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Assumptions in quantitative risk assessments: When explicit and when tacit?

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ABSTRACT

In quantitative risk assessments, several explicit assumptions need to be made, to compute the risk metrics addressed. Such assumptions may, for example, relate to the number of people exposed to specific hazards, to the reliability of safety systems, or to the response of the system exposed to the hazards. In addition, come potential tacit assumptions, for example, when making a probability judgement about an event to occur. The probability judgement is based on some knowledge – which essentially captures data, information, and justified beliefs – and here tacit assumptions may exist, even if explicit assumptions have not been formulated: for example, a belief about how the system works. The probability and resulting risk metrics are conditional on this knowledge including these assumptions, and the strength of this knowledge and the 'risk' related to potential deviations from these assumptions needs attention. This paper discusses the concept of a risk assessment assumption, the main aims being to clarify the issues raised and to provide guidance on how to formulate the background knowledge to distinguish between explicit and non-explicit (tacit) assumptions. The paper thus provides a sharper conceptual basis for addressing such assumptions, and also some recommendations for dealing with these in practice.

1. Introduction

Assumptions are an essential and unavoidable part of quantitative risk assessments (QRAs). The following is the list of subjects for which assumptions were made in the QRA of a liquid natural gas (LNG) bunkering operation at a passenger ferry terminal in Norway ([11, 12]):

- Description and background data: manning level, meteorological data, meteorological parameters, ignition sources – equipment/traffic/people/hot work, bunkering installation – base case design and inventory, escape and evacuation of passengers and personnel.
- LNG accidents:
  - Representative scenario assumptions: release location/height, release sizes.
  - Frequency analysis assumptions: leak frequencies.
  - Event tree modelling assumptions: detection and isolation times, isolation failure, immediate ignition probability, event tree framework, event tree probabilities.
  - Consequence modelling assumptions: dispersion parameters, consequence modelling parameters.
- Storage and loading – specific: bunkering frequency
- Impact criteria: end point (impact) and vulnerability (fatality) criteria.

As the following examples show, the assumptions in the QRA of the LNG bunkering operation were made with respect to observable quantities (1), events and conditions (2 and 3), models (4) and model parameters (5), as well as probabilities (6):

1. Manning level: 'A total number of 4 workers (1st party) will be present at the bunkering terminal.'
2. Escape and evacuation of passengers and personnel: 'It is assumed that the escape and evacuation of passengers and personnel are following the LNG plan evacuation ...'
3. Ignition sources – equipment/traffic/people/hot work: 'The analysis is based on no hot work taking place within the bunkering area.'
4. Immediate ignition probability: 'The probability of immediate ignition is derived as a function of the release rate and release phase using the framework set out below. This immediate ignition probability model is the same as derived for [a corresponding QRA]'
5. Meteorological parameters: '… certain meteorological constants are defined as inputs to the consequence modelling. These values are summarised below: […] Surface roughness parameter | 0.3 for land 0.05 for water …'
6. Isolation failure: 'For liquid and gas sections, a probability of failure on demand of 2% is assumed.'

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The above examples illustrate how assumptions relate to a wide variety of aspects in a QRA. As an example, many QRA assumptions relate to human behaviour. The second example assumption in the above list can be seen as a (very crude) human reliability assignment. Normally, in human reliability assessment (HRA) so-called performance shaping factors (PSFs) are introduced and, when analysed quantitatively, these factors can be used to adjust base-case human error probabilities (HEPs) (e.g., [18, 22]). Assumptions could then, for example, be underlying a PSF assignment, or the PSF assignment itself could be made as an assumption, due to lack of information. In the QRA that the above example assumption is taken from, the concept of PSFs is not introduced; however, the assumption relates to human behaviour and essentially says that the human error probability related to escape and evacuation is zero. The assumptions that are made in relation to human reliability, and thus in HRA, could involve conflicts between beliefs – so-called dissonances – which need to be taken into account; cf. Vanderhaegen [30].

The above and remaining assumptions are documented in an assumption register included as an appendix [12] to the QRA report [11]. Other, more general categorisations than the ad hoc one shown above are also sometimes seen; for example, a categorisation into technical/design, operational, and analytical assumptions.

An assumption can be defined in various ways, for example:

- 'A fact or statement (as a proposition, axiom, postulate, or notion) taken for granted.' (Merriam-Webster Online)
- 'A [planning] assumption is a judgement or evaluation about some characteristic of the future that underlies the plans of an organisation.' ([10] p. 14)
- 'Defaults are functional forms or numerical values that are assigned to certain models or parameters in risk assessment, based on guidance and standard practice, in the absence of good data. […] Assumptions are equivalent to defaults but are derived for a specific assessment rather than being taken from guidance. They may be complex, implying functional forms or sets of parameters. […] Ad hoc assumptions must be individually justified.' ([29] pp. 134–135)
- 'Nonetheless, an assumption is a very weak scientific statement because it is based on inductive logic.' ([27] p. 97)
- 'By assumptions we understand conditions/inputs that are fixed in the assessment but which are acknowledged or known to possibly deviate to a greater or lesser extent in reality.' ([8] p. 46)

The last three quotes are taken from what can be labelled as the risk analysis literature. The penultimate statement is perhaps more of a characterisation than a definition. We see that the definitions range from the strong characterisation of an assumption as being a 'fact', via the more neutral 'statement' and 'fixed conditions/input', to the weaker 'judgement or evaluation'.

All the example assumptions included at the beginning of the introduction are what can be labelled as explicit assumptions. The (simple) Merriam-Webster definition of 'explicit' includes 'very clear and complete', 'leaving no doubt about the meaning' and 'openly shown'. An antonym for 'explicit' is 'tacit', defined by Merriam-Webster as 'expressed or understood without being directly stated'. And, in addition to explicit assumptions, there will be more or less tacit assumptions in a QRA, for example, when making a probability judgement about the occurrence of an event: the probability judgement is based on some knowledge – which essentially captures data, information and justified beliefs – and here tacit assumptions may exist, even if explicit assumptions have not been formulated: for example, a belief about how the system works. The risk metrics are conditional on this background knowledge including these assumptions, and the strength of this knowledge and the 'risk' related to potential deviations from these assumptions needs attention; cf. Aven [2].

The purpose of the present paper is to discuss the concept of a risk assessment assumption, the main aims being to clarify the issues raised and to provide guidance on how to formulate the background knowledge to distinguish between explicit and non-explicit (tacit) assumptions. Assumptions are made in all risk assessments, making these a foundational issue of relevance across different application areas. Being able to formally relate risk assessment assumptions to the background knowledge of the risk description, and, in the next step, to distinguish between assumptions that are acknowledged and stated openly and assumptions that are 'hidden in the background knowledge' and thus represent a potentially unacknowledged 'risk' related to deviations (cf. the paragraph above), gives a sharper conceptual basis for the thinking and discussion about risk assessment assumptions. It also provides a framework within which to formulate recommendations and guidelines for how to address such assumptions in practice, as will be shown in the present paper.

In light of the different basic types of research described and contrasted by Kothari [19], the scientific contributions of the present paper can be described as conceptual as opposed to empirical, fundamental as opposed to applied, and analytical as opposed to descriptive. These three features are the hallmarks of generic conceptual risk research, as defined and discussed by Aven [6]. The research described in the present paper is primarily conceptual, in that it relates to abstract concepts and ideas – e.g., the risk description, knowledge, and assumptions – rather than empirical evidence, though there are empirical elements, such as the list of example assumptions above. Conceptual contributions are created in a process involving one or more among several possible features, as described by MacInnis [21]; see also Aven [6]. The features of the present paper are identification (of existing definitions of [risk assessment] assumptions, and of different types of uncertain quantities in QRA), differentiation (between explicit and tacit assumptions), integration (of the formal set-ups for conceptualising assumptions and the risk description), and advocating (that risk assessment assumptions can be operationalised as fixed uncertain quantities). The research in the present paper is fundamental, in the sense that the results and recommendations made are general and thus applicable in different context. Finally, the research in the present paper is analytical as it uses information that is already available rather than collecting new information. For example, it builds on existing strategies for treating explicit assumptions and existing criteria for evaluating strength of knowledge.

Risk assessment assumptions have been addressed by several authors. Aven [4] discusses conservative assumptions specifically, using a conceptualisation of assumptions that the present paper builds on. Rosqvist and Tuominen [24] discuss modelling assumptions in relation to bias, conservatism and precaution in risk assessment, relating assumptions to 'functional relationships of system inputs and outputs, temporal interdependencies between events, etc.' (p. 110). Tacit assumptions are commonly referred to and acknowledged in the literature, as exemplified by the following quotes:

- 'Indeed, most estimates of parameter uncertainty are contingent on the tacit assumption that the model containing these parameters is entirely appropriate and correctly specified.' ([13] p. 11)
- 'There is also a tacit assumption in many risk assessments that the plant is built as designed and is adequately maintained. Violations of safety technical specifications and sabotage are rarely included in the studies.' ([20] p. 241)

However, tacit assumptions, and specifically their distinction from explicit assumptions, do not appear to have been conceptually discussed at much depth, at least in the risk analysis/assessment literature. A paper discussing tacit and/or explicit assumptions conceptually, in the context of risk assessment/analysis, like in the present paper, would presumably mention these words in the title, abstract or keywords. The results of a Scopus title, abstract and keyword search is shown in Table 1. Only one of the seven publications resulting from the first search string comes close to addressing tacit assumptions conceptually

Table 1
Scopus search results.

Search string	Number of results
'tacit assumption' AND 'risk assessment' OR 'risk analysis'	7
'explicit assumption' AND 'risk assessment' OR 'risk analysis'	9
'tacit assumption' AND 'risk assessment' OR 'risk analysis' AND 'explicit assumption'	0
'implicit assumption' AND 'risk assessment' OR 'risk analysis'	61

in some degree of detail, by linking assumptions to background knowledge, in line with what is done in the present paper: 'Moreover, the reasoning on the assessment is based on background knowledge that very often is tacitly described in documents or on area maps' ([7] p. 180). The remaining six publications only refer to specific tacit assumptions having been made as part of the study reported on in the publication. Eight of the nine publications resulting from the second search string refer to explicit assumptions in general, but do not conceptually analyse and discuss this term as is done in the present paper. The remaining one publication refers to a specific explicit assumption made in the study that the publication reports on. Neither of the two publications quoted in the bullet points above appeared among first two search results, presumably because the first quote is from a report in a report series not indexed by Scopus and because the second quote comes from an article that does not mention tacit or explicit assumptions in the abstract. Finally, a review of the 61 abstracts resulting from the fourth search revealed that only one of these [23] addresses implicit assumption in some degree of detail and specifically in relation to beliefs and knowledge, then in the context of expert knowledge elicitation for risk analysis.

The remainder of this paper is organised as follows: in Section 2, we introduce a formal set-up with an example, providing a basis for a discussion and some recommendations in Section 3. Finally, Section 4 gives some conclusions and final remarks.

2. A formal set-up with an example

In this section, we present a formal set-up for addressing assumptions in QRA. The set-up includes a risk description/metric and a typology of uncertain quantities, as well as a way of conceptualising assumptions in terms of fixed uncertain quantities.

Broadly speaking, and in line with the Society for Risk Analysis (SRA) glossary [28] and Aven [3], a risk description can be seen as comprising specified consequences, C′, interpreted broadly to include risk sources, events/scenarios, and end states; a measure of uncertainty, Q, assigned to these; and the background knowledge, K, on which this assignment is made. As described in the introduction, the background knowledge essentially covers data, information and justified beliefs. The latter include, for example, models and expert judgements [3]. The most commonly used quantitative measure of uncertainty is probability, P, and, if probability is the only measure of uncertainty used, we have Q = P. If the probability assignments are supplemented by qualitative strength-of-knowledge assessments (SoK), as will be described in Section 3, the measure of uncertainty becomes Q x003D= (P,SoK).

In a QRA, the risk level is typically summarised by one or more risk metrics (also sometimes referred to as risk measures or risk indices). A broad class of risk metrics is obtained as the (possibly normalised) expected value of an uncertain quantity N, where N characterises the severity of the consequences and is part of the specified consequences C′. That is, the risk metric, here denoted R, is given by

$$R = c\ E[N|K],$$

where c is a normalising constant. In terms of the risk description conceptualisation, (C′,Q,K), we see that R is an expression in the format Q(C′|K), which includes all the main components of the risk description. The class of risk metrics covered by R includes, for example, common safety risk metrics such as PLL values (potential loss of life; defined as the expected number of fatalities), FAR values (fatal accident rate; defined as the expected number of fatalities per 100 million hours), FN curves (frequency number of fatalities curves; defined as the expected number of events with N or more fatalities for some range of values of N), and frequencies of loss of some main safety functions (e.g., 'loss of structural integrity' or 'loss of escape ways' in an offshore oil and gas platform setting, and 'large early release frequency (LERF)' in a nuclear power plant setting). To see this, note that in the case of PLL values, which can be defined as E[N|K] when N is the number of fatalities in the time period considered, we have c = 1. The same is the case for frequencies of loss of main safety functions, which can be defined as E[N|K] when N is an indicator quantity equal to 1 in case of loss of the main safety function and 0 otherwise; and also in the case of FN curves, which can be defined as E[N(n)|K] when N(n) is the number of events with n or more fatalities in the time period considered. Furthermore, in the case of FAR values, which can be defined as $E[N|K] \times 10^8 / s$ when N is the number of fatalities in the time period considered and s is the number of hours of exposure time for the persons exposed to risk, we have $c = 10^8 / s$.

In the following, we first describe the set-up for conceptualising explicit and tacit assumptions formally. Then follows an example to illustrate the set-up. We focus on framing assumptions in relation to the probability of an event, A, given some background knowledge, K, i.e., in relation to P(A|K). Like P(A|K), the risk metric R = E[N|K] is also a probabilistic statement, with K as conditional argument, and the set-up thus also applies to R.

Consider the probability assignment for an event A, conditional on particular background knowledge K, including assumptions. Let $H = (H_1,H_2,...,H_n)$ denote the vector of assumptions made, and suppose that each assumption H_i is operationalised as a quantity (parameter), V_i, possibly vector valued. We can then write H_i as a function of V_i, and H as a function of $V = (V_1,V_2,...,V_n)$. To simplify the notation and presentation, in the remainder of this section we use H and V, instead of H_i and V_i, to denote a single assumption and associated quantity, respectively. In the set-up, we distinguish between different types of quantities:

- Type X quantity: V = X, where X is fixed at some base case value, x_0. The link between X and H is acknowledged by the analyst, and H is openly stated in the risk assessment. In this case, we refer to H as an explicit assumption.
- Type Y quantity: V = Y, where Y is fixed at some base case value, y_0. The link between Y and H is not acknowledged by the analyst, and/or H is not openly stated in the risk assessment. In this case, we refer to H as a tacit assumption. If the link between H and Y is acknowledged by the analyst but H is not openly stated, we refer to H as an acknowledged but undocumented tacit assumption. If the link is not acknowledged and H is not openly stated, we refer to H as an unacknowledged an undocumented tacit assumption. We may refer to these two sub-types of quantities as type Y′ (link between H and the quantity acknowledged but not openly stated) and type Y″ (link between H and the quantity not acknowledged and not openly stated), respectively, to distinguish these formally whenever there is a need to do so.

In addition to explicit and tacit assumptions, operationalised as fixed quantities, the uncertainty related to some quantities, say Z, may affect the uncertainty assessment of A, and the uncertainty related to Z is represented quantitatively using a probability distribution F_Z and formally integrated into the overall probability of A using the law of total probability (the law of total expectation, in the case of R). That is, the probability P(A|K) can be formulated as:

$$P(A|K) = \int P(A|Z, K)dF_Z.$$

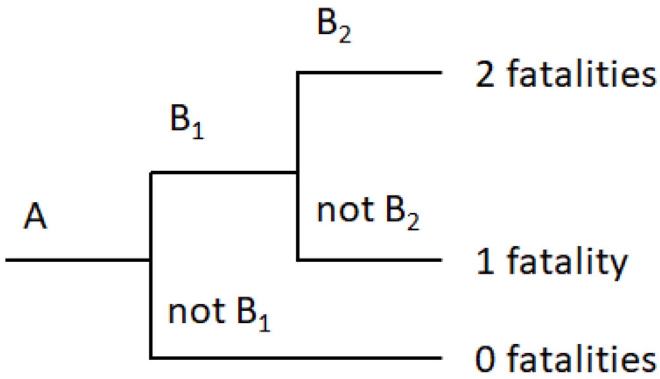

Fig. 1.. Event tree example.

Finally, there may be quantities, say W, that also affect the uncertainty assessment of the event A and which are neither fixed nor formally integrated in the same way as Z using the law of total probability. Instead, they are informally incorporated into the assignment process by the person assigning the probability, who intuitively weighs the potential values of W and the associated probabilities into the overall probability assignment.

We thus obtain a typology of uncertain quantities, covering (X,Y,Z,W). Next, we introduce a simple example to illustrate the above set-up and this typology. The example will also be used to support the discussion in Section 3. Consider the event tree shown in Fig. 1, modelling the sequence of events from a gas leak (event A) at an offshore oil and gas platform, via the performance of barriers in place to avoid ignition (event B_1) and escalation (event B_2), to the number of fatalities, which could be 0, 1 or 2, depending on which of the events B_1 and B_2 occur and not.

Let L denote the number of gas leaks (events A) in a specified time period and N the number of fatalities in the same period. Then, some natural risk metrics to consider are (suppressing the conditioning on K from the notation)

$$E[N] = E[L]P(B_1|A)[2 \times P(B_2|B_1, A) + 1 \times P(\text{not } B_2|B_1, A)],$$

and

$$P(N = 2) \approx E[L]P(B_1|A)P(B_2|B_1, A),$$

where the approximation holds for sufficiently small gas leak frequencies E[L]. The different types of quantities related to assumptions and influencing factors described above can be identified in relation to this example:

Type X quantity: the number of hours of hot work. Suppose that the probability of ignition given a gas leak, $P(B_1|A)$, is judged to depend on the amount of hot work taking place on the platform. Let T denote the number of hours of hot work on the platform during one year. Then we can indicate this dependence by writing $P(B_1|A,T)$. Finally, suppose that an assumption is made that $T = t_0$ for some number t_0, based on, say, the operations and maintenance policy and plans developed for the platform. The probability used in the risk assessment would thus be $P(B_1|A,T = t_0)$. Note that defining the quantity T and making the assumption $T = t_0$ changes neither the event A nor the event B_1.

Type Y quantity: a finite number of discrete consequences. A tacit assumption is that the number of consequences (end states) can be classified into a finite number of discrete outcomes, three in the case of the event tree in Fig. 1. The type Y quantity could then be the indicator function of the condition that the actual consequences, C, is an element in the set of modelled consequences, Ω. The assumption is then that this indicator function, $I(C \in \Omega)$, is equal to 1, which is just a way of saying that the condition is true. Given that the risk analyst acknowledges that this is a simplification of reality, which most risk analysts would likely do, in terms of sub-type this would be a type Y′ quantity.

Type Z quantity: the wind speed during a gas leak. Suppose that it is judged that the probability of ignition given a gas leak also depends on the wind speed, S, during the gas leak. We may indicate this dependence by writing $P(B_1|A,T,S)$. Also, suppose that, based on weather statistics, a probability distribution, F_S, is assigned for S. Then the probability of ignition given a gas leak can be assessed as

$$P(B_1|A,t_0) = \int P(B_1|A,\ T{=}t_0,\ S)dF_S.$$

Type W quantity: the number of personnel in the process area. Suppose that the probability of ignition given a gas leak is judged to also depend on the number of personnel in the process area, J, during the gas leak. We may indicate this dependence by writing $P(B_1|A,T,S,J)$. Assessing the probability of ignition also involves assessing the probability of manual detection of the leak, which clearly depends partly on the number of people present. Suppose that, as a simplification, a direct subjective probability assignment of P(manual detection|A) is made, without establishing a probability distribution of J and using it to integrate over $P(B_1|A,T,S, J)$ with respect to J. The risk analyst simply makes a judgement using all sources of information, weighing different possible scenarios regarding J and other relevant conditions, and assigns the probability directly.

Table 2 summarises the links between the type X and Y quantities and the associated assumptions, H, as well as the operationalisation of these assumptions by fixing their associated quantities, V, at values, v_0.

3. Explicit and tacit assumptions – discussion

In this section, we discuss some key premises, related to the formal set-up and example in Section 2, and provide some recommendations. First, we discuss the premise that knowledge covers data, information and justified beliefs, and that assumptions can be considered justified beliefs. Second, we discuss the premise of defining explicit and tacit assumptions in terms of fixed uncertain quantities. Third, we give some recommendations, by outlining some potential practical uses of the set-up and typology described in the previous section.

3.1. *Assumptions as justified beliefs: relation to the background knowledge*

The formal set-up described in Section 2 is based on the premise that risk assessment assumptions are part of the background knowledge of the risk assessment, where (propositional) knowledge is understood as justified beliefs; cf., e.g., SRA [28] and Aven [3]. These beliefs are based on data and information, modelling and analysis; and it is often useful to talk about knowledge in a wide sense as covering data, information and knowledge (in a narrow sense, as justified beliefs) [3]. Within this framework, an assumption can be considered a justified belief, noting that the belief may be a chosen belief from a set of possible beliefs, each supported by different (levels of) justifications. The risk analyst thus does not have to believe that the assumption is correct. Often different assumptions can be made, each with some justification but not enough for the analyst to necessarily believe that the assumption is correct. In

Table 2
Type X and Y quantities in the example and their relation to assumptions and the operationalisation of these.

Uncertain quantity	Type of quantity	Assumption (H)	Operationalised assumption ($V = v_0$)
T	Type X	The number of hours of hot work will be t_0	$T = t_0$
$I(C \in \Omega)$	Type Y	The number of consequences (end states) can be classified into three discrete outcomes	$I(C \in \Omega) = 1$

the limit, an assumption for which no justification can be provided would be a degenerate justified belief. Consider, for instance and with reference to the example in Section 2, the following alternative assumptions:

H: There will be 100 h of hot work during production per year.
H′: There will be no hot work during production.

Suppose that the operations and maintenance policy and plans for the platform state that there will be no hot work (e.g., welding) during production. The plan is to perform whatever hot work is necessary during planned production shutdowns. This policy and plan justify the assumption H′. However, based on experience that a need to perform hot work that cannot wait sometimes does arise, and to avoid having to perform a new (revised) risk assessment if and when such need arises, the risk assessment is performed based on the assumption H. Experience and the argument related to avoiding having to perform an adjusted risk assessment justify H. As another example, consider the use of models. A model can be seen as expressing justified beliefs related to a phenomenon. Returning again to the example introduced in Section 2, let G denote a model of gas dispersion, for example a crude model that predicts the gas dispersion pattern as a simple function of distance from the release point. An alternative, computational fluid dynamics model, G′, may exist, where the analyst has far greater confidence in the predictive ability of G′ compared to G. However, the model G may still be the one used in the risk assessment, due to time and/or resource constraints.

A tacit assumption (or, even an explicit assumption), may have no other justification than "we have always made this assumption", i.e., no other justification than convention/custom. That an assumption is customarily made can be seen as a (first level) justification, which of course needs to be further investigated and challenged. If it turns out that there is virtually no justification behind this convention, we may be approaching a degenerate justified belief.

Suppose that we can formulate the background knowledge as a vector of knowledge components, i.e., that we can write $K = (K_1, K_2, \ldots, K_m)$. Then, by considering assumptions and models as knowledge components, we have $K_j = H_j$ for a set of j's, and $K_j = G_j$ for a different set of j's.

The point above concerning the model G versus the model G′ illustrates a key point, namely that the background knowledge, K, is the specific knowledge used to assign a probability, or, more generally, to establish the risk description. It is not, for example, the grand total of knowledge that exists in relation to the activity or phenomenon being analysed or even the total knowledge of the risk assessment group. Consider two sets of knowledge in relation to the example introduced in Section 2. One is denoted K and the other K′, where K is the specific knowledge on which the risk description is based and K′ is the total knowledge of the risk assessment group. Suppose that one difference between K and K′ is that the former includes the model G and the latter also includes the model G′. We may refer to both K and K′ as (alternative) sets of knowledge; however, the background knowledge of the risk description includes only the knowledge components that are actually used to establish it, in this case G rather than G′ (in general, of course, more than one model of the same phenomenon could form part of the background knowledge if several models are combined, for example using model averaging). The grand total of knowledge, say K″, would include both G and G′, as well as other models of gas dispersion in air.

Risk assessments are in most cases performed by groups of risk analysts, so that an acknowledgement of the link between a tacit assumption and a type Y quantity may only be partial if just one or some of the risk analysts is aware of this link. Since the background knowledge, K, is the specific knowledge used to establish the risk description, if a tacit assumption affects the value of a (type Y) quantity in the risk assessment, then by definition that assumption is part of K, even if the link between the tacit assumption and the type Y quantity is not acknowledged by all of the risk analysts. The value of making tacit assumptions of this type explicit is highlighted in one of the papers identified in the literature search and review presented in Section 1 [16]:

> 'By making interdisciplinary hazards teams' implicit assumptions explicit, the sharing meanings approach offers an operational process to seize on moments of difference as productive tension and to see such challenges as opportunities—rather than obstacles—for innovating toward hybrid methodological research designs in hazards research.'

Risk assessments deal with situations of uncertainty, and risk assessment assumptions are commonly made in the face of epistemic uncertainty, i.e., when there is lack of knowledge. Assumption may also be made in the face of aleatory uncertainty, i.e., when there is variation in the phenomena involved; for example, assumptions about the parameters in the model used to characterise the variation. The explicit assumptions made are often conservative, meaning that they lead to a higher level of described risk, compared to 'best estimate' or 'best judgement' assumptions [4]. Here, we can probably understand 'best judgement' assumptions as reflecting the strongest beliefs of the risk analyst. A conservative assumption can, however, also be given a justification (albeit possibly weaker than the best judgement one) and can thus be considered a justified belief, in line with how assumptions are conceptualised in the present paper. Tacit assumptions, on the other hand, understood as assumptions that are not acknowledged, or at least not openly stated (documented), can clearly be seen as justified beliefs. Consider a probability judgement based on some knowledge. If the probability judgement is based on a belief about how a system works, and this belief is not stated, then this belief can be considered a tacit assumption. The belief may be very strong, at least if held subconsciously or if it was considered unnecessary to document that the probability judgement was made under that condition.

One consequence of seeing knowledge as justified beliefs is that the knowledge may be wrong [3]. It also opens the door for assessing the strength of knowledge (e.g., [2, 3]), which is then understood as an assessment of how well justified the beliefs making up the knowledge are. We would, for example, judge the strength of knowledge related to K and K′ in the paragraph before the previous one differently. The strength of knowledge related to K′ would be judged as stronger than that related to K, in part due to the greater confidence in the predictive ability of G′ compared to G. Various schemes have been proposed for performing what may be labelled strength-of-knowledge assessments. One example is the so-called NUSAP notational scheme for uncertainty and quality in science for policy [15], which involves a qualitative evaluation of the 'pedigree' of a scientific study. Another example is the qualitative scheme proposed by Flage and Aven [14], whereby the strength of knowledge related to the background knowledge of a risk metric is classified as 'weak' if one or more of the following conditions are fulfilled [14]:

- 'The phenomena involved are poorly understood; models are non-existent or known/believed to give poor predictions.
- Data/information are/is non-existent or highly unreliable/irrelevant.
- There is strong disagreement among experts.
- The assumptions made represent strong simplifications.'

If the opposite holds for all the above conditions (whenever they are relevant), the strength of knowledge is classified as 'strong'. In cases with conditions in-between weak and strong, the classification is 'moderate'. This classification scheme has been extended and adapted to the security risk setting by Askeland et al. [1]. Using such a classification scheme would, for example, imply a less strong focus on single-valued risk acceptance criteria than what is the case today. The scheme can be used to judge risk acceptance as follows ([2] p. 141):

1 'If risk is found acceptable according to probability with large margins, the risk is judged as acceptable unless the strength of knowledge is weak (in this case the probability based approach should not be given much weight).
2 If risk is found acceptable according to probability, and the strength of knowledge is strong, the risk is judged as acceptable.
3 If risk is found acceptable according to probability with moderate or small margins, and the strength of knowledge is not strong, the risk is judged as unacceptable and measures are required to reduce risk.
4 If risk is found unacceptable according to probability, the risk is judged as unacceptable and measures are required to reduce risk.'

Ever more dynamic aspects are introduced in QRA; see, e.g., the review by Villa et al. [31]. The formal set-up adopted in this paper could be extended to a time-indexed version to account for this aspect. The risk description adopted, (C′,Q,K), could be conceptualised instead as $(C',Q,K)_t = (C'(t),Q(t),K(t))$, where C′(t) denotes the consequences specified at time t, Q(t) the uncertainty assessments at time t, and K(t) the knowledge underlying the consequence specifications and the uncertainty assessments at time t. By time-indexing the knowledge element, also the set of assumption and the vector of quantities operationalising these assumptions become time-dependent. The result is a vector H(t) and a vector V(t), reflecting the set of assumptions made and the value of the quantities operationalising these at time t, respectively. In the era of big data, with real-time information increasingly becoming available, for example due to development of sensor technology, the data part of the knowledge element will become increasingly important. Let D(t) denote the data available at time t, where, like H(t), also D(t) is an element in K(t). With the advent of statistical and machine learning, where algorithms build data-driven models in a more or less black-box fashion, we can expect a number of tacit assumptions to be made. Exploring the consequences of this development is, however, a substantial task that is beyond the scope of the present paper, which instead aims to define and conceptualise explicit and tacit assumptions in the context of risk assessment and the risk description.

Having addressed the premise of assumptions as justified beliefs and part of the background knowledge of the risk description, we next discuss the premise of defining explicit and tacit assumptions in terms of fixed uncertain quantities.

3.2. Defining explicit and tacit assumptions in terms of fixed uncertain quantities

Another key premise of the formal set-up in Section 2 is that risk assessment assumptions are conceptualised in terms of fixing the values of the uncertain quantities involved in the risk assessment (modelling). There are numerous qualitative assumptions in a risk assessment; for example, related to system boundaries, to what consequence dimensions (values) to consider in the analysis, to how a particular consequence should be measured/operationalised, and whether future trend should be included or not. In the formal set-up presented in Section 2, these qualitative assumptions are captured by the (non-quantitative) vector of assumptions $H = (H_1,H_2,...,H_n)$, where each assumption H_i is operationalised in the form of a quantity (parameter), V_i. A risk assessment assumption then needs to be operationalised in such a way that it influences the risk description/metric, and linking assumptions to uncertain quantities (i.e., going from H_i to V_i) and the changing and fixing of these quantities ensures this.

Considering the examples mentioned above, an assumption related to system boundaries could be operationalised by a risk metric $R(x_0) = \sum_i x_{i,0} R_i$, where R_i denotes the risk metric contribution from risk source i, and $x_0 = (x_{1,0},x_{2,0},...,x_{n,0})$ is a vector of 0–1-valued quantities where $x_{i,0} = 1$ if risk source i is within the assumed system boundary and 0 otherwise. Furthermore, if $R_i = c_i E[N_i|K]$ denotes the risk metric related to a consequence dimension/value measured by the quantity N_i, then the overall risk metric is given by the vector $R(x_0) = (R_1^*,R_2^*,...,R_n^*)$, where the element $R_i^* = x_{i,0} R_i$ equals 0 if the consequence dimension/value related to N_i is not considered in the assessment. If N_i is allowed to be a function and not just a quantity, different ways of measuring a consequence dimension/value can also be accounted for. Finally, a future trend could be operationalised by introducing a multiplication constant x_0 in a risk metric expression, yielding a linear model but of course more complex trends could also be reflected in an analogous way.

These formal definitions in the above paragraph may not be particularly useful in a given, practical risk assessment, where, for example, only the risk metric chosen would be included, and not a vector of those that were not. There is, however, of course a value in showing that it is possible to express the assumption in terms of quantities.

Defining explicit and tacit assumptions in terms of different types of uncertain quantities allows for building a typology of uncertain quantities in QRA, as described in Section 2. Such a typology is useful for addressing uncertainty treatment in QRA, as will be shown in the next subsection. Strictly speaking, it is not the quantities that are of different types but rather the way these quantities are treated in the risk assessment (modelling). However, for simplicity, we refer to different types of quantities. An uncertain quantity can essentially be dealt with in two ways in a QRA:

- Fix the quantity at a specific value.
- Account for the uncertainty related to the quantity.

The first strategy amounts to making an assumption. According to the definitions in Section 2, the assumption is explicit (type X quantity), if fixing the quantity is linked to a stated assumption, and tacit (type Y quantity) if not. The second strategy involves either establishing a probability distribution on the uncertain quantity (type Z quantity) and formally incorporating the uncertainty assessment reflected by this distribution, using the law of total probability/expectation, or informally incorporating uncertainty assessments related to the quantity (type W quantity), when performing a direct probability assignment for an event that is influenced by the outcome of the quantity.

In such a set-up, the type X and Z quantities are 'closed', in the sense that the risk description/metric is conditional on these quantities taking the fixed values x_0 and y_0, respectively. Assumptions can thus be seen as constraints that need to be satisfied for the conclusions of the risk assessment to remain valid. The type Z and W quantities, on the other hand, are kept 'open', in the sense that the risk metric/description is not conditional on these quantities taking any particular value. These quantities are allowed to vary, and the validity of the conclusions of the risk assessment do not depend on these quantities taking particular values.

Finally, note that the uncertain quantities in a risk assessment, and the values these are fixed at, if any, are part of the set of specified consequences, C′, in the risk description (C′,Q,K). The fixed quantities, $X = x_0$ and $Y = y_0$, associated with the assumptions, H, are thus part of C′, while H is part of the background knowledge, K, as described in Section 3.1.

Having addressed the premise of defining explicit and tacit assumptions in terms of fixed uncertain quantities, we next provide some recommendations related to the suggested set-up and typology.

3.3. Recommendations

The next two subsections outline some potential practical uses of the set-up and typology described in Section 2.

3.3.1. Procedure for linking assumptions with uncertain quantities and for identifying tacit assumptions

The formal set-up described in Section 2 allows for formulating different strategies to deal with tacit assumptions:

- Accept the potential presence of tacit assumptions (i.e., do not attempt to identify these).
- Identify tacit assumptions and address these:
  - Transform the tacit assumption into an explicit one (i.e., move from a type Y to a type X quantity).
  - Account for the uncertainty related to the quantity associated with the tacit assumption instead of fixing the quantity (i.e., move from a type Y to a type Z or W quantity).

A procedure for linking assumptions with uncertain quantities and for identifying tacit assumptions and transforming these into explicit ones follows. As in Section 2, to simplify the notation and presentation, we here use H and V, instead of H_i and V_i, respectively, to denote a single assumption and associated quantity:

I For a given assumption H: identify the relevant quantity V affected by the assumption, incorporate this quantity into the risk assessment modelling, and fix the quantity at a specific value v_0, as appropriate in line with H.

II For a given uncertain quantity V, fixed at a specific value v_0: identify the rationale for fixing the value at v_0 and, if relevant (i.e., if the fixed value reflects an as-yet unstated assumption), specify an assumption H, in line with the fixed value.

The first strategy (I) represents a top-down approach and the second one (II) a bottom-up approach. When identified and linked to an assumption H, the uncertain quantity V is a type X quantity. If the second step results in the specification of a new assumption, a tacit assumption has been identified and the uncertain quantity has been transformed from a type Y to a type X quantity.

Returning to the example introduced in Section 2, an example of strategy I is to consider the potential need to perform hot work during production and, based on this consideration, to formulate the assumption that the number of hours of hot work during production will be 100 h per year. Next, this assumption is operationalised by introducing the quantity T and defining it to denote the number of hours of hot work per year during production, and then fixing T at 100, i.e., defining $T = t_0 = 100$. Finally, this quantity and value is incorporated into the risk assessment modelling by, say, multiplying it with a per hour hot work ignition probability, r, assumed to be equal to a fixed value p, to obtain a hot work ignition probability. An example of strategy II is to consider a review of the risk assessment model for hot work, in which it is discovered that the per hour ignition probability value used, p, applies to hot work in a pressurised habitat, whereas the associated assumption, H′, specified hot work in open air. If this was a correct tacit assumption, the assumption H′ is revised into an assumption H, stating that the number of hours of hot work in a pressurised habitat during production will be 100 h per year. If the tacit assumption was incorrect, the per hour hot work ignition probability is replaced by a per hour open air hot work ignition probability, p′.

Once a type Y quantity is transformed into a type X quantity, what was a tacit assumption can be treated as an explicit assumption. In the following, we briefly review some available strategies for treating explicit assumptions.

3.4. Sensitivity analysis

A well-known treatment strategy for explicit assumptions is to perform sensitivity analysis of changes in the assumptions by specifying one or more alternative values, $x_1 \neq x_0$, at which X is fixed, and then assessing the effect this has on the relevant risk metric(s). Numerous techniques for sensitivity analysis exist, as described in, for example, the textbooks by Saltelli et al. and Saltelli et al. [25, 26].

3.5. Assumption deviation risk assessment

An alternative to sensitivity analysis is to perform an assumption deviation risk assessment. This term was coined by Aven [2] and comprises an assessment of i) a deviation (or a set of deviations) from the assumptions made and the associated changes to the specified consequences, ii) an uncertainty measure of the deviation(s) and of the changed consequence specifications, and iii) the background knowledge that the deviation and consequence specifications are based on [2]. Using the general risk description notation (C′,Q,K) introduced in Section 2, and letting D denote an assumption deviation, the assumption deviation risk is assessed as $(\Delta C', Q, K_D)$, where ΔC′ denotes the changes in the specified consequences (including D), and K_D refers to the knowledge that ΔC′ and Q are based on [2]. Note that an assumption deviation risk assessment is not the same as traditional sensitivity and uncertainty analyses, as it extends beyond just asking ‘what if’ questions which is characteristic of traditional sensitivity analysis; see the discussion in Khorsandi & Aven [17].

3.6. Assumption classification system

Building on the concept of assumption deviation risk, Berner and Flage [8] suggest a scheme for classifying (explicit) QRA assumptions. The classification scheme is intended to serve as a basis for determining strategies for treating the assumptions in the risk assessment itself [8], as well as in the subsequent risk management [9]. The belief in deviation from an assumption (i.e., from $X = x_0$, which is how the assumption is operationalised) is classified as either low or moderate/high, the same for sensitivity of the risk metric with respect to changes in the assumption (i.e., deviations from $X = x_0$), and, finally, the strength of knowledge is also classified as either strong or moderate/weak, evaluated according to the criteria by Flage & Aven [14] described in in Section 3.1 of the present paper. This results in six different assumption settings, as illustrated in Table 3, for which different treatment strategies are suggested.

For example, for assumptions in Setting I, the recommendation is that the risk metric is reported conditional on the assumption and that the assumption is listed as non-critical [8]. In the set-up and typology of the present paper, this strategy corresponds to a case of proceeding with and accepting an assumption H operationalised as $X = x_0$. On the other hand, in Setting V, the recommendation is to formally integrate a probabilistic uncertainty assessment of alternative assumptions into the risk metric, using the law of total expectation/probability. In the set-up and typology of the present paper, this strategy corresponds to a case of moving from a type X to a type Z quantity. Reference is made to Berner and Flage [8] for further details and for recommended strategies for the remaining settings.

3.6.1. Using the typology of uncertain quantities descriptively or as a screening tool

The typology of uncertain quantities can be used both descriptively and ing tool. Used descriptively, as illustrated in the bullet point list below, using and extending the example introduced in Section 2, the

Table 3
Assumptions settings based on Berner & Flage [8].

Belief in deviation from $X = x_0$	Sensitivity of risk index with respect to deviations from $X = x_0$	Strength of knowledge	
		Strong	Moderate / Weak
Low	Low	Setting I	Setting II
	Moderate / High	Setting III	Setting IV
Moderate / High	Low		
	Moderate / High	Setting V	Setting VI

risk analyst simply categorises and lists all the uncertain quantities of the different types, specifying their fixed values and possibly their associated assumptions or the means by which the associated uncertainty is accounted for.

- Type X quantities not transformed from type Y quantities (initial explicit assumptions):
  - Number of hours of hot work during production ($T = t_0$)
  - (Frequentist) probability of failure on demand of the gas detection system
  - Number of crane lifts above the process area
- Type X quantities transformed from type Y quantities (identified tacit assumptions):
  - The per hour pressurised habitat hot work ignition probability ($r = p$)
- Type Z quantities (risk influencing factors formally accounted for in the risk assessment by means of probability distributions):
  - Wind speed during gas leak (S)
  - Wind direction during gas leak
  - Release location of gas leak
- Type W quantities (risk influencing factors acknowledged and informally reflected in probability assignments but not formally accounted for by means of probability distributions):
  - Number of people in the process area during gas leak (J)
  - The time of day of a gas leak
  - The number of inspections per year of the gas detectors

As discussed by Aven [5], the risk analyst produces a risk description in the format (C′,Q|K), i.e., in a conditional format where the consequence specifications and uncertainty assessments are conditional on the background knowledge. The decision-maker, however, needs to reflect on the unconditional risk description, i.e., on (C′,Q,K), viewing K as a potential source of, for example, assumptions that turn out to be wrong. By presenting to the decision-maker what is the acknowledged and stated basis for the risk description (i.e., the type X quantities), the extent to which tacit assumptions have been identified during the risk assessment (i.e., the type Y transformed into type X quantities), as well as the extent to which the uncertainty associated with non-fixed quantities is accounted for formally versus informally (i.e., the type Z versus type W quantities), the decision-maker is provided with one type of structured basis for evaluating the background knowledge of the analyst. Relevant questions to ask during such an evaluation are: Are any of the explicit assumptions seen as unreasonable? Does the number and nature of the type X quantities transformed from type Y quantities indicate that sufficient effort has been made to identify tacit assumptions? Are sufficient of the quantities, for which the associated uncertainty has been accounted for, accounted for in a formal manner?

As a screening tool, the categorisation and listing of uncertain quantities described above and illustrated in the bullet point list above can be extended to include explicit judgements by the risk analyst of his/her background knowledge, according to the assumption classification system described in Section 3.3.1 and as illustrated in Table 4. Table 4 provides the risk analyst with a format for reviewing and justifying the uncertainty treatment strategies chosen for the different uncertain quantities involved. For example, for the wind speed during gas leak quantity, S, the moderate/high sensitivity of the risk metric and the strong knowledge involved justifies treating S as a type Z quantity; cf. the assumption classification system described in Section 3.3.1. Such a presentation provides the decision-maker with a structured judgement of the background knowledge of the risk analyst. For the type Z and W quantities, the belief in deviation and the assumption deviation risk columns are not relevant, as these quantities are not fixed. Also, for type Z quantities, the sensitivity of the risk metric R can be directly assessed through the risk assessment model used, whereas this cannot be done for type W quantities, as these quantities do not explicitly enter the model. However, for both type Z

Table 4
Categorisation, listing and screening of uncertain quantities.

Type of quantity	Uncertain quantity	Belief in deviation (from $X = x_0$)	Sensitivity (of the risk metric R)	Strength of knowledge	Assumption deviation risk
Type X quantities not transformed from type Y quantities	Number of hours of hot work during production ($T = t_0$)	Low	Low	Strong	Low
	(Frequentist) probability of failure on demand of the gas detection system	Moderate/ High	Moderate/ High	Moderate/ Weak	High
Type X quantities transformed from type Y quantities	The per hour pressurised habitat hot work ignition probability ($r = p$)	Low	Low	Strong	Low
Type Z quantities	Wind speed during gas leak (S)	NA	Moderate/ High	Strong	NA
Type W quantities	Number of people in the process area during gas leak (J)	NA	NA	Moderate/ Weak	NA

and W quantities, the strength-of-knowledge assessment indicates whether it is reasonable or not to formally account for the associated uncertainty by means of probability distributions, considering the basis and justification for the distribution.

4. Summary and conclusions

Assumptions are made in all risk assessments. This makes risk assessment assumptions a foundational issue of relevance across different application areas. In the present paper, we describe a formal set-up for conceptualising assumptions in the context of quantitative risk assessment. We also illustrate the set-up using an example, discuss the key premises and outline some potential practical uses of the set-up and typology.

The set-up includes a general risk description/metric and links assumptions to the background knowledge of this description/metric. The set-up is based on a conceptualisation of assumptions as knowledge components and on a distinction between assumptions and associated uncertain quantities, where the assumptions are operationalised by fixing the associated quantities at specific values. The conceptualisation of assumptions as knowledge components allows for delineating assumptions from other parts of the background knowledge of the risk description/metric. Moreover, the distinction between assumptions and associated (fixed) quantities, as well as a broader typology of uncertain quantities introduced for the quantitative risk assessment context, allows for delineating explicit assumptions from tacit assumptions and delineating what is ‘closed’ versus what is kept ‘open’ in the risk assessment. Explicit and tacit assumptions are defined and delineated in terms of whether the assumption is openly stated and whether the link between the assumption and the fixed quantity is acknowledged by the risk analyst.

The premise of linking assumptions to the background knowledge of the risk description, and thus of seeing assumptions as knowledge, is discussed in the paper. The conclusion of this discussion and a main conclusion of the paper is that assumptions represent knowledge, understood as justified beliefs, noting that the belief may be a chosen belief from a set of possible beliefs, each supported by different (levels of) justifications, such as in the case of simplifying or conservative assumptions.

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Supplementary materials

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