MODELLING PRACTICES OVER TIME: A COMPARISON OF TWO SURVEYS TAKEN 20 YEARS APART

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Abstract

Although modelling tools are intensively used within companies, the modelling process itself is still scarcely researched. The few related works focus on the steps encompassed when developing a model, without taking into consideration the context surrounding it. Nevertheless understanding this context is crucial since this influences the modelling process in terms of objectives, available data and tools. A survey conducted among expert modellers in 1994 provided insights into this context by establishing a profile of the modeller and highlighting the qualities needed to improve modelling practice. However software, technology and businesses have evolved over twenty years, which may have impacted the modelling practice. Twenty years later, we conduct a similar survey. Comparing the results enables studying the evolution of modelling practice over time. The findings are discussed in the light of potentially impacting technological progress and provide insight for future research concerned with improving the modelling process.

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1 INTRODUCTION

Computer-based modelling entered engineering practice in the 1950s and has become prevalent nowadays. Boosted by extended capabilities (powerful processors, huge visualisation capacities, data-based platforms such as PLM, CRM, etc.), its introduction has progressively changed engineering practice, replacing hand calculations and physical testing with modelling tasks of various natures (Dodgson et al. 2007). Although modelling tools strongly influence the modelling process (Foss et al. 1998) and are intensively used in many companies, the modelling process itself attracted only limited interest in design and operations research (Robinson, 2004). To the knowledge of the authors, a limited number of studies has been done on this topic in the last 30 years. Amongst them, a questionnaire proposed by Willemain (1994) particularly caught our attention. He realised a short survey with experienced modellers in order to provide a description of experts' traits, their style of work and their opinions on what constitutes good practice. This yields interesting insights by establishing a modeller profile and highlighting the qualities needed to improve modelling practice.

Robinson (2005) states that developments in computing such as the increase in computational capacity, software usability and low budget simulation software has brought changes in the way simulation models are developed and used. We are interested in determining the effect of these changes on modelling practice with the ultimate goal of providing improved modelling tools and methodologies. The questionnaire proposed by Willemain (1994) provides a good start to do so. Twenty years later, we have conducted a similar survey, which enables us to investigate if and how modelling practice evolved over time.

In the following section, we provide an overview of research work related to modelling activities and potentially technological advances impacting them. Section 3 presents the context of this study as well as the survey itself and its sample. Section 4 describes the survey results and compare them with those of Willemain's survey. Section 5 discusses the differences and similarities pointed out by comparing the two surveys, as well as their implication for future modelling methodology.

2 BACKGROUND ON MODELLING THEORY

2.1 Evolution of technology

Since the 1980s, modelling activities have been mostly impacted by software improvement, organisational changes and the growth of the Internet. On the software side, utilisation of Visual Interactive Modelling Systems (Pidd 1998) made model use and development less reliant on specialist computing skills although it still requires modelling skills (Robinson 2005). With the increase of computational capability, more complex systems can now be modelled. Additionally, virtual reality animations, often included in simulation tools, improve understanding of the system being modelled as well as communication with stakeholders, particularly with senior management (Waller & Ladbrook 2002). In parallel, investment in data centres and information systems enabled companies to collect data through various legacy systems, and store them in commercial relational database management systems (Chen et al. 2012). Depending on the type of company, these data are used mainly for collaborative work, when designing a system for example, or for business intelligence and analytics in order to better fit customer demand. Such use of data was mainly enabled by the growth of the worldwide web, which has also facilitated the international development of many organisations and resulted in an increase of organisational complexity of companies. The consequent geographical dispersion and temporal differences observed in engineering design (Détienne et al. 2004) may also impact modelling practice, in particular when it requires collaboration between teams with different geographic area.

2.2 Modelling practice

This study investigates whether and how the evolution of software and technology has impacted model development in industry. A number of modelling processes have been proposed in the literature (Shannon 1998; Balci & Nance 1987; Pidd 2004), particularly for simulation modelling. They all identify and structure the tasks to be encompassed when developing a model. In essence, modelling process consists in firstly understanding the problem; secondly, conceptualising and coding the model and finally implementing it after testing and validation. Other works (Pidd 1999; Sánchez 2007) complement these approaches by enunciating the main principles to follow and pitfalls to avoid, mainly built on the experience of their authors as modellers. In parallel to this, a few empirical studies (Willemain 1995; Wang & Brooks 2007; Tako & Robinson 2010) have been conducted in order to better understand the process employed when developing a model. They found that experts spend considerable time on every modelling task but do so in many short chunks, therefore inducing many switches between the different tasks.

Very few works addressed the modelling process with a wider perspective. However, considering the surrounding context is essential since it will constrain the activity of developing a model in terms of objectives, data, tools to be used, etc. At the organisational level, Cameron and Ingram (2008) show that the main barriers for modelling may be cost, time, lack of experts, lack of awareness in potential benefits and access to tools. In particular, most organizations impose a limited number of tools (Foss et al. 1998); thus, a change in the software policy or a migration to a new information system may have a major impact on the use of operational models, in particular when those rely on historical data. Strategic changes in business policy may also result in changing the requirements for a model even before it is finished. Changing requirements have been noticed as a recurrent problem in both studies of Foss et al. (1998) and Cameron and Ingram (2008).

In order to manage this uncertainty, it is essential to understand how a model is developed within its surrounding context. Willemain (1994) presented a study in which modellers were asked:

1. to describe their experience with modelling by locating themselves between two extremes on a 7-points Likert scale. This self-description concerned themselves as modellers, the models they make, the problems they model and the modelling process they usually follow.
2. to state the qualities of an effective model, an effective modeller, an effective modelling process and a desirable modelling client;
3. to tell a personal modelling story that they thought interesting.

Although this survey relies on a small sample of 12 modellers, it reveals interesting insights. Based on the self-description, Willemain paints the portrait of a typical modelling situation. Usually, a model serves to represent an existing complex system. Modellers generally prefer to start small and add, and make use of alternative models. At the end a unique final model emerges, generally after heavy client contact. Derived from the qualities enunciated by the participants, the effectiveness of a model depends on its validity and its usability. These qualities may be better achieved when the modeller spends enough time on understanding the problem as well as validating the model. These two steps are done in collaboration with the model client; their success does not only rely on technical skills but also on personal capabilities like communication skills of both model client and modeller. The personal modelling stories support the view that problems related to modelling are most often related to difficulties in communicating results, or computational and issues related to data.

2.3 Motivations

Willemain used this survey to point to weaknesses of OR education, but it is also interesting in terms of its insights and its capabilities to capture the modelling context (with the Likert scales) and reveal improvement opportunities based on qualities expressed by modellers. However, modelling capabilities have evolved in twenty years and it remains unclear how much technological progress has impacted modelling practice with regards to skills, types of models or collaboration. We decided to reuse part of this survey with twofold objectives: to obtain a snapshot of current modelling practice and therefore have an updated view on current modelling needs; and to compare our results with those of Willemain (1994) in order to estimate the effect of technical advances on the modelling process. Therefore, some items in the Likert scale are particularly interesting:

- the item "Specialist/Generalist" indicates how modellers perceive their own skills;
- the items "Simple/Complex systems", "A few/Hundreds of variables" and "Little/Extensive computation" provide insights about the complexity of systems to be modelled and models;
- the item "A few/Many data available" reflects the impact of information systems on modelling.

The qualities of effective modellers, clients, models and modelling process may also have changed with the evolution of technology and updating them should validate existing or open up new research directions for model development.

3 METHODOLOGY

3.1 Context and objectives

This study is part of an in-depth investigation of modelling activities as practised both in industry and academia with the overall objective to identify the gaps between developers' practice and model users' expectations. From these, requirements for new modelling methodologies and tools will be derived with the aim of improving and facilitating modelling activities.

A necessary first step consists in obtaining an overview of current modelling practice. The study of Willemain (1994) provides interesting insights on modelling practice, but 20 years ago. Hence the necessity to update these insights. Semi-structured interviews with experts were first carried. Although these interviews are not presented in this article, they help to discuss some of our findings. In addition, parts 1 and 2 of the study made by Willemain (1994), i.e. the questionnaire, are repeated on a preliminary sample that can be extended in later stages. The additional benefit of using the questionnaire is that it makes collection of structured and quantitative data possible.

The main objective of this work is not to draw definitive conclusions, but rather to gain insights on modelling practice in order to develop a new research that will focus on the challenges identified in this study.

3.2 Survey

3.2.1 Contents

The survey consists of a questionnaire mainly repeating the parts 1 and 2 of the original one proposed by Willemain (1994). The questionnaire comprised three sections:

- **Information about educational background and experience with modelling:** the participants are asked to indicate their formal qualifications as well as the number of years in modelling. They also indicate the types and the application domains of their models.
- **Self-description in modelling activities:** this section is composed of 44 items represented on a 7-point Likert scale and divided into four sections (modeller, models, modelled problems and modelling process). The respondents are asked to locate themselves between two extremes. Originally, this section contained 37 items. We added 6 items that we thought were important (qualitative/quantitative), or on which we wanted additional insights (model granularity in particular). Finally, we divided the item "Strategic, large-scale / Tactical, small-scale" into the items "Strategic/Tactical" and "Large-scale/Small-scale" since we considered that these two characteristics were not necessarily correlated.
- **Opinions about effective modelling activities (optional):** the participants are invited to offer three important qualities of an effective model, an effective modeller, an effective modelling process and a desirable modelling client.

3.2.2 Samples

The sample is composed of 20 modellers amongst which 5 are researchers in engineering design and 15 are engineers for the most part in big aerospace, telecommunication or energy companies. Apart from 2 modellers who are novices and 4 experts who have more than 20 years of experience, they have between 4 and 12 years of experience. Their modelling expertise ranges from system design to performance optimisation, through to process modelling.

3.3 Data gathering and analysis

This study was conducted using either an online questionnaire sent via email, or a hard copy. To allow a comparison of our results with those of the previous study, we adopted the same analysis methods. The items in our table below are sorted in decreasing order of consensus. The experts' opinions are firstly overviewed using word clouds and then classified in the same categories as the previous study. In case some responses do not belong to any category, we took the liberty to add a more adapted one.

In each section, the current results are compared with those of Willemain's study using median comparisons for the Likert scales and comparing the number of answers in each category for the experts' opinions. Possible explanations for the observed differences and similitudes are also discussed.

The following section presents the results by section. In view of the large amount of data, most of the results are visualised. To facilitate the comparisons, we used the dataset and included some insights of the previous study.

4 RESULTS AND COMPARISON

4.1 Self-description

Figure 1 summarises the results of the self-description parts of both studies. For each item, the diameter of each circle represents the number of responses for the corresponding value on the Likert scale. Since the two studies do not have the same total number of respondents, the results have been normalised. The items have been sorted in decreasing order of consensus. The consensus score *C* is calculated as the difference between the number of responses on the more popular side of the Likert scale, and those on the less popular side, as shown in Equation 1:

$$C_j = Max(\sum_{i=1}^{3} n_i, \sum_{i=5}^{7} n_i) - Min(\sum_{i=1}^{3} n_i, \sum_{i=5}^{7} n_i) \quad (1)$$

with: *n* the number of answers,
i the index of the value on the Likert scale,
j the index of the item.

The items that have at least two thirds of the total number of responses on one side are indicated with ©. The items recognised as most significant in Willemain's study are indicated with ©. When the items have raised consensus in both surveys, they are indicated with ©. This visualisation provides a complete overview of responses and enables a rough comparison between the surveys.

Based on the consensus on various points, Willemain proposed a typical profile of modellers: *"They develop a unique model for each problem, though all their models involve extensive computation. They develop their models not in one burst but over an extended period of time marked by heavy client contact. Guided by analogies, drawing and doodling, they develop more than one alternative model, in each case starting small and adding"*(Willemain 1994, p.214). The profile which emerges from our study is largely similar. In our study, the modellers develop models to gain insights about complex existing systems, often at a large scale. They work over extended time and have in-depth contact with the client. In particular, this enables them to make alternative models for which the right level of granularity emerges during the modelling process. They focus on application rather theory, and model to get the job done instead of modelling for fun.

However, some differences can be noted. In order to evaluate the impact of technology advances on modelling practice, the evolution trend of each item has been calculated by comparing the median values found in both studies, which is illustrated in the central column of *Figure* 1. The black cursor indicates the current median value whereas the grey surface illustrates the shift with the median values found in Willemain's survey (1994). We particularly focused on the following items:

- "Specialist/Generalist": from a medium value in Willemain survey (indicating in this case a regular distribution of answers over the Likert scale), most of the modellers of our study now consider themselves as generalist, thus corroborating the observations made by Robinson (2005) and Dodgson (2007).
- "Simple/Complex systems": the systems to be modelled were perceived as complex twenty years ago. They are still perceived as complex. This tendency is quite well explained by the fact that modelling exist to support and improve the understanding of complex behaviour. In that sense this observation is not surprising.
- "Little/Extensive computation": computation seems less extensive than twenty years ago. Taken literally, this contradicts the hypothesis that software is used for more extensive computation. However, it must be considered that the Likert scale only reflects the perception of modellers about the amount of computation. Modelling software with today's powerful computational capabilities means that this is not now seen by modellers as a significant limitation.
- "A few/Hundreds of variables": modellers tend to use more variables. This last observation endorses our interpretation of the previous one, suggesting that even though many data are used, extensive computation is not a problem in view of computing progress.

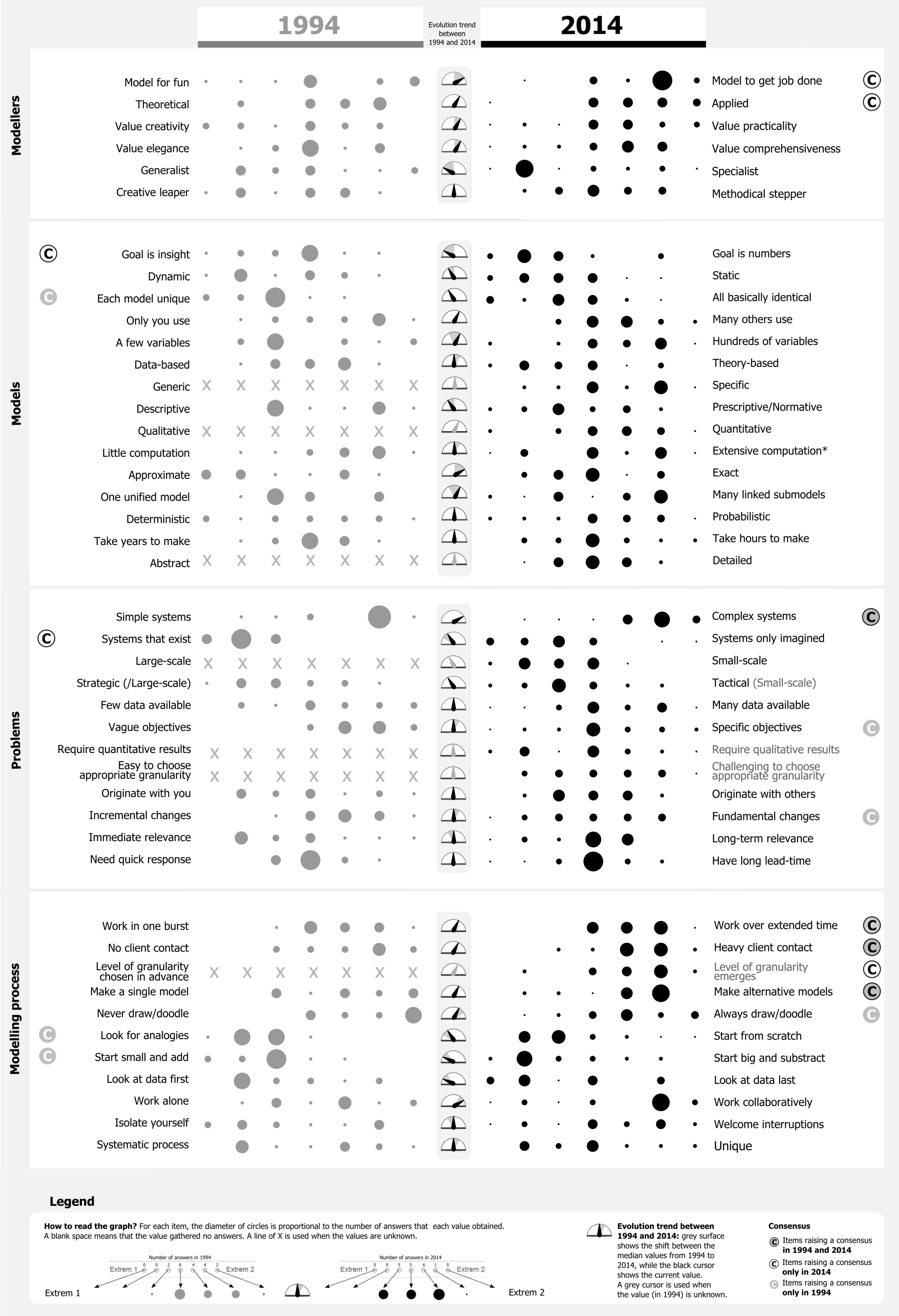

Figure 1. Results and comparison of self-description

- "A few/Many data available": the amount of available data seems to not have changed. However, here again we should interpret this result with care. Our opinion is that although nowadays there is a greater consumption of data by models (see the previous point), the objectives tend now to be more focussed on gaining insights in very complex areas of decision making. The data to support these insights need to be extensive and from many sources, with varying degrees of accuracy and provenance. This complicates and extends the nature of the models and makes sourcing good data a continuing difficulty.

It is worth noting two additional insights gained from other items. Firstly, the only consensus in the section "Model" is that the main objective of models is to provide insights more than numbers; but these insights must be based on rigorous calculations involving a high number of variables. Secondly, the modelling objectives tend to be less clear. These two observations combined together suggest that the objectives are less predefined at the start and the models themselves help clarify the questions being asked, in an iterative manner, hence the importance of gaining insights rather than purely numerical results.

4.2 Expert opinions

The respondents were asked to state up to three qualities that define an effective modeller, an effective model, an effective modelling process and a desirable modelling client. Due to the limited space of this paper, their answers are presented in Figure 2 in the form of word tags, which enables to provide a concise overview of the responses content while highlighting the main emerging trends (Sinclair & Cardew-Hall 2008).

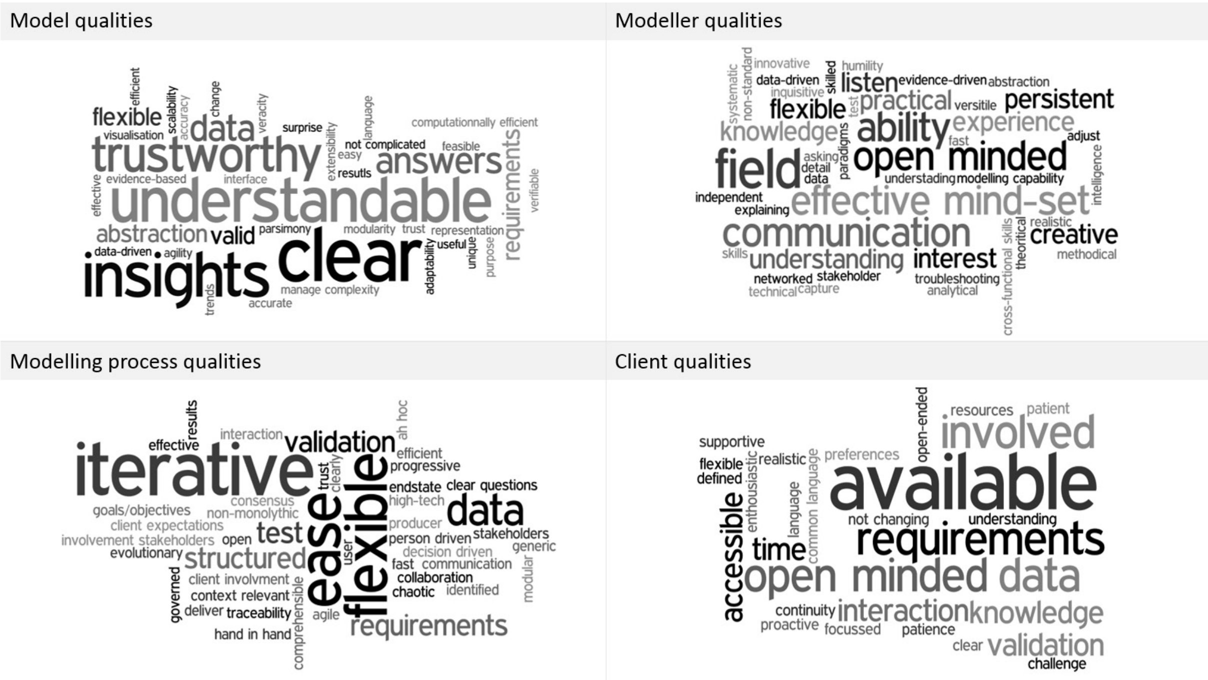

Figure 2. Word clouds

Based on these answers, the modellers' opinions can be summed up as follows:

- An effective model is a model which is clear, both in terms of how it works and the insights it delivers. This greater understandability yields trustworthiness in the client's mind.
- An effective modeller is open minded, with good knowledge and interest in modelling and the problem field. Communication, practicality and flexibility are strongly appreciated.
- An effective modelling process is highly iterative and flexible. The steps of requirements definition, data collection and model validation are of importance and the modelling process should be structured to facilitate their elicitation.
- A client is ideal if he is open-minded concerning the modelling outcomes and involved in modelling activities. This implies that he is available to either clarify the model requirements, to provide data input or to validate the model.

In order to compare these insights with those of twenty years ago, all the qualities proposed by the experts have been classified according to the categories proposed by Willemain. Table 1 shows how responses fitted these categories both in 1994 and 2014. Further explanation about each category is available in Willemain (1994).

Table 1. Distribution of experts' opinions

Category	1994	2014
Models		
Validity	44%	31%
Aptness for client problem	8%	4%
Feasibility	10%	10%
Value to client	13%	14%
Usability	25%	24%
Ilities	0%	14%
Requirements	0%	4%
Modellers		
Mind-set	43%	34%
Nontechnical expertise	26%	43%
OR/MS expertise	20%	15%
Subject-matter expertise	5%	9%
Modelling Process		
Context	39%	26%
Assessment	37%	36%
Structure	17%	26%
Realization	7%	10%
Implementation	0%	3%
Client		
Personal Capabilities	41%	37%
Mind-set	31%	19%
Behaviour	15%	33%
Resources	13%	12%

When comparing current values with previous values, an interesting fact is that the global distribution has not significantly changed. This means that modellers' expectations follow the same trend:

- Validity and usability of models are still predominant model qualities.
- For the modelling process, emphasis is given to discovering the problem and validating the results.
- The mind-set and personal capabilities are the most important for both modeller and client.

But a few changes also emerged. Firstly, some model qualities concern the right definition of model objectives and requirements. We thus added a new category that we called "requirements". Secondly, a greater attention is paid to the step of structuring the problem during modelling process. Likewise, respondents indicated a new category of qualities such as flexibility, scalability, adaptability, agility, etc. These refer to model properties that have a long life-cycle value, in contrast to other properties such as validity or robustness that have immediate impact. In system development, such properties can be called "ilities" (Crawley et al. 2004). By analogy we included them into a new category that we call "ilities". In Willemain's survey, only one quality, i.e. "*Easy to modify, either to include additional aspects or to reflect change in conditions*" (Willemain 1994, p.219) belonged to it. This hints at a major change in modelling practice since it suggests that the model needs to be architected carefully in order to adapt to change over time, which could imply a trend towards middle to long term use of models.

5 DISCUSSION & CONCLUSION

This study includes a number of biases, which must be kept in mind when interpreting the results. Compared to the original survey, seven Likert scale items were added. We believe that these did not influence the results. The main bias may come from the difference between the samples used in each survey. Whilst the first survey relies on a sample mainly consisting of academics, ours relies on a sample mostly composed of industrial practitioners. The differences and similitudes observed in our comparison must therefore be carefully interpreted. Additionally, the size of the samples limits the generalizability of our observations. The new sample, although more diverse than the previous one, should not be taken to be representative of the modeller community as a whole. However, we believe that the insights highlighted in this study are mostly consistent with changes in modelling technology and the nature of business. They are of interest to those involved in modelling practice and justify further investigation.

From the results of our study, the main insights are as follows:

- **Modellers tends to be more generalist.** This can be explained by the differences in the samples (academics vs. industrials) but also by the fact that current software requires less specific skills and make modelling accessible to more people than twenty years ago.
- **Modelling goal is to acquire insight.** 75% of participants stated this point of view. However, models continue to be more quantitative than qualitative. There exist several explanations for this. The first one is that modern modelling software has much greater computing capability, which enables fast, exact and accurate calculations as well as improved visualisation features, which makes trends in results more easily readable. In addition, modellers interviewed alongside this study pointed out that although the modeller is aware that the model only provides insights, modelling clients still need quantified estimations and results.
- **Detailed and regular client contact is one of the keys for a good modelling process.** This item on the Likert scale generated consensus. 20% of the qualities of a good modelling process underlines the need for interaction and communication with stakeholders, mainly in order to define the objectives, access data and validate model results. Although this process gets the clients to trust a model, the number of iterations may be reduced using an appropriate methodology.
- **Access to data is still a problem.** Based on the interviews we conducted alongside the survey, it seems that data collection is a fundamental problem many modellers face. Nowadays, the models demand more data, driven by the type and scope of issue being modelled, and therefore it remains as much of a problem to source it as 20 years ago. This increased supply and this increased demand constitute a bottleneck that needs to be supported by the appropriate tools.
- **Like systems, model have "ilities".** These properties, which bring longer term value to models, are now a matter of increased concern for modellers. There is greater interest in model re-use and continuous development than was the norm a few years ago. Therefore, developing theories and methods which support "ilities" when developing models is increasingly important. This argues for a continuation of the work initiated in this area (Davis & Anderson 2004; Teo & Szabo 2008; Edwards 2013).

In summary, this paper presents the results of a short survey that we conducted with 20 modelling experts. These results have been compared with those of a similar survey, done twenty years ago. By reducing the computing skills to make a model, software are now accessible to more generalist modellers. However, the increasing use of relational database management systems makes the storage of more data and models possible. This provides more modelling opportunities but also requires more modelling skills. Developing a model in an effective way raises new methodological needs in terms of:

- Problem statement, data collection and model conceptualisation: "How to identify the relevant data and make the best use of them to solve the problem?"
- Model architecture: "How to architect the model so that it is resilient to changes and can be potentially adapted for other problems?"

This constitutes new research directions for improvements in modelling practice. Future work will concentrate on conducting deeper studies in these areas to understand their core problems and propose adapted methods and tools to handle them. Amongst them, a particular focus will be put on the early stages of model development, combined with a more thorough consideration of model "ilities" for longer term benefits.

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