that seem to largely contribute to the limits and problems of CM are outlined in this section: the problem of meaning in artificial agents and a specific kind of research bias, associated with cognitive science paradigms and their presuppositions. To be able to outline these issues, the term ‘computational’, which is the cause of many misunderstandings when trying to theorise on CM, will be examined first.

The history of cognitive science and especially the rein of cognitivism have obscured the meaning of ‘computational’ to the degree where it may have become unusable in theoretical contemplations. Riegler, Stewart and Ziemke [21] agree that “the concept of ‘computational model’ is ambiguous and depends on whether it is used in the sense of the computational(ist) theory of mind or simply as a tool” [21; p.1]. They present two different senses in which ‘computational’ is used and which cause theoretical confusion:

> “The first sense of the term is that the processes being modeled are conceived of as being themselves computational in nature. This is the sense that is deliberately, honestly and openly taken on board by the proponents of the classical ‘computational theory of mind’ (CtM) – notably by Jerry Fodor and Noam Chomsky, who were historically the prime advocates of this view. […]
>
> The second sense of the term is that the author has used a computer as a tool to express a vision, to render certain aspects or properties of his model salient, to make them graspable by relatively direct intuition. This second sense of the term is quite different from the first. It is not (just) ‘wider’ or ‘looser’: that would invite an assimilation of the two, which would lead us back to the very conflation and confusion that we are trying to avoid” [21; p.2].

This differentiation is only the first step in uncovering the ambiguity of ‘computational’. Even if a researcher subscribes to CtM, the question remains whether any model where the world is simulated can be thought of as computational in the first sense – as being computational in nature. This means that even if a part of the model, the agent, is faithfully modelled, a large part, the world around the agent, is not. Why is that? Many natural phenomena, other than those related to living organisms, can be, to different degrees, described with mathematical formulas. They can therefore be modelled – e.g., the behaviour of winds can be described with differential equations, simulated and the result will be a useful approximation [22]. However, as opposed to the mind, no one believes that the winds are doing computations in and for their behaviours [21]. The idea is therefore that living organisms perform computations which are expressed by their behaviour in the world, while non-living nature does not. What happens then when the two are interacting – the modelled living organism and the modelled environment? If one is supposed to represent the true nature of the world (computational workings of living beings), while the other is supposed to represent approximate description of how the world works through mathematics, the ordeal seems to work against the first sense in which Riegler et al. [21] describe 'computational' – "processes being modeled are conceived of as being themselves computational in nature" [21; p.2]. But there is much deeper issue in this turmoil of modelling the mind and the world in different ways while using the same ambiguous concept. It is firmly connected to the confusion the term 'computational' has caused, and it has become thoroughly ingrained in theory and practice. Riegler [23] labelled this issue the PacMan Syndrome:

> "[I]t is useless to implement agents in artificial intelligence or artificial life with an a priori defined set of concepts, and to claim they were 'intelligent'. […] Artificial agents interact with anthropomorphically defined entities, such as 'food' and 'enemy', which make sense only to the programmer of the system. No attention is paid to questions like: How have organisms arrived at the idea that something is a source of food? How do they 'know' that another creature is a dangerous opponent?" [23; pp.4-5].

Riegler describes how agents are being modelled in the same way as the world is – by approximating observable behaviour from a third-person point of view rather than creating minds that would truly conform to the first sense of 'computational'. The problem is therefore not in creating agents through paradigms that conform to CtM, but rather a much more puzzling enigma. The enigma seems to be stronger than Riegler et al.'s delineation between the two senses of 'computational'. It is, as Füllsack [24] implies, that living organisms self-create knowledge and therefore behaviour, while the non-living natural world does not. He is somewhat pessimistic in his thoughts on modelling self-creation of knowledge by artificial agents instead of their creators, saying that CM can support the case for such ideas, but can never succeed in definitively producing it [24], therefore going by the second definition of 'computational' by Riegler et al. Peschl [25] argues similarly, claiming that "it is the designer who plays the role of evolution if he/she designs the network architecture and the structure of the artificial cognitive system" [25; p.2213].

Undertaking 'computational' matters means that one is describing systems from a third-person point of view, and it is this that causes core predicaments in using CM to investigate cognition[2]. Even if the mind performs symbolic computations with arbitrary symbols to function, the mind cannot be computationally described by a third-person observer by inputting knowledge, goals, the rules of the game of living and so on into the agent[3], as what defines living agents is, biologically speaking, their inherent self-determination [31]. The researcher as the ultimate creator cannot faithfully create agents, even if she can approximately describe behaviours.

But what if the researcher has different ideas about the mind, different from the ones CtM offers? The first definition of 'computational' by Riegler et al. does not seem to apply in that case at all. And what if the researcher's theories on cognition, her epistemological presuppositions and her decisions on which aspects to include in CM have significant impact on the results of her research? In his doctoral dissertation, Kjellman [32; p.i] concluded that "the efforts of computer modelling and simulation analysis revealed a pronounced observer-dependency regarding investigation." A considerable number of conditions of the modelled system is at the whim of its creator. Computational methods themselves carry a certain bias as well, as optional parameters and other features of various algorithms that are arbitrarily set make many theoretical issues overlooked or trivial and therefore removed from the phenomena as such [33]. Even CM of solely behavioural approximations carries a huge risk of observer bias, of the researcher's ideas on the mind influencing the research itself.

One such case of presuppositions and ideas about the mind affecting the results was investigated by Kolenik and Kordeš [34]. They investigated the relationship between mind and world by using CM with genetic algorithms to study whether it is isomorphic or non-isomorphic perception that is more evolutionary beneficial for modelled organisms. They introduced two computational models – a model by Hoffman, Singh and Prakash [35], which possessed cognitivist presuppositions, and a newly designed model, which built on Hoffman et al.'s model by replacing certain cognitivist presuppositions for enactivist ones, mostly focusing on the addition of a sensorimotor loop [36]. Both models produced the same final result, as they showed that non-isomorphic perception is evolutionary more beneficial than isomorphic. However, the sensorimotor loop caused the newly designed model to evolve faster, a feat that had not been anticipated in advance. Different ideas about cognition therefore made a significant impact on the results, which makes exploring the influence of different presuppositions on models' behaviour relevant in general, especially as this is an issue researchers are mostly not aware of. However, awareness seems to be the hard limit to trying to solve this – one cannot model cognition without starting from a set of epistemological and other presuppositions on the mind and how it works. Inevitably, these will be different amongst researchers, manifesting in different models and different outcomes even in research concerning the same cognitive phenomena.

Being aware of the presence of hard problems in CM, Peschl and Riegler [37] try to formulate an answer to what CM offers. They argue that CM and computer simulations have to be taken in a certain way, that what is important and insightful "are not so much results about details, but concern conceptual knowledge which can be used as input and stimulation for both empirical and epistemological investigations" [37; p.15]. They distinguish CM from other empirical investigations in cognitive science and its constituents, where most of the approaches to cognition "were more or less speculative and common-sense interpretations of cognitive phenomena" [37; p.15], as progress "in empirical sciences is based on a continuous process of construction, negotiation, and adaptation to the 'empirical data' " [37; p.15]. They point out the downsides of such an approach, as often "the complexity of cognitive processes and their substratum does not match the comparably poor empirical approaches and understanding of cognitive phenomena …" [37; p.15]. They feel that the more speculative areas of cognitive science open the door to CM and simulation:

> "Fortunately, the simulation method introduces a new dimension to cognitive science […]. Simulation models are especially interesting in the context of cognitive neuroscience, as its empirical results and theories are sometimes so rich in detail […] that it is almost impossible to relate them to cognitive phenomena. In other words, there is an explanatory gap and a strong tension between the epistemologically inspired questions on cognition […] and the empirical and highly detailed results from neuroscience. In this context the connectionist approach – in the broadest sense – plays a crucial role as mediator: it stands between the two poles of the rather speculative epistemological theories and the empirically grounded neuroscientific details and – in many cases – makes them compatible. This compatibility is achieved by the trick of focusing on the conceptual level of neural processes" [37; p.15].

Peschl's and Riegler's faith in computer modelling is limited, and precise in that limitation. They feel it is an extremely important method, not for "the technical details of simulation which we are interested in, but rather in the conceptual implications which these models have on the problem of knowledge representation" [37; p.15]. They claim that that conceptual level "can bring about both an empirically and epistemologically sound understanding of the ancient problem of representation in cognitive systems" [37; p.16] and "guide empirical research not only on the level of technical details, but – and this seems to be even more important—on a conceptual level (e.g., concerning the assumptions/premises of a research strategy, the epistemological framework and foundations, etc.)" [37; p.16]. Peschl [38] sums it up: "Computers are playing an important role as simulating instruments for artificial neural networks in order to achieve a deeper understanding of cognitive processes in an interdisciplinary context" [38; p.192].

It is apparent that the term 'computational' comes with a conceptually ambiguous burden, which has theoretical and practical consequences when it relates to being used to investigate natural phenomena. This is one of the reasons that some approaches have branded themselves or have been branded as anti-computational, which begs the question whether non-computational accounts of the mind can be computationally modelled. Like wind, which does not perform computations itself, yet can be usefully computationally modelled, non-computationalist accounts of the mind may follow suit. What is more, Riegler et al. [21] question the sentiment that enactivist approaches, for example, are necessarily anti- or non-computationalist. They are not completely clear on why that is, but a strong case is to be made for computational methods being used in regards to enactive approaches. What is clear is that enactive approaches have made considerable progress partly due to the use of computational and robotic models – and vice versa, enactive approaches definitely inspire CM [17, 29, 39]. Without presupposing that particular phenomena are computational in nature as such means that everything can be (descriptively) modelled and simulated [4, 40] – and many phenomena have been. This means that even non-computationalist approaches can benefit from being modelled and vice versa – CM can benefit from non-computationalist approaches. The deeper question of further addressing what the differences between living and non-living nature mean for modelling, however, remains wide open.

DISCUSSION AND CONCLUSION

Computational modelling as an investigative method in cognitive science has a long and rich history of successes and failures. Both have been essential in furthering the role of CM as well as furthering our understanding on the mind. However, after a good number of decades of research in cognitive science, CM has persistently encountered (at least) two monumental obstacles, described in this article, which do not seem to be solvable. Unlike most other obstacles CM has faced in that time, the ones described in this article do not seem to be connected to the lack of technological advancements.

Research bias in terms of CM of the mind is not something that can be avoided. To model the mind, some initial position on what the mind is has to be taken, inevitably contaminating the modelling and influencing the outcome. This is not inherently good or bad – it is simply the nature of such investigation. The PacMan Syndrome, the problem of designing models where the designer determines what is meaningful for her creations instead of designing artificial agents that self-determine, which seems to be an essential feature of living organisms, seems unavoidable as well. It may therefore be beneficial to rethink whether the question of what the scope and limits of CM for researching cognitive phenomena are is the correct one. Since CM clearly has limits, albeit only somewhat identified, the attention has to be turned to cognitive science for answers on what parts of cognitive phenomena behave in a way that can be faithfully modelled. H. von Foerster, the famous cyberneticist, may be one of the few thinkers that began exploring this important question precisely and non-abstractly. He argued that phenomena can be divided into trivial and non-trivial forms (or machines, as von

Foerster termed it) [41]. A trivial form is one that is independent from previous and other operations, analytically determinable, repeatable and predictable. A non-trivial form is one where this is not true. A non-trivial form is unpredictable, its workings cannot be deduced from outcomes, and past outcomes do not allow for prediction of future outcomes. What are then the conditions under which cognitive phenomena are trivial, or become trivial? Which cognitive phenomena are trivial in the first place? What happens when the non-trivial becomes computationally described? What gets lost in the process of trivialisation? How is the trivialised form of a phenomenon connected to its non-trivialised form? And last, but not least – is von Foerster's idea on the trivial and non-trivial a complete account of how to think about this issue? One thing remains certain – computational modelling is not going away, and its successes in describing cognitive behaviour and mimicking it keep on coming [42]. Truly gaining knowledge on the nature of (human) cognition from these successes is another issue.

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REMARKS

[1]Opposition is not meant to be taken as a coherent, organised movement, but many voices from different areas of cognitive science that mainly converged in their critique.

[2]This insight is very similar to the insights of second-order cybernetics, a discipline born out of the discipline of cybernetics, the study of systems. Second-order cybernetics studies systems that study systems. For more on second-order cybernetics, see [26-27].

[3]This conclusion is echoed in the enactive paradigm in cognitive science with its concept of autonomy, which is why CM may not be so important in enactivism, as was described in the previous section on the history of cognitive science. Autonomy is highly relevant to the limits of CM this article is tackling, but is, due to the specific nature of enactivism as a biologically-inclined paradigm, outside this article's immediate scope. To find out more on enactive autonomy, see [28-30].

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