Data-to-Text Generation Improves Decision-Making Under Uncertainty

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Abstract

Decision-making is often dependent on uncertain data, e.g. data associated with confidence scores or probabilities. This article presents a comparison of different information presentations for uncertain data and, for the first time, measures their effects on human decision-making, in the domain of weather forecast generation. We use a game-based setup to evaluate the different systems. We show that the use of Natural Language Generation (NLG) enhances decision-making under uncertainty, compared to state-of-the-art graphical-based representation methods. In a task-based study with 442 adults, we found that presentations using NLG led to 24% better decision-making on average than the graphical presentations, and to 44% better decision-making when NLG is combined with graphics. We also show that women achieve significantly better results when presented with NLG output (an 87% increase on average compared to graphical presentations). Finally, we present a further analysis of demographic data and its impact on decision-making, and we discuss implications for future NLG systems.

I. Introduction

Natural Language Generation (NLG) technology can achieve comparable results to commonly used data visualization techniques for supporting accurate human decision-making [1]. Current data-to-text systems assume that the underlying data is precise and correct – an assumption which is heavily criticized by other disciplines concerned with decision support, such as medicine [2], environmental modelling [3], climate change [4], or weather forecasting [5]. In this paper, we investigate whether NLG technology can be used to support decision-making when the underlying data is uncertain. However, simply presenting numerical expressions of risk and uncertainty is not enough. Psychological studies on decision-making have found that a high percentage of people do not understand and cannot act upon numerical uncertainty

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[6], [7]. For example, about 30% of participants in a German-American study were unable to correctly answer the question:

> Which of the following numbers represents the biggest risk of getting a disease: 1 in 100, 1 in 1000, 1 in 10?" [7].

The novelty of this paper is that unlike previous work, we investigate the potential of NLG to automatically produce textual descriptions of uncertainty in order to support decision-making and help with the numeracy problem. The *generation* task is defined as follows: the input to the data-to-text system is uncertain data – specifically weather data associated with probabilities – and the output is weather forecasts in Natural Language (NL) which express the uncertain nature of weather linguistically. This article extends our previous work [8] in the following ways: We provide a more extensive discussion of related work and clarify our unique contribution. In addition, we report more detail on the experimental setup of the study, as well as the implementation of the WeatherGame. We report and discuss results in more depths, including detailed results of statistical analyses. Furthermore, this article includes new material, analysing demographic factors and their influence on the performance of NLG strategies.

The main contributions to the field are as follows:

- We study a principled mapping of uncertainty to NL and provide recommendations and data [9] for future data-to-text systems;
- We introduce a game-based data collection environment which extends task-based evaluation by measuring the impact of NLG on decision-making (measuring user confidence and game/task success);
- We show that effects of the different representations vary for different user groups, which suggests that user adaptation is necessary when generating multi-modal presentations of uncertain information.

The rest of the article is organized as follows. Section II reviews existing approaches to conveying uncertainty in data-to-text systems. Section III describes how the generation task is formulated and Section IV briefly describes the game-based setup used for data collection. Section V describes the data-to-text strategies we use for describing uncertainty. Section VI presents the evaluation setup and an overview of the collected data emphasizing the demographics of the population, followed by the results (Section VII). Finally, Section VIII discusses implications for multi-modal systems and potential directions for future work.

II. Related Work

The work presented in this article relates to two research fields: NLG and Linguistic Description of Data (LDD) using Soft Computing. We review related work in these areas below.

A. Natural Language Generation

A common task for NLG is to summarize time-series data (i.e. data with changing values over time), commonly known as *data-to-text generation* [10]. This paper focuses on the summarization of uncertain time-series data in the context of decision support systems. We use automatic weather forecast generation as an exemplar task, since weather data is associated with probabilities (e.g. 30% chance of rain) and therefore it is considered *uncertain*.

Weather forecast generation is a common topic within the NLG community, e.g. [11], [12], [13], [14]. Previous approaches to data-to-text generation in the weather domain have not focused on how to communicate uncertain information, and neither have they looked into the best ways of referring to probabilities of meteorological phenomena to occur. In addition, NLG evaluation is usually based on user ratings of, e.g. grammatically, semantic correctness, fluency, and coherence, or via post-edit evaluation. Although these metrics are commonly used for evaluating the quality of the generated text, they cannot measure the effect that they have on people's comprehension of uncertainty and on the decisions they will take.

Decision support systems (especially commercial tools, such as energy consumption websites) traditionally use graphical representations to visualize data and associated uncertainty. However, there is recent evidence that NL text, and NLG in particular, can have a positive effect on human decision-making [1], [8], [15]. Data-to-text systems have been successfully used for decision support, including weather forecasts [16], [17], medical care [1], [18], student feedback [19] and nature conservation [20]. Unlike traditional concept-to-text generation which typically generates texts from underlying semantic representations, data-to-text generation takes as input real-world observations and automatically generates descriptions in NL [10]. So far, most data-to-text systems assume that the underlying data is precise and correct with some notable exceptions:

Gatt and Portet [21] present a framework for quantifying and communicating temporal uncertainty and show an implementation for different languages. They find that there are differences on how different languages (English, French, and Maltese) use propositions to indicate uncertainty, e.g. using "may have/definitely/certainly" to indicate the likelihood whether an event has occurred. For generation, they train a predictive model to select expressions to convey uncertainty based on human data.

Power and Williams [22] present recent work on automatically translating numbers into NL expressions, using a constraint-based framework for verbalizing numbers (proportions) at different levels of precision. Chaganty and Liang [23] investigate how to give numbers more meaning by setting them into perspective, e.g. 30 minutes can be described as "time taken for lunch".

Gkatzia et al. [24] propose an approach to handling unknown first-time users in the context of automatic report generation from time-series data in the health domain. For this task, the uncertain factor is the users and their preferences to which the output needs to be adapted. To solve the issue, they proposed a framework which initially clusters existing users of a system according to their preferences, then they model the preferences of each user cluster as an objective function and finally multi-objective optimisation is used in order to simultaneously optimise for the preferences of each user cluster. Considering that a first-time user would belong to any of the existing user clusters, the output is optimised for this user. In contrast, in order to address two *known* user groups with competing preferences, such as lecturers and students in the domain of feedback generation a different approach was followed by Gkatzia et al. [25]. Principal Component Regression analysis was used in order to identify the most important preferences of each group and then they were included in a single objective function which was optimised using Reinforcement Learning.

Van Deemter [26] proposes a game-theoretic model for choosing vague expressions with the highest "utility". A recent study on vague referring expressions [27] shows that contextually appropriate approximations can significantly reduce cognitive load and increase task efficiency. Finally, Gkatzia [28] presents a comprehensive review on content selection methods for data-to-text systems.

B. Linguistic Description of Data using Soft Computing

Soft Computing is a sub-area of Artificial Intelligence which investigates methodologies and approaches which aim to cope with uncertainties such as imprecisions and missing data [29]. Several studies in this area investigate the linguistic description of data (LDD):

Herrera et al. [30] describe a "Computing with Words" approach to expressing and summarizing input data using (deliberately) vague NL expressions, such as "small", "big" and "tomorrow will be cloudy but not very cold". Ramos-Soto et al. [31] describe an approach to short weather forecast generation using a combination of fuzzy sets and NLG approaches. Conde-Clemente et al. [32] also present an approach which combines soft computing with NLG in the domain of decision support for energy saving at home. Alonso et al. [33] describe an approach to LDD in the context of medical support systems using fuzzy modelling. Finally, Marin and Sanchez [34] present a comprehensive literature review of approaches and concepts used for linguistic descriptions of time-series data within the Soft Computing community. The main methods used here are knowledge extraction and linguistic expression processes, whereas the NLG community applies a series of tasks, including Signal Analysis, Microplanning, and Realisation.

Following on from prior research, we investigate whether conveying uncertainty in NL can support decision-making. In particular, we are interested in how natural language expressions of uncertainty, i.e. the probability of a future event to happen, will influence confidence and precision for human decision makers. One of our main contributions is that we introduce an online task-based evaluation scenario in order to measure the extrinsic effects of different realisations on the primary task, following similar efforts for generating referring expressions [35].

III. The Generation Task

In this work, we consider the exemplar task of weather forecast generation. We initially present two NLG strategies which present the uncertainty in the input data. The two strategies are based on (1) the World Meteorological Organization (WMO) [5] guidelines, and (2) commercial forecast presentations (e.g. from BBC presenters). We then evaluate the strategies against a state-of-the-art graphical system [36], which presents the uncertain data in a graphical way. Figure 1 shows an example of this baseline graphical presentation. We use a game-based setup [37] to perform a task-based evaluation, to investigate the effect that the different information presentation strategies have on human decision-making.

IV. The Extended Weather Game

In this section, we present our extended version of the MetOffice's Weather Game [36]. In this game, the player has to choose where to send an ice-cream vendor in order to maximize sales, given weather forecasts for four weeks and two locations. These forecasts describe (1) predicted rainfall (see Figure 2), and (2) temperature levels (see Figure 1) together with their likelihoods in three ways: (a) through graphical representations (which is the version of the original game), (b) through textual forecasts, and (c) through combined graphical and textual forecasts. We generated the textual format using two rule-based NLG approaches as described in the next section. Users are initially shown the temperature graphs for two locations and they are asked to choose the best destination for the ice-cream vendor. Following their

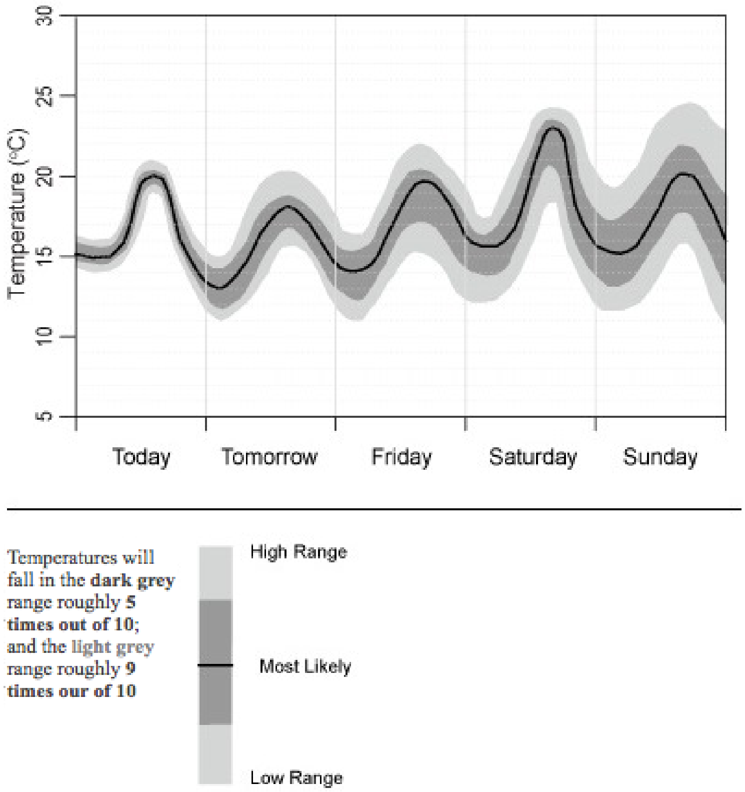
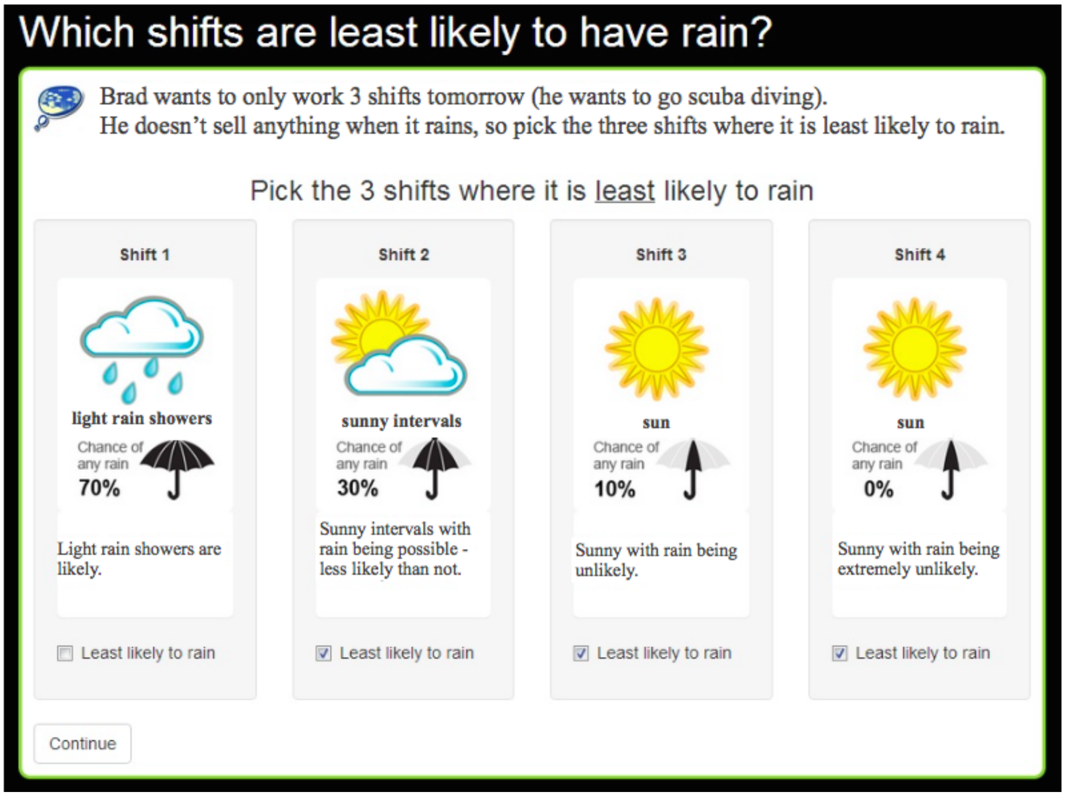


Fig. 1: Graphics for temperature data.

decision, they are asked to state how confident they are with their choice. Then, they are shown four potential shifts (see Figure 2) and they are asked to choose three of the shifts where it is least likely to rain. Again, they have to declare how confident they are with their decisions. This process is repeated four times.

Based on their decisions and their confidence levels, the participants are presented with their *monetary gain*, i.e. game score, after each week (and in the end of the game), which gives them the chance to improve their decision-making strategy. The monetary gain function works as follows: the higher the likelihood of sunshine, the higher the monetary gain if the player has declared that s/he is confident that it is not going to rain and it does not actually rain. In the opposite scenario, the player would lose money. The decision on whether rain occurred is estimated by sampling the probability distribution, in order to simulate the real weather phenomena.

Users were additionally required to provide demographic details such as age, gender and educational level (see also Section VI). At the end of the game, users were scored according to their *risk literacy* following the Berlin Numeracy Test [6]. The Berlin Numeracy Test is a psychometric test introduced by Cokely et al. [6], which quickly assesses statistical numeracy and risk literacy. The Extended Weather



Which shifts are least likely to have rain?

Brad wants to only work 3 shifts tomorrow (he wants to go scuba diving).
He doesn't sell anything when it rains, so pick the three shifts where it is least likely to rain.

Pick the 3 shifts where it is least likely to rain

Shift 1	Shift 2	Shift 3	Shift 4
light rain showers	sunny intervals	sun	sun
Chance of any rain 70%	Chance of any rain 30%	Chance of any rain 10%	Chance of any rain 0%
Light rain showers are likely.	Sunny intervals with rain being possible - less likely than not.	Sunny with rain being unlikely.	Sunny with rain being extremely unlikely.
□ Least likely to rain	☑ Least likely to rain	☑ Least likely to rain	☑ Least likely to rain

Fig. 2: Screenshot of the Extended Weather Game.

Game uses the **1 minute literacy test** in order to minimize the tasks that the participants have to perform. This test includes only one numeracy question:

> Imagine we are throwing a five-sided die 50 times. On average, out of these 50 throws how many times would this five-sided die show an odd number (1, 3 or 5)?

The Extended Weather Game can be accessed here:http://www.macs.hw.ac.uk/InteractionLab/weathergame/.

V. Natural Language Generation from Uncertain Information

We developed two NLG systems, WMO-based and NATURAL, using SimpleNLG [38], which both generate textual descriptions of rainfall and temperature data addressing the uncertain nature of forecasts. **WMO-based:** This is a rule-based system which uses the guidelines recommended by the WMO [5] for reporting uncertainty, as shown in Table I. This system directly maps the probabilities of weather to corresponding linguistic interpretation. Consider for instance a forecast of sunny intervals with 30% probability of rain. This WMO-based system will generate the following forecast: “Sunny intervals with rain being possible - less likely than not”.

TABLE I: Mapping of likelihoods with accordance to World Meteorological Organisation.

Likelihood of occurrence	**Lexicalisation**
$p > 0.99$	“extremely likely”
$0.90 \leq p \leq 0.99$	“very likely”
$0.70 \leq p \leq 0.89$	“likely”
$0.55 \leq p \leq 0.69$	“probable - more likely than not”
$0.45 \leq p \leq 0.54$	“equally likely as not”
$0.30 \leq p \leq 0.44$	“possible - less likely than not”
$0.10 \leq p \leq 0.29$	“unlikely”
$0.01 \leq p \leq 0.09$	“very unlikely”
$p < 0.01$	“extremely unlikely”

NATURAL: This system imitates forecasters and their natural way of reporting weather. The rules used in this system have been derived by observing the way that experts (e.g. BBC weather reporters) produce forecasts. For the previous example (sunny intervals with 30% probability of rain), this system will generate the following forecast: “Mainly dry with sunny spells”. This system is more natural than the WMO-based, in that the probabilities are mapped to linguistic interpretation of weather (e.g. “sunny spells”) rather than the linguistic mapping of uncertainty (e.g. “likely”).

VI. Experimental Setup

In order to investigate what helps people to better understand and act upon uncertainty in information presentations, we initially use five conditions within the context of the Extended Weather Game grouped in three categories:

Graphics only:

- This representation shows the users only the graphical representation of the weather forecasts. For this condition, we used the graphs that scored best in terms of human comprehension in a study by Stephens et al. [36], [39].

Multi-modal representations:

- **Graphics and NATURAL:** This is a multi-modal representation consisting of graphics (as described in the previous condition) and text produced by the NATURAL system.
- **Graphics and WMO-based:** This is also a multi-modal representation consisting of graphics and text produced by the WMO-based system.

NLG only:

- **NATURAL only:** This is a text-only representation as generated by the NATURAL system.

- **WMO-based system only:** This is also a text-only representation as generated by the WMO-based system.

In the next sections, we treat the NLG systems under one category (NLG only) in order to be able to explore the effects that NLG has on decision-making in general (also the results obtained for the two NLG systems were not significantly different) compared to graphics only and to multi-modal representations.

Data

We recruited 442 unique adult players using social media (197 females, 241 males, 4 non-disclosed). We collected 450 game instances (only a few people played the game twice). Further to the Extended Weather Game results and the Berlin Literacy test results, we also collected demographic data. A description of the data is provided in Table II. The full dataset has been made available online[1].

TABLE II: Description of collected demographic data.

Variable	Description
Age	User could specify their age as free text
Postcode	Only three first letters were requested
Gender	Male/Female/Other
Native speaker of English	Yes/No
Familiarity with science models	Have you ever been taught or learnt about how scientists use computers to model the environment? Potential answers can be: Yes/No/Not Sure
Experience with risk	Do you often make decisions or judgements based on risk, chance, or probability? Potential answers can be: Yes/No/Not Sure
Education	What is the highest qualification you have achieved so far? Potential answers can be: Degree level or above, 2+ A-levels or equivalent, Apprenticeship, 5+ GCSEs or equivalent, 1-4 GCSEs or equivalent, Other qualifications, No qualifications. We only found significant differences between BSc holders and non-holders.

The distributions of demographic features amongst our adult participants are shown in Table III. In the next section, we describe the results with regard to game performance and information presentation and their interaction with these demographic factors.

TABLE III: Demographics of the adult cohort.

	Females (out of 197)	**Males (out of 241)**
Native speaker of English	170 (86%)	199 (83%)
Familiarity with Science models	79 (40%)	145 (60%)
Experience with risk	132 (67%)	185 (77%)
Education (BSc holders)	161 (82%)	205 (85%)

[1] https://github.com/dimi123/WeatherGame

VII. Results

In order to investigate which representations assist people in decision-making under uncertainty, we analyzed both the players' scores (in terms of monetary gain) and their predictions for rainfall with regard to their confidence scores. As we described in Section IV, the game calculates a monetary gain based on both the decisions and the confidence of the player, i.e. the decision-making ability of the player. Regarding confidence, we asked users to declare how confident they are on a 10-point scale. For example, we assume that if there is 70% probability of rain, the player should have been 70% confident that is going to rain. The 10-point scale was chosen for two reasons. Firstly, it was the one used at the original weather game [36] so we followed the same design in order to be able to compare our results. Secondly, since the weather uncertainty is communicated with percentages, e.g. "There is 30% probability of rain" and since the confidence scores are also represented with percentages, i.e. one can be 30% confident that it will rain when there is 30% probability of rain, a 10-point scale is used to measure confidence level in order to accurately capture confidence levels.

In the following, we present the results for monetary gain scores and reported confidence. In order to assess significance we used ANOVA, following [36], and we also report effect sizes.

A. *Results for all adults*

1) Game Score:

- **Multi-modal vs. Graphics only:** We found that the use of multi-modal representations leads to gaining significantly higher game scores (i.e. better decision-making) than the Graphics only representation ($p = 0.03$, effect = +36.36). This is a 44% average increase in game score.
- **Multi-modal vs. NLG only:** However, there is no significant difference between the NLG only and the multi-modal representation in terms of game score.
- **NLG vs. Graphics only:** We found that the NLG representations resulted in a significant 24.8% increase in average game score (i.e. better decision-making) compared to the Graphics-only condition (see Table IV).
- **WMO-based vs. NATURAL:** There was no significant difference found between the WMO and NATURAL NLG systems. For the WMO-system, being native speaker of English (or not) does not influence confidence levels. However, native speakers of English score significantly higher than non-native ($p < 0.006$, effect = 73.23%). One reason for this might be that in different languages there are

TABLE IV: Average monetary gains and confidence scores (All Adults).

	Monetary gains	**Confidence**
Graphs only	81.15	78.5%
Multi-modal	117.51	83.7%
NLG only	101.33	66%

TABLE V: Average monetary gains and confidence scores (Females).

	Monetary gains	**Confidence**
Graphs only	60.83	74.6%
Multi-modal	118.41	81.3%
NLG only	113.86	65.8%

different words which express different levels of uncertainty and they cannot be directly translated into English. This does not hold true for NATURAL, which expresses uncertainty using weather phenomena (e.g. "dry spells") instead of probability mentions (e.g. "more likely than not").

2) Confidence: For confidence, the multi-modal representation is significantly more effective than NLG only ($p < 0.01$, effect = 17.7%). However, as Table IV shows, although adults felt less confident when presented with NLG only, they were able to make better decisions compared to being presented with graphics only.

3) Demographic factors: We further found that the following demographic factors are predictors of the players' understanding of uncertainty, which is translated in both confidence and game scores:

- prior experience on making decisions based on risk,
- familiarity with science models,
- correct literacy test results,
- gender.

In contrast, we found that the education level and being native speaker of English do not contribute to players' confidence and game scores. However, we did find that gender was a significant factor when using different presentation strategies, as shown in the next sections.

B. Results for Female Participants

1) Game Score: We found that female participants score significantly higher at the decision task when exposed to either of the NLG output presentations, when compared to the Graphics only presentation ($p < 0.05$, effect = +53.03). This is an increase of 87%, also see Table V. In addition, the same group scores significantly higher when presented with the multi-modal output as compared to graphics only ($p = 0.05$, effect = 60.74). Interestingly, for this group, the multi-modal presentation adds little more in effectiveness of decision-making than the NLG-only condition, but the multi-modal presentations do enhance their confidence (+15$\%$). As expected, female participants who answered correctly the literacy test, they also performed significantly higher than the ones who did not answer correctly ($p < 0.01$, effect = +56.87). Non-educated females are also more likely to score higher if they are native speakers of English [2]. This suggests that text-simplification techniques might be necessary in order to leverage the positive effect of NLG for non-educated, non-native users.

2) Confidence: We furthermore found that female participants, who correctly answered the risk literacy test, feel significantly more confident when presented with the multi-modal representations than with NLG only ($p = 0.01$, effect = 16.7%). We see that, for confidence, correctly answering the literacy test is a better predictor than education.

C. Results for Male Participants

1) Game Score: We found that males obtained similar game scores with all the types of representations. This suggests that the overall improved scores (for All Adults) presented above, are largely due to the beneficial effects of NLG for women. As expected, males with experience of using science models of uncertainty, scored significantly higher than males who do not ($p = 0.013$, effect = 48.05%). Similarly, the ones who often make decisions based on uncertainty score significantly higher than the ones who do not ($p < 0.001$, effect = 72.83%).

2) Confidence: In terms of confidence, males (either educated or not) are more likely to be more confident if they are presented with graphics only (81$\%$ of the time) or a multi-modal representation (85$\%$ of the time) ($p = 0.01$). Similarly to the results for game score, males who use science models of risk or uncertainty are more confident in their decisions than males who do not ($p = 0.047$, effect = 6.5%). In addition, males who often make decisions based on uncertainty are more likely to feel confident with their decisions than the ones who do not ($p = 0.004$, effect = 10.79%). This is also true for non-educated males ($p = 0.008$, effect = 56.32%).

D. Discussion

The main question of this article is to investigate whether NL descriptions of uncertainty can improve decision-making. Our results suggest that it does enhance decision-making and there are some findings which can prove useful for future research and are summarized below.

[2] Note that, although the results are significant ($p = 0.030$), the sample size is very small (only four non-native non-educated females).

From the results we can infer that linguistic expressions of uncertainty (e.g. *probable*, *very likely*) might be interpreted differently by people. For instance, for a native speaker the word *possible* might hold less probability for an event to occur than a non-native speaker might think and vice versa, see e.g. results by [21] on speakers of different languages. On the other hand, specific phenomena such as *dry spells* seem to be interpreted similarly by both native and non-native speakers. This implies that generally people tend to comprehend specific entities more accurately than expressions of uncertainties and therefore this might lead to better decision-making. Therefore, it is recommended to use specific entities rather than linguistic expressions of uncertainty.

The results also showed that people tend to feel significantly more confident when presented with multi-modal representations rather than Graphs only or NLG-only representations, although in terms of decision-making they perform similarly when presented with multi-modal and NLG representations. This implies that the graphs might boost peoples' confidence, although it might be easier to miss information and make worse decisions with graphs only. For this reason, it is recommended to include graphs with NL text.

Finally, the results obtained in this domain can have implications for other domains with similar characteristics. People often have to make decisions in other domains such as health or energy consumption. These domains have similar characteristics with the weather domain, since they also involve uncertainty. For instance, energy consumption at home might be influenced by the weather as well as the family's changes in routine (spending fewer or more hours at home), unexpected visitors, home repairs, and so on. Companies normally issue *projected* energy consumption for their customers in monetary terms, which is calculated based on similar households in the area, the home's size, etc. However, the projections do not include explanations on how other factors might influence the energy rates, although they include the numerical values of units. It is very likely that people would make better decisions on energy based on NL descriptions of projections.

VIII. Conclusions and Future Work

We present results from a game-based study on how to generate descriptions of uncertain data – an issue which so far has been under-explored by data-to-text systems. We show that, NLG leads to better decision-making with 24% relative increase in task success over conventional graphical representations. However, using graphics can boost the user's confidence.

We furthermore find that there are significant gender differences between multi-modal, NLG, and graphical versions of the task, where for women, the use of NLG results in an 87% increase in task success over graphics. Multi-modal presentations lead to a 44% increase for all adults, compared to graphics. People are also more confident of their judgements when using the multi-modal representations. These are significant findings, as conventional (systems commonly used by professionals) decision-support systems commonly rely on graphical representations only. Furthermore, previous work on data-to-text systems has not distinguished between genders when comparing different representations of data, e.g. [1]. It also confirms research on gender effects in multi-modal systems, as for example reported in [40], [41], [42]. An interesting investigation for future research is the interplay between uncertainty, risk-taking behavior, and gender, as for example reported in [43].

Another interesting direction for future work is adaptive NLG approaches which can generate text (or multi-modal representations) based on the user's gender, or other demographic factors which have shown to have an effect, such as education, etc. The work presented in this article can act as a starting point for potential user models which can inform the generation decisions.

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