Article

Examining Rock Engineering Knowledge through a Philosophical Lens

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Abstract: This paper presents a philosophical examination of classical rock engineering problems as the basis to move from traditional knowledge to radical (innovative) knowledge. While this paper may appear abstract to engineers and geoscientists more accustomed to case studies and practical design methods, the aim is to demonstrate how the analysis of what constitutes engineering knowledge (*what rock engineers know and how they know it*) should always precede the integration of new technologies into empirical disciplines such as rock engineering. We propose a new conceptual model of engineering knowledge that combines experience (practical knowledge) and a priori knowledge (knowledge that is not based on experience). Our arguments are not a critique of actual engineering systems, but rather a critique of the (subjective) reasons that are invoked when using those systems, or to defend conclusions achieved using those systems. Our analysis identifies that rock engineering knowledge is shaped by cognitive biases, which over the years have created a sort of dogmatic barrier to innovation. It therefore becomes vital to initiate a discussion on the subject of engineering knowledge that can explain the challenges we face in rock engineering design at a time when digitalisation includes the introduction of machine algorithms that are supposed to learn from conditions of limited information.

Keywords: rock engineering; knowledge; engineering philosophy; cognitive biases

1. Introduction

Rock engineering can be defined as the application of engineering and geology principles for the purpose of integrating geological factors to engineering design, and for the purpose of understanding the mechanisms of natural phenomena (e.g., landslides and rockslides) and extracting natural resources (e.g., open pit and underground excavations). Rock engineering seeks to blend two apparently contrasting knowledge perspectives [1], namely Episteme (scientific knowledge) and Phronesis (practical knowledge). We could say that practical knowledge, interpreted as a collection of experiences that cannot be studied in a deductive manner, dominates rock engineering. We understand the content of this paper may appear abstract to engineers and geoscientists more accustomed to engineering case studies and practical design methods. Therefore, how can a paper presenting an examination of rock engineering knowledge be of interest to engineers seeking practical solutions to their design problems? The answer is that knowledge is what helps us to make valued engineering decisions. Indeed, without knowledge, our engineering decisions could be fraught with safety implications. As engineers, we are trained to work with numbers, but rock engineering design is more than just a problem of calculating the factor of safety or the probability of the failure of a given engineered structure. It is important to consider how individuals perceive risk, knowing that it may be difficult to convey complex technical messages to individuals who, paraphrasing the title of Vincenti's book [2], are not familiar with what rock engineers know and how they know it.

The authors believe it is important to initiate a discussion on the subject of engineering knowledge that can explain the challenges we face in rock engineering design at a time when digitalisation includes the introduction of machine algorithms that are supposed to learn from conditions of limited information. Geoscientists have long recognised the important role of knowledge and cognitive bias in the study of geology [3–5]. However, except for studies concerning reliability methods and uncertainties, little attention has been given to the impact that subjectivity, human factors, and lack of scientific replicability have on the empirical methods used in rock engineering design. We are too concerned with the introduction of new technology and numerical simulations, while ignoring the difference between the science behind technological advancement and the empirical knowledge that is driving our design decisions. More importantly, this paper offers an opportunity to contextualise the teaching of rock engineering outside of the domain of mechanical and technological matters to better account for the societal perception of engineering design (e.g., the design of an underground nuclear waste repository or a large tailing storage facility).

The following questions frame the motivation behind the importance of looking at what engineering knowledge is in the context of a very practical discipline such as rock engineering:

- What is the risk of introducing new technology without addressing the underlying role that human factors play in rock engineering design?
- Are we creating a digital illusion of technological advancement, driven by scientific knowledge, but constructed on the empirical foundation of engineering knowledge?
- Would our empirical methods have been developed differently had the same level of technology and digitalisation we use today been available 50 years ago when those empirical methods were first introduced? As an example, engineers in the 1960s and 1970s used to log core samples obtained using twin tubes, compared to the more standard triple tube in use today. Like staring at a painting before and after restoration, would our interpretation be different?

Philosophy applied to rock engineering originates from the natural disposition of the human mind to question concepts that cannot be explained by empirical knowledge alone. Critical reasoning is key to innovation in any engineering discipline. The discussion that follows is not a critique of actual engineering systems; rather, it is a critique of the reasons that are invoked when using those systems, or to defend conclusions achieved using those systems. We are more preoccupied with justifying the removal of instances that do not agree with our assumptions, or with finding explanations when data do not conform to commonly accepted rock engineering systems, rather than accepting that those systems are limited or not entirely applicable to specific situations [6]. Inevitably, a dogmatic approach ensues. Revisions are not so immediate, and are often met with criticism, on the premise of a false equivalency between experience and engineering knowledge, upon which many empirical industry standards used in rock engineering have been created over the years. Engineering knowledge is not—and should not—be validated upon a temporal dimension alone.

Notwithstanding specific references and examples made to rock engineering problems, our findings could be generalised to all forms of engineering that either deal with natural materials or rely on a quantitative interpretation of qualitative data. The framework of engineering knowledge we propose goes beyond the observation of principles used in rock engineering, and we believe it could help us understand how engineering knowledge is shaped.

2. Why Philosophy Matters When Discussing Rock Engineering Principles

Engineers may have little interest in philosophical problems, and epistemological questions about the source of engineering knowledge also rarely draw attention [7]. Nonetheless, engineering decisions are not immune from behavioural factors, and therefore this creates the opportunity for considering philosophical questions that impact how decisions are made. The authors, who are engineers and not philosophers, believe that philosophy offers

the opportunity to adopt a reflective learning approach, and as such it does matter to engineers, since without such a reflective approach we would not be able to challenge the fundamentals of current engineering practice. This echoes Bulleit et al. [8], who stated that reflective and philosophical engineers would be better engineers. From the other end, philosophers, too, have largely neglected the topic of engineering philosophy and its epistemic foundations due to the misconception that engineering can be classified as applied science [1]. Contrary to this belief, in his elaborate reflection on engineering knowledge and practice, Vincenti [2] argued that engineering should be understood as an independent knowledge-generating activity that transcends the limits of applied science.

With this in mind, what is philosophy applied to engineering? In simple terms, engineering philosophy could be defined as the study of engineering concepts explained considering philosophical principles. However, any refinement to this definition would have to reflect the multifaceted nature of engineering [9]. Engineering philosophy seeks to integrate two apparently contrasting fields: engineering, dominated by empirical knowledge, precisions, probability, and driven by measurable results; and philosophy, which searches for truth and objective knowledge, and that is not afraid to focus on abstract concepts.

According to Grimson [9], engineers who were asked their opinion on the relevance of key areas of philosophy to their engineering practice reported ethics and epistemology as very important, with logic attaining only an average credit, and aesthetics and metaphysics given muted or no credit, respectively. We could argue that aesthetics contributes to rock engineering, since the study of natural environments and human influences on the natural world have an aesthetics connotation in the desire to preserve natural environments. The fact that engineers are unlikely to accept unobservable phenomena, even when those reflect an objective reality, would apparently preclude metaphysics from playing a role in engineering systems. However, examples from the natural world would speak to the contrary, as in the case of rock bridges [10], that is, the invisible portion of intact rock known to control the stability of rock structures (Figure 1). Despite what we might think we know as engineers, we found ourselves debating the reality of what prevents natural rock structures from failing, other than rock bridges must exist and must provide the required strength. What these rock bridges look like, how many there are, and where they are, we do not know. Because we can just postulate their existence, rock bridges become metaphysical entities, and their engineering impact can only be captured through the definition of rock bridge strength as a potential strength [10].

Quoting Fookes [11]:

> *"There are some geological conditions that are unforeseeable, and when those conditions are encountered there will inevitably be some undetectable variations in the geology that can never be completely investigated within practical limits".*

This statement is a demonstration of how addressing rock engineering problems requires a mindset capable of understanding the nature and the role of knowns and unknowns. Numbers are required in rock engineering design to calculate the stability of man-made structures such as buildings, bridges, and tunnels. However, due to the nature of geological/geotechnical materials, the approach to design rests on observations, experience, and engineering judgement (all very subjective), often used to infer the behaviour of a poorly defined problem. We call this process a quantification of qualitative assessments. Because of its qualitative origin, the design approach will inevitably be subjected to cognitive bias and human factors. Despite the increasing use of numerical models and advanced remote sensing technology, the next major challenge faced by practitioners is not developing new technologies, but rather finding new and more objective ways to interpret the vast amounts of information we are now collecting in a truly objective manner [12]. However, to do so would require overcoming a cognitive resistance that is all too common in rock engineering practice [6].
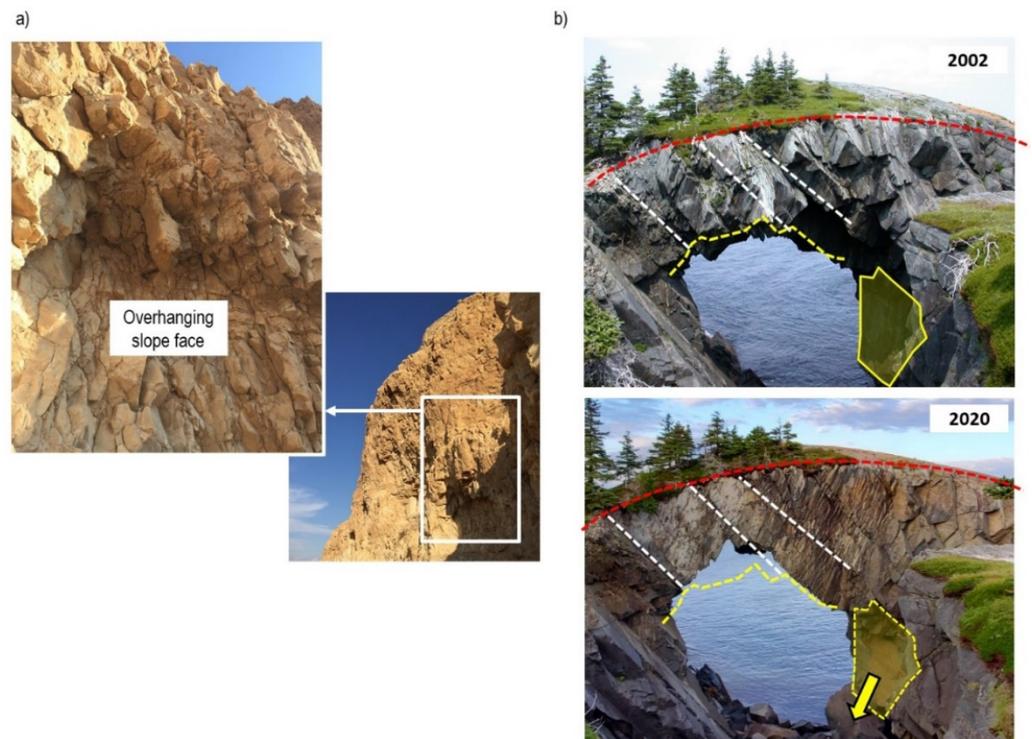
Figure 1. Examples of natural structures whose stability is controlled by the presence of rock bridges: (**a**) Masada fortress, Israel; and (**b**) Berry Head Arch, Canada, in 2002 and more recently in 2020.

It is possible to draw an analogy between rock engineering and Plato's Allegory of the Cave [13], which Plato used to describe the contrasting nature of belief and knowledge. As illustrated in (Figure 2):

- The fire casting the shadows along the cave walls represents the process of quantification of qualitative assessments of commonly accepted data collection methods.
- The chains holding the engineers as prisoners in the cave are qualitative methods accepted as industry standards despite important limitations.
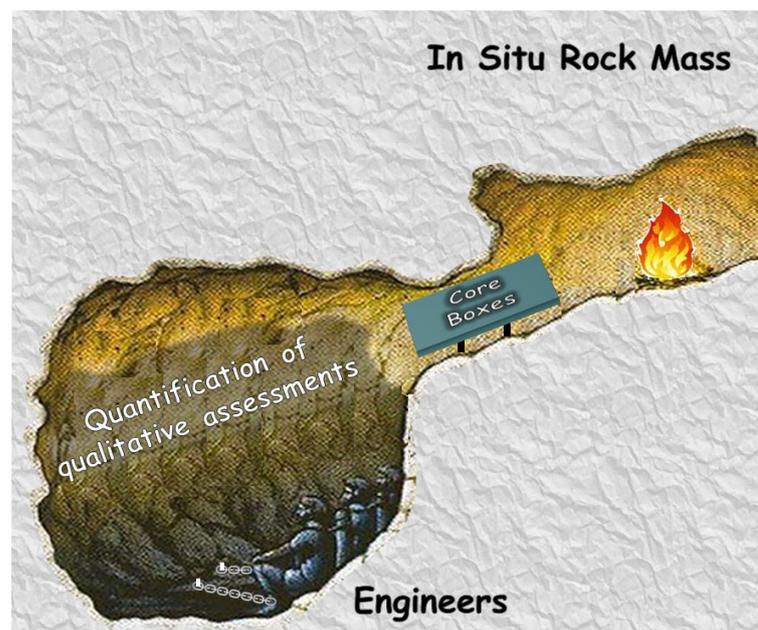

Figure 2. The allegory of the rock engineering cave.

Engineering judgement alone is not sufficient to set engineers free from the confined spaces of the cave and see things for what they really are. What is required are objective data collections and design methods. However, that may be problematic, considering the challenges of assigning numbers to geology [14]. However, there is another solution, and that is to accept that geological processes are variable and therefore focus our attempts to better characterise variability rather than seeking to describe rock masses through a single numerical input. Exadaktylos and Stavropoulou [15], for example, suggested thinking of rock mass characterisation in the context of "*mechanics of materials*" by focusing on rock mass damage processes. Their idea is analogue to the concept of rock bridge potential described by Elmo et al. [10].

Clearly, the allegory of the rock engineering cave teaches us that there cannot be innovation without a shift in the way we approach rock engineering design, by prioritising data interpretation and mechanisms rather than collecting large amounts of subjective data. Referring to Kahneman's behavioural science concepts [16], the former represents conscious reasoning, in contrast to the latter, which is a manifestation of intuitive reasoning.

3. A Novel Interpretation of Engineering Knowledge

Researching advanced techniques such as machine learning and neural networks applied to solving rock engineering problems should be preceded by an attentive analysis of engineering epistemology. When it comes to defining what constitutes engineering knowledge, the boundaries between personal judgement and engineering judgement are not always well defined. It is reasonable to assume that ethics principles do indeed dictate how personal beliefs influence our engineering decisions. However, the role played by human factors and cognitive biases in rock engineering is often overlooked. In this paper, we explore the important role of uncertain conditions and heuristics, introducing a new framework for engineering knowledge. In our discussion, we will distinguish between *Engineering Moral Knowledge* and *Engineering Technical Knowledge*, respectively:

- Engineering Moral Knowledge. Most of the studies concerning engineering philosophy available in the literature focus on ethical challenges and how engineers behave when faced with an ethical dilemma [8,17–19] or are directed to improve engineering education [20,21]. The tenets of various professional engineering associations, despite slight differences in the actual wordings, are good examples of the moral knowledge required and expected from individuals to conduct themselves as engineers.
- Engineering Technical Knowledge. Knowledge may begin with experience, but it would not be correct to say that the full compendium of engineering knowledge arises from experience. Experience is a subset of technical knowledge (Figure 3), and it manifests itself through a series of "learning nodes" [6]. However, the aggregate knowledge transcends sequential connections, and additional connections exist (dashed lines in Figure 3) that represent a form of a priori knowledge, i.e., knowledge that is independent of experience using Kant's definition [22]. Conversely, a posteriori knowledge is the knowledge that originates solely from experience. Empirically derived intuitions are still a form of a priori knowledge, and those intuitions represent jumps across sequential learning nodes.

In the context of rock engineering, individuals can learn from experience, but experience alone cannot explain natural mechanisms in full. Therefore, empirical knowledge is not universally correct, and exceptions may always be possible. For instance, because of the impact of cognitive biases, there is no such thing as a linear connection between learning nodes (Figure 4). Undulating lines (Figure 4b) are better representations of the way different people may process the same experience. As the undulation grows larger, different conclusions may be achieved by two different persons observing the same phenomenon. Human factors are therefore responsible for these undulations. As explained by Elmo and Stead [6], eventually the question arises as to whether engineering judgement should be able to counter and minimise those undulations such that they converge to the same learning node, or a correction must be introduced in the process (Figure 4c). Kruger and

Dunning [23] defined engineering judgement as a metacognitive skill required to evaluate the validity of one's experience. The degree of engineering judgement applied when moving between adjacent learning nodes is not universal, as it would depend on one's experience. Therefore, there is no assurance that engineering judgement may lead to clearly identify conclusions that are not correct. In some instances, corrections may not be adopted solely because of an individual's cognitive biases. For experience to be considered a true synonym of knowledge, it would require experience to be a process by which uncertainty is always reduced as more experience is gained. However, the highly variable nature of rock masses and the cognitive bias introduced in the analysis makes it impossible for engineers to have a complete knowledge of the rock mass [6].
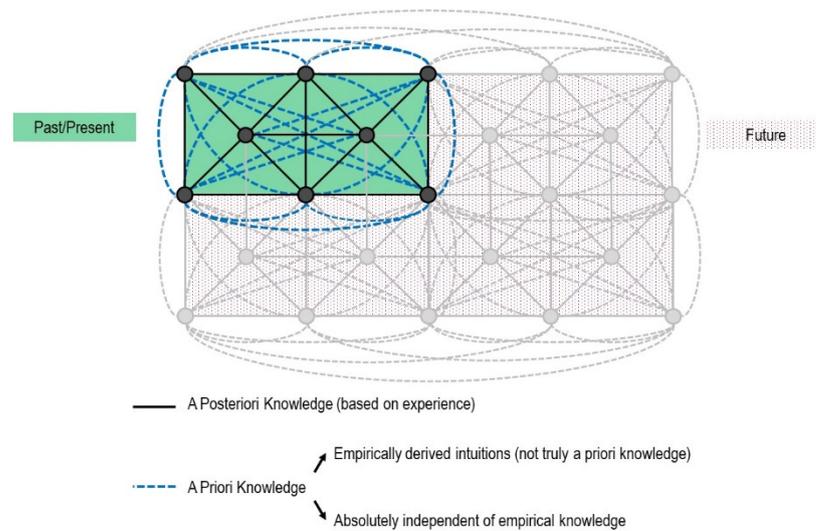

Figure 3. Conceptual scheme of engineering knowledge in the form of a network of learning nodes.
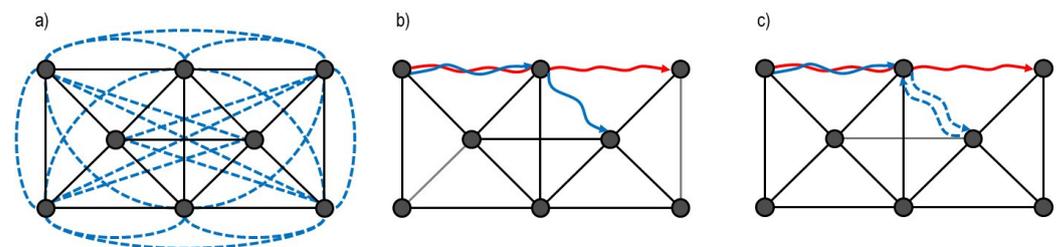

Figure 4. Influence of cognitive biases and engineering judgement on engineering knowledge. (**a**) Experience, intuitions and aggregate (a priori) knowledge; (**b**) Role of cognitive biases potentially influencing experience; and (**c**) Role of engineering judgement in assessing the validity of our conclusions and intuitions.

The visual depiction of engineering knowledge as an array of learning nodes connected by either direct links (a posteriori knowledge) or indirect links (a priori knowledge and intuitions) shown in Figure 3 is not necessarily limited to a 2D plane, and there are no reasons why the array could not be extended into a third dimension (Figure 5a). The proposed framework of engineering knowledge assumes that the 3D array evolves from a singularity, and it expands over time. This concept directs us to the metaphysical connotation of engineering knowledge. The singularity could be approximated to a particular point in time in the life of a person, or even traced back to the actual development of the first brain cells in utero.
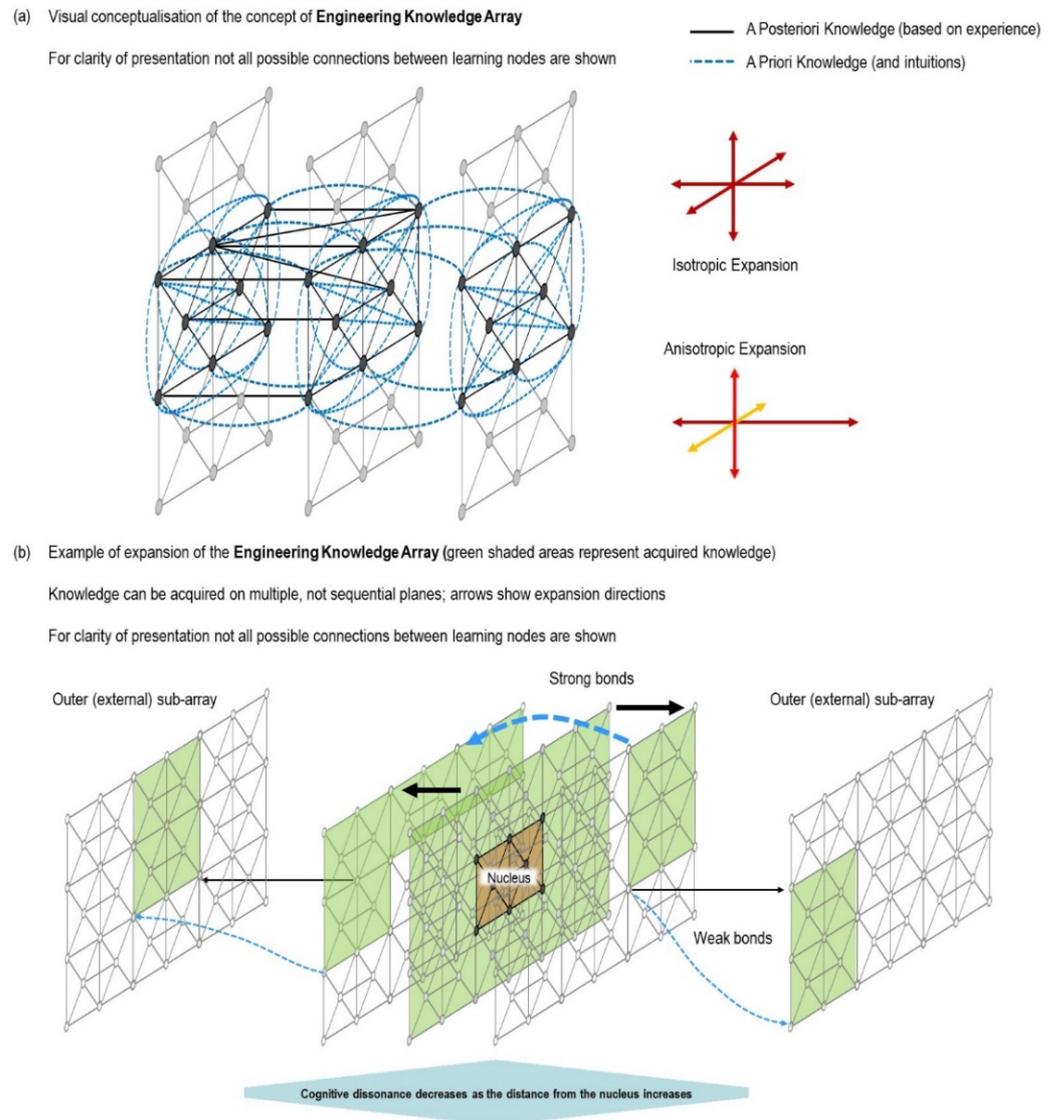
Figure 5. (**a**) Concept of 3D engineering knowledge array; and (**b**) example of knowledge expansion showing how knowledge could, in principle, be transferred across multiple planes in a non-sequential manner.

In our proposed model, the nucleus of the expanding engineering knowledge array is surrounded by outer layers of bonded external sub-arrays (Figure 5b), and knowledge transfer may occur in an analogous way to chemical bonds, whereby weak or strong bonds may develop upon which the engineering knowledge array grows and mutates its shape. The links may represent either empirical knowledge or intuitions. Systemic knowledge (and bias) belongs to the nucleus, while the sub-arrays are the domain of superficial knowledge. For example, knowledge acquired while studying for an engineering degree would reside close to the nucleus, while changes in our interests in different engineering and science disciplines, and the degree to which our mind is subject to external influences and biases, would manifest in the creation of sub-arrays.

Knowledge transfer between individuals occurs when fragments of an individual's engineering knowledge array attach themselves to the array of a different individual. The transfer may only occur superficially, or may involve deeper and stronger bonds. Our engineering knowledge inevitably expands in an anisotropic manner, since isotropic expansion would lead to a state of complete knowledge, which is theoretically possible, but not practically attainable by any individual. Group work may confer little advantage in

terms of contrasting anisotropic knowledge expansion since, as explained by Dunbar [24], members of the same group are more likely to have similar knowledge imprints. Established group practices are not necessarily correct practices; over time, they become habits [25], which, perpetuated through a lack of critical teaching and learning, become difficult to change.

Equally, the experience and the biases coded in the nucleus largely remain unchanged over time, and a deep and inwards self-examination is required for significant changes to happen. Expanding on the definition of behavioural rock engineering given by Elmo and Stead [6], we could conclude that the nucleus is most likely to be exposed to cognitive dissonance forces that resist changes [26]. These forces decrease as we move away from the nucleus, and therefore biases that reside in the external sub-arrays are easier to remove and correct. The proposed framework for engineering knowledge supports the notion that progress and discovery could only occur when external actions disrupt the nucleus and impose a new direction of anisotropic expansion [27]. We could interpret this process through the concepts of fragility and antifragility [28]. The nucleus is where rock engineering fragility resides: the larger the cognitive dissonance forces, the larger the sensitivity to stressors that would trigger deflecting (concave reaction) defensive mechanisms in response to increasing criticisms. In contrast, an antifragile knowledge would respond to criticisms by focusing (convex reaction) actions that would prevent cognitive dissonance from taking hold.

The description of engineering knowledge as a 3D expanding array raises the question of whether infinite knowledge is possible, or whether there are recursive mechanisms at play that somehow counteract the expansion of the aggregate (universal) engineering knowledge. Knowledge transfer is an example of a recursive mechanism; no new knowledge is immediately created in the process, though the transfer itself may later contribute to growth. The important characteristic of the proposed 3D engineering knowledge array is that connections between learning nodes can potentially occur in every direction, to represent our ability to learn very different disciplines. Sub-arrays can be created that refer to specific knowledge categories, which, in turn, may later combine with different types of knowledge sub-arrays. The integration of engineering with philosophy is an example of the combination of different categories of knowledge sub-arrays.

The engineering knowledge conceptualisation proposed in Figure 5 is fundamentally different from a neural network in which data move only in one direction. In our proposed framework, data are allowed to move across non-sequential learning nodes by means of intuitions. If qualitative, biased knowledge is introduced in the 3D array, there may be a bias amplification, whereby knowledge is transferred and created without removing the initial bias. Can this process of *bias correction* be simulated in numerical algorithms that are supposed to mimic the human brain? For instance, if biases are present in the training data fed to a neural net, can the bias be filtered out through the neural layers? Examples from major industry [29] speaks to the contrary, and therefore we should not expect machines to learn and apply rock engineering principles. Authors such as Marcus [30] have compared machine learning algorithms to a form of "*passive dredging system*", therefore highlighting the challenge of removing bias from automated processes. In a wider context, this can be related to the question of AI and trust, discussed by Chen [31] and von Eschenbach [32].

The Role of Knowns and Unknowns

Prototypes are preliminary models used in engineering design created to test a design idea [33]. However, rock engineering is, by nature, a non-prototypal discipline due to time and scale constraints. Natural structures (see Figure 1) are created due to slow geological processes over a long period of time (millions of years), while rock engineering structures are created by handling rock materials over a much shorter period (tens of years). The direct testing of artifacts is generally limited to laboratory-scale (centimetre dimensions) experiments, while large-scale problems are usually tested through numerical solutions based on some understanding of natural processes. Nonetheless, even when the

processes are well understood, the subject of the problems inevitably leads to approximate solutions [1], since:

> *"Site conditions always pose unknowns, or uncertainties, which may become known during construction or operation to the detriment of the facility and possibly lead to damage of the environment or endanger public health and safety".*D'Appolonia [34]

> *"We must realize that most of the volume of rock of immediate concern is hidden and inaccessible and, unfortunately, what we do see is rarely representative of what we don't".* Goodman [35]

The philosophical nature of rock engineering indeed rests on the dichotomy between the laboratory scale vs. field scale and the non-prototypal nature of geological problems. The properties we measure in the laboratory (intact rock) do not represent the properties of the rock in the field (rock mass), and we can only infer some mechanistic equivalency between the laboratory scale and field scale.

The aforementioned statements lead to the examination of the role of knowns and unknowns, and how they shape engineering decisions. Using the framework illustrated in Figures 3–5, the concepts of known knowns, known unknowns, unknown knowns, and unknown unknowns can be explained as follows:

- Known knowns represent accessible data and a posteriori knowledge (achieved learning nodes).
- Known unknowns result from recognised but poorly understood phenomena [34]. They represent questions and hypotheses developed based upon a posteriori knowledge; they are constrained by the evolving sequence of adjacent learning nodes (they represent knowledge to be confirmed).
- Unknown knowns are the cognitive biases that may influence our decisions and thus yield different learning paths from the same initial learning node.
- Unknown unknowns are conditions that cannot be expected, because there has been no prior experience or theoretical basis for the conditions to occur [34]. In this context, unknown unknowns exist in the dimension of a priori knowledge. Intuitions may guide us towards the critical information required for the successful design of an engineered structure, thus allowing us to narrow the impact of uncertainty; the latter can be considered a material manifestation of unknown unknowns. However, unknown unknowns are also the realm of unknown uncertainty, a complex form of uncertainty that engineers, despite their practical experience, cannot remove from the design process. To make matters worse, the inherent variable nature of rock material is such that in rock engineering, the role of unknown uncertainty increases as the scale of the engineering problem increases [36].

The methods used to both acquire and apply knowledge in rock engineering include field observations, lab experiments, theoretical analyses, numerical simulations and, more recently, big data-based methods. A comprehensive review of those methods, albeit important, is outside the scope of this paper. In this paper, we have attempted to frame the discussion as a high-level overview rather than focusing on specific rock engineering problems. Indeed, the use of mathematical laws and formulations used in rock engineering design would be implicitly included in the knowledge framework and the series learning nodes illustrated in Figure 5.

Nonetheless, it is important to recognise the role that both knowns and unknowns play in the overall rock engineering process. This is illustrated in Figure 6. In an idealised design scenario, unknowns would disappear as a project approaches completion. Known-unknown frameworks are used as part of the risk analysis in aerospace engineering, focusing on moving unknowns to the known domain. Different forms of uncertainty exist at different times during the rock engineering process. However, uncertainty cannot be reduced to zero, because site conditions always pose unknowns or uncertainties, some of which may remain unknown and possibly lead to important societal and environmental consequences. Ultimately, we can manage uncertainty (known unknowns and unknown

knowns), but we cannot eliminate it (unknown unknowns). Some forms of uncertainty can be managed better than others. However, human uncertainty may potentially increase throughout the process as a result of cognitive biases.
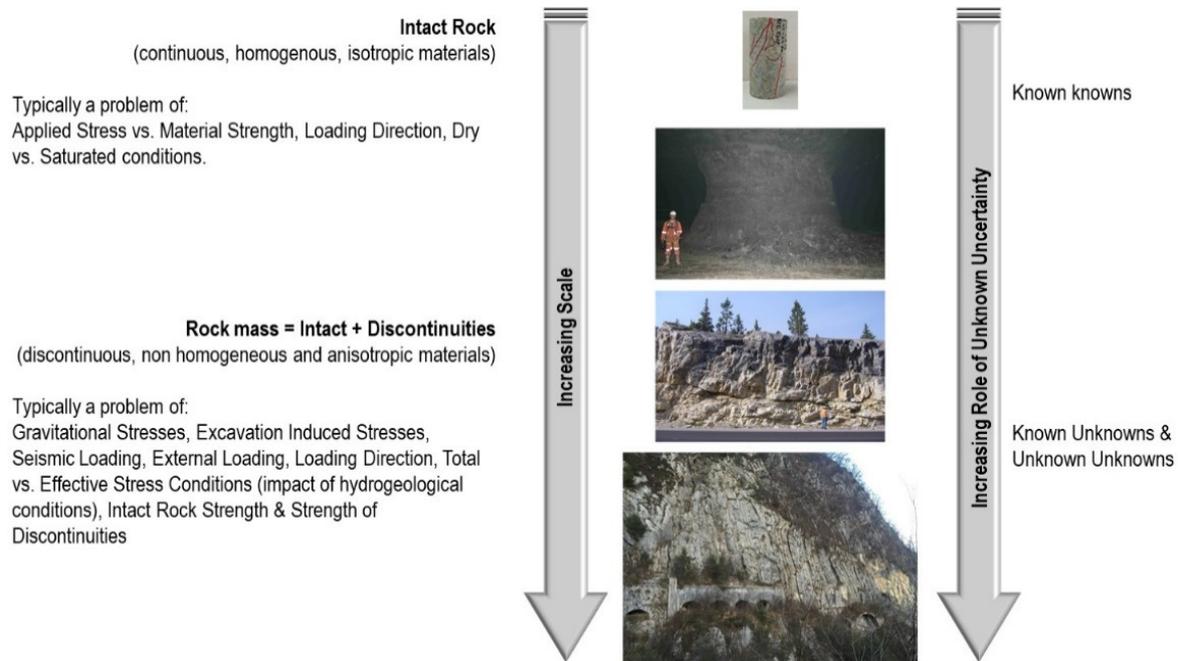

Figure 6. The role of knowns and unknowns in the rock engineering process.

4. Unknown Reality and Realistic Models

Rock engineering design has an impact on the environment, whether that involves remediation work to minimise the impact of natural phenomena such as rockslides and debris flows (passive impact) or the construction of underground excavations, dam foundations, and open pit slopes (active impact). Either way, we, as engineers, are part of a system that produces changes to the world we live in. Rock engineering design concerns a variety of information about natural materials. Some of the information consists of quantitative measurements, while the majority of information concerning rock mass components is presented through a classification approach, where numbers are assigned to a set of qualitative information. To understand the process, Elmo and Stead [6] compared it to attempting to build a wooden train track set without referring to the manual describing the intentional configuration as envisioned by the manufacturer (nature). The challenge of assigning numbers to geology is to recreate the intentional configuration, or at least recreate a realistic configuration. In the natural world, there is information beyond what our eyes or instruments can observe, and therefore our solution to the problem would reflect the natural variability of geological processes and factors that could be either known or unknown. As a result, a problem with a unique—unknown—solution (intentional configuration of the wooden train track) must be solved by considering multiple configurations and evaluating their realistic potential. The larger the number of pieces, the larger the variety of the shapes of those pieces, and the larger the number of arrangements possible. Engineers could select some pieces from the box (1D borehole data), but there is a limited number of pieces that they can select (1D boreholes are a limited sample of the 3D rock mass), or engineers could pick pieces that are two sided and therefore can result in different arrangements (subjective interpretation of data). Sometimes engineers may attempt to fit pieces together based on their intuition, or over time, pieces become lost and replaced with copies recreated from memory, akin to using engineering judgement in lieu of factual data.

The question of the epistemology and ontology of scientific theories that explain entities that are unobservable to the human eye has long been debated in the philosophy of

science. Realists hold that scientific theories are models of reality, while anti-realists do not accept entities not detectable to the human senses as non-existent. Similarly, many of the details considered in the rock engineering design process are unknown and unknowable. Models are constrained by the impossibility to reduce the uncertainty associated with data collection (geological uncertainty), modelling (parameter and model uncertainty), and persons (human uncertainty). Hence, the validity of rock engineering models should be questioned by realists, as we cannot completely reduce uncertainty and the potential permeation of cognitive biases in the modelling process. Accordingly, a complex numerical model does not necessarily provide more accurate predictions than a simple one [37]. To quote Borges [38], a model is not and cannot be a perfect imitation of reality:

> "[. . .] *In that Empire, the Art of Cartography attained such Perfection that the map of a single Province occupied the entirety of a City, and the map of the Empire, the entirety of a Province. In time, those Unconscionable Maps no longer satisfied, and the Cartographers Guilds struck a Map of the Empire whose size was that of the Empire, and which coincided point for point with it*".

Under the hypothesis that very complex scenarios could be analysed in numerical models (e.g., automated solutions to the wooden train track problem), would the added modelled complexity provide a means to detect the relative impact of known unknowns and unknown unknowns? Bayesian methods are accepted by geoscientists [39] to facilitate the use of subjective geological information. Nonetheless, the issue at hand here is not so much the qualitative nature of the data, but rather the qualitative uncertainty created by the very same methods used to collect the geological information.

As time progresses, one may expect simple solutions to evolve into more complex ones. Yet, the role of the simpler solutions is not absolute. In some cases, simpler solutions become superfluous, and the complicated systems drive the simpler ones to extinction; in other cases, the simple solutions prevail and even flourish. It is evident generally that if older and simpler solutions have a clear advantage in terms of durability and/or efficiency, even if this advantage is restricted to a limited purpose, they continue to exist and evolve. This principle applies to scientific and engineering analysis methods as well [40]. One such notable example in geotechnical engineering is Coulomb's model for retaining walls. Coulomb studied the problem of lateral earth pressures on retaining structures as early as 1773. Coulomb used the failing soil block as a free body to determine the limiting horizontal earth pressure. Although rock engineering has advanced incredibly, the equations based on Coulomb's simple theory are still in use today.

5. The Role of Subjectivity in Engineering Design

The past decades have witnessed the increased digitisation and digitalisation of rock engineering processes. Kerr [41] discussed the epistemic problem of perceptual tasks done by different software in the context of sub-surface geological investigation in petroleum engineering. Kerr interviewed engineers and data analysts and concluded that although our eyes can lie, automated data interpretation processes should not replace "*eyeball tests*" and human judgement altogether. Indeed, digitalisation is seldom applied to change or improve the principles behind data collection, data characterisation, and data classification. Suggested guidelines and standards for the collection of rock engineering data have not significantly changed in the past 30–40 years.

We agree with the paradigm that the primary aim of science is different to that of design and engineering [1]. The act of designing implies an active, non-neutral approach to a given subject. Design is not solely driven by questions (cognitive knowledge), but foremost by the objectives that the design itself is supposed to fulfil, entwined with socioeconomic constraints. This intimate relationship between the engineer and the act of designing creates the perfect conditions for cognitive biases to thrive, since the engineer's mind becomes distracted by the practical aspects of the design process, some of which are driven by socioeconomic factors, and therefore he becomes less interested in understanding the scientific rules that underpin the design process. Vincenti [2] expressed the view that

science does not always play a role in providing the solution to an engineering problem. Indeed, rules of thumb and practical solutions—not necessarily driven by science—are often invoked in engineering design practice. When considering the field of rock engineering, we could claim that there is an abundance of qualitative schemes, some of which are elevated to the rank of "*industry standard*" for no reason other than the idiosyncratic stances of individual engineers. This provocative statement is supported by research by Reese [42] and Azoluay et al. [27], and in a way it agrees with the notion expressed by the physicist Max Planck that the success of a theory depends more on the reluctance of the proponent to challenge the orthodoxy defended by luminaries in their field rather than its actual scientific validity. The concept introduced earlier about rock engineering fragility is consistent with Planck's argument that the opportunity for knowledge to evolve in novel directions depends on the ability to penetrate and significantly alter the nucleus of our engineering knowledge. One apt example of rock engineering fragility is the commonly adopted method of hitting intact core samples with a geological hammer to estimate—in a rather qualitative manner—a likely range of rock strength [43]. Not only is there the irony of comparing the fragility resulting from cognitive dissonance to the fragility of rock samples, but we could hardly imagine any scientist estimating the temperature of a certain liquid substance based on the degree of burning they would observe on their skin following direct contact with the substance. It would be easy to attribute the popularity that the R hardness scale enjoys amongst practitioners in rock engineering to its simple definition. In reality, the resistance to deploy existing, less qualitative and reproducible alternatives (e.g., systematic point loading) is a clear manifestation of preferential attachment biases, which are further reinforced by not exposing students (i.e., future engineers) to the difference between scientific and engineering knowledge.

Preferential attachment biases resulting, amongst others, from different styles and schools of rock engineering practice are also responsible for the irreversibility of engineering knowledge when applied in the form of classification systems [10]. Rock mass classification systems are traditionally used in rock engineering to link observable geological and geotechnical qualities to a numbered rating scheme to derive quantitative data for engineering design and to provide a quantitative measure to compare geological conditions at different sites.

To illustrate the irreversibility problem, let us examine a system in which the number of fracture sets and fracture frequency is measured along the Y-axis (vertical axis) and the characteristics of the fractures' surfaces are measured along the X-axis. The measurements could be either ordinal measurements (qualitative characterisation transformed into quantitative values) or interval measurements [44]. We could use a decreasing scale of 10 to 1 on the Y-axis (notation 10Y, 9Y, etc.), and similarly a decreasing scale of 10 to 1 on the X-axis (notation 10X, 9X, etc.). Note that the result of the discussion would not change if reversing the scale (1 to 10). If rock mass quality was indeed a true physical property, that is, the calculated rock mass quality rating was a unique reflection of rock mass behaviour allowing us to compare conditions at different sites, then we would expect the combinations (10X, 9Y) and (9X, 10Y) to yield different results. Matrix A assumes the calculated rock mass quality is equal to the ratio of the parameter Y to the parameter X. Conversely, for Matrix B, the rock mass quality is calculated as the product of the parameters Y and X. It is apparent that Matrix A has very distinct ratings (every cell value on the opposite side of the diagonal is distinct from the others). On the contrary, Matrix B has a clear symmetric pattern, and equivalent ratings are repeated for different combinations of the parameters X and Y. Figure 7 compares Matrix A and Matrix B with the GSI classification system [45]. The GSI table resembles the behaviour of Matrix B, in which the same emerging value can be obtained using different combinations of [Yi, Xj]. Vice versa, given the emerging value, it is not possible to identify the corresponding unique combination (e.g., [Y3, X1] and [Y1, X3]) that created it.
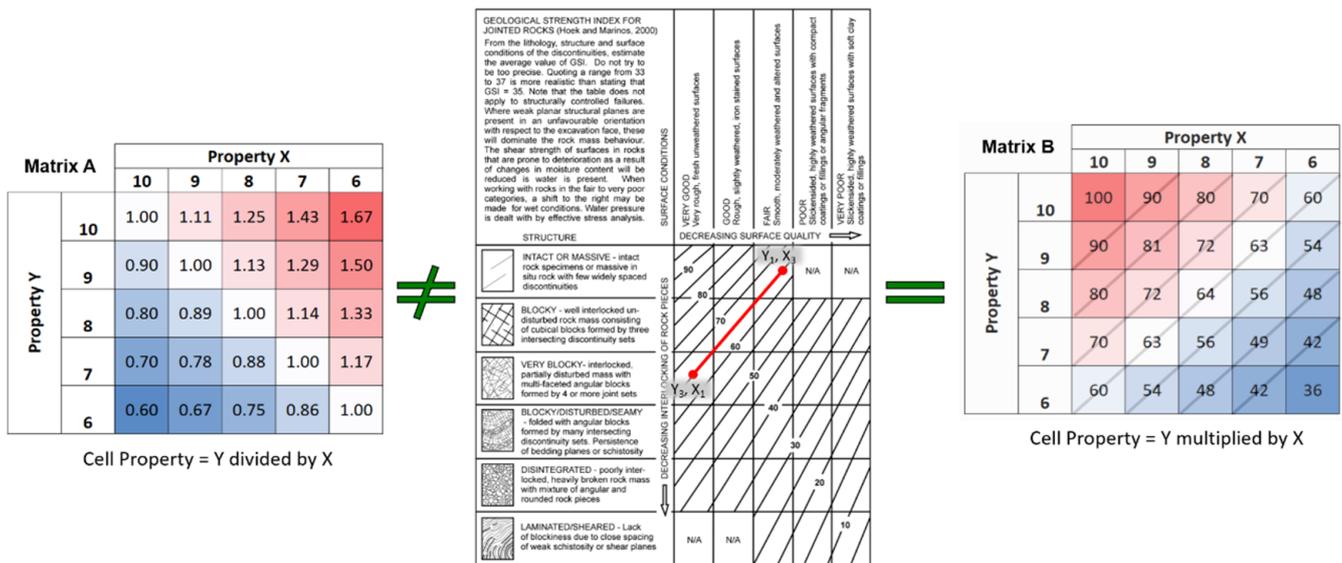
Figure 7. Comparison between Matrix A and Matrix B with the format of the GSI system [45].

The irreversibility problem is a clear example of the danger that we incur when we sterilise (i.e., remove) qualitative geological knowledge to transform it into quantitative engineering information. By superimposing rock types from actual field studies (data from [12,46]), a geological trend becomes apparent (Figure 8), which agrees with the trend of Matrix A, for which the same emerging value cannot be obtained using different combinations of [Yi, Xj].
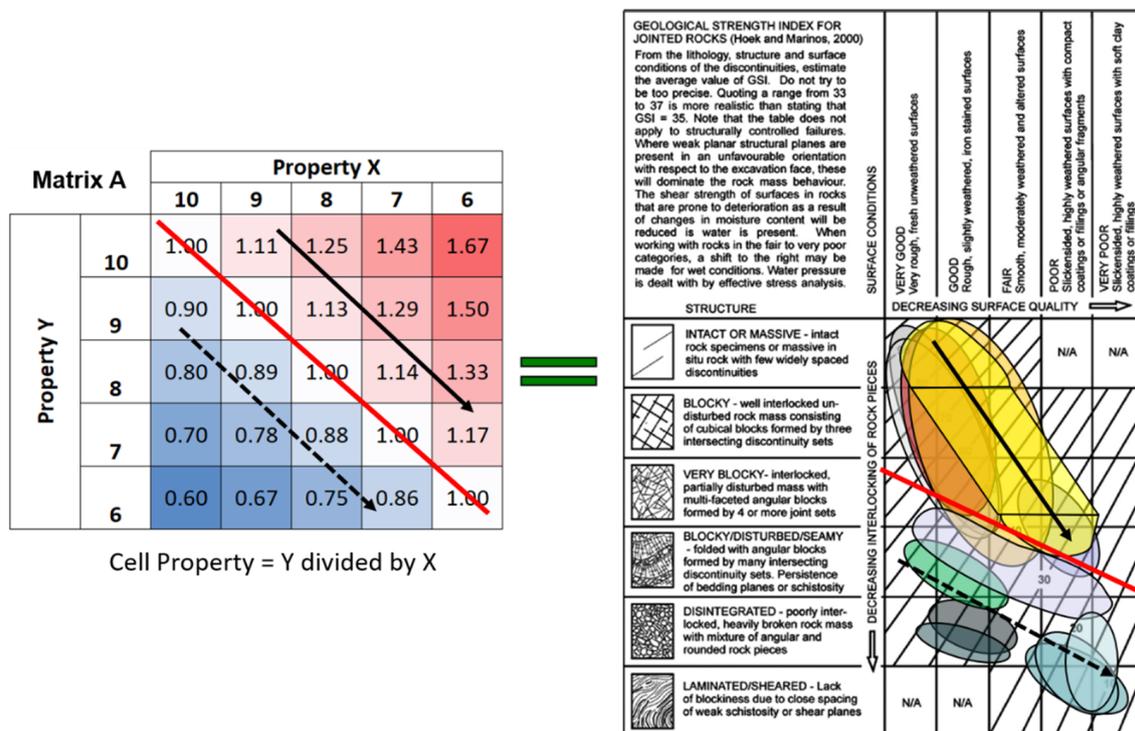

Figure 8. Comparison between Matrix A and the GSI system [45] when new (geological) knowledge is included.

To demonstrate the inherent subjectivity behind the assessment of rock mass quality, and the artificial variability that may result, we asked 16 persons with different levels of experience (ranging from recent graduates to professional engineers with 5+ years of

experience) to estimate the GSI of a rock mass based on the study of a series of photos. We recognise that the observation of photographic evidence is not as convincing as direct field observations, but there are many instances in which engineers may be asked to rely on photographic evidence, or to analyse digitally acquired information (e.g., photogrammetry and laser scanning data). Figure 9 shows the three outcrops used in the survey. Unknown to the persons taking the survey, the three images represent the same outcrop, with two images showing a 5 m wide rock exposure, and the larger image showing a 10 m wide exposure. Furthermore, the two smaller exposures are part of the larger one, and the original images are rotated and slightly decoloured to give the impression of three different rock outcrops. The survey assumed that the jointing conditions did not change across the outcrop and the respondents were instructed to assume good jointing conditions for all three cases (A, B, and C).
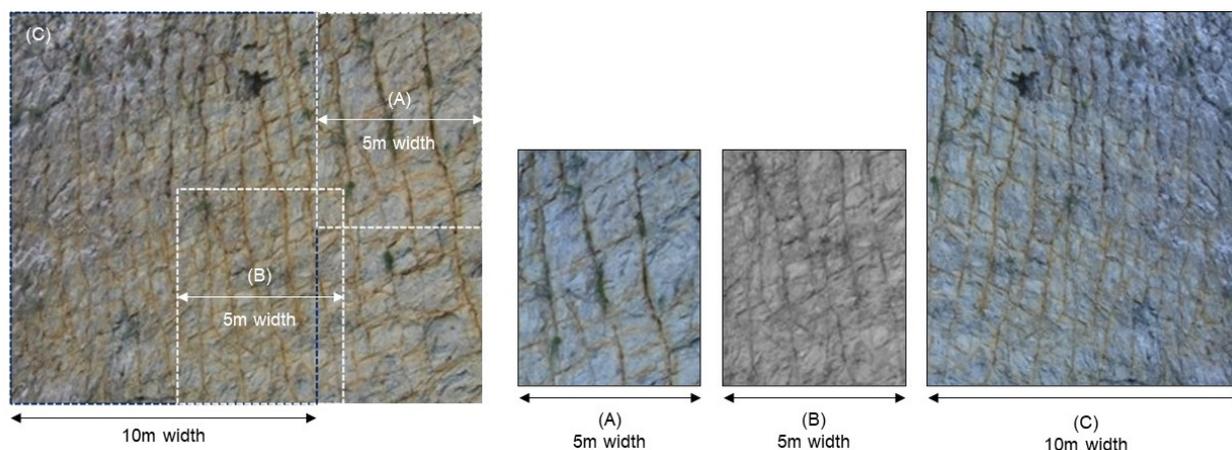

Figure 9. Outcrop used as part of the survey described in the text to analyse the subjectivity of the processes by which different persons would determine GSI.

The results are summarised in Figure 10. The estimated GSI values are 70 ± 10, 62 ± 12, and 60 ± 15 for outcrops A, B, and C, respectively. While the midpoints for outcrops B and C are in close agreement (62 and 60, respectively), the estimated midpoint for outcrop A is significantly larger (70), indicating the governing role of scale effects and spatial variability in the determination of rock mass quality.

While the difference between the maximum and minimum GSI is quite large for all three outcrops (± 10, ± 12, and ± 15), the resulting variability agrees with the original intent of the GSI table, which was to create an essentially qualitative classification system [47]. Engineers tend to perceive variability as a lack of certainty and therefore a lack of knowledge; indeed, many attempts have been made in the literature to accurately quantify GSI [48–52]. Many of those attempts use parameters that are either qualitative (hence subjective) or even non-measurable in the field (e.g., persistence factor). From an epistemological perspective, these attempts could be explained as an attempt to switch from rules of thumb to the rule of science [1], by claiming a more accurate type of knowledge, even though most of the proposed quantification methods continue to rely on parameters that are themselves very subjective or simply not directly measurable (as in the case of persistence factors). Other parameters can be measured objectively; however, there remains much criticism on how much these measurements reflect upon the actual capacity of the rock mass.

The results of the survey confirm examples from engineering practice where it is not uncommon to see disputes and conflicts between experts regarding rock mass conditions [53]. There is somehow a cognitive resistance to accept that rock mass quality does not represent a measurement of well-defined physical rock mass properties, and therefore attempts to quantify it would only provide an illusion of accuracy.
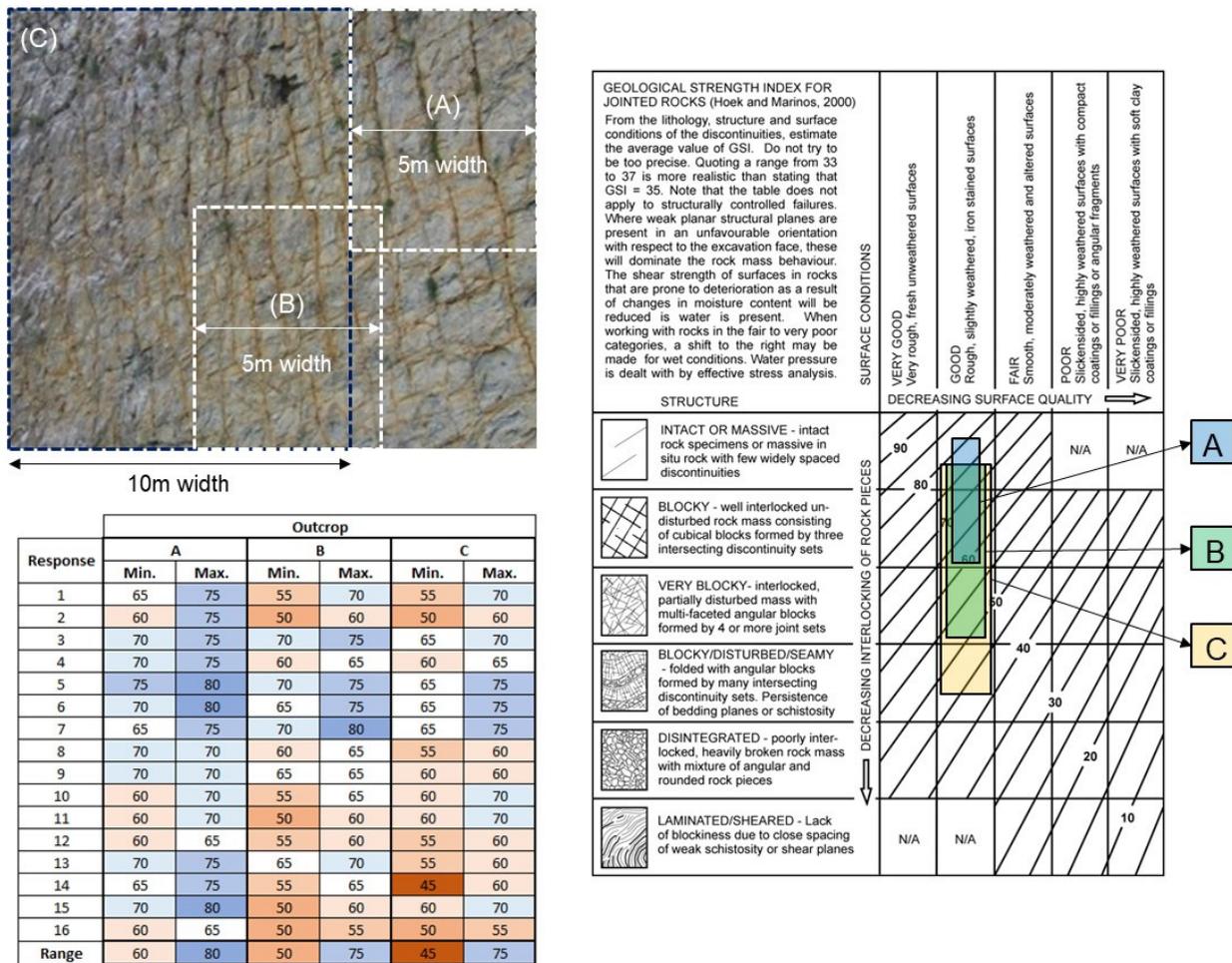
Response	Outcrop					
	A		B		C	
	Min.	Max.	Min.	Max.	Min.	Max.
1	65	75	55	70	55	70
2	60	75	50	60	50	60
3	70	75	70	75	65	70
4	70	75	60	65	60	65
5	75	80	70	75	65	75
6	70	80	65	75	65	75
7	65	75	70	80	65	75
8	70	70	60	65	55	60
9	70	70	65	65	60	60
10	60	70	55	65	60	70
11	60	70	50	60	60	70
12	60	65	55	60	55	60
13	70	75	65	70	55	60
14	65	75	55	65	45	60
15	70	80	50	60	60	70
16	60	65	50	55	50	55
Range	60	80	50	75	45	75

Figure 10. Results of the survey analysing the subjectivity of the processes by which different persons would determine the GSI of the three—only apparently different—rock outcrops.

6. Discussion on the Limitations of Rock Engineering Knowledge

The examples below demonstrate how rock engineering knowledge is subsumed to scientific knowledge. In particular, we discuss the limitation of developing new knowledge based on a validation approach rather than a more scientific replication approach. There is no assurance that new knowledge would be immune from cognitive biases if it were to be validated against existing subjective knowledge.

6.1. The Importance of Language

Language is not neutral, and words are important [54]. Even more important is the perception that those words leave in the mind of an audience, particularly when the audience is not made of engineers and geoscientists. The language we use is in part to blame, as demonstrated by looking at the words that describe two main design methods: Factor of Safety and Probability of Failure. Which of those words would instil more confidence in an individual? Which words could be perceived in more negative terms? Finally, which words could be perceived to suggest a lack of knowledge? There is no doubt that the use of the term "*failure*" in any statement concerning the stability of a given structure would increase an individual's perception of risk. Likewise, the use of the term "*probability* "conjures more the idea of randomness compared to using the term "factor".

Similarly, are the terms "*accuracy*" and "*trueness*" [4] applied and interpreted correctly by engineers when our designs rely on qualitative assessments used as proxy for quantitative measurements, and the expected true value of a given property is either unknown or interpreted in a subjective manner? We could define the uncertainty range of GSI assess-

ments (e.g., 45 to 75 for Outcrop C in Figure 9), but we would not be able to define the error, since we do not know the expected GSI value.

By acknowledging Bruce's [55] assertion that science rather than technology drives progress, the advantage of using terminology and methods that have an underlying scientific tone when presenting and explaining engineering problems becomes apparent. Bruce [55] criticised the spreading popular assumption that everything in technology (and, by extension, in engineering) is somehow rooted in science.

6.2. Why Empirical Correlations Should Not Be Interpreted as Mathematical Solutions

Empirical correlations are common in studies of rock mass properties [12]. At a more fundamental and epistemological level, the classification of a rock mass as being *"good"*, *"fair"*, *"poor"*, etc., is more dependent upon human judgement than on objective material measurements. This raises the methodological question: how can the assessment of a rock mass be verified? The onset of slope failure or tunnel collapse indeed marks a boundary between what would be acceptable design and what would not; however, there remains a long list of cases that cannot be assessed directly without some degree of human subjectivity. The classification of pillar conditions by Roberts et al. [56] is an example of the visual interpretation of stability conditions.

Empirical correlations are often introduced in textbooks and papers as *"Equations"* without proper mention of their origin and their limitations, which may lead to contrasting conclusions. As an example, let us consider two equivalences often referred to in the rock engineering literature:

$$RMR_{76} = GSI \tag{1}$$

$$GSI = 1.5\,J_c + 0.5\,RQD \tag{2}$$

where RMR is the rock mass rating system [57], defined as the summation of the ratings attributed to five different parameters (intact rock strength, RQD, joint spacing, joint conditions, and water conditions) and J_c is the rating assigned to joint conditions in the RMR system. Equivalency (1) was proposed by by Hoek et al. [58], while Equivalency (2) was proposed by by Hoek et al. [48]. RQD is the rock quality designation index [59], defined as the ratio between the sum of all core pieces greater than 10 cm and the core run length (note that the core run length may be interpreted differently by different engineers when logging cores).

Under the assumption that Equivalences (1) and (2) are correct, then mathematically, we could conclude that:

$$RMR_{76} = 1.5\,J_c + 0.5\,RQD \tag{3}$$

and similarly,

$$RMR_{76} - 1.5\,J_c = 0.5\,RQD \tag{4}$$

From a mechanistic perspective, it is not clear how the quality of a given rock mass could be defined by the contribution of five different components (left side of Equivalencies (3) and (4)) and equally by the contribution of either two or even just one of those five components (Figure 11). Equivalences (1) and (2) are a clear example of accidental functions [60], whereby their use is linked to the possibilities of misuse as well as to personal interpretations, which may lead to extending their use outside of the limited scope for which they were defined. In the case of RQD, personal interpretations would correspond to the choice of the run length, threshold length, and direction along which the RQD is calculated. Claiming that, historically, Equivalency (2) has now superseded Equivalency (1) would create more confusion, since it would no longer be possible to compare GSI ratings estimated prior to and post 2013. The fact that engineers rely on empirical equivalences to indirectly estimate rock mass conditions at different sites should raise important concerns, particularly when empirical equivalences are being used to define a database of rock mass quality for machine learning applications.
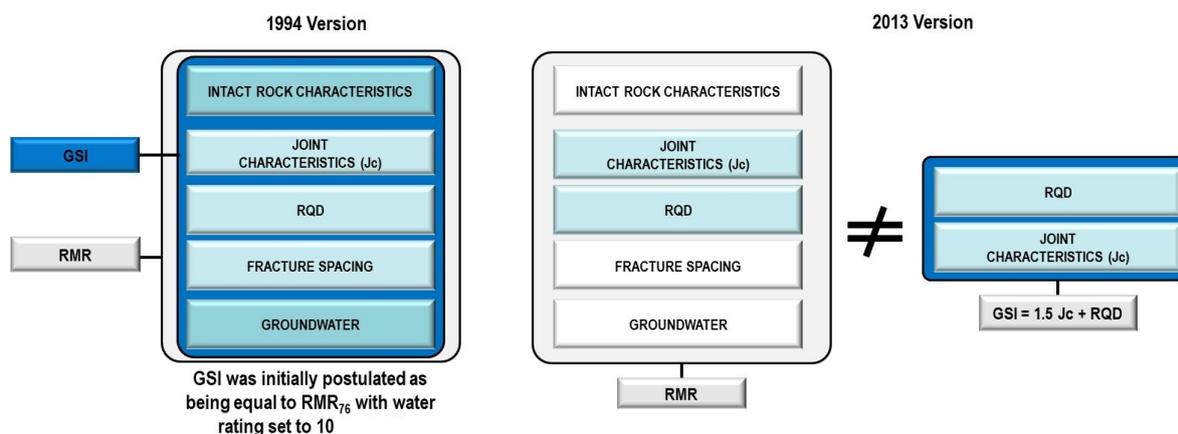
1994 Version
2013 Version

Figure 11. Issue of using empirical correlations between definitions that consider a different number of variables.

6.3. On the Subjectivity and Limitations of Industry Standards in Rock Engineering Practice

It is undoubted that some engineering methods are constrained by practices that have emerged over the years in relation to personal and indeed national preferences. In the specific case of rock engineering, we could think of engineering methods as engineering styles, shaped by education and practice. For instance, the adoption by different engineers of different versions of the Bieniawski RMR system, or referring to different GSI tables [48–52], can only be explained on the basis of personal preferences, and not on the scientific validity of the different versions under consideration. Kant and Kerr [1] mentioned that:

"Science is the same all over the world, at least in its aims. On the other hand, it would be difficult to deny that there are national engineering practices".

The term "industry standard" refers to criteria generally accepted by industry. However, the definition does not necessarily imply that those criteria are the best technical solutions, nor it does imply those criteria are correct [12]. By referring to, for example, a core logging standard, one may assume that there exists one unique core logging standard in the industry. However, the industry has the habit of relying on different core logging manuals that are proprietary to specific companies and not open to external review; at best, those manuals would meet the definition of internal standards.

The purpose of industry standards (and guidelines) is to act in ways that ensure regular and predictable engineering decisions can be made. However, the same regularity and predictability may become the natural enemy of change, since engineers—like most humans—tend to perceive change as a loss [61]. Echoing Constant [61], it is important not to let industry standards become an obstacle between normal and radical knowledge. The former encompasses what we do routinely as engineers; the latter, on the other hand, represents what we must do to innovate. Paraphrasing the words of Smith [62], we need to consider that in the discipline of rock engineering, most practitioners and academics continue seeking answers in the same research areas that yielded answers before, ignoring that research yields a diminishing return if we do not search for new directions. We conclude that industry standards should not be immune to revisions and well-informed improvements to ensure that they are the best available solution, as well as reflecting technical advances made over the years, particularly when it comes to data collection [12].

6.4. Replicability: The Schrödinger's Cat Experiment and Rock Engineering Knowledge

To illustrate the contemplative power of engineering philosophy, we propose a thought experiment analogous to Schrödinger's cat. Physicist Erwin Schrödinger devised an experiment in 1935, in which a hypothetical cat may be considered concurrently both alive and dead as a result of its destiny depending on an event that may or may not occur. In our version of the experiment, two crews are dispatched to drill new boreholes in the exact locations used by Deere et al. [63] in their studies culminating with the introduction of

RQD. Both crews have the latest drilling technologies and procedures at their disposal. One crew has been trained on the use of RQD, while the second crew has no prior knowledge of RQD (i.e., they completely ignore the existence of RQD, and they have never been trained by other engineers familiar with RQD). During the site investigation, the two crews are not allowed to communicate their results to each other. The objective of the experiment is to confirm whether, 60 years later, it is possible to reproduce the work by Deere et al. [63], therefore objectively validating the assumptions behind the definition of RQD. We could reasonably assume that the conclusions reached by the crew trained on using RQD would be more likely to be influenced by their prior experience with the system. At the same time, there is no certainty that the crew who was never educated on the definition of RQD would derive the same conclusions and adopt the same assumptions used by Deere et al. [63] to justify its definitions (e.g., the use of the rather subjective 10 cm threshold [12]). Ultimately, replication would be key to claiming the scientific merit of RQD as a classification tool. As a result, until we find a way to perform the proposed experiment, we can therefore think of the RQD method as being equally correct and not correct.

The problem of rock bridges (see Figure 1) offers additional evidence with respect to the adoption of non-scientifically validated engineering knowledge. As discussed by Elmo et al. [10], rock bridges follow the physical principle of complementarity—that is, to directly measure, for example, the extent (intensity) of rock bridges that exist in a rock mass excludes the possibility of measuring their location a priori. The former can only be measured upon observing visible failed surfaces [64], in which case the latter cannot be resolved, since to reconstruct the location of the rock bridges prior to failure would imply a knowledge of the failure mechanisms, which is itself based upon a knowledge of the extent and location of rock bridges. This problem is generally ignored by the industry, and engineers still insist on using the severely limited concept of rock bridge percentage and continuity factor [65].

The two examples above demonstrate that invoking the continuous use of a given practical method as evidence of its validity does not constitute scientific validation; neither does comparing new results to those obtained with the same method. We need to accept the fact that in rock engineering practice, the term "validation" does not always carry a scientific meaning. The risk is that a new system may be adopted based solely on a rather subjective validation process.

7. Conclusions

During the past decades, the rock engineering community has been witnessing an increasing trend of digitisation and digitalisation of engineering processes. As machines are gradually replacing humans in various technical tasks (e.g., data collection, analysis, and design), the authors argue that it is becoming more crucial to apply critical thinking and to question the foundations of rock engineering as an empirical science. The challenge faced by engineers is not so much the introduction of new systems, but rather the need to adopt a self-reflective approach to understand how engineering knowledge develops and expands. Empirical knowledge is shaped by cognitive biases, which, over the years, have created a sort of dogmatic path along which rock engineering knowledge has expanded. Engineering judgement alone is not sufficient to reset the anisotropic expansion of engineering knowledge, since engineering judgement is affected by the very own experience that created it, and therefore an individual's empirical knowledge may be self-guided solely by information that supports their view. We have proposed a new conceptualisation of engineering knowledge, which combines experience (empirical knowledge) and a priori knowledge (intuitions and knowledge that is not linked to experience).

Unlike engineering disciplines, philosophy and other social sciences have been the centre of controversy for decades. Arguments against methodological flaws of the social sciences have not gone overlooked by researchers, and different solutions have been proposed and implemented. The authors believe that it would be highly instructive to examine whether some of these solutions can be applied to rock engineering. Particularly,

the field of metascience seeks to improve scientific practice by researching research itself, and examining possible reforms. For instance, preregistration is a novel method used in some research publication journals, where the hypotheses, methods, and/or analyses of the study are registered prior to conducting the actual research. The registered report undergoes a peer review process, and if approved, the publication of the research is assured. Hence, the researchers are less inclined to present their results in a misleading manner to display significance and improve their chances of publication.

Another possible solution that has been advocated is encouraging researchers to conduct replication research. Most often, researchers are keen on publishing their own original ideas and work, rather than attempting to reproduce studies conducted by others. However, replication is a crucial part of better validating scientific hypothesis. Replication attempts can be viewed as a more rigorous form of review compared to the traditional peer review processes, where the reviewers regularly do not test the conclusions of the reviewed manuscript. A prerequisite for allowing replication is that the original researchers provide the full information to allow others to replicate their work. A comprehensive study by Baker [66] found that this requirement is far from being satisfied in the natural sciences. In addition to merely publishing the relevant information for the purpose of replication studies, it has been argued that it is essential that data should be shared on online platforms. While some researchers may fear that by implementing such reforms, their work may be falsified, it is important to remind one of the tenets of the philosophy of science, attributed to Karl Popper: that a theory in empirical science can never be proven, only falsified. However, as this principle stands in contrast to human bias, it is necessary to incentivise researchers to conduct themselves in a manner that is beneficial for the greater good of society, rather than being fixated on their personal scientific career.

In addition, it is the authors' opinion that it is vital that these philosophical questions should be addressed as part of the basic academic training of engineers. We need to recognise the difficulty of combining practical in-person experience with online training [67]. Similarly, to conform with international requirements, some university programmes in geotechnical engineering have had to decrease the extent of their theoretical courses [68]. Decreasing hands-on experience and reducing theoretical knowledge would have a significant impact in terms of developing good engineering judgement, with a cascade effect on the overall expansion of an individual's engineering knowledge and the strength of the links between the knowledge sub-arrays shown earlier in Figure 5. There is now significant emphasis in rock engineering academic curricula and technical publications on computer simulations and coding applications (machine learning). However, experiential disciplines such as rock engineering require the critical consideration of both inputs and outputs. There is, therefore, a case for incorporating philosophy in rock engineering practice and education. Ultimately, rock engineering teaching and research should always be preceded by the questions of why, whether, and how.

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