

Towards an Evidence-Based Approach to Communicating Uncertainty in Intelligence

Analysis

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Towards an Evidence-Based Approach to Communicating Uncertainty in Intelligence Analysis

Intelligence products have a degree of uncertainty associated with them. This is typically expressed using linguistic probabilities (e.g., ‘likely’), and some organizations have adopted standardized lexicons for communicating uncertainty. This paper empirically shows that intelligence analysts use a wide heterogeneity of language to communicate uncertainty. This does not include all of the phrases in standardized lexicons used by the intelligence community. In addition, analysts may use some phrases differently to that advocated. Miscommunication of uncertainty can have deleterious effects on decision-making, and so standardization of uncertainty communication should be evidence-based. This paper discusses ways in which such evidence can be generated.

Keywords: intelligence analysis; uncertainty; probability

Introduction

Intelligence organizations are required to know and predict situations and events characterized by underlying epistemic (or internal) uncertainty – meaning that answers to questions are theoretically knowable but typically not fully known in practice¹. For instance, how many British citizens are currently fighting with Islamic State in Syria? What are the chances that the national electrical grid computer network will be compromised in the next 12 months? Efforts to answer intelligence questions are constrained by the fact that relevant data may be missing, data

collection may be biased, and data may be unreliable as well as purposefully misleading. Thus, the judgments of current and future situations and events provided in intelligence reports have a degree of uncertainty associated with them. This uncertainty is expressed using subjective probabilities.²

The effective communication of uncertainty is important. Customers of intelligence products (e.g., Government, defence, security and law enforcement) must make critical decisions based upon them, and so miscommunication of uncertainty can lead to poor outcomes (of even good analysis). In addition, cross-agency working and collaborative analysis necessitate reliance upon prior intelligence reporting, and so miscommunication of uncertainty can lead to compound errors in reporting. Erroneous and biased decisions that may result from the miscommunication of uncertainty have the potential to erode trust and confidence in intelligence products as well as undermine cross-agency working and collaborative analysis. In sum, it is critical that analysts convey the degree of uncertainty associated with their judgments in an unambiguous way.

Communication of Uncertainty in Intelligence Analysis

Typically, uncertainty in intelligence analysis is communicated using linguistic probabilities (e.g., ‘likely’, ‘very likely’), rather than numerically (e.g., percentages, probabilities). Indeed, research has demonstrated that people generally prefer to communicate the uncertainty in their judgments linguistically rather than numerically.³ This is particularly so when judgments are made under conditions of underlying epistemic uncertainty.⁴

Linguistic probabilities may be preferred because people find it is easier and more natural to use language rather than numbers, and because linguistic probabilities allow expression of judgment uncertainty.⁵ Friedman and Zeckhauser (2012) found that US intelligence analysts used

linguistic probabilities to indicate the degree of confidence in their conclusions. Barnes (2015) observed that Canadian analysts were reluctant to communicate uncertainty numerically for a number of reasons. These included the perceived difficulty in calculating a numerical value for events with underlying epistemic uncertainty; a concern that numeric estimates would mislead by providing a false sense of precision; and anxieties over numerical values being used to evaluate analytic performance because they can be easily tested (e.g., by the use of Brier scores).⁶

However, the use of linguistic probabilities can be problematic. Research demonstrates that there is considerable inter-individual variability in linguistic probability lexicons i.e., different people may use different phrases to refer to the same degree of uncertainty and/or they may use the same phrase to refer to different degrees of uncertainty.⁷ There is also sizeable intra-individual variability such that people have broad or fuzzy interpretations of phrases in their lexicons. Finally, research has revealed that the interpretation of linguistic probabilities may be affected by the context in which they are used.⁸ The context may be externally provided such as describing a military operation as being a potential success or failure⁹ or internal to the person such as his/her attitudes towards the phenomena being judged (e.g., ‘global climate change’¹⁰).

This has led some researchers and policy-makers to suggest that the use of linguistic probabilities should generally be avoided or minimized.¹¹ One proposed alternative approach eschews both numbers and language, in favor of communicating uncertainty visually.¹² For example, a ‘fuzzy’ pie chart can be used illustrate the subjective probabilities associated with alternative outcomes by dividing the pie into sections for each outcome and then shading each section in a color (such as black) so that it fades (e.g., into grey and then white); whereby the degree of fading represents increasing uncertainty.¹³

The most commonly recommended alternative approach is to communicate uncertainty numerically.¹⁴ This can be done in various ways, including using numerical point values that are precise (e.g., .85 or 85%) or imprecise (e.g., 75% plus or minus 10% or 65% to 85%).

However, given the aforementioned preference for communicating uncertainty linguistically, some proposed approaches retain the use of linguistic probabilities. It is suggested that organizations should adopt a standardized lexicon for communicating uncertainty using linguistic probabilities.¹⁵ This refers to a list of selected phrases ordered from those representing the lowest to the highest degree of uncertainty (i.e., 0% to 100% or 0 to 1). An approach that builds upon this combines the selected phrases such as ‘very likely’ with numerical values which may be point estimates such as 80% or ranges such as 70% to 90%.¹⁶

Finally, some have suggested that organizations could implement a specially designed translation tool that converts phrases from one person’s lexicon to another person’s.¹⁷ For instance, when Person A uses the lowest ranked phrase in her lexicon to communicate the likelihood of an event occurring to Person B, the tool would translate this into the equivalent (lowest) ranked phrase in Person B’s lexicon.

Perhaps unsurprisingly, the intelligence community has opted for approaches that retain the use of linguistic probabilities. Specifically, some organizations have adopted a standardized uncertainty lexicon. Sherman Kent (1964), a director and scholar of intelligence analysis, was the first to advocate such an approach. His proposed seven-category lexicon included phrases associated with numerical point values and ranges. However, Kent’s proposal was not adopted by the CIA (for whom he worked) or other intelligence organizations at the time. In more recent years, organizations have been prompted to reconsider the use of standardized lexicons, partly in

response to the invasion of Iraq that was later regarded as having been based on misleading intelligence about the presence of weapons of mass destruction.¹⁸

Standardized lexicons were introduced in the mid-2000s by the National Intelligence Council (NIC) in the US and by Defence Intelligence (DI) in the UK. Table 1a shows the most recent version of the NIC lexicon¹⁹ and Table 1b shows the current version of the DI lexicon²⁰. As can be seen, the NIC lexicon comprises seven categories containing a total of 14 phrases that represent numerical values from 1% to 99%. Each category contains two phrases that are meant to be fully interchangeable. Two phrases are used to represent a broad midpoint of the numerical scale (i.e., 45% to 55%). The categories cover different numerical ranges (i.e., from 5% points to 25% points), and so analysts are forced to use some parts of the uncertainty scale in a less precise way than other parts. Each category slightly overlaps with the next, thus potentially making it difficult for analysts to select specific phrases when communicating uncertainty at the top or bottom points of a category.

INSERT TABLES 1A AND 1B HERE

The DI lexicon comprises six categories containing a total of 10 phrases that represent numerical values from 0% to 100%. Some categories contain two phrases which are meant to be fully interchangeable. There is no language to represent some parts of the uncertainty scale (e.g., 11% to 14%), including the midpoint, thus potentially forcing analysts to distort their communication of uncertainty by making their judgments fit with other parts of the uncertainty scale. As with the NIC lexicon, the categories cover different numerical ranges.

Unfortunately, the standardized lexicons advocated by Kent, the NIC and DI have not been informed by empirical evidence (it is notable that Barnes [2015] developed a lexicon for a Canadian intelligence unit based on a review of research on the use of linguistic probabilities).

The value of lexicons that are not evidence-based may be limited. In particular, it is unclear if the phrases in the lexicons are those that would normally be used by analysts to communicate uncertainty i.e., language they are familiar with and comfortable using. It is unclear if analysts would consider phrases to be substitutable as advocated in the lexicons. It is also unclear if analysts would use the phrases in the lexicons as intended i.e., to communicate the degree of numerical uncertainty associated with them. Finally, given that there are some gaps in the numerical values associated with certain categories of phrases in the DI lexicon, it is unclear what language analysts would use to communicate uncertainty representing these gaps.

Past Research on Intelligence Analysts' Uncertainty Language

There is a small body of research on how uncertainty is communicated by intelligence analysts. Freidman and Zeckhauser (2012) conducted a content analysis of 379 declassified National Intelligence Estimates (NIEs; US intelligence reports) written between 1964 and 1994. They found that analysts confounded likelihood judgments with judgments of confidence. Only four percent of the NIEs contained numerical expressions of uncertainty (e.g., percentages, odds). Eighteen percent did not provide any assessment of the uncertainty associated with the outcome being forecast. Freidman and Zeckhauser (2012), however, did not identify the specific phrases that analysts used to communicate uncertainty.

In an unpublished Masters' thesis, Kesselman (2008) searched the contents of NIEs written between the 1950s and 2000s. She counted the occurrence of an a priori list of 50 words and 13 phrases (e.g., 'will' and 'almost certainly', respectively), including the phrases in the NIC's original lexicon. This revealed trends in language used across the decades. For instance, the use of 'likely' increased from the 1950s to 1990s, the use of 'probably' decreased over time,

whereas the popularity of ‘impossible’ was fairly constant. Historically, ‘will’, which can be interpreted as representing a high degree of certainty, was the most commonly used word by analysts. ‘Fifty-fifty’ did not appear in any of the NIEs, and phrases such as ‘even chance’, ‘very likely’ and ‘very unlikely’ were not particularly common. Kesselman (2008) also noted that the phrases in the NIC’s lexicon were not all commonly used by analysts in the NIEs. Overall, there was considerable variability in the language used to communicate uncertainty. By only searching for an a priori list of words and phrases, however, Kesselman (2008) was unable to identify the full variety of language that analysts use to communicate uncertainty.

Although the external validity of a content analysis of actual intelligence reports is high, this methodology is limited because it does not enable researchers to determine how analysts numerically interpreted their phrases, unless they also provided numerical values in the reports. The preference for communicating uncertainty linguistically rather than numerically suggests that this will be relatively uncommon. In fact, even under the circumstances when analysts are required to produce numerical values, these are typically not presented in the final intelligence report.²¹ Therefore, an alternative method for studying the language that analysts use to communicate uncertainty is warranted.

Methods for Measuring Numerical Interpretations of Linguistic Probabilities

Mathematical psychologists and decision scientists, Thomas Wallsten and David Budescu, have developed several methods for eliciting people’s lexicons for communicating uncertainty, as well as measuring how people numerically interpret linguistic probabilities.²² The methods (to be described below) are based on Wallsten and Budescu’s (1995) theory of linguistic probabilities.²³ This borrows from Zadeh’s (1965) theory of fuzzy sets in mathematics, and states that phrases

such as ‘very likely’ can be represented as fuzzy subsets of the 0 to 1 probability interval (or 0% to 100% percentage scale).

Wallsten, Slomi and Ting (2008) used the method of eliciting individuals’ ‘probability signatures’ in their study of the language used by 119 CIA intelligence analysts to communicate uncertainty. This method was developed by Dhami and Wallsten (2005) and validated by Wallsten and Jang (2008). In Wallsten et al.’s study, analysts were first asked to list the phrases in their linguistic probability lexicons (with the size of the lexicon a priori limited from three to 12). They were next asked to rank order their phrases from those representing the lowest to highest degree of (un)certainty. Then, analysts were asked to use their rank ordered phrases to describe the chances of a pointer landing on red in a spinner (or probability wheel) radially divided into red and black (analysts could use more than one phrase). The proportions of red randomly varied in 1% increments from 0% to 100%, and so participants responded to 101 spinners. Each phrase is thus associated with a probability distribution.

Wallsten et al. found that the average lexicon size across analysts was eight. The most commonly used phrases that appeared in approximately 70 analysts’ lexicons were ‘likely’ and ‘unlikely’. There was considerable inter-individual variability such that 119 analysts used 170 distinct phrases, and the rank ordering of these within lexicons varied by lexicon size. By contrast, there was much less intra-individual variability suggesting that individual analysts used phrases consistent with their rank order. This study therefore reveals both the language that analysts use to communicate uncertainty as well as their numerical interpretation of specific phrases.

Most recently, Ho, Budescu, Dhami and Mandel (2015) used the ‘multi-stimuli membership function’ method to study Canadian and UK intelligence analysts’ use of the NIC

and DI lexicons. The method was developed by Karelitz et al. (2000) and validated by Karelitz and Budescu (2004) and Dhami and Wallsten (2005). It involves presenting individuals with a series of scales that each correspond to a numerical value in ascending order from 0% to 100%. The number of scales depends on the intervals used (e.g., employing 10% intervals results in 11 scales). Each scale consists of 21-points, and is labeled at each end from ‘*not at all*’ to ‘*absolutely*’. Participants are asked to determine how well they think each numerical value (e.g., 0%, 10% etc.) substitutes for a specific phrase (e.g., likely). Responses are provided by circling one of the 21 points on each scale. This method yields several measures, namely the ‘minimum’ and ‘maximum’ values that can be substituted for a phrase to some degree, the ‘peak’ value that absolutely substitutes for a phrase, and the ‘spread’ of values that can be substituted for a phrase. In Ho et al.’s study, a total of 61 analysts were each asked to rate the extent to which specific numerical values (from 0% to 100%, in 10% intervals e.g., 0%, 10%) could be substituted for phrases in the NIC and DI lexicons. For example, “To what extent, from *not at all* to *absolutely*, does 90% substitute for ‘likely’?” “To what extent, from *not at all* to *absolutely*, does 90% substitute for ‘very probable’?” and so on.

Ho et al. found that the ordering of phrases was similar to that in the NIC and DI lexicons. In addition, some of the phrases considered to be interchangeable in the NIC and DI lexicons (i.e., remote chance/very unlikely, probably/likely, and very likely/almost certain) were numerically indistinguishable. However, the numerical interpretation of phrases differed from that advocated by the NIC and DI.

The Present Study

The main aim of the present paper is to illustrate how an evidence-based approach can be used to inform the development of a standardized lexicon for communicating uncertainty. The study presented identifies the language that intelligence analysts use to communicate specific degrees of numerical uncertainty (e.g., 70%) by adopting a simpler method than that employed by Wallsten et al. (2008). The present study uses the ‘spinner’ task developed by Wallsten (1971). Variants of this task have been used to reliably and validly study peoples’ perceptions and communication of uncertainty.²⁴

The present study had three specific objectives. One was to measure the size of analysts’ uncertainty lexicons. A second objective was to examine the variety of language used by analysts. The third objective was to explore consistency in analysts’ use of phrases.

In addition to the above, the present paper suggests that the spinner method can be used to empirically evaluate existing standardized lexicons and offer suggestions for their improvement. Although this was not the main aim of the present study, an illustration is provided to this effect by comparing the phrases in analysts’ lexicons with those in the NIC and DI lexicons.

Method

Participants

A sample of 26 practicing intelligence analysts participated in the study. They were drawn at random from one UK intelligence organization (see below for more details). Fifty percent were male. The average age of the sample was 38.54 years ($SD = 11.18$). Eighty-one percent of the sample worked as analysts on a full-time basis. Fifteen percent of the sample described their

current analyst reporting skill level as ‘novice/awareness’, 26.9% as ‘fundamental’, 26.9% ‘practitioner’, and 30.8% as ‘expert’. Across the sample, the average number of years of experience working in the intelligence community was 9.73 years ($SD = 9.23$, range = .67 to 34).

Spinner Task

The phrases analysts use to communicate uncertainty were elicited using a spinner task. In the present study this involved presenting analysts with 11 circles radially divided into two sectors of different color (i.e., grey and black), over which a theoretical pointer can be spun, coming to a random stop. The proportion of area shaded black ranged from 0% to 100%, with 10% intervals (hence 11 circles). Although 10% intervals provide a cruder measure than 1% intervals, the former is less time-intensive.

For each spinner, analysts were asked to state in words (and not numbers) what they thought were the chances of the pointer landing on black. Analysts were told that they could use the same phrase more than once if they needed to (see Appendix). This task, therefore, reveals the precise language that analysts use to communicate specific degrees of uncertainty. For example, it is taken that an analyst uses the phrase ‘highly probable’ to represent 90% if she uses this phrase when stating the chances of a pointer landing on black in a circle where 90% is shaded black.

Procedure

The intelligence organization provided a sampling frame of analysts who were formally responsible for writing reports. A sample of 60 analysts was selected at random to participate. They were contacted individually by the author, and told the purpose of the study, that it was unclassified, that they were chosen at random, that their participation was voluntary, and that there were no negative consequences for those who chose not to participate. The response rate

was 43%. Most of the non-respondents were those whose automatic 'out of office' reply indicated that they would be away during the study period. A few non-respondents replied to say they were no longer formally responsible for writing reports or that their current work commitments precluded them from participating during the study period.

Analysts completed the study online, during their normal workday, over the two-week study period. The spinner task was presented before questions asking about the analysts demographic details (e.g., age, experience etc).

The proportions of black in the spinner task were presented in three different orders, which were designed so that one version presented higher values before lower ones (i.e., order A = 90%, 100%, 70%, 80%, 50%, 60%, 30%, 40%, 10%, 20%, and 0%). Another version presented mid and extreme values before intervening ones (i.e., order B = 50%, 0%, 100%, 10%, 90%, 80%, 20%, 70%, 30%, 60%, and 40%). A third version presented lower values before higher ones (i.e., order C = 10%, 0%, 30%, 20%, 50%, 40%, 70%, 60%, 90%, 80%, and 100%). The version presented was counter-balanced across analysts so that, for example, the first analyst contacted was sent order A, the second was sent order B, the third was sent order C, the fourth was sent order A, and so on. An inspection of the data revealed no systematic order effects. The study took approximately 15 minutes to complete.

Findings

The analyses and findings are presented below in order of the objectives of the research.

Size of Analysts' Uncertainty Lexicons

The size of the lexicons (i.e., number of phrases) used by individual analysts ranged from eight to 19 with a mean of 10.19 ($SD = 2.55$).

Variety of Language Used by Analysts to Communicate Uncertainty

Table 2 presents the phrases used by analysts to represent each degree of numerical uncertainty from 0% to 100%, in 10% intervals. In total, 160 phrases were used. Some of these phrases may be considered variants of each other (e.g., no possibility/not possible; a possibility/possible; less likely/less likely than the alternative; equal/equal chance; even/an even chance; half/half and half; possible/possibly; probable/probably; certain/certainly/certainty; definite/definitely).

Excluding variants, across analysts, 145 unique phrases were used to represent the 0% to 100% uncertainty interval.

INSERT TABLE 2 HERE

The number of phrases used across analysts to represent each 10% interval of uncertainty is shown in Table 3. When excluding variants, there was slightly less variety of language or fewer phrases used by analysts to describe the end-points (0% and 100%) and mid-point (50%) of the uncertainty scale, than the intervening points. The number of unique phrases used to describe each 10% interval ranged from six (representing 100%) to 18 (representing 10%).

INSERT TABLE 3 HERE

Forty-eight phrases appeared more than once (i.e., by being used more than once by an analyst or being used by more than one analyst). Thirty-nine of the 48 phrases appeared in more than one analyst's lexicon – in other words they were 'mutual'. As Table 4 shows, half of the analysts used 'likely' and more than half (i.e., 58%) used 'certain' and 'unlikely'. Twenty-one of the 48 phrases that appeared more than once either within or across analysts' lexicons, were used to represent the end- and mid-points of the uncertainty scale.

INSERT TABLE 4 HERE

Consistency in Analysts' Use of Phrases

Of the 48 phrases that appeared more than once either within or across analysts' lexicons, 21 were used to represent only one value. For example, 'impossible', 'no possibility/not possible', 'nil', 'non-existent', 'none' and 'no chance' were all used to represent 0% only. '50/50', 'as likely as not', 'equal/equal chance', and 'even/an even chance' were all used to represent 50% only. 'Certain/certainty/certainly' and 'definite/definitely' were used to represent 100% only. The remaining 27 phrases were used to represent values that ranged from 10% to 50% points. For example, as Table 5 shows, 'highly unlikely' was used to represent 10% and 20%. 'Possible' was used to represent 10%, 20%, 30%, 40%, 50%, and 60% (see Table 5).

INSERT TABLE 5 HERE

Comparing Analysts' Lexicons and Existing Standardized Lexicons

In the present study, analysts were asked which language they would use to represent uncertainty in 10%-point intervals, whereas the NIC and DI lexicons contain phrases that in addition to representing 10%-point intervals also represent 5%-point, 15%-point and 25%-point intervals. Thus, a comparison of the phrases in analysts' lexicons with those in the standardized lexicons is necessarily limited for some parts of the NIC and DI lexicons. Nevertheless, a comparison can illustrate how data collected via the spinner method may be used to evaluate existing standardized lexicons.

Table 6 shows the proportion of analysts who used phrases in the current NIC and DI lexicons. Some phrases (i.e., 'almost no chance', 'highly improbable', 'roughly even chance', 'roughly even odds', 'realistic possibility', 'nearly certain') were not used by any of the analysts. By contrast, other phrases in the NIC and DI lexicons (i.e., 'unlikely', 'likely') appeared in approximately half of the analysts' lexicons.

INSERT TABLE 6 HERE

For those analysts who used phrases contained in the current NIC and DI lexicons, Tables 7a and 7b show a comparison of how analysts used the phrases and how the NIC and DI advocate their usage. According to Table 7a, there were several points of divergence between analysts' use of phrases and that advocated by the NIC.

INSERT TABLES 7A AND 7B HERE

Discussion

Analytic judgments about current or future threats can contribute to consequential decisions about national and international security. The fact that analytic judgments have a degree of uncertainty associated with them suggests that it is imperative that this uncertainty is communicated in an unambiguous way. The effective communication of uncertainty can help customers of intelligence products make informed decisions. It can also enable other analysts to build appropriately upon prior intelligence reports. The present paper illustrates how an evidence-based approach can be used to inform the development and evaluation of standardized lexicons for communicating uncertainty in the intelligence community.

The findings of the present study can be discussed in light of the small body of past research on intelligence analysts' uncertainty language, as well as in relation to the existing policies for communicating uncertainty in some intelligence organizations as the NIC in the US and DI in the UK. There were some similarities and differences between the present findings and the findings of past research. For instance, the small, but representative sample of analysts in the present study had a somewhat larger lexicon size than that found by Wallsten et al. (2008).

The present study demonstrated considerable variety in the phrases that analysts' use to describe uncertainty in line with Wallsten et al. (2008) and Kesselman (2008). As in Wallsten et

al.'s (2008) study, 'likely' and 'unlikely' were also some of the most commonly used phrases by analysts in the present study. The popularity of 'likely' in the present study reflects Kesselman's (2008) observation of its increased use in recent years, whereas the popularity of 'impossible' reflects its continued use over time. Similarly, the less common use of 'probably' among analysts in the present study concurs with Kesselman's (2008) reports of the decreased use of this phrase over time. However, the use of 'will' was much less common in the present study than in Kesselman's study, and 'very unlikely' was more common.

Finally, akin to the findings of Ho et al. (2015), we found that analysts' numerical interpretation of phrases in the NIC and DI lexicons differed to that advocated by the NIC and DI, although the ordering of phrases was somewhat similar. By contrast to Ho et al. (2015), however, the phrases considered to be interchangeable in the NIC and DI lexicons were typically not interpreted as such by analysts in the present study.

It could be argued that the wide heterogeneity of uncertainty language used by analysts in the present study underscores the need for a standardized lexicon to communicate uncertainty. In addition, the fact that approximately a third of the phrases in the NIC lexicon and one of the phrases in the DI lexicon (that represents a quarter of the uncertainty scale) were not used by any of the analysts, reinforces the importance of using an evidence-based approach to the development of such standardized lexicons.

Indeed, although the comparison of phrases in the analysts' lexicons with those in the NIC and DI lexicons is limited, the present study demonstrated several potential inconsistencies in how analysts communicate uncertainty and how intelligence organizations such as the NIC and DI currently mandate it should be communicated. Future research can use the spinner method to conduct a more precise comparison which can be used to evaluate several aspects of

the existing lexicons. For instance, whether analysts' use of specific phrases falls within or outside the advocated ranges, and if outside, whether the phrase is used to represent a greater or lesser degree of (un)certainty. Another aspect that can be considered is if analysts do indeed use those phrases that are deemed inter-changeable as such. Finally, a comparison can reveal any discrepancies in the rank order of phrases as used by analysts and the order of these phrases in the existing lexicons.

Potential Recommendations for Improving Existing Standardized Uncertainty Lexicons

Although further, larger-scale research is necessary, the present findings point to several potential ways in which the standardized uncertainty lexicons can be improved. First, it was found that analysts' average lexicon size is more than the seven and six-category lexicons currently used by the NIC and DI, respectively. This suggests that these lexicons could be expanded, and doing so would render a somewhat more precise communication of uncertainty because the numerical ranges associated with each phrase would be smaller.

Second, the numerical ranges associated with each category of phrases should be of equal size. This means that analysts would be able to communicate uncertainty across the whole 0% to 100% with the same degree of precision. Currently, there is greater opportunity for precision at the top and bottom of the scale than the middle.

Third, analysts were less likely to agree on the phrases to be used to communicate uncertainty between the intervening points of the bottom, middle and top of the uncertainty scale. Thus, it may be necessary to use multiple phrases for these intervening points on the scale (e.g., those from 10-40% and 60-90%). The NIC and DI lexicons currently have approximately two phrases for these points, and more may be warranted. Indeed, it has been argued that providing interchangeable phrases or synonyms allows for stylistic expression in intelligence reports.²⁵ It is

of course important to ensure that interchangeable phrases are actually interchangeable in the minds of analysts.

Fourth, although a comparison between the analysts' lexicons and the NIC and DI lexicons is limited, it was found that analysts did not use the phrases 'roughly even chance' and 'roughly even odds' which appear in the NIC lexicon. This is of concern because both of these phrases is used to represent the mid-point of the uncertainty scale. Similarly, the phrase 'realistic possibility' which covers the mid-point of the uncertainty scale in the DI lexicon did not appear in any of the analysts' lexicons. This phrase is used by DI to represent a quarter of the scale (i.e., from 25% to 50%). Barnes (2015, p. 11) "banned" the use of this phrase in his Canadian military intelligence unit because it is a compound probability. Thus, the current NIC and DI lexicons contain language not used by analysts to communicate uncertainty, potentially leaving large and important portions of the uncertainty scale open to the use of other language or avoided altogether. Based on the present findings, potential phrases that could be used to represent the mid-point of the scale are 'even chance', 'as likely as not', and 'equal chance'. These phrases not only appeared more than once either across- or within-analysts, but were also invariable – they were only used to represent one value i.e., 50%.

Fifth, although some phrases in the existing NIC and DI lexicons (i.e., 'unlikely' and 'likely') were more commonly used amongst analysts in the present study, these also demonstrated variability. 'Unlikely' represented from 10% to 40% and 'likely' represented from 60% to 80%. Research also suggests that negatively worded phrases such as unlikely should be avoided because they are interpreted with greater variability than positively worded phrases (e.g., likely).²⁶ Another phrase to avoid is 'possible', because although this was a phrase used by more than one analyst and has many variants, it represents too wide a range of uncertainty (i.e., 10% to

60%). It would be prudent to select phrases that demonstrate less variability in their usage. In the present study, these were phrases such as ‘impossible’ and ‘certain’.

Barriers to Standardized Uncertainty Lexicons

There are several potential barriers to the successful development and implementation of a standardized uncertainty lexicon, and future research is needed to deal with these challenges. One barrier is that standardization is problematic because people find it difficult to suppress their normal meanings of linguistic probabilities i.e., how they would use a phrase in an everyday context such as talking about the weather.²⁷ An evidence-based approach to the development of a standardized lexicon may overcome this challenge i.e., selecting phrases that are not only commonly used across people, but are also used in the same way as do people, and with little variability in their usage by people. In addition, research could examine ways in which analysts can be trained to use a standardized lexicon. Furthermore, the technology employed by analysts when producing their reports could be designed to aid and guide them in using a standardized lexicon.

Another barrier is that linguistic probabilities can be subject to context effects²⁸, and be prone to self-serving interpretations²⁹, as well as interpretations affected by one’s attitudes to the subject matter.³⁰ Further research ought to be directed at examining how specific intelligence contexts (e.g., the affirmation or negation of an event, the base-rate of an event, or the severity of an outcome) can affect the interpretation of phrases in a standardized lexicon. Mandel (2015) recently reported that a combined sample of intelligence analysts and university students had higher numerical interpretations of linguistic probabilities when they were used to describe a negative outcome rather than a positive one (i.e., a military operation failing v. succeeding). Research could also examine how interpretations of phrases in a standardized lexicon are

affected by relevant attitudinal variables (e.g., for or against military interventions), and analysts could be made aware of such biases. Overall, phrases whose usage is less sensitive to context effects ought to be selected for inclusion in standardized lexicons.

Finally, the discrepancies in standardized lexicons used by different intelligence organizations means that they might employ different phrases to represent the same numerical values and/or the same phrase to represent different numerical values. This can lead to misunderstanding and miscommunication across agencies, and so a standardized lexicon that can be used across agencies is preferable. Since there are cultural differences in language use³¹, research ought to be conducted across intelligence organizations in countries that routinely share intelligence reports in order to develop a ‘universally’ useful standardized system.

Beyond the directions for future research identified above, studies should also examine the communication of uncertainty in the context of the ‘big picture’. For instance, the existing NIC and DI lexicons ought to be evaluated from the perspective of the consumer of intelligence products. Mandel (2015) recently found that the average meaning assigned by consumers (in this case, students) to the probability phrases used by a Canadian intelligence unit corresponded well to the intended meaning. It is currently unknown if real consumers of intelligence products employing phrases from the NIC and DI lexicons would correctly understand the degree of uncertainty being communicated. Relatedly, research could also examine the effects of miscommunication (e.g., in terms of errors in decision-making, erosion of trust, and reputational damage, etc.).

Concluding Remarks

The approach of using a standardized uncertainty lexicon that contains a list of ordered phrases which map onto numerical values is essentially a compromise between those in the intelligence community who hold dear to their preference for communicating uncertainty linguistically and critics who argue that uncertainty in the intelligence domain should be communicated numerically. At some point in the future, attitudes and preferences may change, and so analysts may feel comfortable using numerical estimates. Amongst the many advantages of the numerical approach is that it affords scrutiny of intelligence products in terms of evaluating the accuracy of analytic judgments.³² For instance, Mandel and Barnes (2014) used a widely accepted quantitative procedure involving Brier scores (which can be partitioned into components measuring calibration and discrimination) to assess the accuracy of analysts' forecasts. Such scrutiny can ultimately increase the intelligence community's sense of accountability.³³ In the meantime, the development of a standardized lexicon ought to be informed by research demonstrating how analysts as well as people generally numerically interpret linguistic probabilities. The present paper provides an illustration of how such research evidence can be gathered.

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Table 1a. Standardized uncertainty lexicon used by the US National Intelligence Council

Phrase	Numerical value (%)
Almost no chance/remote	1-5
Very unlikely/highly improbable	5-20
Unlikely/improbable (improbably)	20-45
Roughly even chance/roughly even odds	45-55
Likely/probable (probably)	55-80
Very likely/highly probable	80-95
Almost certain(ly)/nearly certain	95-99

Table 1b. Standardized uncertainty lexicon used by UK Defence Intelligence

Phrase	Numerical value (%)
Remote/Highly unlikely	< 10
Improbable/Unlikely	15-20
Realistic Possibility	25-50
Probable/Likely	55-70
Very probable/Highly likely	75-85
Almost certain	> 90

Table 2. Phrases used by analysts to represent 0-100% uncertainty

Uncertainty value (%)	Phrases*
0	Certain not to occur, definitely not, impossible, negative, nil, no chance, <i>no possibility</i> , none, non-existent, <i>not possible</i> , virtually non-existent, without doubt, zero
10	Doubtful, highly unlikely, low, low probability, minimal, possible, probably but not possible, remote, slim, slim but still possible, slim possibility, small, unlikely, unlikely but possibly, very low likelihood, very slight, very small, very unlikely
20	A little chance, <i>a possibility</i> , highly unlikely, low but still possible, low possibility, maybe, not very likely, <i>possible</i> , possible but unlikely, significantly less than alternative, slight, small, unlikely, unlikely but not improbable, unlikely but possibly, very unlikely
30	A possibility, improbable, <i>less likely</i> , <i>less likely than the alternative</i> , low, more likely, not probable, plausible, poor but still possible, possible, possible but less likely than not, probably not, reasonable, significantly less than alternative, some chance, unlikely
40	Almost as likely as not, fair, good chance, highly possible, improbable, just under half, less likely, marginally less likely than not, more likely than not, possible, possible but unlikely, probably not, reasonably likely,

	slightly less likely than the alternative, somewhat less than alternative, strong possibility but less likely, unlikely
50	50/50, <i>an even chance</i> , as likely as not, <i>equal, equal chance</i> , equally likely, equally likely as unlikely, <i>even, half, half and half</i> , medium chance, mixed, <i>possible</i> , possible either-way, <i>possibly</i> , undecided
60	Fair, just above average chance, likely, marginally more likely than not, more likely than not, more than likely, over half, <i>possible, possibly, probable, probably</i> , quite likely, reasonably likely, slightly more likely than the alternative, somewhat greater than alternative
70	Fairly likely, good, greater chance, likely, more likely than not, more likely than the alternative, more than likely, <i>probable, probably</i> , quite likely, significantly greater than alternative, very likely
80	Greater likelihood, high, high but not certain, highly likely, highly probable, large, likely, more likely than not, more likely than the alternative, more than likely, <i>probable, probably</i> , quite likely, significantly greater than alternative, very likely
90	Almost certain, extremely likely, highly likely, highly probable, <i>probable, probably</i> , significant, significantly high, very great, very high chance, very likely, very likely but not certain, very probable
100	Absolutely certain, <i>certain, certainly, certainty, definite, definitely</i> , definitely will, overwhelming, will

Note. * Phrases in italics may be considered variants of one another.

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Table 3. Number of unique phrases used to represent each degree of uncertainty

Uncertainty value (%)	Number of unique phrases (excluding variants)
0	13 (12)
10	18
20	16 (15)
30	16 (15)
40	17
50	16 (12)
60	15 (13)
70	12 (11)
80	15 (14)
90	13 (12)
100	9 (6)

Table 4. Proportion of analysts using the 39 ‘mutual’ phrases

Mutual phrases	Analysts (%)
As likely as not, certainty, definite, definitely, improbable, low, no possibility, not possible, not very likely, possible but unlikely, reasonably likely, very probable	8
50/50, almost certain, certainly, highly probable, less likely, more than likely, none, non-existent, probably, slim	12
More likely than not, nil, small chance, very unlikely	15
Equal, even chance, highly unlikely, no chance	19
Highly likely, quite likely	27
Impossible, probable	35
Very likely, possible	39
Likely	50
Certain, unlikely	58

Table 5. Variability in analysts' use of the 48 phrases that appeared more than once (see bolded)

Uncertainty (%)	Phrases*
0	Impossible, nil, no chance, <i>no possibility</i> , none, non-existent, <i>not possible</i>
10	Highly unlikely, low, possible, slim, small, unlikely, very unlikely
20	Highly unlikely, not very likely, <i>possible</i>, possible but unlikely, small, unlikely, very unlikely
30	Improbable, <i>less likely</i>, low, possible, unlikely
40	Improbable, less likely, more likely than not, possible, possible but unlikely, reasonably likely, unlikely
50	<i>Even chance, as likely as not, equal, possible</i>
60	Likely, more likely than not, more than likely, <i>possible, probable, probably, quite likely, reasonably likely</i>
70	Likely, more likely than not, more than likely, <i>probable, probably, quite likely, very likely</i>
80	Highly likely, highly probable, likely, more likely than not, <i>probable, probably, probably, quite likely, very likely</i>
90	Almost certain, highly likely, highly probable, <i>probable, probably, very probable</i>
100	<i>Certain, certainly, certainty, definite, definitely</i>

Note. * Phrases in italics may be considered variants of one another.

Table 6. Proportion of analysts using phrases in the NIC and DI lexicons

Phrase in NIC lexicon	Phrase in DI lexicon	Analysts (%)
Almost no chance		0
Remote	Remote	4
	Highly unlikely	19
Very unlikely		15
Highly improbable		0
Unlikely	Unlikely	58
Improbable (improbably)	Improbable	8
Roughly even chance		0
Roughly even odds		0
	Realistic possibility	0
Likely	Likely	50
Probable (probably)	Probable	35
Very likely		39
Highly probable		12
	Highly likely	27
	Very probable	8
Almost certain(ly)	Almost certain	12
Nearly certain		0

Table 7a. Comparison between analysts' use of phrases and NIC lexicon

Phrase	Numerical value in analysts' lexicon (%)	Numerical value in NIC lexicon (%)
Almost no chance*	--	1-5
Remote	10	1-5
Very unlikely	10-20	5-20
Highly improbable*	--	5-20
Unlikely	10-40	20-45
Improbable (improbably)	20-40	20-45
Roughly even chance*	--	45-55
Roughly even odds*	--	45-55
Likely	60-80	55-80
Probable (probably)	60-90	55-80
Very likely	70-90	80-95
Highly probable	80-90	80-95
Almost certain(ly)	90	95-99
Nearly certain*	--	95-99

Note. *This phrase did not appear in any of the analysts' lexicons.

Table 7b. Comparison between analysts' use of phrases and DI lexicon

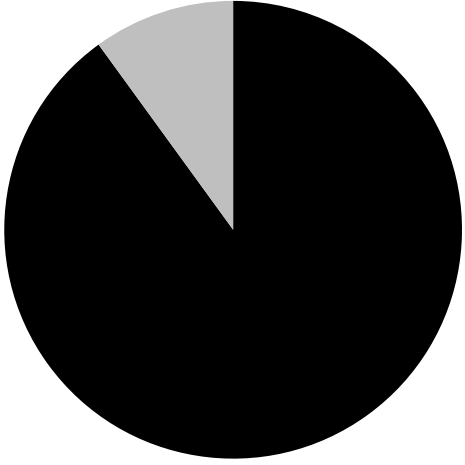
Phrase	Numerical value in analysts' lexicon (%)	Numerical value in DI lexicon (%)
Remote	10	<10
Highly unlikely	10-20	<10
Improbable	30-40	15-20
Unlikely	10-40	15-20
Realistic possibility [*]	--	25-50
Probable	60-90	55-70
Likely	60-80	55-70
Very probable	90	75-85
Highly likely	80-90	75-85
Almost certain	90	>90

Note. ^{*} This phrase did not appear in any of the analysts' lexicons.

Appendix

When communicating uncertainty about various events (e.g., terrorist attacks etc), people often use probability phrases such as “likely”. We are studying the way analyst reporters use and understand these phrases. Can you please respond to the 11 questions below. Your responses are anonymous.

Imagine a pointer in the middle of the circle that a machine can spin. **Without** using numbers, please state in words what you think are the chances of the pointer landing on **black**? You may use the same phrase more than once if you need to.

The chances of landing on black are:	
--------------------------------------	--

¹ Hacking, *The Emergence of Probability*, 1975; Kahneman and Tversky, *Cognition*, 1982.

² Weiss, *International J. of Intelligence and CounterIntelligence*, 2007.

³ For example, Brun and Teigen, *Organizational Behavior and Human Decision Processes*, 1988; Erev and Cohen, *Organizational Behavior and Human Decision Processes*, 1990; Wallsten, Budescu, Zwick, and Kemp, *Bulletin of the Psychonomic Society*, 1993.

⁴ Olson and Budescu, *J. of Behavioral Decision Making*, 1997.

⁵ Wallsten et al., 1993 at note 3.

⁶ See Mandel and Barnes, *Proceedings of the National Academy of Sciences*, 2014.

⁷ For example, Budescu, Weinberg, and Wallsten, *J. of Experimental Psychology: Human Perception and Performance*, 1988; Dhami and Wallsten, *Memory and Cognition*, 2005; Erev and Cohen, *Organizational Behavior and Human Decision Processes*, 1990; Karelitz and Budescu, *J. of Experimental Psychology: Applied*, 2004; Zwick and Wallsten, *International J. of Man-Machine Studies*, 1989.

⁸ For example, Budescu, Por, and Broomell, *Climate Change*, 2011; Harris and Corner, *J. of Experimental Psychology: Learning, Memory and Cognition*, 2011; Mandel, *Policy Insights from the Behavioral and Brain Sciences*, 2015; Smithson, Budescu, Broomell, and Por, *International J. of Approximate Reasoning*, 2012; Wallsten, Fillenbaum, and Cox, *J. of Memory and Language*, 1986; Weber and Hilton, *J. of Experimental Psychology: Human Perception and Performance*, 1990.

⁹ Mandel, 2015 at note 8.

¹⁰ Budescu et al., 2011 at note 8.

¹¹ For example, Friedman and Zeckhauser, *Intelligence and National Security*, 2014; von Winterfeldt and Edwards, *Decision Analysis and Behavioral Research*, 1986.

¹² For example, Weiss, 2007 at note 2.

¹³ See also Barnes, *Intelligence and National Security*, 2015.

¹⁴ For example, Dhami, Mandel, Mellers, and Tetlock, *Perspectives on Psychological Science*, 2015; Friedman and Zeckhauser, *Intelligence and National Security*, 2015, *Intelligence and National Security*, 2016; Friedman et al., "The Value of Precision...", 2015; Mandel, 2015 at note 8.

¹⁵ For example, Barnes, 2015 at note 13; Kent, "Words of Estimative Probability", 1964.

¹⁶ For example, Barnes, 2015 at note 13; Budescu et al., 2011 at note 8; Budescu, Por, Broomell, and Smithson, *Nature Climate Change*, 2014; Dhami, *J. of Applied Psychology: Applied*, 2008; Hamm, *Organizational Behavior and Human Decision Processes*, 1991; Kagehiro, *Psychological Science*, 1990; Kent, 1964 at note 15; Mosteller and Youtz, *Statistical Science*, 1990.

¹⁷ For example, Dhami and Wallsten, 2005 at note 7; Karelitz and Budescu, 2004 at note 7.

¹⁸ Butler, Chilcot, Marshall, Mates, and Taylor, *A Review of Intelligence on...*, 2004; National Intelligence Council, *Prospects for Iraq's Stability...*, 2007.

¹⁹ Office of the Director of National Intelligence, "Intelligence Community Directive 203...", 2015.

²⁰ Defence Intelligence, *Analysis Guidance Note. Communicating...*, 2012, see also Joint Intelligence Organisation, *Analytic Tradecraft Guidance Note*, 2013.

²¹ See Barnes, 2015 at note 13.

²² See Dhami and Wallsten, 2005 at note 7; Karelitz, Budescu, and Wallsten, "Validation of a New Technique...", 2000; Wallsten, *J. of Experimental Psychology*, 1971.

²³ See also Budescu and Wallsten, "Processing Linguistic Probabilities: General...", 1995.

²⁴ For example, Dhami and Wallsten, 2005 at note 7; Wallsten and Jang, *Psychonomic Bulletin and Review*, 2008.

²⁵ Barnes, 2015 at note 13.

²⁶ Smithson et al., 2012 at note 8.

²⁷ Wallsten and Budescu, *Organizational Behavior and Human Decision Processes*, 1990.

²⁸ For example, Harris and Corner, 2011 at note 8; Mandel, 2015 at note 8; Smithson et al., 2012 at note 8; Wallsten et al., 1986 at note 8; Weber and Hilton, 1990 at note 8.

²⁹ Fox and Irwin, *Basic and Applied Social Psychology*, 1998; Piercey, *Organizational Behavior and Human Decision Processes*, 2009.

³⁰ Budescu et al., 2011 at note 8.

³¹ For example, Budescu et al., 2014 at note 16.

³² Barnes, 2015 at note 13.

³³ For example, Dhami et al., 2015 at note; Friedman et al., 2015 at note 14.