December 1997

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Peter O'Donnell
Monash University

David Arnott
Monash University

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Peter A. O'Donnell, David R. Arnott and Vincent P. Yeo
Department of Information Systems
Monash University

Abstract
When making judgements or predictions, humans are generally subject to various cognitive biases. One such cognitive bias is the so-called 'linear' bias. It is an effect that causes humans to severely under-estimate their forecast of an exponential data series. The main aim of this study is to investigate if the use of a decision support system (DSS) can assist in overcoming the effect of the linear bias.

A laboratory experiment was conducted where the participants were asked to make a prediction based on an exponential data series. The quality of their predictions were then determined by comparing their prediction to the 'actual' solution. The results indicate that the use of a DSS can help the decision makers to overcome, at least in part, the effect of linear bias.

1. Introduction
Many of the problems that decision makers encounter involve making judgements and decisions under uncertainty in which the derivation of a final judgement often requires the processing of a combination of different information sources (Hogarth, 1987). Such processing is often based on a limited number of simplifying decision strategies called heuristics. In certain circumstances, these heuristics can lead to severe misjudgements. Judgement errors that result from the inappropriate application of these heuristics are usually called cognitive biases (Yates 1990, Dawes 1988, Hogarth 1987, Kahneman and Tversky 1973). One cognitive bias, the linear bias, is an effect that causes human decision makers to under-estimate forecasts of exponential data series (Bar-Hillel 1973, Cohen, Chesnick and Haran 1972, Wagenaar and Sagaria 1975, Wagenaar and Timmers 1977, Wagenaar and Timmers 1978, Wagenaar and Timmers 1979). This is an important bias for managers as they often make forecasts of variables that are growing at an exponential rate. It has been suggested that the use of a decision support system (DSS), if designed appropriately, can help to negate the effect of the linear bias (Jacobs and Keim 1988, Kydd 1989, Mason and Moskowitz 1972, Remus and Kotteman 1986, Sage 1981, Silver 1991 and Wright 1983). However, this proposition has not been empirically tested.

This paper describes an experimental study that was undertaken to investigate whether the use of a DSS could help overcome the effect of the linear bias. Experiments investigating the influence of DSS on decision performance have reported mixed outcomes (Benbasat and Nault 1990). This study focuses on a very narrow aspect of decision making in order to increase the validity of the experiment. The paper begins by discussing the linear bias and previous experimental studies that have investigated its nature. It is hypothesised that a DSS could be used to negate the effect of the linear bias. The possible effect of different task representations is also discussed. The design of an experiment to test the hypothesis is then discussed and the results presented. The paper concludes with a discussion of the limitations of the research and the implications of the experimental results.

2. The Linear Bias
The linear bias is a cognitive effect that causes humans to under-estimate their forecasts of exponential data series. In several experimental studies humans have been found to be unable to interpret or extrapolate exponential functions in an accurate manner. (Wagenaar and Sagaria 1975, Wagenaar and Timmers 1977, Wagenaar and Timmers 1978, Wagenaar and Timmers 1979, Keren 1984). In these experiments, subjects were provided with a data series that was derived from an exponential function and asked to estimate the next element or elements in the series. The subject's estimates were consistently below the normative values generated from the exponential function.

In the seminal study conducted by Wagenaar and Sagaria (1975) four separate experiments (E1, E2, E3, E4) were performed. The experiments were based upon an exponential data series that represented a pollution index. The data, shown in Table 1, was derived using the simple exponential relationship $y = e^x$, where x represents the number of years since 1969. In E1 the data was provided to the subjects in a tabular format; in E2 graphically; in E3, both graphical data and prior instructions regarding the effect of the linear bias were provided to the subjects. The subjects for E1, E2 and E3 were students from Pennsylvania State University. The structure of E4 was similar to that of E2 except that managers, whose jobs encompassed making important decisions, were used as the subjects.

Table 1: Pollution Index data provided to participants in Wagenaar and Sagaria's (1975) experiment

Year	Pollution Index
1970	3
1971	7
1972	20
1973	55
1974	148

There were three groups of subjects for each of the experiments. The first group of subjects were asked to predict the pollution index for 1979. The second group were asked to predict the indexes for the years ranging from 1975 through to 1979 while the third group were asked to predict the year in which the index would surpass 25,000.

In E1, each of the groups under-estimated the forecast: 90% of group 1 subjects produced estimates that were below half of the normative value and 66% of the subjects produced estimates at or below 10% of the correct value. About 50% of group 3 subjects expected the value of 25,000 to be surpassed after the 2000. (The correct answer was 1979.)

There was no statistically significant difference between the results for the E2 and E1. If anything, the use of a graphical data presentation had elicited even more conservative estimates from the participants. The subjects in E3 who were provided with instruction about the effect of the linear bias before they made their prediction did perform better. However, their estimates were still significantly lower than the correct values. Wagenaar and Sagaria hypothesised that the subjects had been willing to increase their estimates by adding a compensating factor to their intuitive prediction. However, this compensating factor that was not large enough to correct for the effect of the bias. In E4 it was found that the forecasts and estimates produced by the managers were no better than those produced by the students.

The linear bias has also been found to be resistant to changes in the format of the presentation of the data series (Wagenaar and Timmers 1979), to the direction of the exponential growth (Wagenaar and Timmers 1977) and to the amount of information about the data series made available to subjects (Wagenaar and Timmers 1978, 1979). In general, the more information that is provided to subjects, for example the number of data points, the worse the estimation error becomes (Wagenaar and Timmers 1978). In another study, Keren (1984) compared the prediction of exponential growth between Canadian subjects and Israeli subjects. It was thought that the experience of the Israeli subjects, having been exposed to years of high rates of inflation, might make them better predictors of exponential growth. The magnitude of the under-estimation of the Israeli subjects was slightly less than the Canadian subjects, but nevertheless significant.

There is some controversy as to the causes of the linear bias. For example, Keren (1984) argues that the error arises from the misapplication of an exponential model. Jones (1984) argues that the underlying cause of the effect is the misapplication of a polynomial model. Both explanations can account for the experimental results (Keren 1984). In general, predictions and evaluations are often made based on a combination of different information sources. However, given the nature of human information-processing capacity, it is generally difficult for them to aggregate information from various sources in an effective manner (Hogarth, 1987). It has been suggested that humans' inability to aggregate data effectively is the major cause of their conservative behavior in making predictions (Edwards 1968). This

is because even though they can perceive each datum of a data series and its individual diagnostic meaning accurately, they are generally unable to combine all of the diagnostic meanings together when revising their opinion.

3. The role of DSS in overcoming the linear bias

DSS are computer-based information systems developed with the purpose of improving the process and outcome of managerial decision making. As the linear bias may be influenced by the method of data presentation, the use of a DSS, if designed appropriately, may help to reduce the negative effects of the bias.

When making a prediction for an exponentially growing data series, it is often difficult for decision makers to envisage the outcome of their predictions. One way a DSS might help to overcome this is by providing them with interacting numerical and graphical representations of the data and the historical series i.e. the value of a prediction could be displayed automatically in a table and or a graph.

The linear bias may also be negated by transforming the data by presenting it using a logarithmic scale as the exponential nature of the data is reduced to a linear form. Remus (1984) believes that humans consider the differences, rather than the ratio, between data points when extrapolating. This means that humans, while under-estimating exponential growth, will reasonably extrapolate linear data series. A DSS may assist this process by automatically converting between logarithmic and normal scale data series.

4. The Hypotheses

Most managers make decisions involving the forecasting of exponential data by using information that is presented to them in a paper-based report. This static presentation could be in table or graph from, or both. Managers could also use an interactive decision aid to enable them to explore different options before making a decision. The first hypothesis involves a comparison of the efficacy of these two modes of support.

H1: Subjects using a decision aid will have better forecast accuracy than subjects using a report.

As mentioned above, managers may be able to better forecast growth if it is presented in a linear form i.e. when an exponential growth series is presented in a logarithmic scale. A fundamental tenet of DSS design is that managers should understand the logic of the system they are using (Courbon 1996, Keen 1980). In terms of forecasting exponential growth, managers should be able to clearly see the relationship of the data plotted on a normal scale and the same data plotted on a logarithmic scale. This implies that a combined representation using normal and logarithmic scales may be superior of the presentation of data on a normal scale alone.

H2: Subjects presented with a combined representation will have better forecast accuracy than those presented with a normal representation.

A more detailed consideration of the different representations (normal and combined) and support modes (report and decision aids) gives rise to hypotheses three and four.

H3: Subjects using a decision aid with a combined representation will have better forecast accuracy than those using a decision aid with a normal representation.

H4: Subjects using a report with a combined representation will have better forecast accuracy than those using a report with a normal representation.

5. Experimental Design and Procedures

The experiment manipulated two independent variables, each at two levels. The primary factor was mode of support (report or decision aid) and the second factor was the representation (normal or combined). The dependent variable was forecast accuracy which is the difference between the forecast estimate and the normative solution. This set of variables represents a 2 by 2 factorial design, a common

experimental design in the behavioral sciences (Keppel 1991).

The experimental task was based upon previous studies (Wagenaar and Sagaria 1975, Wagenaar and Timmers 1977, 1978, 1979). Subjects was asked to make an estimate of a population index in the year 2050 based on a data series of population indexes from 1870 to 2020, in 30 year intervals. The data series and the normative solution was derived using Formula (1) which is based on Malthus's Law of Population (Kreyszig 1988).

$$y(t) = y_0 \, e^{\,k\,(t - t_0)} \tag{1}$$

where t is the time in years, y_0 is the population index at time t_0 and k is the size of the exponent. In this experiment $t_0 = 1870$, $y_0 = 5.3$ and $k = 0.0299$. The resultant data series is shown in Table 2.

Table 2 : Data series and normative solution

Year	Population Index
1870	5.3
1900	13
1930	31.89
1960	78.21
1990	191.84
2020	470.56
2050	1154.2

Two decision aids (D1 and D2) were constructed to assist subjects in making forecasts of data that exhibited exponential growth. Each aid comprised three screens: the first explained the nature of the task (to predict the value of a variable at a particular time); the second provided support for the decision; and the third was used to collect demographic data about the subjects. The prediction screen of D1 is shown in Figure 1 and that of D2 in Figure 2.

D1 presented population index data in a normal scale in both tabular and graphical formats. Subjects could enter their population index estimate for the year 2050 in a text box or they could click on a point in the graph space and the value of the population index of that point appeared in the text box. Subjects could experiment with different points without restriction. They clicked "OK" to confirm their prediction.

D2 presented the same data but in both normal and logarithmic scales. The user operations were similar to D1 with the addition that when a subject clicked on a point in the normal scale graph, the corresponding point in the logarithmic scale graph was indicated, and visa-versa. Further, the numerical value of the identified population index was displayed in the table as well as in the text answer box. Subjects were free to trial as many values as they liked. As in D1, they could use the graph to assist their judgement or could simply type in their prediction.
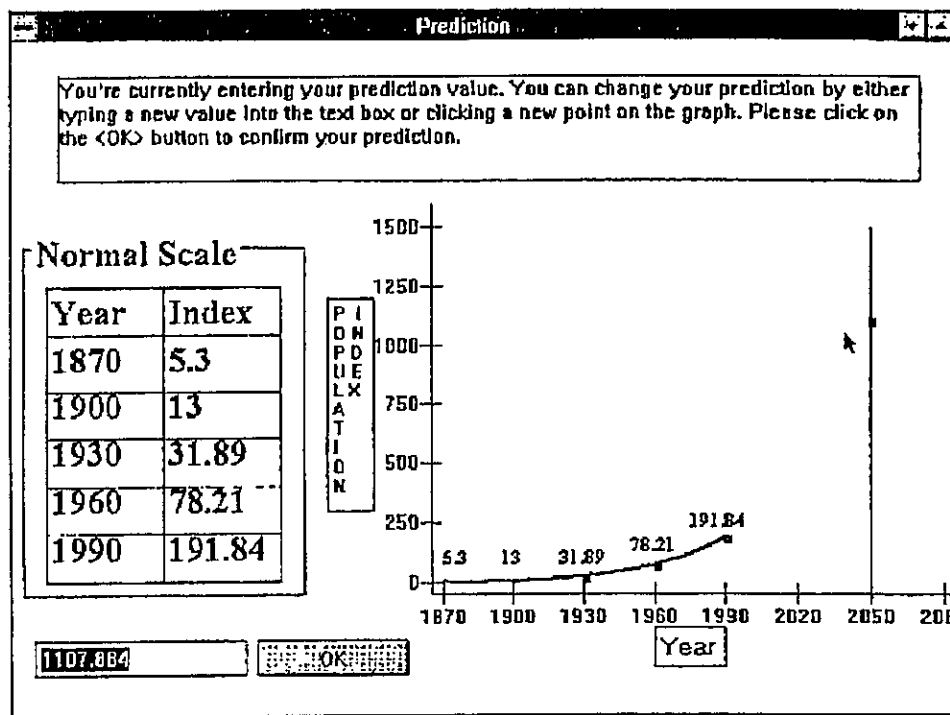
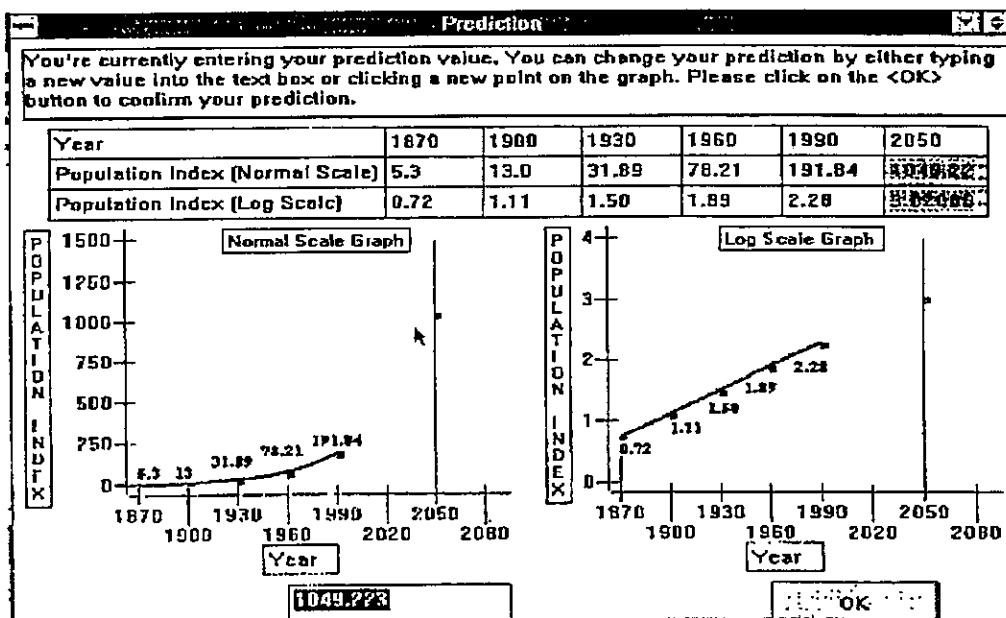**Figure 1: 'Prediction' Screen of Decision Aid D1**

Figure 2: 'Prediction' Screen of Decision Aid D2

Paper-based report versions of the normal and combined representations of the forecasting task were developed. These appear in Appendix A.

The 73 subjects were undergraduate information systems students. Subjects were randomly allocated to four groups as shown in Table 3. In total, 39 subjects used reports and 34 used a decision aid. There was no significant difference in the age, gender or education in forecasting between groups. No monetary or

other incentives were provided. All subjects were given the same explanation about the nature of the task. Subjects in the decision aid groups performed the task in computer laboratories. The report groups performed the task in a large classroom. No time restrictions were imposed. In both venues a laboratory assistant was present to answer questions.

6.   Results

The mean of forecast error (along with the associated standard deviation and standard error) for each combination of the variables *support* (decision aid or report) and *representation* (normal or combined) is shown in Table 3. The analysis and hypothesis testing was performed using ANOVA which is the usual technique applied to experiments of factorial design. In this case, however, as the sizes of the samples for each combination of the variables *support* and *representation* was unequal an adaptation of the standard ANOVA technique was required. This adaptation involves the calculation and use of the harmonic mean of the sample sizes in the ANOVA calculations (the procedure is described in Keppel 1991:289-291).

Table 3: Sample Sizes and Mean Forecast Error for each Combination of Support and Representation

	Count	Mean	Std. Dev.	Std. Err.
Decision Aid, Combined	19	192.637	428.007	98.192
Decision Aid, Normal	15	110.200	610.780	157.703
Report, Combined	20	371.630	217.937	48.732
Report, Normal	19	547.726	326.028	74.796

Table 4: ANOVA Table

	DF	Sum of Squares	Mean Square	F-Value	P-Value
Support	1	1712686.712	1712686.712	10.425	.0019
Representation	1	39526.445	39526.445	.241	.6253
Support * Representation	1	301173.553	301173.553	1.833	.1802
Residual	69	11335885.643	164288.198		

A summary of the ANOVA calculations is shown in Table 4. This table shows that the value of the F statistic associated with the variable *support*, 10.425, is significant at the 99% level. This allows the rejection of the null form and acceptance of the alternative form of hypothesis H1. The value of the F statistic for the variable *representation* , 0.241, is not significant. This means that the alternative form of hypothesis H2 must be rejected in flavor of the null form. Similarly, the value of the F statistic for the interaction of the variables (*support * representation*) is not significant which means that the alternative form of both hypothesis H3 and H4 must be rejected in favor of the respective null forms. Figure 3 shows an interaction line plot of the variables *support* and *representation*. The plot shows an ordinal interaction between these variables (Lehman 1991). This confirms the interpretation of the ANOVA table and the hypothesis tests. The tests and plot show that the use of a decision aid results in better performance (measured by forecast error) than the use of a report regardless of the *representation* that is used.

Figure 3: Interaction Line Plot of Mean Forecast Error
for Support * Representation
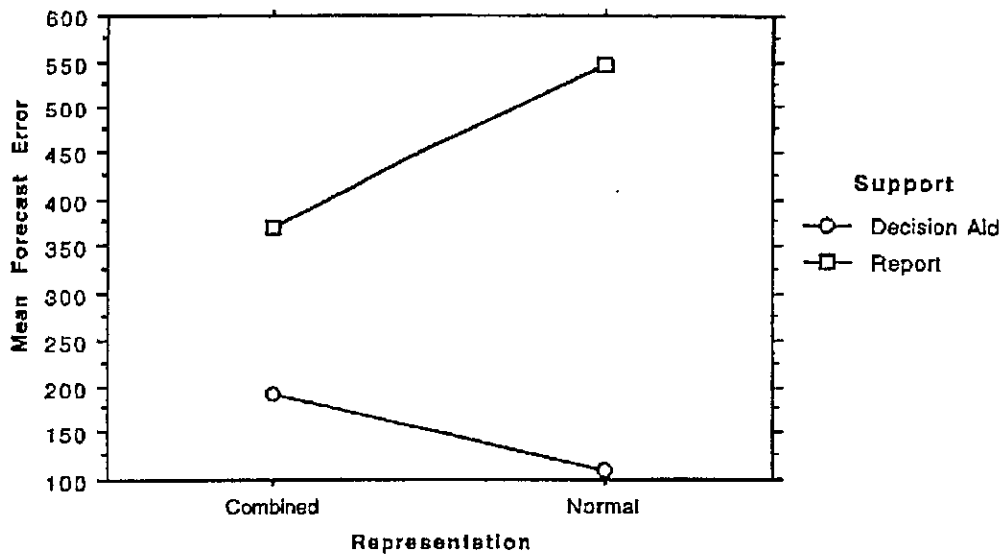
7. Discussion And Concluding Comments

The results of this experiment suggest that the use of a computer based aid improves decision performance when forecasting exponential growth. The representations used in the paper reports and the decision aids were as similar as possible. The major difference between the modes of decision support was that the users of the decision aids were able to use the computer to trial their decision. This interaction was as simple as possible (simple clicking data points followed by automated calculation or translation). The minimal nature of the intervention into the decision process adds to the power of the results given such a minor change to the support provided has such a significant effect.

The results show the combined presentation of growth data on a normal scale and on a logarithmic scale did not significantly improve decision performance. This suggests that it is the use of the computer based decision aid that improved performance, not the logarithmic transformation of the growth function.

This study is subject to a number of limitations. First, the use of university students as subjects may bias the results as it can be argued that these students are not representative of the general population. They are however, more representative of managers, who are the commercial target of decision support systems, than the general population. Also, previous studies have found no difference in the performance of students and managers in a growth forecasting task (Wagenaar and Sagaria 1975). Second, the problem is relatively artificial and subjects may not relate well to the task definition. Third, the subjects were not decision stakeholders in that they were not personally affected by the consequences of poor decision performance. Finally, there may be a Hawthorne Effect with those using the decision aids. This possibility was minimised as when the groups were split up none knew what support mode the other groups were using.

Nevertheless, the results present a *prima facae* case for the use of DSS to support decisions involving exponential growth. The reasons for the efficacy of the decision aid cannot be provided by the experiment. One possible explanation is that the use of decision aids reduces cognitive effort (Jarvenpaa 1989, Todd and Benbasat 1992). This view of the decision process hypotheses that decision makers make meta-judgements about the value of decision accuracy and the cognitive cost or effort involved in making the decision. Even in a simple decision task, such as the one used in this experiment, a decision maker will commonly opt for reduction of cognitive effort over decision accuracy. The simple act of assisting a decision maker in reading a graph and typing in the estimate can reduce cognitive effort. It is also possible that the decision aid may have provided the minimum sufficient assistance to the subject

that justified exploring the decision in more detail. The importance of this experiment is that is suggests that improvement in decision performance can be achieved by using a simple decision aid. DSS analysts should be encouraged to first developed simple tools, rather than rushing into the development of complex and technically impressive tools. The latter may not be required.

Further experiments are planned with subjects that regularly make decisions using growth data and who have a significant stakeholding to investigate the influence of domain experience and interest in the decision on DSS performance.

References

Bar-Hillel, M. (1973) "On the Subjective Probability of Compound Events" *Organisational Behaviour and Human Performance*, 9,396-406

Bazerman, M.H. (1986) *Judgement in Managerial Decision Making*, Wiley.

Benbasat, I. and B. Nault (1990) "An Evaluation of Empirical Research in Managerial Support Systems" *Decision Support Systems* 6:2, July, 203-226.

Cohen, J., E.I. Chesnick and D.A. Haran (1972) "A Confirmation of the inertial-y Effect in Sequential Choice and Decision" *British Journal of Psychology*, 63, 41-46

Courbon, J-C. (1996) "User-centred DSS Design and Implementation" in P. Humphreys L. Bannon, A. McCosh, P. Migiarese and J-C Pomeral (Eds) *Implementing Systems for Systems for Supporting Management Decisions: Concepts, Methods and Experiences* Chapman and Hall.

Dawes, R.M. (1988) *Rational Choice in an Uncertain World* Harcourt Brace Jovanovich: San Diego, CA.

Ebbesen, E.B. and V.J. Konecni (1980) On the External Validity of Decision-Making Research: What Do We Know About Decisions in the Real World?" in Wallsten, T.S. (eds), *Cognitive Processes In Choice and Decision Behaviour*, Hillsdale, NJ

Edwards, W. (1968) "Conservatism in Human Information Processing" in Kleinmuntz, B. (eds), *Formal Representation of Human Judgment*, Wiley, NY

Fischhoff, B. (1975) "Hindsight Foresight: The Effect of Outcome Knowledge on Judgment under Uncertainty" *Journal of Experimental Psychology: Human Perception and Performance*, 1, 288-299

Hogarth, R.M. (1981) "Beyond Discrete Biases: Functional and Dysfunctional Aspects of Judgmental Heuristics" *Psychological Bulletin*, 90, 197-217

Hogarth, R. (1987) *Judgement And Choice: The Psychology of Decision*, Second Edition, Wiley, NY

Jacobs, S. M. and R.T. Keim (1988) "An Experimental Study in Overcoming Hypothesis-Confirming Search Strategies in Computerised Information Retrieval Systems" in DeGross and Olson (eds), Proceedings of the Ninth International Conference on Information Systems, Minneapolis, Minnesota, 81-89

Jarvenpaa, S. (1989) "The Effect of Task and Graphical Format Congruence on Information Processing Strategies and Decision Making Performance" *Management Sceince* 35:3, March, pp295-303

Kahneman, D. and A. Tversky (1973) "On the Psychology of Prediction" *Psychological Review*, 80, 237-251

Keen, P. (1980) "Decision Support Systems: A Research Perspective" in Arnott, et al. (eds), Readings in Decision Support Systems, CISR, Monash University Melbourne

Keppel, G. (1991) *Design and Analysis: A Researchers' Handbook* 3rd Ed. Prentice Hall: Englewood Cliffs, NJ.

Keren, G. (1984) "Do Not Inflate Exponentially the Evidence for the Polynomial Model: A Reply to Jones" *Perception and Psychophysics*, 36:5, 488-489

Kreyszig, E.(1988) *Advanced Engineering Mathematics*, Sixth Edition, Wiley, NY

Kydd, C.T. (1989) "Cognitive Biases in the Use of Computer-Based Decision Support Systems" *Omega*, 17:4, 335-344

Lehman, R.S. (1991) *Statistics and Research Design in the Behavioral Sciences* Wadsworth: Belmont, CA.

Mason, R.O. and H. Moskowitz (1972) "Conservatism in Information Processing: Implications for Management Information Systems" *Decision Sciences*, 3:4, 35-54

Oskamp, S. (1962) "The Relationship of Clinical Experience and Training Methods to Several Criteria of Clinical Prediction" *Psychological Monographs*, 76

Remus, K.E. (1984) "An Empirical Investigation of the Impact of Graphical and Tabular Data Presentations on Decision Making" *Management Science*, 30:5

Remus, K.E. and J.E. Kottemann (1986) "Toward Intelligent Decision Support Systems: An Artificially Intelligent Statistician" *MIS Quarterly*, 10:4, December

Sage, A. P. (1981) "Behavioural and Organisational Considerations in the Design of Information Systems and Processes for Planning and Decision Support" *IEEE Transactions on Systems, Man, and Cybernetics*, SMC-11:9, 640-678

Todd, P. and I. Benbasat (1991) "An Experimental Investigation of the Impact of Computer Based Decision Aids on Decision Making Strategies" *Information Systems Research*, 2:2, 87-115

Todd, P. and I. Benbasat (1992) "The use of Information in Decision Making: An Experimental Investigation of the Impact of Computer Based Decision Aids" *MIS Quarterly*, Sept, pp373-393

Vessey, I. (1994) "The effect of information presentation on decision making: A cost-benefit analysis" *Information and Management*, 27, 103-119

Wagenaar, W.A. and H. Timmers (1977) "Inverse statistics and misperception of exponential growth" *Perception and Psychophysics*, 21(6), 558-562

Wagenaar, W.A. and H. Timmers (1978) "Extrapolation of Exponential Time Series is not Enhanced by Having More Data Points" *Perception and Psychophysics*, 24:2, 182-184

Wagenaar, W.A. and S.D. Sagaria (1975) "Misperception of exponential growth" *Perception and Psychophysics*, 18:6, 416-422

Wagenaar, W.A. and H. Timmers (1979) "The Pond-and-Duckweed Problem; Three Experiments on the Misperception of Exponential Growth" *ACTA Phychologica*, 43, 239-251

Wright, W. (1983) "An Empirical Test of a Bayesian Decision Support Procedure in a Financial Context" in Ross and Swanson (eds), Proceedings of the Fourth International Conference on Information Systems, Houston, Texas, 241-249

Yates, J.F. (1990) *Judgement and Decision Making* Prentice Hall: Englewood Cliffs, NJ.

Appendix A

Question Sheet Provided to Subjects where Support = Report and Representation = Normal

QUESTION SHEET

The information given in the table and graphs below are the population index from the year 1870 to the year 1990 at a 30-year interval. Please predict the index for the year 2050 by writing down your prediction in the entry box provided below.

Year	1870	1900	1930	1960	1990	2050
Population Index	5.3	13	31.89	78.21	191.84	????

Population Index in Normal Scale
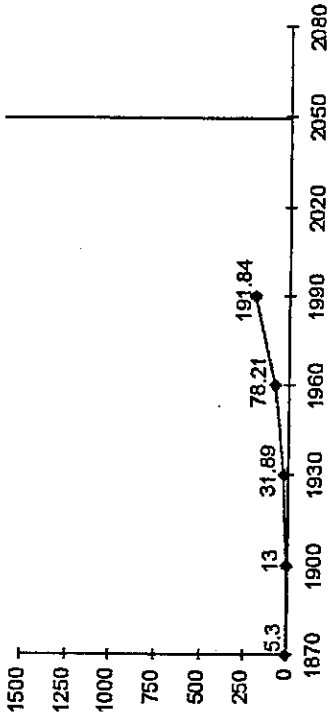
Please enter your prediction here:

## Question Sheet Provided to Subjects where Support = Report and Representation = Combined

QUESTION SHEET

The information given in the table and graphs below are the population index from the year 1870 to the year 1990 at a 30-year interval. Please predict the index for the year 2050, in normal OR log scale, by writing down your prediction in the entry box provided below and ticking the scale of your prediction.

Year	1870	1900	1930	1960	1990	2050
Population Index in Normal Scale	5.3	13	31.89	78.21	191.84	????
Population Index in Log Scale	0.72	1.11	1.50	1.89	2.28	????

Population Index in Normal Scale
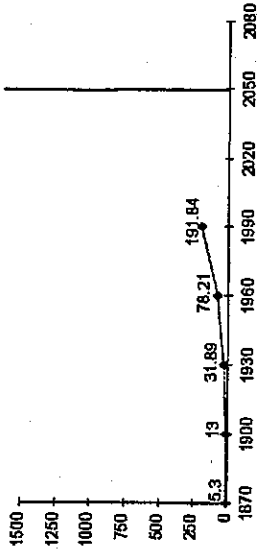
Population Index in Log Scale
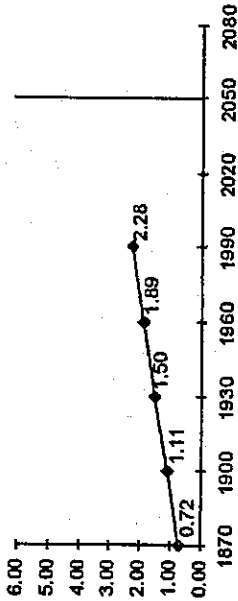
Please enter your prediction here:
Please tick the scale of your prediction:☐ Normal Scale ☐ Log Scale

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