Chapter 11
Components of Personal Knowledge: Characterising the Learner's Conceptual Resources

> It was the HC [Handsome Cognitivist]'s view that almost nothing reduces to almost anything else. To say that the world is so full of a number of things was, he thought, putting it mildly; for the HC, every day was like Christmas in Dickens, ontologically speaking. In fact, far from wishing to throw old things out, he was mainly interested in turning new things up. "Only collect", the HC was often heard to say. (Fodor, 1985, p. 1)

This book is about how we should go about modelling learners and learning in science education, and earlier in the book (Chap. 3) it was suggested that a wide range of entities have been posited as components of human minds – and so potentially components of our models of learning. As Fodor mischievously suggests, there is a sense in which the cognitive perspective invites the inclusion of a wide range of types of 'things' in minds. These entities include, inter alia, concepts, conceptions, schemata, mental models, etc. As I have previously observed, the challenge for the research programme is 'to develop models which are capable of explaining all the existing empirical content of the research area (which seems to require a multilevel, diversely populated cognitive system) but which are still able to offer useful falsifiable predictions to allow empirical testing' (Taber, 2009b, p. 318).

Who Ordered That? An Analogy with Particle Physics

Indeed the situation seems somewhat analogous to the situation in physics as the twentieth century proceeded, and newly discovered subatomic particles were regularly added to the physicists' 'particle zoo'. The simple model of protons, electrons and neutrons became supplemented by neutrinos, muons, quarks, etc. that physicists sought to 'tame' by finding a subsuming pattern reflecting a simpler underlying order:

> The muon … was a particle beyond the standard model of physics at the time and …The central question "Who ordered that" was raised by I. I. Rabi when in 1947 the nature of

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> the muon as a lepton became known – a particle which differs in all its behavior from the electron only by its mass. Up to now, this basic question why there is a second (and third) generation of particles is a strong driving force behind all modern (particle) physics. (Jungmann, 2001, p. 463)

A fundamental commitment to expecting nature to be at some level ordered and simple (see Chap. 15 for a consideration of scientific commitments and worldviews) directed scientists to develop testable models of what that assumed order might be. Whilst this programme is still active, it is widely thought that considerable progress has been made through following (what Lakatos, 1970 might have described as) the positive heuristic developed from the hard-core assumption that the messy diversity of the particle zoo reflected a simpler underlying order.

Indeed it is possible to see modern physics as one source for development of a form of realism, critical realism (Bhaskar, 1975/2008), that considered the experienced world to be real, but having an underlying nature that is only experienced indirectly through intermediate levels, and where science should be interested in the underlying level with its potentials and tendencies which are not always actualised in experience. Patomäki and Wight (2000) refer to the analogy of finding out about a nuclear arsenal, in that although the arsenal might (one would certainly hope) remain in its inert state, it is not fully understood unless the changes brought about by its potential use are considered. Critical realism suggests that approaches to science that ignore the nature of this underlying level of potentials tend to conflate two distinct levels – what is actually experienced and the underlying level of tendencies that are sometimes but not always expressed – and misjudge the nature of reality.

Finding Order in the Mental Zoo: Classifying the Cognitivist's Collection

The purpose of introducing analogy is to offer potentially fruitful comparisons. The mental zoo of concepts, and schemata, and mental models, and intuitive theories and the like, represents a level of description that is useful for many purposes. However, throughout the book I have argued that many of these notions are problematic when we use them in research in science education, because they have not been carefully operationalised for use within a research programme. Therefore, it is often possible to find research reports in the peer-reviewed literature which use the same terms in apparently inconsistent ways (Taber, 2009b).

This is perhaps to be expected given the indirect and sometimes uncertain nature of much of our understanding of human cognition, as suggested by the analysis earlier in the book. However, this also means that any attempt to set out a clear account of the distinctions and similarities between these terms is unlikely to be consistent with all uses in the research literature. My approach here will be to seek to identify the major distinctions that underpin the range of terms that have been employed, and to suggest a model for how terms might best be used in consideration of those distinctions.

I do not intend here, then, to review all shades of meaning that have been given to these different terms by various authors within science education and beyond; but rather to suggest an approach to using terms which reflects much common usage, yet gives the terms different intellectual work to do in relation to what seem important distinctions we should make.

Ultimately, however, we always face the problems outlined earlier: the tendency to talk about cognition in the taken-for-granted lifeworld mental register and the difficulty of deciding how something as abstract as knowledge can best be described at the cognitive system level (most useful for describing research into learning that can inform science education) when the underlying level of structure actually occurs at the physiological level (i.e. networks of connected neurons).

Key Distinctions

The first distinction to emphasise is one that has already been established in the book, which is between knowledge *represented in* the cognitive system, with our *experiences of* the output of cognitive processing. This is always going to be a difficult distinction in practice because of two factors explored earlier:

- The processes of thinking may themselves become represented in the underlying physical structures through which knowledge is represented, that is, our ideas both reflect and modify our knowledge.
- Conscious awareness does not have direct access to all our knowledge and at any one time is only aware of a small part of our 'explicit' knowledge.

Terms Excluded as Not Representing Knowledge Elements

So from this way of thinking, an *idea* is best understood as the output of processing drawing upon knowledge represented in the cognitive system, but not in itself a knowledge component. 'Having' an idea, perhaps as a novel juxtaposition of different existing knowledge elements, and evaluating it as fruitful, is likely to lead to that idea itself becoming represented in cognitive structure (i.e. at the physical level certain links are established or strengthened in the association cortex) in the sense that it becomes more likely that the combination of elements giving rise to that idea will be activated in the future (i.e. activation of one of what were discrete elements will more readily activate the whole new 'association'). At the mental level of description, we would say that we are likely to later recall the idea in certain contexts. However, the representation is not the idea, but a modification to cognitive structure that makes it more likely the same, or a very similar, idea will be generated again.

Similarly, the term *gestalt* is probably best not considered a knowledge element, but as the outcome of processing through such elements. The term gestalt was originally largely associated with perception (Koffka, 1967), relating to consideration of how in perception we are usually aware of whole patterns, not discrete sensations (see Chap. 4). That is, processing of sensory information involves pattern-detecting apparatus that is able to discriminate figures from their background and to associate patches of colour and edges, for example, as being discrete objects in our environment. This apparatus therefore represents a form of knowledge in the system. However, the term 'gestalt' referred to the output of that processing, and it would seem useful to use terminology that refers to the knowledge elements, the processing and the conscious experience of its output, separately.

So from this perspective the terms 'ideas' and 'gestalt' would certainly not be excluded from scientific discourse within the research programme into learning in science but would not be used to describe knowledge elements represented in the cognitive system. Rather, they would 'do intellectual work' in describing the learner's subjective experience of cognition.

Concepts as Knowledge

A key term used in relation to a learner's knowledge is that of *concepts*, and indeed key issues in science education relate to a learner's *conceptual development* (discussed in Chap. 14), and how teaching can influence *conceptual change* (considered in Chap. 15). Moreover, research into student knowledge and understanding is sometimes understood as investigating a learner's *conceptual structure*.

A problematic aspect to our understanding of concepts has been revealed by the work undertaken in psychology and cognitive science about the nature of conceptual knowledge. Much research in psychology has concerned the ability of learners to acquire artificial concepts (along the lines of being given (i) examples of different shapes in different colours and (ii) feedback on which are, and which are not, examples of plaks to test questions such as can the learner acquire the concept *plak = a blue or green shape with no curved surfaces and less than five sides*). Such artificial concepts have strict rules for membership (Seger & Miller, 2010). Yet many concepts used in everyday life are not defined through a small set of clear rules. Concepts, or categories (Ashby & Maddox, 2005), may be formed through perceptual similarity and linguistic cues in the talk of others (Gelman, 2009).

Children learn the concepts of tree, car, chair, etc., and neither are they taught these concepts through sets of membership rules nor do they apply these concepts in such a way (concept learning will be discussed in more detail in next part). We recognise an object as a tree without going through a mental checklist of attributes.

Most such concepts are 'fuzzy' in that they have somewhat blurred boundaries, and it has been shown that for some concepts we distinguish between examples which seem more typical and those which are seen as somehow less good examples of the concept. For example, perhaps a child, or an adult for that matter, knows that eels and sea horses are both types of fish, but is very unlikely to suggest them when asked for a few examples of fish, rather than perhaps salmon, cod, trout or goldfish.

However, in science classes, students can also learn about concepts that are tightly defined and do have strict membership rules. For example, the alkali metals do not comprise a fuzzy set, and there are clear criteria for whether or not something should be considered an alkali metal.

Two Types of Conceptual Knowledge

This would suggest that our conceptual knowledge is not all of the same form. Some of it is of the kind of lifeworld everyday concepts, reflecting 'the natural attitude' (Schutz & Luckmann, 1973), that was highlighted earlier in the book as being typical of how we commonly talk about thinking, learning, memory, etc. However, we also learn what Vygotsky called academic (Vygotsky, 1934/1994) or scientific concepts, which are often definition and rule based. That is the kind of thing I referred to earlier as being understood in 'technical' terms rather than everyday terms (e.g. see Table 3.1).

The term 'concept' therefore seems to have a broad referent and to relate to more than one kind of knowledge element. In particular it refers to both knowledge that is accessible to introspection and often readily represented in propositional form, and that tacit knowledge that is not directly accessible, but which operates at preconscious levels in the cognitive system.

Implicit and Explicit Knowledge Elements

This seems to be an important distinction to make, as clearly the way we use our knowledge is quite different when we are able to consciously act upon it, than when we have to rely on tacit knowledge that we only become aware of, if at all, after the event. In many aspects of our lives, such tacit knowledge is extremely valuable as it leads to quick processing and decision-making without committing of executive resources that can therefore be invested elsewhere.

However, in the sphere of academic learning, tacit knowledge can be deficient as it is inflexible and not open to justification and critique. In crossing a busy road, we need to make the right decision quickly, but in a formal academic assessment we need to be able to explain and justify *why* we suggest the answers we do. It seems useful therefore if in our research into student learning, we distinguish between these two basic types of knowledge element contributing to the learner's conceptual understanding of science topics.

The Notion of Intuitive Theories

One of the terms that have been used to describe aspects of science learners' knowledge is *intuitive theories*. This term actually has at least two meanings in the research literature. So, for example, in the context of electron diffraction in crystals, it has been claimed in a natural science context that 'there is need for a simple intuitive theory that is valid for larger crystal thicknesses' (Van Dyck & Op de Beeck, 1996, p. 99). In this context the term seems to mean a formal theory, but one that *fits with* the intuitions about the process developed by scientists working in that field.

However, in the context of science education, the term intuitive theory has been used in a somewhat different way (Pope & Denicolo, 1986). So, for example, Kaiser, McCloskey and Proffitt (1986, p. 67) refer to how, through frequent experience of moving objects, 'people develop from these encounters a systematic intuitive theory of motion'. A key feature of this 'intuitive theory' is that it is inconsistent with the scientific models. The scientific models are based around the Newtonian idea of inertia, where force brings about a change in the state of motion. However, the common intuitive theory is based around an impetus notion, something that is imparted by a force, but which somehow gets 'used up', causing motion to naturally diminish (Gilbert & Zylbersztajn, 1985). The use of the term 'systematic' by Kaiser and colleagues is quite important, as the adoption of the label 'theory' implies more than just a hunch or intuition. As McCloskey explained in another publication,

> Recent studies on the nature, development and application of knowledge about motion indicate that many people have striking misconceptions about the motion of objects in apparently simple circumstances. The misconceptions appear to be grounded in a systematic, intuitive theory of motion that is inconsistent with fundamental principles of Newtonian mechanics. Curiously, the intuitive theory resembles a theory of mechanics that was widely held by philosophers in the three centuries before Newton. (McCloskey, 1983, p. 114)

Carey and Spelke (1996), in discussing theories, whether labelled scientific or intuitive, suggest 'theories are central knowledge systems widely available to guide reasoning and action', as well as being 'open to revision' (p. 519). In this regard such 'theories' do not seem to be implicit knowledge structures, and indeed Carey and Spelke suggests that intuitive theories are distinct from what they term 'core knowledge structures' on these and other characteristics. For these commentators such core knowledge structures are 'theory-like in some, but not all, important ways' (p. 515). Carey and Spelke suggest that such core systems are largely genetically endowed and develop naturally in the child and should be considered quite different from intuitive theories:

> core systems are conceptual and provide a foundation for the growth of knowledge. Unlike later developing theories, however, core systems are largely innate, encapsulated, and unchanging, arising from phylogenetically old systems built upon the output of innate perceptual analyzers. These differences make it unlikely that the development of core systems engage the same processes as the development of intuitive theories in childhood or the development of scientific theories in the history of science. (Carey & Spelke, 1996, p. 520)

The question of whether or not children's informal ideas should be considered to be based on theory-like knowledge has been debated in the literature, and I have previously suggested that the research evidence based on students at different ages asked about various science topics suggests that the real issue is *the extent* to which such knowledge can be considered theory-like in particular cases (Taber, 2009b). The literature suggests this varies a great deal. This would seem to be what we should expect if our knowledge is partly based on implicit knowledge structures and partly on explicit representation of propositional knowledge that is available to conscious inspection and development.

The term 'intuitive theories' is itself potentially unhelpful, as it would seem knowledge must be *either* intuitive *or* theoretical but cannot really be simultaneously both. Yet if intuitive theories are understood as theory-like knowledge components that are *developed from* intuitive knowledge, then this looks less of an oxymoron. Nevertheless, it is not clear that 'intuitive theories' earn the status of being a basic category of knowledge component.

Personal Constructs

The theory of personal constructs was developed by George Kelly and was very influential in early constructivist research in science education (Pope & Gilbert, 1983). Kelly devised his system for use in therapy and suggested that it tended 'to have its focus of convenience in the area of human readjustment to stress' (Kelly, 1963, p. 12). However, Kelly considered that people modelled and understood the world through a system 'composed of a finite number of dichotomous constructs' (p. 59). That is, Kelly considered that people understood the world by making discriminations based on a set of bipolar constructs that were organised into some form of system.

Kelly thought that although we could often give labels to our constructs after the event, the process of making discriminations was not conscious or based on verbalisation. His clinical method of exploring clients' construct systems involved asking them to make discriminations by suggesting the odd one out when shown triads of 'elements', so there was no requirement to initially label the basis of the discrimination, or to rationalise why they selected a particular elements as being the one which did not fit. This was an idiographic method (see Chap. 6): there was no assumption of a right response, but rather the aim was to work through enough examples to be able to infer the constructs that were operating. Personal constructs were then envisaged as largely implicit knowledge elements that allow us to parse the world without the need for conscious deliberation or verbal labels and definitions.

Kelly believed the system of personal constructs encompassed knowledge that was primarily perceptual, as well as that which would normally be thought of as conceptual. That is, he saw continuity in the cognitive system that operated with knowledge elements at different levels: so that for Kelly the same *type of operations* would be involved in making discriminations of tone as making discriminations in the quality of doctoral theses. From this perspective, verbal description and rationalisation of judgements would seem to be considered almost as like a veneer placed on the outputs of the implicit but potentially quite sophisticated system of personal constructs.

The perspective offered earlier in this book considered a great deal of cognitive processing to take place 'out of mind', and much of that to be largely automatic, but did leave room for the executive to direct some preconscious processing (cf. Fig. 7.5). These two descriptions could be seen as consistent, depending on precisely how one interprets Kelly's distinction between the construct system and the verbal reporting that occurs after discriminations are made. Kelly would certainly have accepted that a client could censor a particular discrimination made from being reported to the therapist but saw the role of the constructs as central to how the world was understood.

Kelly included in his system discriminations that were not obviously bipolar, giving the example of discriminating red from 'the non-redness of white, yellow, brown or black. Our language has no special word for this non-redness, but we have little difficulty in knowing what the contrast to red hair actually is' (p. 63). This suggests that personal constructs may be linked to knowledge elements that can identify particular features: that is, small processing units that recognise red (or not). Whilst Kelly's notion of personal constructs is not universally adopted, it would seem to reflect important aspects of the way knowledge is represented in the human cognitive system.

Phenomenological Primitives

A slightly different type of intuitive knowledge element that has been mooted as a key part of the cognitive system is the phenomenological primitive, or p-prim. This idea has been developed in particular by Andrea diSessa, who published an extended (if intended to be somewhat provisional) account of intuitive physics based on this notion in the journal *Cognition and Instruction* (diSessa, 1993). The term phenomenological primitive is a fairly accurate label for these entities, as they relate to our implicit interpretations of the world based on abstractions from direct experience of the world. From extensive interviews with physics students, diSessa set out the case for a wide range of these primitives. Each p-prim could be understood as abstracted from common experience, and then used as part of the interpretive apparatus for making sense of the world at a preconscious level, which then feeds into our conscious thinking. In other words, although diSessa's data was largely based on elicitation of college students' explanations about physics problems, that is, an advanced academic context, he considered that much of their thinking was built upon very simple primitive discriminations that matched what was perceived with common general patterns that had been abstracted from prior experience.

So, for example, young children may come to realise that a lot of phenomena fit a pattern that might be labelled 'dying away', that is the magnitude of some qualities seem to diminish with time. The significance is that the abstraction becomes part of the intuitive model of how the world is, and the basis of implicit explanations. That is, if a novel phenomenon is understood to fit the 'dying away' pattern, then it does not pose a 'problem' for the cognitive system, as it fits within the existing model of how the world is. Dying away is treated as a natural effect, that is, one that does not need more explanation. That of course represents the 'natural attitude' (Schutz & Luckmann, 1973), not the scientific attitude, and in learning science students have to learn to question the natural mechanisms of the world that lead to these patterns. Yet many phenomena make sense to us intuitively since they are recognised as matching patterns that we have come to accept as common to experience.

A key problem with p-prims from the perspective of learning science is that they seem to only work to discriminate what fits prior patterns from novel phenomena, and so contrasting phenomena can equally fit (different) p-prims, making them of limited explanatory value. So if a person has a p-prim that we might label 'dying away' and another we might label 'building up', then both these patterns would intuitively seem natural and needing no further explanation. Simply *recognising* that something diminishing is dying away, or that something increasing is building up, would 'satisfy' this level of the cognitive system as what was being observed made sense in terms of existing expectations of how the world is. Students asked to explain phenomena will often respond that certain things are just 'natural', just the way things are, reflecting how in everyday life we do not see many familiar events as inviting explanation as we have become comfortable in accepting them as how the world is (Watts & Taber, 1996).

Research exploring school learners' thinking about chemical phenomena identified a set of potential intuitive knowledge elements that partially fitted with diSessa's scheme (Taber & García Franco, 2010) but also having some distinct features – suggesting research across different domains may help refine an account of commonly acquired p-prims. P-prims seem very similar to what Vygotsky labelled as a 'potential' concept which 'is an embodiment of a rule that situations having some features in common will produce similar impressions' and 'result from a series of isolating abstractions of such a primitive nature that they are present in some degree not only in very young children but even in animals' (Vygotsky, 1934/1986, p. 137).

Intuitive Rules

Stavy and Tirosh have suggested that one source of many of the reported student 'alternative conceptions, preconceptions, and misconceptions in science and mathematics' may be the application by the student of what they term 'intuitive rules' (Stavy & Tirosh, 2000, p. vii), which they consider to be 'expressions of the natural tendency of our cognitive systems to extrapolate' (p. 87).

Stavy and Tirosh (2000) report three examples of intuitive rules that they identify as being found in students' reasoning across a wide range of contexts: 'more A – more B', 'same A – same B' and 'Everything can be divided'. These types of general intuitive rules would seem to be the kind of primitive cognitive element that diSessa has described as p-prims and will here be assumed to be subsumed into the same class of knowledge element in the cognitive system.

P-Prims and Gestalts

Sometimes the term gestalt is used in a way quite similar to diSessa's notion of p-prims. So the 'experiential gestalt of causation' proposed by Lakoff and Johnson (1980a), and applied in the context of science learning by Andersson (1986), set out how causality in the world can often be understood in terms of a common pattern or 'a "prototypical" or "paradigmatic" case of direct causation' (Lakoff & Johnson, p. 479) which involves an 'agent' acting on a 'patient' to bring about some change in it. This would seem to be the kind of pattern recognition assigned to p-prims, and in keeping with the use of 'gestalt' elsewhere, it may make sense to consider the 'gestalt' to be *the perceived pattern*, due to the operation of an underling implicit knowledge element that is part of cognitive structure (i.e. the p-prim). That is, the gestalt is experienced due to the activation of the p-prim.

Watts and Taber (1996) used the idea of an 'explanatory gestalt of essence' to describe how it is that often, when asked for explanations in interviews, students would soon reach a point where they replied that something was 'just natural' – that is the way things were. Watts and Taber found that students varied in the extent to which they would offer layers of explanation before reaching this point, but sometimes students were clearly satisfied with recognising something as being naturally the way things were and so not needing further explanation before they exhausted the depth of explanation expected in the school or college science curriculum.

Ultimately science aims to find out the ways things naturally are, and so there is nothing wrong in principle in reaching such a point in a succession of explanations. However, science looks for underlying patterns that have explanatory value across a wide range of phenomena, whereas the natural attitude is to simply accept as natural anything that fits one of the available familiar patterns (i.e. p-prims). The explanatory gestalt of essence, the recognition that that is just the way things are, would again seem to be a way of describing the learners' subjective experience, which *draws upon* implicit knowledge elements, such as p-prims. So these mooted gestalts would seem to be related to, but ontologically different to, p-prims.

Explicit Knowledge

Whereas implicit knowledge elements are considered to do their work out of the purview and control of consciousness, explicit knowledge is directly accessible and open to deliberation. Earlier in the book, when considering memory, it was suggested that there is declarative memory, and non-declarative memory that includes both procedural memory and 'implicit' learning that takes place without conscious awareness. Procedural memory is associated with motor function and allows us to build up routines of motor actions to carry out complex tasks such as tying shoelaces or focusing a microscope. Some of this is at the level where it is open to conscious awareness and control. These elements are probably not the smallest 'grain size' and draw upon more primary, encapsulated knowledge elements, which we consciously build up into routines.

So there is parallel within this branch of cognition with declarative knowledge discussed below, in that it has both implicit and explicit components. However, the focus here is on conceptual learning, so the nature of procedural knowledge will not be developed in any detail here.

Declarative memory refers to representation of factual information that is accessible to consciousness and includes both episodic and more generalised semantic memory. By definition declarative memory refers to representations of past experience that can be reported verbally as they are consciously accessible, although that does not mean that these declarative memories are themselves representations of verbal information. So one's memory of a significant past event may well include imagery, for example. However, as one is able to access the memory leading to a conscious experience, that experience can be reported verbally.

Imagistic memory has been given most attention in the science education literature, but of course other sensory modes may provide experiences of memories that we can verbalise. We may hear the voices of others not present (e.g. in sleep), and Proust used memory evoked by a smell as a key device in for his novel *À la recherche du temps perdu* (translated as *In search of lost time* or *Remembrance of things past*). However, the visual mode would seem to be of particular importance in conceptual learning, as suggested by the incidence of eidetic memory in children and the conjectured visuo-spatial scratch pad as a major adjuvant of the cognitive system's executive module, that is, working memory (see Chap. 5).

However, the ability to rote learn passages or prose, or technical definitions, demonstrates that some knowledge representation of verbal material can and does take place. Therefore, it would seem that explicit knowledge elements within cognitive structure that are of interest in learning science can be considered to be of at least two different types. This links to Bruner's (1964, p. 2) notion of three modes of representation:

- Enactive: 'a mode of representing past events through appropriate motor response'.
- Iconic: summarising events 'by the selective organisation of percepts and of images, by the spatial, temporal and qualitative structures of the perceptual field and their transformed images'.
- Symbolic: represents 'things by design features that include remoteness and arbitrariness' (i.e. words are associated with objects and events by convention).

Enactive representation supports what has been called here procedural knowledge; imagistic memory is a form of iconic representation, and much of the knowledge of interest in science education concerns propositional knowledge represented symbolically.

Propositional Knowledge Elements

One type of knowledge represented in the cognitive system is propositional knowledge that allows us to 'know' such things as:

- Atoms are very small.
- Horses are mammals.
- Energy is conserved.
- Potassium is more reactive than calcium.
- Humans have 23 pairs of chromosomes.
- Electromagnetic radiation is a transverse wave.

This type of knowledge element is often a key focus of research given the central role played by language in communication and formal learning.

Conceptions

The term 'conception', and the variants 'misconception', 'alternative conception', has been widely used in science education when describing aspects of students' (inferred, assumed) personal knowledge. The term is widely used in phenomenography, research which looks to describe, analyse and understand experiences (Marton, 1981). In this context different conceptions are 'qualitatively distinct ways' in which what is objectively the same referent is understood (Anderberg, 2000, p. 94).

Gilbert and Watts recommended that the term conception should be used in science education to focus on 'the personalised theorising and hypothesising of individuals' (Gilbert & Watts, 1983, p. 69), as one way to distinguish between personal and public systems of knowledge (as discussed above, see Chap. 10). This distinction is shown in Table 11.1.

As suggested above (see Chap. 10), public knowledge is a problematic notion and indeed is arguably in some ways a fiction, but nonetheless remains a useful fiction as a referent. So following Gilbert and Watts, a learner may be said to have *a conception of* energy, or photosynthesis, or oxidation, which can be evaluated against (someone's, e.g. the researcher's) understanding of *the scientific concept* or of some curriculum model of that *concept* (cf. Fig. 1.3).

Table 11.1 Recommended use of 'concept' versus 'conception' following Gilbert and Watts (1983)

Term	Recommended use – to describe	Notes
Concept	Formal meanings as part of public knowledge systems	'World 3' objects: ideals as represented in public knowledge systems
Conception	Personal understandings	'World 2' objects: understandings as personally experienced in thinking

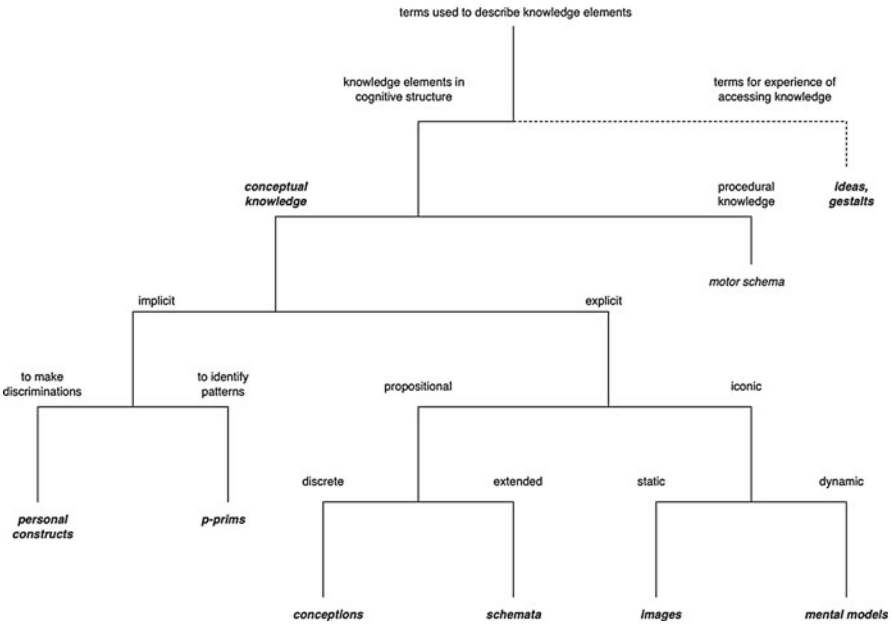

Fig. 11.1 A model typology of the main types of knowledge components represented in cognitive structure

Maintaining a distinction between the formal concept that is part of a public system of knowledge and an individual's personal conceptions might help clarify reports in science education. However, in practice there is widespread use of the term concept to refer to both formal concepts and the versions of those concepts formed by individuals, that is, their conceptions. The literature includes many examples of references to concept formation and acquisition (i.e. the appearance of new conceptions in individuals) and conceptual (rather than concept*ion*al) development, conceptual (rather than concept*ion*al) change and conceptual (rather than concept*ion*al) structure. These topics will be discussed in Chap. 15.

Ezcurdia (1998) suggests that 'concept'/'conception' can refer to the distinction between possession and mastery of a concept. That is, for Ezcurdia, 'one can possess a concept without having an appropriate conception, without mastering it' (p. 188). This approach may be especially helpful for the conceptions that learners have that are considered to be versions of normative concepts. So, as an example, in a secondary science class it could be said that all the students had acquired the concept of a metal, but that their specific conceptions varied considerably, or that a learner acquired a concept of a metal, and that same concept developed as his conception of metal changed (see Chap. 15). In the present chapter, the term *conception* is used to refer to aspects of the learner's personal system of knowledge representation (see Fig. 11.1), following Gilbert and Watts.

Schemata

A term that has not been so widely used in science education research but is commonly used to describe aspects of an individual's knowledge in psychological and cognitive science is schemata. A schema refers to a knowledge *structure* represented in memory: for example, 'the information that is required if a learner is to be able to solve problems [such that] if the required information (knowledge components) and the relationships among these knowledge components is incomplete then the learner will not be able to efficiently and effectively solve problems requiring this knowledge' (Merrill, 2000, p. 245). Schemata, then, are envisaged to be more complex knowledge representations than individual conceptions and indeed are perhaps not best understood as knowledge 'elements' but more, if we draw on an analogy from chemistry, as 'compounds' of knowledge elements.

Problem-solving involves more than just applying routine knowledge as in completing exercises and requires some novelty in task response by the problem-solver (see Chap. 7). So genuine problem-solving requires the learner to coordinate existing knowledge components into a more complex structure, that is, to *construct* a schema. However, the way the term schema is often used, it is also applied to schemata that have previously been compiled and therefore have some permanent 'structural integrity' within cognitive structure: so, in effect, once a schema has been constructed, that construction can be retained if it is then applied sufficiently to develop strong associations between the component elements (see Chap. 5).

So, for example, if a secondary school student is asked to complete a word equation, such as (the example used in Chap. 7)

$$\text{nitric acid} + \text{potassium hydroxide} \longrightarrow \text{—————————} + \text{water}$$

One way that a learner might be able to correctly respond to such an item would be if they had rote learnt sets of word equations, including this one, and so were able to access the correct word equation represented in memory by matching with the information presented and then fill in the gap by comparing the incomplete word equation with the learnt correct one. Certainly much learning of this type goes on, but such learning does not require, or demonstrate, understanding of chemistry and is only effective for specific reactions where the word equations have been (correctly) represented in memory.

More likely, this task will require the learner to coordinate a range of knowledge elements to find a solution, and for many secondary students such a question presents a genuine problem (Taber & Bricheno, 2009). More advanced and successful students might well have developed an effective strategy for answering a question of this type (see Table 11.2), which they can routinely call upon (Taber, 2002a).

The approach shown in Table 11.2 is not the only approach to attempting this task, and if students do not know the general equations, they may rely on the conservation principle (that the same elements must be represented before and after a reaction) to see what was 'missing' on the product side (Taber & Bricheno, 2009): although the coordination of other knowledge would still be needed to ensure a

Table 11.2 Suggested components of a schema to identify an unknown reagent in a word equation

Step in strategy	Note
Identify the type of reaction represented: neutralisation, acid plus alkali	Draws upon knowledge that chemical reactions are commonly classified into particular types, deepening upon the categories of reactants
	Identifies the reactants given as an acid and an alkali (i.e. classifies type/identifies set membership)
	Identifies specific knowledge that one such type involves the reaction between an acid and an alkali
Write out the general reaction: *acid* + *alkali* → *salt* + water	Applies knowledge that each type of reaction can be represented by a general equation, where the *class of substance* stands for particular reactants and products that vary in different specific reactions of the type
	Recalls general form of equation for this class of reaction
Identifies the missing term as a salt	Compares the general equation recalled with the presented example
	Maps
	Nitric acid: the *acid*
	Potassium hydroxide: the *alkali*
	Missing term: the *salt*
	Redefines task as identifying the particular salt
Identifies the salt as potassium nitrate	Recalls/applies knowledge that salts have a two-part name, reflecting the cation and the acid radical
	Identifies the cation as potassium from the alkali
	Identifies the acid radical as nitrate from the nitric acid

correct solution, as that principle by itself underdetermines the answer. For example, potassium nitrite and potassium nitride would be possible alternative answers.

Although schemata are composed by the coordination of other existing knowledge elements, they should be considered as separate components of cognitive structure because they can be retained as long-term associations and so in effect unitary components in their own right. Merill (2000, p. 246) argues that 'solving a problem requires the learner to not only have the appropriate knowledge representation (schema or knowledge structure) but he or she must also have algorithms or heuristics for manipulating these knowledge components in order to solve problems'. He argues that,

> If the learner knows the knowledge components and knowledge structure for a conceptual network, then he or she has a meta mental model for acquiring a conceptual network in a specific area. This meta mental model allows the learner to seek information for slots in the model. It provides a way for the learner to know if they have all the necessary knowledge components to instantiate their mental model (Merrill, 2000, p. 246)

The example of completing a simple word equation in chemistry supports Merill's assertion that such problem-solving, for those learners at a stage where this task can still be considered a problem, does require knowledge of operations – of what kind of knowledge to access and coordinate – as well as knowledge of the base domain (in this case knowledge of reactions types, reagent types, etc.). However, it would seem that this 'how to' knowledge is also propositional (see Table 11.2), whereas it will be suggested below that the term 'mental model' is often reserved for something rather different. Arguably, in an example such as that used here, knowledge of how to carry out the stages of problem-solving are a part of the schema as much as knowledge of the chemical substances and reactions that need to be operated on to solve the problem.

Visual Representations in Cognitive Structure

Although there is often a focus on verbal representation when discussing [sic] students' science knowledge, it is clear that we are also able to recall images that we do not seen to construct ab initio from other kinds of representation on recall. We are also able to *form* images – from verbal descriptions, for example – but some of our memories seen to be accessed as images: the representation in cognitive structures when activated leads us to experience an image.

As suggested earlier (eidetic memory, see Chap. 5), it is considered that visual memory plays an important role in the memory of children but usually diminishes during development. However, some adults seem to retain strong visual 'photographic memories', and we all have some ability to represent visual information in cognitive structure.

Imagery as a Form of Knowledge

Images contain information, and so representing imagery in cognitive structure amounts to a form of knowledge in the system. Earlier in the book it was suggested that it was easier for a person to remember and reconstruct an image such as that showing the resonance between two canonical forms of benzene (e.g. Fig. 5.11) if they understood what the image meant, and we might imagine that in trying to reconstruct such an image some learners might draw upon propositional knowledge: I know the formula is C_6H_6, I know carbon has valency 4, I know it is described as a cyclic compound, etc.

However, it is equally the case that recalled images can support verbal recollections: mental inspection of a recalled image of, for example, the experimental set-up for measuring Young's modulus of a piece of wire, could provide information to support recall of the formula for Young's modulus, or recollection of an image of a beetle might be the source of recalling how many legs beetles have. In general, recall is supported by being able to access and coordinate both representations of images, and propositional knowledge, from memory (Cheng, 2011). Images are static, although they can be mentipulated in the mind. Moving beyond static images, there is the possibility of visual models that can act as mental simulations that can be 'run' in the mind, that is a form of mental model that is dynamic and visualisable.

Mental Models

Whilst there has been relatively limited attention in the science education literature to students' imagistic representations compared with their propositional knowledge, there has been a wide use of the term 'mental models' in the literature. Once again the point needs to be made that often such terminology is used without definition, and it is not *always* clear what researchers' reports referring to mental models (as opposed to say, student conceptions) in science education contexts are meant to refer to.

There is quite a developed literature about mental models, which can inform the use of the term within science education, although even here different authors do not seem to agree on quite how mental models should be understood (Johnson-Laird, 2003b; Merrill, 2000; Norman, 1983): as 'a consensus view about issues such as the format of the mental models and the process involved in using them has not been reached among different research camps' (McClary & Talanquer, 2011, p. 397). So, as reported above, Merrill (p. 244) suggests that 'a mental model consists of two major components: knowledge structures (schemata) and processes for using this knowledge (mental operations)', but commonly mental models are understood to represent knowledge in non-propositional form.

The notion of mental models was popularised by Norman who described how:

> In interacting with the environment, with others, and with the artifacts of technology, people form internal, mental models of themselves and of the things with which they are interacting. These modes provide predictive and explanatory power for understanding the interaction. (Norman, 1983, p. 7)

Norman describes mental models as 'naturally evolving models that must be 'functional', in that people will continue to modify the mental model in order to get a workable result'.

Johnson-Laird suggests that people construct mental models 'from perception, from imagination, and from the comprehension of language' (2003b, p. 42) and argues that a key feature of mental models is 'iconicity' in that 'a mental model has a structure that corresponds to the known structure of what it represents' (2003a, p. 11). He suggests that 'mental models can represent spatial relations, events and processes, and the operations of complex systems' (2003a, p. 19), yet he also argues that 'visual images are a special case of mental models, and many mental models do not yield images' (2003a, p. 12) and that 'many mental models cannot be visualized' (2003a, p. 11). This is an interesting attribute for an iconic form of representation and perhaps suggests that for Johnson-Laird not all mental models are part of explicit knowledge.

McClary and Talanquer (2011, p. 397) suggest that a mental model is 'a structural, behavioral, or functional analog of a real or imaginary object, process, event, or situation [that can] support understanding, reasoning, and prediction', and they use the term to mean 'dynamic internal representations that may be constructed on the spot to deal with the demands of a given problem or situation, although it is possible that in some cases mental models may be stored in long-term memory'. For these authors the construction and/or application of a mental model is

> guided and constrained by the explicit and implicit cognitive resources available to any given individual (e.g., prior knowledge, ontological presuppositions, intuitive heuristics), as well as by the most salient features of the task at hand… (2011, p. 397)

This sense of the moment-by-moment construction of mental models is something reflected by Shepardson and colleagues who refer to mental models as 'always under construction and based on new knowledge, ideas, conceptions, and experiences' (Shepardson, Wee, Priddy, & Harbor, 2007, p. 330).

It would seem there is no clear consensus on exactly how 'mental models' should be understood, but it is suggested here that what is useful about the idea is the notion of knowledge structures that are non-propositional, and more extensive than single images, and so 'runnable' in the sense of allowing the individual to set up an 'input' state, run the model mentally and observe a simulated process suggesting the output state that arises from running those initial conditions through that model.

In a sense, mental models seem to have a similar function to computer simulations of complex processes (e.g. ecological interactions) that allow learners to change initial conditions (e.g. population sizes) and then observe how a situation unfolds. In the case of the computer simulation, the outcome is observed on the computer monitor screen. In the case of a mental model, the simulation is imagined inside the mind.

A Model of the Ontology of Knowledge in Cognitive Structure

This analysis has considered the main types of entities that have been proposed as allowing knowledge to be represented in cognitive structure, and the key distinctions between them, as well as examining how some of the terms that have been mooted might do useful work within science education to describe distinct aspects of a learner's personal knowledge. The project here is to consider if a model can be offered which includes the main types of knowledge elements that are assumed in the literature and provide clear labels for the different components of the model.

Given the lack of consistency in how terms are used in different literature, the analyst has two options in proposing such a model: either to suggest a completely new set of terms with no history and so no semantic baggage or to draw upon the available terms and use them to do work within the model with the best fit that seems possible. Given that the field is already heavily populated with terms that although often poorly defined are widely used, I have chosen the latter course, and the outcome of the analysis developed above is represented in Fig. 11.1.

So Fig. 11.1 shows the main distinctions discussed above, with conceptual knowledge being either implicit or explicit, and explicit knowledge being proposition or iconic. The model is set up in the form of a taxonomic dichotomous key, and this almost certainly simplifies the actual complexity of knowledge structures in cognitive structure. This is considered justified in order to offer a basic system with the use of a limited number of categories (and terms) to describe the knowledge elements that may be invoked in research on learning in science. One purpose

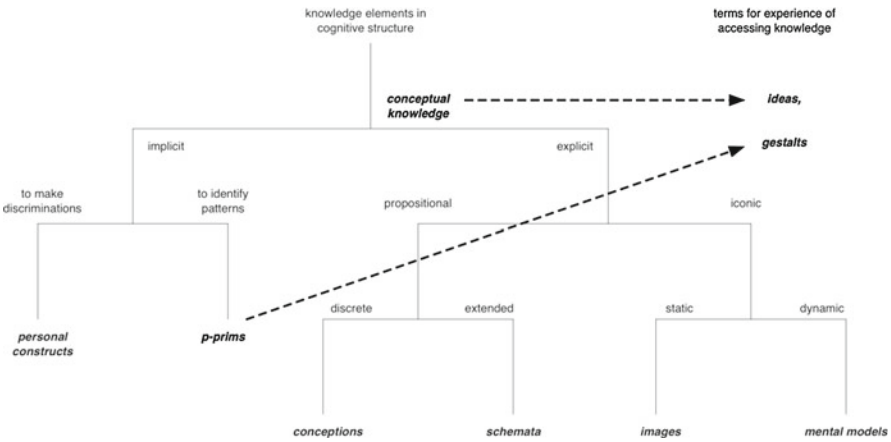

Fig. 11.2 Ideas and gestalts seen as experience of the outcomes of processing through available knowledge structures

of a model is to offer a simplified account that still reflects key features of the complexity being modelled. The model offered here is intended to include key discriminations identified in research, whilst being simple enough to be of value to those working in science education.

As suggested above, ‘ideas’ (or ‘thoughts’) and ‘gestalts’ may be best understood not as knowledge elements but as the experience of the outcomes of the operation of those knowledge elements: gestalts very much referring to perceptual experience and ideas more generally to the output of processing through the cognitive system (see Fig. 11.2).

Figure 11.1 neither directly represents the level of the cognitive system at which different components occur nor how they might be related, but simply the classes of knowledge component in the system. These are important issues that will be addressed separately.

The scheme presented in Fig. 11.1 excludes some terms that are commonly used in the field. So misconceptions are not included as a category, as this term inherently combines a reference to a type of knowledge element with a judgement about understanding in terms of someone else’s knowledge (see Chap. 6). In terms of its nature as *a type of knowledge element* within a cognitive system, a conception has the same status whether it is judged as mistaken or not by a teacher or researcher. So some student conceptions may be judged ‘alternative’, whilst others with similar status within the cognitive system will be considered canonical. In the present analysis all the learners’ conceptions are seen as part of a personal knowledge system which can only be labelled as misconceptions or alternative conceptions by someone making judgements from outside the system (see Chap. 10).

The scheme presented here does not distinguish between conceptions that the individual is strongly committed to, those that he/she has learnt but finds unconvincing and those that are recently formulated and are being entertained as potentially fruitful. Rather, it is assumed that these are all the same basic kind of knowledge element (see Chap. 6) yet given different weightings as representations of the external world within the system. This reminds us that although we might think of discrete knowledge components, this is certainly a simplification as our conceptions are linked into an extended conceptual structure (considered further in the next chapter).

A key feature of explicit knowledge is that it can be accessed and considered, and a judgement made about its relevance to the problem in hand, whereas implicit knowledge presents conclusions and recommendations to consciousness without providing access to the basis on which they were reached. A well-known human trait is to reach a tentative decision based upon implicit knowledge and then seek justifications for that decision based on available explicit knowledge. Arguably, the scientific attitude differs not in the exclusion of the role of implicit knowledge (Polanyi, 1970) but in the extent to which explicit knowledge is used to view one's 'hunches' and intuitions critically.

One common term used in the field is that of a conceptual framework, and I have not seen the need to include that in Fig. 11.1. The term framework is used in at least three different ways in science education research (Taber, 2009b, pp. 188–189): (1) as a synonym for a conception, (2) as a more extended conceptual structure (most like a schema in the present analysis) or (3) a technical term used to label the *abstractions* developed by researchers to describe common patterns in student conceptualisations and so distinguish these models from the personal conceptions of the individual learners.

The first sense of framework is already covered here, and the third is inherently excluded from being part of an individual's knowledge structure – at least, apart from that of the researcher, whose personal conception it is.

Conceptual Frameworks and Common Alternative Conceptions

Yet it is important not to ignore this notion of 'conceptual framework', as a key area of research has been based around identifying, and quantifying, 'common' alternative conceptions – those conceptions that learners commonly hold which are considered at odds with canonical science (Duit, 2009). In this sense, a number of alternative conceptual frameworks have been referred to in this volume: such as that motion naturally dies away, that atoms form bonds to fill electron shells, that heat is a kind of fluid substance.

It should be clear from the analysis in this volume that there are a number of problems that face researchers who make claims that some proportion of a population share a particular conception. The issue of knowing what can be taken to be canonical knowledge, given the elusive nature of public knowledge (Chap. 10) should warn researchers that definitive statements about what a scientific concept actually is should be made with caution. That is not to suggest that researchers should avoid seeking to compare student knowledge with canonical knowledge as such research is directly useful and relevant to teaching. Rather researchers need to be aware that at best they can have *a model of* canonical knowledge for comparison, and that in reporting their work they should be explicit about what they take to be scientific and/or curriculum target knowledge and on what they base this judgement (e.g. Treagust, 1988).

However, it should be clear from the discussion in this volume that when we explore students' conceptions of any topic in depth, we tend to find nuanced, often complex patterns, often with idiosyncratic ranges of application, and with evolving levels of commitment. This means both that any simple statements about student conceptions (such as the examples above about motion, bonding, heat) are likely to considerably simplify what are often actually nuanced conceptualisations.

Yet such gross simplifications are often needed when we want to produce information of direct use in the classroom. They also allow us to categorise large numbers of students into a small number of categories – a range of 'alternative conceptual frameworks' (Gilbert & Watts, 1983). This certainly has 'headline' value – so, for example, if we inform teachers that something like 80–85 % of students are likely to hold impetus-like ideas of force and motion (Watts & Zylbersztajn, 1981), then this gives a clear indication of the extent of the problem – if at the cost of loosing much of the richness of what our research can tell us (see Chap. 6). It certainly does not mean that these students are all drawing upon precisely the same cognitive resources and so would always interpret and answer different questions in the same way.

In particular, where research relies upon written instruments informed by research reports of particular conceptions, then response patterns will often vary with wording, question sequence, examples used, etc. So where instruments include a range of items about the same conception, it is quite likely that the outcome will need to be reported as a range, suggesting that more respondents applied 'the' alternative conception on some items than others.

A particular issue links to the understanding of knowledge we have adopted here (see Chap. 9): as the range of notions a person has under current consideration as possibly reflecting some aspect of how the world is, rather than only what is strongly committed to. Offered a range of statements reflecting apparently contradictory conceptions, learners will commonly agree with logically inconsistent statements (see Chap. 6) because of the tendency to agree with different positions that seem feasibly convincing. So it is sometimes possible to show students agree with both canonical positions, and also contrary alternative positions, and if we do not bear this in mind then instruments designed only to find level of support for one conception are likely to offer a distorted view.

The process of selecting particular positions from different students' conceptions as sufficiently distinct to be considered alternative conceptual frameworks is a matter of forming a model of the elicited conceptual 'phase space' which is in some way akin to factor analysis but is not supported by the statistical apparatus employed for that type of work. Designing instruments that can be used to survey populations in order to 'assign' student positions to the different alternative frameworks draws directly on these 'metal models'. This should be borne in mind when reading and writing about this kind of research, which can otherwise appear to be suggesting that given proportions of a population share *the same* cognitive components (the same conceptions).

The analogy here with statistical methods is that when quantitative analysis identifies different clusters (of schools, of students, of teachers, etc. depending upon the study), this suggests that those within the same cluster tend to be more similar than those in different clusters. It certainly does not mean that those in a particular cluster are the same in terms of what is being measured. Research looking at common alternative frameworks tends to rely on qualitative analysis, but the same caveat applies. When different students are classed as demonstrating the same conceptual framework (i.e. a particular category of elicited conceptions created by the researcher), this should be understood to be a statement about similarities in conceptual knowledge of some topic and not identify.

It is necessary and useful to look for general patterns of thinking that will be common across large number of learners in particular groups (English upper secondary students, Australasian chemistry undergraduates, etc.), but important to recognise that for such research to be meaningful, it requires careful consideration of the best ways to form models of the clusters of commonalities among what are likely idiosyncratic ways of makings sense of scientific topics. If this is so when it comes to thinking about student conceptions relating to particular topics, it is even more the case when we move to consider the next level of complication: how learners structure their knowledge elements into broader systems.