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Artificial Intelligence in Sports, Movement, and Health

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ISBN 978-3-031-67255-2 ISBN 978-3-031-67256-9 (eBook)
https://doi.org/10.1007/978-3-031-67256-9

This Springer imprint is published by the registered company Springer Nature Switzerland AG
The registered company address is: Gewerbestrasse 11, 6330 Cham, Switzerland

Editorial

Artificial Intelligence (AI) is driving revolutionary advancements and is transforming the landscape in sports, movement, and health. Rapid advancements are continuously reshaping these domains. As we embark on this journey, we recognize that while this book offers a snapshot of significant AI applications, the evolving nature of technology ensures that new breakthroughs will continually emerge beyond what we currently grasp. With this book, we aim to empower readers with knowledge and enhance the understanding of the transformative potential of AI in sports, movement, and health.

To begin our exploration, we delve into the broader realm of **Digital Transformations: AI's Role in Sports Science**. We commence with Lenhard (Chap. 1), who investigates the profound impact of AI on sports science. His work delves into its role in digitization and mathematization while also pondering the philosophical implications inherent in this transformation. Furthermore, Lenhard unravels the effects AI has on scientific practices within the field. Next, Latzel and Glauner (Chap. 2) shed light on the future of academic writing empowered by AI. Their inquiry explores how AI is reshaping research and writing across various disciplines, focusing on sports science. Our discourse concludes with Menges (Chap. 3), who examines the application of AI in endurance sports. She showcases how AI-driven technologies are revolutionizing training and how AI assists coaches and athletes in decision-making processes beyond training, encompassing elements such as race selection and strategy formulation.

AI has the power to enhance medical and health-related aspects in sports contexts, which we want to focus on in the part **AI in Medical and Health Aspects of Sports**. It is important to note that the focus of this part is not on general applications in the healthcare sector, which encompasses a myriad of other works. Instead, within the scope of this book, the focus is on movement-related health aspects, which significantly intersect with sports science. Kemmler (Chap. 4) starts the part by exploring cutting-edge fall prevention strategies and how AI-based fall technology revolutionizes fall prevention for older adults. Find out how sensor-based AI concepts enhance safety and effectiveness in training, even in unsupervised settings. This is followed by

Owen, Owen, and Evan's (Chap. 5) chapter, showcasing the future of injury prevention through the lens of AI technology. It is presented how AI not only enhances prediction accuracy but also enriches our comprehension of the multifaceted factors influencing sports-related injuries. Afterward, we want to have a look at doping in sports, a persistent issue that involves the misuse of prohibited substances to boost performance. In this context, the paper of Rahman and Maass (Chap. 6) explores the use of generative modeling to create synthetic blood sample data, aiming to enhance anti-doping analysis. A method is proposed not only for data augmentation but also to address ethical concerns regarding athletes' biological data.

After examining medical and health implications of AI, our attention turns to the realm of **Human-Computer Interaction** (HCI). Speicher and Berndt (Chap. 7) illuminate HCI's crucial role, offering insights into how AI influences athletic performance, injury management, and healthcare. They advocate for integrating human-centered design principles to elevate user engagement and outcomes in the evolving field. Subsequently, Gillmann (Chap. 8) describes the significance of comprehending and visually representing uncertainty in sporting data. She provides an overview of how uncertainty-aware visualization can contribute to enhancing the reliability and decision-making process of Machine Learning (ML) predictions in sports.

Transitioning, the discourse shifts towards **Motion Capture and Feedback Systems**. Stetter and Stein (Chap. 9) focus on the applications of ML for biomechanical analysis of human movements and the associated challenges. They show how the three major ML paradigms supervised, unsupervised, and reinforcement learning are used in biomechanics and how ML can support the understanding of human movements. Baldinger, Lippmann, and Senner (Chap. 10) give an overview of current technologies and applications focusing on markerless motion capture technologies. Furthermore, they complement this with findings from their studies on the validity of the technologies and conclude the main challenges for future research.

Through **Practical Examples of Machine Learning and Predictive Analytics**, the final part showcases how AI is reshaping the future of sports and unlocking new realms of performance optimization and strategic insights. Vives, Lázaro, Guzmán, Crespo, and Martínez-Gallego (Chap. 11) explore the recent evolution of ML techniques and their potential impact on tennis performance analysis, including a practical example showcasing predictive modeling results, leveraging new technologies like Hawk-Eye and tracking systems. The discussion then transitions to another perspective on tennis by Randrianasolo (Chap. 12), which focuses on how sports predictions can be revolutionized with convolutional neural networks. This is exemplified by forecasting outcomes without the need for extensive historical data, as demonstrated with Men Euro 2020 and Women US Open 2021.

Smyth, Feely, Berndsen, Caulfield, and Lawlor (Chap. 13) explore how ML can enhance recreational marathon running through personalized training insights and race support by mobile devices and wearable sensors. Barbon Junior, Moura, and da Silva Torres (Chap. 14) continue delving into the potential of data-driven methodologies in soccer analysis, outlining a systematic pipeline for automating data collection, transformation, and analysis, offering insights into player interactions and performance optimization through AI. Finally, McAuley, Baker, Johnston, and Kelly (Chap. 15) offer an overview of contemporary research utilizing AI to interpret large datasets in talent identification and development processes within youth sport contexts, outlining the potential of AI to enhance recruitment strategies and highlighting key strengths, weaknesses, opportunities, and threats in this evolving field.

In light of the diverse contributions presented in this book, we have amassed a rich collection of insights, practical applications, and perspectives poised to transform the realms of sports, movement, and health. However, as we stand at this juncture of exploration and innovation, it is crucial to acknowledge that our understanding is merely a snapshot of the immense potential AI holds for these domains. The evolving nature of technology ensures that new breakthroughs will continually emerge, pushing the boundaries of what we currently grasp.

As we reflect on the book's content, it becomes evident that the research approaches and practical implementations showcased within these pages mark just the beginning. The real-world impact of AI on sports, movement, and health is yet to unfold fully. The true test lies not only in the ingenuity of AI-driven solutions but also in their integration into everyday practices and established knowledge. The gap between theory, science, and practical application must be bridged to realize the full potential of these technologies.

We hope to have given our readers a first insight into the large field of AI in sports, movement, and health. Let us remain curious and attentive to how the future of AI technology will develop in the sectors and to what extent the research approaches described will be put into practice.

July 2024

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Part I
Digital Transformations: Artificial Intelligences Role in Sports Science

Chapter 1
Situating Sports Science in the Movement of Digitization

Johannes Lenhard

Abstract This chapter reflects upon how Artificial Intelligence (AI) in sports science is situated in the broader movement of digitization, which in turn takes a special place in mathematization. It addresses the question: If a field is getting into AI, what impact will this potentially have from a philosophical point of view? It argues that epistemic opacity is part-and-parcel of digitization and, all the more, of AI. This makes prediction an even more important criterion for scientific success, whereas the capability for explanation is seriously diminished. Finally, the chapter explores how the use of software leads to a new social organization of science.

Keywords Sport Science · Simulation Modeling · Epistemology · Mathematization · Digitization

1.1 Introduction

Today, digitization is predominantly discussed in terms of Artificial Intelligence (AI). This chapter will take a step back and reflect upon how AI in sports science is situated in the broader movement of digitization, which in turn takes a special place in mathematization. This chapter does not aim at providing an overview of current or future applications of AI in sports science. Other contributions to this book do this in a competent manner. Nor will it act as a philosophical naysayer—asking whether AI is "new dawn or false hope" is topical in the literature (for sports science, see Bartlett, 2006). Rather, the text that follows explores the question: If a field—sports science or any other—is getting into AI, what impact will this potentially have?

The label AI is older than recent Machine Learning (ML) methods. When the label was coined in 1956 at a meeting in Dartmouth, it should mainly avoid any association with the then popular term of cybernetics, as John McCarthy, one of the meeting organizers, reminded later (1988). In the 1950s, poponents of AI believed

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C. Dindorf et al. (eds.), *Artificial Intelligence in Sports, Movement, and Health*,
https://doi.org/10.1007/978-3-031-67256-9_1

that following explicit rules is the key to intelligence. And since the digital computer is a machine that can process such rules with ease and speed, AI was expected to overtake human intelligence in foreseeable time. It was a hard-won lesson that AI did not meet these expectations. Even chess computers, although the game is completely defined by formal rules, had somewhat limited success. When Deep Blue finally won against Kasparov, the long-term world champion, this was based not on a deeper analysis of moves, but on the large database of existing games fed into the machine. Attempts to master language, like generating a translation, proved to be a nut too hard to crack, mainly because language use persistently escaped a fully formalized grammar. To make a long story short, the optimism reversed and led to the "AI winter" of the 1980s. Actually, one can discern a first (late 1970s) and a second AI winter (late 1980s to early 1990s); for highly accessible accounts see Crevier (1993) or the entry "History of artificial intelligence" in Wikipedia. The field of AI re-oriented itself. A leading strand in the 1990s took acting in the world as the leading criterion that characterized intelligent behavior—fetching a cup of coffee without spilling it, rather than playing chess. This robotic turn produced new accounts of what characterizes intelligence, in connection with new visions of what AI is—or ought to become, see Pfeifer and Scheier (2001), or Brooks (2002), among others.

However, while the robotic turn amounts to a modest niche for AI, the recent hype is more expansive and has been called the second wave of AI, rising for more than a decade now. The first wave of symbolic AI was oriented at symbolic rules—the philosopher Haugeland (1985) labeled this approach as "good old-fashioned AI" —GOFAI. Based on this term, Smith (2019) makes a thoughtful distinction between first wave (GOFAI) and second wave (connectionist, neural network) AI. Alien to the logical-symbolic standpoint, and almost contradictory to it, the current second wave is fueled by statistical approaches, with Deep Neural Networks as the paradigm example. Now, knowledge about rules does not count as essential. On the contrary, gaps in such knowledge, even gaping craters, are compensated for by statistical analyses of extensive datasets. In short, one can connect the second wave of AI to a data turn.

A series of popular and astonishing success stories supports the second wave. Very likely, every reader knows how ML jumped from chess to Go with ease (showing the power of neural networks). Image classification made a big splash and most recently, Large Language Models (LLMs) exhibit proficiency in translating texts that was not anticipated by AI nor linguistic experts. Moreover, LLMs like ChatGPT (by the US company OpenAI), or other generative networks even increase the frenzy because many people find uses for a machine that generates text and, additionally, interfaces to these machines are readily available to all internet users (which does not mean that they come free of cost).

All these examples have in common that the rules (for classification, for language) are not explicitly modeled, but implicitly defined. What makes a bird look like a blackbird is what the images labeled with blackbird have in common—in contrast to what the images labeled differently (the non-blackbirds) have "in common". The same applies to language. The rules of grammar are by and large skipped. Instead, the machine produces sentences that are similar to sentences in the database (of course, the notion of similarity is far from trivial). A human translator would proceed very differently, or more precisely, would describe what he or she does very differently: translate words, know the grammar, consider phrasing etc. The ML method just assumes that existing translations somehow entail all this knowledge.

In short, ML makes statistical evaluation of large datasets feasible and, if one has enough data, ML arrives at surprisingly good results. Recent experience with LLMs like ChatGPT makes the case. The universal key then is data from the domain of interest, not knowledge in the sense of having a good model of what happens in this domain.

But wait a moment. The universality of AI (working with Deep Neural Networks) arises from the flexibility of these networks. Mathematically speaking, learning for these networks means to adjust a function that matches input–output behavior. With expensive computing equipment, such as employed by LLMs, literally billions of parameters are adjusted. To do this in a meaningful way, extremely large amounts of data are needed, like the 14 million hand-annotated images on ImageNet, or the vast libraries of text compiled by OpenAI (in a completely non-open way). Thus, the data turn in AI is not only a revelation of how rich implicit knowledge contained in data might be, at the same time, data present a new bottleneck.

Availability and quality of data replace knowledge about rules as the bottleneck. The question is, which fields have adequate data available? There is no formal rule of how many one needs. Optimism reigns and speaking about "exciting possibilities" has become topical for many publications (see, for instance, Torgler, 2020). However, it is not straightforward to distinguish enthusiastic promises from scientific achievements. For instance, Perl noted that in actual practice sufficiently many data are almost never available (Perl 2009, 33).

To the extent that data are the key (other than complicated theories), and that tools for analysis are accessible through software packages, the AI movement is attractive for science and commerce alike. Sports science is a case in point. For instance, Dindorf et al. (2023) warn that scientific research should hurry up to not lag behind commercial application. It is a widespread belief that AI in sports science is driven by commercial application at least as much as by (scientific) modeling. Overviews like that of Chmait and Westerbeek (2021) take *Moneyball* (Lewis, 2003) as the starting point for AI in sports science because it provides a striking and impactful example of how to create data and (commercially) use them.

The following text has three parts. Section 1.2 locates AI in the context of digitization and in the broader history of mathematization. It starts with the famous book-of-nature verdict by Galileo and suggests that ML indicates a profound turn in mathematization. Section 1.3 concentrates on epistemology and argues that epistemic opacity is part-and-parcel of digitization and, all the more, of AI. This makes prediction an even more important criterion for scientific success, whereas the capability for explanation is seriously diminished. The final Sect. 1.4 explores how the use of software leads to a new social organization of science.

1.2 Mathematization—Digitization—Artificial Intelligence

First a paragraph about terminology. The terminology is complicated by the overlap of different traditions. AI is dealing with tasks that would count as based on intelligence if achieved by a human, like playing chess, finding the route back home, recognizing a face, or writing an essay. As was mentioned in the introduction, AI started with manipulating logical rules. The recent successes of AI by and large came from Deep Learning, i.e., from the use of multilayered Artificial Neural Networks (ANNs). At the same time, ML is a label that normally comprises not only these methods, but also Random Forests, among others. Thus, both AI and ML sometimes claim ownership for Deep Neural Networks. In the following, we ignore these complications and assume that AI refers to a set of methods that typically involve the use of multi-layer ANNs.

These can exhibit extremely versatile input–output behavior, depending on the setting of their parameters. Mathematically, such networks approximate an unknown function—think of image classification that is a map from the set of images into a set of labels—with the help of very many adjustable parameters. Current LLMs, for instance, work with billions of such parameters. They are true Behemoths of approximation that are said to “learn” because the parameter adjustment is a process that is guided by a set of training data. The machinery of approximation iteratively finds parameter settings that match these data better and better and in this sense the model learns from the data.

A most important observation is that AI does not simply help to solve problems, but rather influences how problems are formulated. Simply deploying computers to solve existing problems would fail, because the problems are usually not in the right form to be tackled by a computer. Thus, the intention of using AI influences how researchers perceive and formulate problems. Researchers aim at posing problems in a way that makes them amenable to AI.

This point is not particular to AI, rather applies to using computer methods in general. In fact, it generalizes beyond the computer to all sorts of instrumentation. It has been part of scientific activity all the time, or better—and even more general—part of how humans act. They use instruments and these instruments shape the way they see the world and identify solvable problems. A saying of unknown origin captures the point: “If the only tool you have is a hammer, it is tempting to treat everything as if it were a nail.” (The entry “Law of the instrument” on Wikipedia presents a brief selection of possible origins of this saying.) The computer and, most recently, Deep Learning, is scientific instrumentation that exerts such influence in a particularly strong way.

If one discerns the objects that populate the world from the instruments that one uses to investigate these objects, then the case of AI comprises (at least) two layers. Computers are instruments to find out something about how mathematical or formal structures behave. But at the same time, one can see mathematical structures as instruments to find out something about how objects in the world behave. Thus, there are two layers, or two embeddings—AI as part of digitization and digitization as part of mathematization.

A most famous starting point for reasoning about mathematization is Galileo's verdict that the book of nature is written in mathematical symbols. From the seventeenth century on, there was a forceful movement in modern science towards mathematization, i.e. conceiving of nature in mathematical ways (Mahoney, 1998). Galileo's viewpoint rests on the metaphysical assumption that the world is as it is, and that one can find out some of the facts with the help of mathematical methods (and maybe in no other way). Importantly, the world is like a book, everything about nature is written there. That means, scientists are deciphering the book, not writing it. And since mathematical knowledge is the most certain knowledge, the great promise of mathematization is that certainty and truth go hand in hand.

This promise was daring from the start, because it is more grounded in philosophical belief than in actual power. Mathematical methods require a formal framework, usually involving highly idealizing modeling assumptions, whereas in practical applications many factors contribute and interact. Admittedly, there are prime examples of idealizations that work, first of all astronomy and the movement of planets. Newton's achievements maybe created the greatest success story in science, when he showed how laws of mechanics and gravitation plus a new mathematical method (calculus) could derive the elliptical orbits of the planets in full match with observational data. From then on, mathematization was deeply entrenched in the development of science. Still today, mathematical methods count as a pivotal indicator of something being scientific. Much has changed since the seventeenth century. A most obvious point is that computers redefined the arsenal of mathematical instruments.

Let us concentrate on simulation as a major area of computer instrumentation. Basically, we follow the main thesis in Lenhard (2019) that "computer and simulation modelingreally do form a new type of mathematical modeling." (2) Four features of simulation modeling together make it a novel type, namely an explorative and iterative type of modeling.

Experimenting. Simulation experiments build a particular class of experiments. Usually, experiments are described as seeking an answer from nature. Although the question an experiment poses may require extensive theoretical design, like a gigantic tunnel full of high-tech equipment under the lake Geneva (CERN), there remains an important sense in which experiments are not determined by theory, even if they are theory-laden. In the example: does the CERN particle collider register traces of the Higgs particle or not? Simulation experiments are different because they evaluate the model behavior that results from the assumptions (and the implementation) already made. In a way, they question the model-plus-computation part, not nature. Although they differ from ordinary experiments, these computer-experiments still deserve to be counted as experiments because they seek an answer to a question by observing a designed process of open ending. For instance, running a weather model ten times and counting how often it rains in Kaiserslautern, in this way determining the so-called probability of rain.

The exploratory variant of experimentation is particularly relevant for simulation modeling. Here, the focus is on the process of building a model. Often, the model is not only motivated by some theoretical consideration, but by how it behaves. Deep Learning is an excellent example. The ANN is controlled by parameter adjustments, but the values of these parameters usually do not have a meaning. Their value cannot be determined out of theoretical considerations. They are adjusted over the course of repeated experiments that explore the model behavior. “Model assumptions with effects that are hard or even impossible to survey can be tested, varied, and modified by applying iterative experimental procedures. Modeling and experimenting agree to engage in an exploratory cooperation. Such cooperation regularly employs artificial elements” (Lenhard, 2019, 133).

Artificial elements. The parameterizations in Deep Learning are a prime example, but artificial elements are significant for almost all computational methods. Let me replace a full argumentation with an example. If a model is expressed in the language of continuous mathematics, it must be discretized before a computer can evaluate it. There are various approaches to discretization, all need to be designed so that the dynamics of the discrete model closely matches the dynamics of the original continuous model. “When controlling the performance of discrete models (i.e., for instrumentalist—though unavoidable—reasons), artificial components are included. Experiments are necessary to adapt the dynamics of a simulation model, because one cannot judge whether these artificial elements are adequate without such experimental loops. This grants simulation modeling an instrumental aspect that blurs the representation relation and hence weakens the explanatory power” (ibid., 133).

Plasticity. “This denotes the high level of adaptability in a simulation model’s dynamics. The structural core of such a model is often no more than a schema that requires—and allows—further specification before simulating particular patterns and phenomena” (ibid., 134). Again, Deep Learning is a prime example. The neural network usually is almost completely generic. Whether it can be used for image classification or language generation essentially depends on the data and the parameter assignments over the course of learning, i.e., iterated exploratory experimentation. Both structure and specification are necessary to determine the dynamic properties of a model.

Epistemic opacity. “This arises because models are becoming more complex in several respects. The course of dynamic events encompasses an enormous number of steps, so that the overall result cannot be derived from the structure. Instead, it emerges from model assumptions and the parameter assignments chosen during runtime. Additionally, important properties of the dynamics result from the specifications and adaptations made while developing the model. This reveals a fundamental difference compared to the traditional concept of mathematical modeling and its concern with epistemic transparency” (ibid., 134). The expectation was that formal modeling makes graspable what happens in the model and, because the model is about the world, what happens in the world. In essence, this is the promise of reading the book of nature. With simulation modeling, and more generally computer-based modeling, the essential feature of the model is its flexibility. The *new promise* is that, with suitable adaptation machinery, the model can be made to match observed data and phenomena. And exactly the adaptation machinery *creates opacity*.

These characteristics are not independent of each other, but support and reinforce each other. Therefore, they are not just a group of features, but form a distinct type. Simulation modeling is carried out in an explorative and iterative manner, in a process that partly uses and partly compensates for the above-mentioned components (opacity).

Computing instrumentation and the concept of modeling affect each other. One direction seems obvious. Mathematical models support the design and development of computers in various ways. But the other direction is at least as important: by using computers as an instrument, mathematical modelling is channeled. First and foremost, this channeling represents an epistemological shift. Traditionally, mathematical modeling has been performed by human subjects actively modeling to gain insight, control, or whatever. The channelling effect comes about because an additional technological level is added: the modelling must find a balance, namely to compensate for those (extra) transformations that are caused by the use of the computer - that is, as a rule, to neutralize them to a certain extent through further, additional constructions within the model.

The ANNs used in Deep Learning have served as examples throughout the analysis. Lenhard (2019) discusses more and different examples in the same framework. What are typical features of ANNs? They are a special type of model because they are constructed almost independently from the sort of phenomenon they are supposed to capture. They have a very generic model structure. A simple observation is that these networks are often displayed, but all pictures look essentially the same. In fact, the structure does not represent the target phenomena. Therefore, one can call ANNs structurally underdetermined. At the same time, they contain an extremely large number of parameters whose adjustment makes the overall behavior so versatile that it can approximate an almost arbitrary function. In other words, the model behavior depends completely on the specification (of parameters). This is in strong contrast to the traditional idea of model construction where the structure is supposed to capture the phenomena and parameters are for fine-tuning.

From a formal and abstract standpoint, iteration is the typical action connected with ANNs. Their construction is often meaningless, in the sense that elements in the construction do not have an interpretation in terms of the target domain—no champion of Go was necessary to build the network that—when trained over and over by playing games against itself—later beat the world champion reliably. All the more does parameter adjustment matter. And this happens iteratively, i.e. in each learning step each parameter is adjusted—and learning steps are themselves iterated. From a hardware point of view, such procedure requires to execute large masses of simple iterations.

Finally, ANNs stand for a turn in mathematization. Now, mathematization is not about the book of nature. It is not a tool for representing the world. Instead, mathematics is used as a tool to construct and control the gigantic approximation machines that ANNs are. Jost (2017) argues that mathematization now is concerned with the mathematization of tools. How can such inward-looking turn result in something that is successful in real-world tasks like image classification or language generation?

Basically, these successes are grounded in a fundamentally instrumentalist approach, namely a statistical treatment of patterns—irrespective of what these patterns mean.

1.3 Epistemology: Opacity and Understanding

Black box modeling deals solely with input–output behavior, whereas its counterpart, white box modeling, is concerned also with the inner workings of the model. Obviously, a black box model cannot explain why the modeled system behaves as it behaves. For this reason, it is a widely shared goal to replace opaque models that have a black box character by white box, transparent models. A good example is Perl (1997) who diagnoses that modeling is targeting systems of increasing complexity and that this complexity prohibits the sort of analysis possible with white box models. Perl expresses the hope that approaches like neural networks might open up a new way for understanding complex systems (Perl, 1997, 302).

About 25 years ago, the opinion was widely shared that new computational methods might bring new ways of understanding complex systems. However, the quick evolution of ANNs brought predictive successes that come together with utterly opaque models. One can still insist on the goal of making these models transparent to an extent that allows one to explain their prediction. Not very astonishingly, and in response to the successes of ANNs, there is a recent call to develop "Explainable AI" (XAI). However, opacity is part-and-parcel of simulation in general (Humphreys, 2004; Lenhard, 2019) and of Deep Learning in particular—as has been argued above. Up to now, XAI remains an open field for research whose success (or failure) can only be judged in the future.

If one is accepting that opacity is an unwanted, but unavoidable condition for using AI, how does the promise of AI (and digitization in more general) look like? From a historical and philosophical perspective, prediction challenges the search for an explanation. This tension has been a constant companion to the entire discussion about explanation since the beginning of modernity—or actually even longer: ever since mathematics played any role whatsoever in considerations of epistemology and practice. A basic viewpoint is that the ability to predict shows something important. In some way, whatever is able to give good predictions has got something right about the world, or about that fraction of the world under investigation. And this something is the fundament and the true source of the predictive capability.

Remarkably, the new methods seem to turn this upside down: Prediction happens on the basis of a method, or a generic model, whose representational properties are in question or even inaccessible. Is understanding still possible? Understanding is a central but somewhat vague and multifaceted notion in epistemology. A couple of decades ago, understanding sometimes was taken to be antonymous to explanation. There is a vast literature in philosophy of science dealing with explanation, whereas understanding is covered considerably less. Books like the one by de Regt et al. (2009) indicate a change—understanding now is on the agenda in philosophy of science.

In a way, simulation models can provide understanding at a certain standard. Scientists might conduct iterated simulation experiments and create visualizations and in this way sound out how how the input–output dynamics looks like. In doing so they can orient themselves in the model—even if parts of the dynamics are not transparent to them. Of course, this kind of familiarity with the model does not meet the high epistemic demands that are normally placed on mathematical models (cf. Russell's (1905) concept of knowledge by acquaintance). However, this lower standard is still sufficient if the aim is a controlled intervention. In other words, simulation models might remain epistemically opaque, but still provide means to control the dynamics.

A typical example is the possible breakdown of the meridional overturning circulation MOC, i.e. the Gulf Stream. Researchers investigate how the MOC behaves under varying conditions (in the simulation model), like temperature increase. Their goal is to understand how robust it is. But understanding here means the opposite of Feynman's case. Whereas he wanted to know behavior without calculation, getting a picture of the MOC is based on large amounts of calculations. Similarly, structural engineering has changed its face with computational modeling. Daring constructions can be admired that could not have been planned without calculating their structural stability via computer models. Engineers understand how such constructions behave, but in a very pragmatic sense that does not presuppose epistemic transparency.

Of course, one could question whether the pragmatic notion should be called understanding at all. We hence face two options: First, does simulation eliminate understanding in the practices of sciences and engineering, or second, do simulation practices replace a strong notion of understanding by a weaker, pragmatic notion? If one accepts that the complexity of simulation models makes epistemic opacity unavoidable, whereas at the same time, these models still are good for interventions and predictions, then the question is: Will this co-existence lead to a new conception or re-definition of scientific understanding? Devising an answer to this question still is a task for philosophy of science.

Thus, the argumentation leads to a twofold claim. First, that simulations can facilitate acquaintance with, and orientation in, model behavior even when the model dynamics itself remain (partially) opaque. And secondly, simulations change mathematical modeling in an important way: Theory-based understanding and epistemic transparency recede into the background, while a kind of pragmatic understanding comes to the fore that is oriented towards intervention and prediction rather than theoretical explanation.

1.4 Software and How Expertise is Organized

If researchers want to use simulations or other computational methods, especially ML, they have to have available appropriate infrastructure. Everybody immediately thinks of a computer terminal, rightly so. However, in this context infrastructure is far more comprehensive. As a concept, infrastructure is so interesting because it captures, or allows to capture, how modern societies, technology, and regulation are interconnected, see Edwards (2002). Having it available is demanding, in terms of costly technology, and actually using it also demanding, in terms of what sort of questions should be asked in which ways.

One of these infrastructure elements is data. The strength of ANNs unfolds when they statistically identify correlations. The prominent successes have a twofold root. Firstly, ANNs can work through amounts of data that were considered unfeasible not long ago. This data-digestive ability rests on a combined achievement of hardware, such as the use of graphical processing units, and software. Secondly, the sensitivity of ANNs to delicate traces of correlations is of use only when there are really many data available. Else all the parameters and optimization procedures remain idle, or worse, lead to spurious signals. This makes ANNs *data-hungry*. Therefore, researchers are strongly motivated to formulate questions about areas where massive data are available or can be produced. In an apt analysis, Perl (2009) had pointed out that ANN methods in sport science suffer from the fact that they need more data than are available. For a statement that computer methods will lead to data-centered 4th paradigm science, see Hey et al. (2009). It is surely not coincidental that this book comes out of Microsoft, a major company involved in data business.

A second element is the networked character of the entire research workflow. Data such as comprehensive image inventories from the internet are usually not stored locally. One can argue that Google or other companies build gigantic computing centers that duplicate and store the entire internet. But this only strengthens the case, because ordinary researchers must connect to these data storages. Moreover, parts of the actual computation are often outsourced, too. When learning and adjusting the parameters, researchers typically work with a software suite such as TensorFlow (Abadi et al., 2015) that runs on a platform maintained by Google. Thus, the exploratory—iterative mode of modeling—specifying the parameters in iterated learning steps—has been adopted by a new networked and centralized infrastructure. Although it is centralized, it is readily available (or those parts of it are that some company thinks in its interest to make available). Moreover, the exploratory part is automated; it consists in adjusting the parameters almost entirely independently from the modelers, thus contributing to opacity.

Software should be distinguished from computing as a third element of the infrastructure. Classically, creating software that adequately operationalizes research questions is a key component of scientific expertise. In the 1980s and 1990s, the motto was that computing expertise should become part of particular fields, like sports science, because a division between software developer and user would no longer work (Lames et al., 1997, p. 30) In one sense, this motto has been fulfilled. Today, everyone is working with computers. However, in an important sense, something very different happened. Software packages became available that made it easy, or at least doable, for many users to do computational science *without* being experts in actually developing the software. This division of labor amounts to a fundamental shift in how expertise is socially organized. For example, Johnson and Lenhard describe in Chap. 4 of (2024) how quantum chemical simulations are employed by researchers who are specialists in such software, but not in quantum chemical theory. Software and the way in which its uses are organized are a new research topic shared by history, sociology and philosophy of science, see for instance Haigh (2013), Hocquet and Wieber (2021), Johnson and Lenhard (2024).

In AI, a highly visible feature of social organization is that there is a host of competitions set up to achieve a given predictive task to the best degree or with the lowest failure rate (as on the platform Kaggle). Such competitions attract attention from various groups and have established an arena independent of academia (notwithstanding the fact that typical participants have had contact with universities). When data and software are provided on the internet, participants can act independently from resources provided by a university or other academic institution. These competitions function as a market from which big companies recruit scientists and programmers.

Importantly, the methodology together with the infrastructure create a new situation when it comes to policy and regulation. The quality of predictions depends on the quality of the (training) data. Because the quality of data is (still) ill defined, main actors take the quantity of data as a proxy. Today, data such as those that Tesla collects while developing its automated car count as a commercial treasure (not to mention Facebook and other actors in the field). Whereas the collected data are proprietary, government interventions such as regulating when a car has to apply its brakes depend on access to these data. And therefore, practice is heading for a conflict as far as regulatory measures—or better, their justifiability—is concerned.

Finally, a short wrap-up concerning the point raised at the beginning of this chapter: If a field is getting into AI, what effects will that potentially have? Overall, digitization brings about new research instruments. The wide distribution and uptake is depending on a comprehensive infrastructure that makes the use of software possible also for non-experts and also directs new research toward fields and questions that lend themselves to these new instruments. Concretely, since data are a potential bottleneck, creativity is required from the researchers to address questions for which they have available or can produce sufficient amounts of data. Philosophically, simulation and AI methods come with epistemic opacity. They yield predictions, but tend to be unpromising regarding explanations.

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Chapter 2
Artificial Intelligence in Sport Scientific Creation and Writing Process

Richard Latzel and Patrick Glauner

Abstract This chapter examines the transformative role of Artificial Intelligence (AI) tools in enhancing academic research and writing, with a focus on their application within sports science. It highlights the integration of technologies such as ChatGPT, Grammarly, and other generative AI tools into the academic landscape, demonstrating their impact on improving learning environments, promoting academic integrity, and streamlining administrative tasks. Through a detailed exploration of AI's contributions to literature research, data management, analysis, visualization, and writing support, the chapter delves into the efficiencies and depths these tools bring to academic work. It also addresses the limitations and challenges of AI integration, emphasizing the crucial balance between technological advancements and the indispensable value of human expertise in scholarly research. This discussion underscores AI's potential to facilitate innovation in academic writing and research, marking a significant shift towards more efficient, insightful, and comprehensive scholarly work if applied properly.

Keywords ChatGPT · AI · Scholarly Work

Declaration of the Use of Artificial Intelligence Tools in This Book Chapter

In the development of this book chapter, we selectively utilized Artificial Intelligence (AI) tools, primarily to support and enhance the writing process. This declaration outlines the extent and manner of AI tool integration within our work, emphasizing our approach to leveraging technology while ensuring the integrity and originality of our scholarly contribution.

1. **Literature Research**: We incorporated AI tools, specifically ResearchRabbit and Elicit, to assist in the initial stages of literature research. These platforms facilitated the identification of relevant studies and provided insights that informed our understanding of the topic. It is important to note that while these tools

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C. Dindorf et al. (eds.), *Artificial Intelligence in Sports, Movement, and Health*,
https://doi.org/10.1007/978-3-031-67256-9_2

were helpful, they complemented a broader manual research effort, ensuring a comprehensive and nuanced review of existing literature.

2. **Writing Assistance**: The primary application of AI in the creation of this chapter was in the realm of writing support. Tools like ScholarAI and ChatGPT were used to enhance the clarity, grammar, and coherence of our text. These AI-driven aids offered suggestions for language improvement, helping us refine our argumentation and presentation. However, the critical evaluation of these suggestions and the final writing decisions were made by us, the authors, to maintain the academic integrity and intellectual rigor of our work.
3. **Originality and Integrity**: Despite the availability of AI-based plagiarism detection tools, we chose to ensure the originality of our content through manual verification and adherence to best practices in scholarly writing. This approach was guided by our commitment to academic ethics and the production of work that is both authentic and contributes meaningfully to the field.

By detailing the use of AI tools in the composition of this chapter, we aim to transparently acknowledge the role of technology in facilitating our academic writing process. The integration of AI was done with careful consideration, ensuring that it served to augment our capabilities as researchers and writers, rather than diminish the scholarly value of our contribution. The insights, interpretations, and conclusions presented in this chapter are the result of our professional judgment and expertise, underscored by a judicious application of AI for specific, supportive tasks in the writing process.

2.1 Introduction

The integration of Artificial Intelligence (AI) tools like ChatGPT, Grammarly, and other generative AI models into academic writing and educational platforms has been the subject of various studies, highlighting both their advantages and potential drawbacks. These tools have been shown to potentially enhance the learning environment by providing personalized tutoring, automating essay grading, facilitating translation, and creating interactive learning environments. AI tools have also been acknowledged for their role in promoting academic integrity through plagiarism detectors and assisting in administrative tasks like grading and feedback provision. This technological advancement has notably reduced the paperwork and workload for instructors, allowing them more time to dedicate to instruction and content dissemination (Duymaz & Tekin, 2023; Escalante et al., 2023).

This chapter explores the benefits and limitations of AI tools for academic research and writing, providing insights into their practical application in sports science and other academic fields. It includes a brief overview of AI tools' basic functionality before delving into their potential benefits in academic literature research, data analysis and management, and academic writing.

2.2 Overview of Artificial Intelligence

AI aims to automate human decision-making. AI has become one of the most transformative technologies of our time, reshaping industries, augmenting human capabilities, and pushing the boundaries of what machines can do. Typical tasks include learning, reasoning, problem-solving, perception, and language understanding (Russell & Norvig, 2021).

Historical sketch

The journey of AI began in the mid-twentieth century, with the term "artificial intelligence" being coined in 1955 by John McCarthy and others in a proposal for the Dartmouth Conference for the following year (McCarthy et al., 1955). This period marked the optimistic beginnings of AI, with researchers setting ambitious goals for machines to mimic human intelligence. Early AI research largely focused on symbolic approaches, attempting to encode human knowledge into machines. However, the complexity of human cognition proved to be a formidable challenge, leading to the realization that achieving true AI would require more than just programming explicit rules.

Machine Learning

The rise of Machine Learning (ML) in the latter part of the twentieth century marked a significant shift in the AI landscape. ML is a subset of AI that focuses on developing algorithms that enable computers to learn from and make predictions or decisions based on data. This approach diverged from the rule-based methods, offering a new pathway to achieving AI through data-driven learning (Bishop, 2006). The field of ML can broadly be divided into three so-called "pillars":

- Supervised learning: learn to predict a label y, i.e. a class (classification) or quantity (regression), from input data X.
- Unsupervised learning: find hidden relationships, such as clusters or lower dimensional representations, in the input data X.
- Reinforcement learning: learn which action to take in which state to achieve the best outcome.

Deep Learning

Deep Learning involves (Artificial) Neural Networks with many layers (hence "deep") that learn representations of data with multiple levels of abstraction. This approach has enabled significant advances in computer vision, natural language processing, and other areas requiring complex feature extraction in recent years (Bishop & Bishop, 2024).

Natural Language Processing

Natural Language Processing (NLP) is a domain of AI focused on the interaction between computers and humans using natural language. The goal of NLP is to enable computers to understand, interpret, and generate human languages. Techniques in NLP have evolved from rule-based systems to ML and sophisticated Deep Learning models, significantly improving the ability of machines to process and understand human language.

Large Language Models and prompt engineering

Large Language Models (LLMs), such as ChatGPT, represent the cutting edge of NLP. These models are trained on vast text datasets, learning to predict the next token in a sequence given the preceding tokens. This training enables them to generate coherent and contextually relevant text, translate languages, answer questions, and even write code. Prompt engineering has emerged as a crucial skill in leveraging LLMs, involving designing inputs (prompts) that guide these models to produce the desired output. It requires an understanding of the model's capabilities and limitations, creativity, and strategic thinking.

2.3 Role of Artificial Intelligence-Supported Tools in Literature Research

In the evolving landscape of academic research, Artificial Intelligence (AI) tools have emerged as pivotal instruments, reshaping the way research and analysis of data is conducted and findings are compiled. Some of the key advantages AI tools can offer in academic research are (Chubb et al., 2022; Pinzolits, 2023):

1. **Efficiency and Time Management**: AI tools, when used in the right way, can markedly reduce the time researchers spend on literature reviews and data analysis. They can quickly sift through extensive databases to identify relevant research papers, abstracts, and even specific sections within papers that address particular research questions. This capability allows researchers to focus more on analysis and less on the time-consuming process of finding information.
2. **Comprehensive Literature Analysis**: With access to vast databases of peer-reviewed articles, AI tools enable researchers to conduct thorough literature reviews. Some tools offer literature mapping features that help identify related research, references, and recommended readings, ensuring that researchers have a comprehensive understanding of their topic.
3. **Detailed Research Insights**: Beyond just identifying relevant papers, AI tools can analyze the full text of research documents. This deep dive into the content provides detailed insights into methodologies, results, and discussions, which are crucial for understanding the nuances of each study. Some tools can extract and summarize information from multiple research papers at once and might even aid in the development of a well-informed hypothesis and research design.