


An Empirical Study on Memory Bias Situations and Correction Strategies in ERP Effort Estimation

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Abstract. An Enterprise Resource Planning (ERP) project estimation process often relies on experts of various backgrounds to contribute judgments based on their professional experience. Such expert judgments however may not be bias-free. De-biasing techniques therefore have been proposed in the software estimation literature to counter various problems of expert bias. Yet, most studies on de-biasing focus on systematic bias types such as bias due to interdependence, improper comparisons, presence of irrelevant information, and awareness of clients' expectations. Little has been done to address bias due to experts' memory. This is surprising, knowing that memory bias retrieval and encoding errors are likely to affect the estimation process outcome. This qualitative exploratory study investigates the memory bias situations encountered by ERP professionals, and the possible coping strategies to problems pertaining to those situations. Using interviews with 11 practitioners in a global ERP vendor's organization, we explicate how experts retrieve and encode stored memory, what kind of errors they experience along the way, and what correction techniques they were using. We found that both errors due to memory retrieval and due to memory encoding seemed to lead to project effort underestimation. We also found that the most common memory correction strategy was the use of mnemonics.

Keywords: Memory bias · Expert judgments · Project effort estimation · Empirical study · Exploratory qualitative research method · Grounded theory

1 Introduction

Experts-judgement-based estimation plays an important role in Enterprise Resource Planning (ERP) project management [1]. If an ERP implementation project happens in a client organization that has been collecting data on their ERP projects, then expert-judgment-based methods complement quantitative approaches to sizing and estimating projects (e.g. such as in [2]). If client organizations and consultants find themselves in situations where historical data from past projects are unavailable or are irrelevant (e.g. if the projects differ significantly), then expert-judgment-based methods are the only viable option for the project team to come up with an estimate. Unfortunately, using expert-judgment based methods is far from straightforward, due to various biases that interfere with the experts' willingness to provide a fair and well-grounded judgment. The 2012 systematic review of Halkjelsvik and Jørgensen on expert-judgement-based

predictions of performance time [3] indicates a number of examples of estimation bias reported in software engineering (SE), in engineering in general, and in psychology. An important bias in expert judgment estimation is due to memory errors [4] that the expert is unaware of at estimation time. While in the field of empirical SE, techniques for de-biasing software estimates have been proposed to counter various problems of expert bias, most studies on bias and on de-biasing focused on systematic bias types e.g. bias due to interdependence [5], due to improper comparisons [6], due to presence of irrelevant information [7], due to awareness of clients' expectations [8]. To the best of our knowledge, we could find no study that dealt with de-biasing of estimates due to memory errors. This seems surprising, knowing that memory retrieval errors as well as memory encoding errors are likely to affect the estimation process outcome [4].

We felt motivated to make a step towards better understanding the project estimation situations in which memory errors may occur and the actions (if any) that experts might take if they recognize that they might have injected memory bias into their estimates. Therefore, this paper sets out to answer the following research questions (RQs): **RQ1:** What memory retrieval errors do ERP experts experience in ERP project effort estimation? **RQ2:** What memory encoding errors do ERP experts experience in ERP project effort estimation? **RQ3:** What memory correction techniques do ERP experts use in ERP project estimation?

We answer these RQs by carrying out an exploratory interview-based multiple case study [9] with 11 practitioners involved in the estimation process of ERP projects. The results of our effort are three conceptual models that are independent from any particular expert-judgment-based estimation technique and that describe on an abstract level situations in which memory bias occurs and the coping strategies that could help with it, according to our case study participants.

The paper is organized as follows: Sect. 2 presents background, related work and our motivation. Section 3 presents our research process and Sect. 4 – our results. Section 5 provides a discussion on the results, comparing them with findings from previously published studies. Section 6 evaluates validity threats and Sect. 7 concludes.

2 Background, Related Work and Motivation

The following streams of related work provide the background to this paper: (1) empirical studies on expert consciousness [10], on expert reconstructive memory [11], on the misinformation paradigm [12], and (2) empirical studies from the area of expert judgment based estimation, in particular, on estimation biases [13–33].

Expert consciousness. Kessel [10] suggests that the consciousness of an expert plays an important role in estimating effort of work activities. It could both increase and decrease the accurateness of an estimate. The consciousness of the expert increases the richness and details of objective awareness and includes both the perceiver and the surrounding environment. Moreover, flexibility of anticipation and memory enable the expert to imagine situations other than the logical ones determined by the project scope. The cumulative result of social perception and interpersonal communication leads to

developing an emotional self-consciousness [10]. It is this self-evaluation of the expert's self-consciousness that is vital for accurate effort estimates. Experts may deviate from their logical projections due to their consciousness. The unfavorable consciousness of the expert could be obscured in situations like: (i) Self-doubt about their own situation and skill may lead to overestimation; (ii) Resource scarcity may cause experts to adopt the pressure on them to provide an underestimated version of the desired outcome; (iii) Experts might make a judgment reflecting on a situation where they could imagine the most skilled person to carry out the task, therefore result in underestimations; (iv) Intimidation by external parties (or even colleagues that take part in the estimation process) could have an impact on an expert's judgment to adjust a logical defined value to satisfy certain stakeholders; (v) Oversimplification might result in the underestimation.

In contrast, the favorable consciousness of experts could be in the form of: (i) insights of typical cause and effects situations in certain conditions – might it be technology-specific or environment-specific; (ii) insight of scalability issues concerning specific technologies; (iii) insight of integration challenges concerning specific technologies and within certain environments; (iv) understanding of customer or industry specific challenges such as the complexity of customer's (or industries) business processes or organizational structure.

Kessel [10] suspects a possible correlation between the accurateness of estimates and the ability to control the consciousness of an expert. Even though it might be very difficult to control the consciousness of an expert, it is more realistic to set the conditions to promote the favorable consciousness where the expert can consider conditions logically and explicitly mention them with the possible effect they might have. Appropriate approaches or techniques can potentially decrease (or eliminate) the unfavorable consciousness which often obscure an estimate from a logical outcome which might contain less bias.

Expert's Reconstructive Memory. This term refers to the idea that remembering the past reflects our attempts to reconstruct the events experienced previously [11]. These attempts are based partly on traces of past events and might affect the memory of the scope and effort incurred of a specific task carried out in the past. Moreover it can also affect our general knowledge, our expectations, and our assumptions about what must have happened. Therefore reconstructive memory might influence an estimates task duration and scope. As such, recollections may include errors when our assumptions and inferences, rather than traces of the original events, determine our recollections. Errors or false memories, constitute the prime evidence for reconstructive processes in remembering. As stated in [11], reconstructive memory refers to the idea that retrieval of memories does not occur in completely accurate form. Memory of past events does not appear like a video might replay a scene, but rather that recollection of memories involves a process of trying to reconstruct (rather than replay) past events. The reconstructive memory is the effect when the mind fills in the gaps of our memory with a reconstructive version of past events, therefore reconstructing the original event or task. The implication for the design of an expert-judgment-based estimation method is that it will need to include a mechanism to reduce imprecisions due to reconstructive memory.

The Misinformation Paradigm. The misinformation effect [12] refers to a case where the memory for an event is not encapsulated in time in the way the event itself is. Information provided after the event can modify our memories for the event itself. The misinformation effect happens when incorrect information received after an event gets incorporated into one's memory for the event. In light of this situation, Burt and Kemp indicate that consistent information improves our later reconstruction, whereas conflicting or misleading information is harmful [11].

Effort Estimation Tendencies Using Expert Judgment. First, studies (e.g. [13–15]), on experts' overestimation and underestimation found that duration of tasks lasting fewer than 5 min tended to be overestimated, while duration of longer tasks (e.g. taking hours/days/weeks to complete) tended to be underestimated. A possible reason for this tendency to make biased predictions of future task durations is that, in making such predictions, people use memories of past durations, and those memories are systematically biased. That is, memories of previous task duration are incorrect; therefore, predictions of future duration for similar tasks are also incorrect. The memory bias account of Christenfield and McKenzie [15] suggests that it is error in memory that causes a corresponding error in prediction.

Second, empirical evidence indicates a person's overall tendency to underestimate task duration in retrospect, remembering tasks that they have completed as having taken less time than they actually did [16–19]. In support of the memory bias account, research has indicated that tasks that are likely to be remembered as taking longer than they actually did, such as novel tasks [20] or short tasks [21], are also likely to be predicted to take longer than they actually will.

Third, an expert's past experience could refer to performing the task directly or observing others completing the task. A prediction then could be made by using this general representation as an anchor and adjusting the prediction up or down on the basis of the specific task at hand. In this way, the process of predicting task duration may be similar to that of remembering task duration using reconstructive memory.

Fourth, empirical research [22–24] has also suggested that people using a top-down approach to planning, do predict for the task as a whole but fail to sufficiently weight the various components of the task. On the other hand, underestimation may result from people using a bottom-up process to planning, so that, when listing the individual components of a task, they neglect key subcomponents in the process [24, 25]. Moreover, it has been suggested that people may, in making their predictions, disregard their memories of how long similar tasks have taken in the past, and so ignore relevant prognostic information [26–28]. For example, Buehler et al. [26] explain that people continue to underestimate how long it will take them to complete future tasks, even though they are aware that similar tasks have taken longer than planned in the past. This narrow focus causes people to disregard their memories of how long similar tasks have taken previously, as well as leading them to discount the possibility of surprises or interruptions that may delay completion.

Solutions to the above problems have also been suggested. E.g. Kahneman and Tversky [28] argue that prediction would be improved if memories of past completion times were fully consulted during the prediction process. Other solutions are: to reflect

on past completion times [27, 29], to break down tasks into their individual components [22, 23, 30], to list possible surprises that could arise during the task [22, 27], to form alternative scenarios of how the task might be completed [22, 23], and to examine the problem as observers instead of as actors [22, 29, 31]. However, evidence from empirical studies on the effectiveness of these solutions is inconclusive. There are studies suggesting that these solutions alone shown little improvement of the overall accuracy of prediction altering behavior subsequent to prediction using implementation intentions [31, 32]. Moreover, in the case of novel tasks, even if experts are supplied someone else's experience with the task [14], they are extremely resistant to using this information [33].

Furthermore, other authors (e.g. [24, 34] found that the most accurate estimations that stood out above the rest, were in situations when estimators receive accurate feedback of past completion times on prediction. These studies indicate that supplying feedback of actual task duration before making a new prediction may be a viable way of increasing predictions. Use of feedback has also been found to improve judgment accuracy for a number of tasks, and forecasting outcomes of time series [35].

We note that with very few exceptions (e.g. [24]) most of the work comes from the sub-fields of psychology (e.g. social psychology, cognitive psychology) and the tasks studied are not in the context of SE. Although there is extensive work on the phenomenon of expert bias in software estimation [5–8], we could find no study dealing with bias due to memory errors. In the context of ERP, projects are usually large, multiple stakeholders often come with incomplete or imprecise requirements [1, 2, 36], all of which is conducive to a situation in which an expert may not be in the position to remember every project implementation detail from the past. Moreover, most project organizations do not have the practice to document experts' assumptions while estimating. Being involved in a variety of ERP projects, we thought we could collect possible experiences from practitioners to help understand what is going on in the field. If we understand the possible ways in which memory errors are experienced, project teams could think of mitigation strategies to de-bias their estimates.

3 Research Plan and Execution

The objective of the present study is to understand how ERP experts participating in project effort estimation, experience memory bias and what they do to cope. Our research plan was to conduct an exploratory case study inspired by Yin's guidelines [9]. We used semi-structured open-end in-depth interviews with 11 practitioners from a global ERP consulting company. Our research process included these steps: (1) Compose an interview guide following the guidelines in [37]; (2) Do a pilot interview to check the applicability of the guide to real-life context; (3) Carry out interviews with practitioners according to the finalized interview script; (4) Sample and follow-up with those participants that possess deeper knowledge or a specific perspective. We note that our interview protocol was not changed after the pilot interview. For this reason, we included the data of this interview to our analysis. The interview guide is receivable from the authors upon request.

Each interview lasted between one and two hours. All took place face-to-face. The interviews included 4 consultants 3 project managers, 2 technology architects and 2 solution architects. A consultant is an individual responsible for the implementation of specific solutions. A project manager is an individual that is responsible for managing a certain project, with a predefined scope, delivered within a specified budget, ensuring a specific quality is delivered within a specified time period. A technology architect is responsible for the high level design and integration across a group of solutions or platforms. A solution architect is an individual that is responsible for the detailed architecture and design for a specific solution or product. These experts had ten to twenty years' ERP experience in their own sub-field of ERP expertise. The experts are based in Germany, Netherland, USA and South Africa. The business domains for which these practitioners implemented the ERP solutions were automotive, banking, health care, and telecom.

At the interview meeting, one researcher (Erasmus) and the interviewee walked through the questionnaire which served to guide the interviews. The questionnaire consisted of three parts: (i) questions referring to the estimation practice in one concrete ERP project of the interviewee; (ii) questions about the general estimation practice in the company, based on the interviewees' experience; and (iii) questions about the role of memory bias in estimation. Examples of the questions asked are: "What roles are involved in the estimation process?", "What information do you provide and to whom?".

For determining the number of practitioners to be interviewed, we followed Charmaz [38], according to whom this number was dependent on the level of 'saturation'. This meant, we had to analyze our data immediately after each interview by using coding practices [38], and compare the codes of one interview with the codes of the previously

Table 1. Interviews and numbers of newly generated codes.

Interview	Number of new codes
Interview 1	63
Interview 2	22
Interview 3	8
Interview 4	12
Interview 5	6
Interview 6	4
Interview 7	5
Interview 8	3
Interview 9	0
Interview 10	1
Interview 11	0

done interviews. As soon as no more new codes were determined during the interview process, we accepted that saturation has been reached. Table 1 illustrates the process of code discovery. As it could be seen from the table, Interview 1 helped us find out 63 codes, Interview 2 revealed 22 more codes, Interview 3 brought 8 new codes to what we already had in Interview 1 and Interview 2. As the interviewing and the coding was progressing, the number of newly identified codes became less and less. In Interview 9, zero new codes were added, in Interview 10 only one new code was added, and in Interview 11 – again zero new codes. At this point we stopped the data collection process.

Our data analysis used the Grounded Theory (GT) practices according to Charmaz [38]. GT is a qualitative approach applied broadly in social sciences to construct general propositions (called a “theory” in this approach) from verbal data. GT is exploratory and recommendable in research contexts where the researcher has no pre-conceived ideas, and instead is driven by the desire to capture all facets of the collected data and to allow the theory to emerge from the data. In essence, this was a process of making analytic sense of the interview data by means of coding and constant comparison of pieces of data that were collected in the case study. Constant comparison means that the data from an interview is constantly compared to the data already collected from previously held interviews, until a point of saturation is reached, i.e., where new sources of data don’t lead to a change in the emerging theory (or conceptual model). We first read the interview transcripts and attached a coding word to a portion of the text – a phrase or a paragraph. The ‘codes’ were selected to reflect the meaning of the respective portion of the interview text to a specific part of the RQ. This could be a concept (e.g. ‘bias’, ‘de-biasing action’), or an activity (e.g. ‘feedback-giving’). We clustered all pieces of text that relate to the same code in order to analyze it in a consistent and systematic way. The results of the data analysis are presented in Figs. 1, 2 and 3 and discussed in Sect. 5.

4 Results

Our multiple iterations of coding, constant comparing of information from the interviews, and conceptual modeling in our GT process yielded the models presented in Figs. 1, 2 and 3. Their overall purpose is to explicate and bring insights into the situations in which memory bias and errors occur and the coping actions that the practitioners use. The models take the perspective of the ERP vendor’s organization and are to help the vendor’s architects, consultants and project managers see those concepts that are important to consider when attempting to de-bias early ERP project estimates, including context. The models describe what happens in all those estimation processes about which we learnt from the participants in the case study. We make the note that in all the three models we take a generic perspective of ERP estimation that is, it abstracts from the use of a specific estimation approach.

In the models in Figs. 1, 2 and 3, we used a dark-colored ellipse to mean an effect of an undesired outcome, a light-colored ellipse to mean a research domain (among those mentioned in our Related Work, Sect. 2), a cloud to mean a cause of undesired outcome, an arrow to mean the relationship between causes, activities, and domains, a hexagon to mean a root cause/problem and a tab note to mean a reason for a problem, respectively.

In what follows, we structure our analysis according to the topics included in our research questions.

RQ1. What memory retrieval errors do ERP experts experience in ERP project effort estimation?

Our case study results (Fig. 1) suggest that there is a consensus among the practitioners that *Memory Bias Retrieval Error* occurs in certain situations while trying to retrieve stored memory by an expert. Retrieval error situations documented in the observations include:

- (1) Failure to retrieve or remember a certain scenario which occurred in the past. There is a general tendency to underestimate in these situations.
- (2) Failure to retrieve or remember details or deeper insights of certain scenarios. There is a general tendency to underestimate in these situations.
- (3) Only remember most important & interesting information. There is a general tendency to underestimate in these situations.
- (4) Knowledge or information that has not been used in the short term is often been forgotten in the long-term. There is a general tendency to underestimate in these situations.
- (5) Deviations or issues that occurred during a certain scenario is often forgotten or not took into account during estimation or prediction. There is a general tendency to underestimate in these situations.

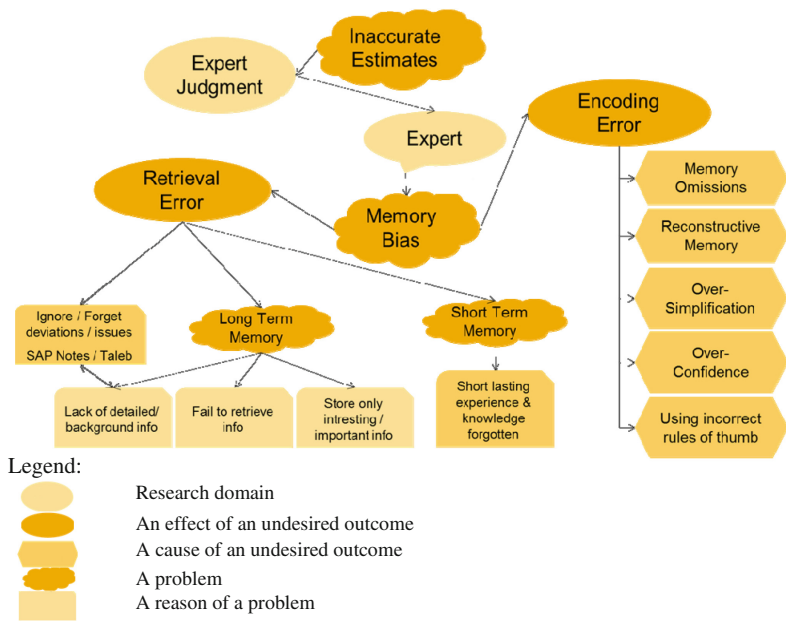


Fig. 1. Memory bias situations.

RQ2. What memory encoding errors do ERP experts experience in ERP project effort estimation?

Memory Bias Encoding Error occurs while trying to encode stored memory. Encoding error situations documented in the observations include (Fig. 2):

- (1) **Memory Omissions:** Difficult to understand or complex activities were left out during estimation. There is a general tendency to underestimate in these situations reported by all (11) interviewees.
- (2) **Reconstructive memory:** Tendency to add incorrect memories not related to a certain scenario. There is a general tendency to overestimate in these situations, as reported by eight interviewees.
- (3) **Oversimplification:** Experts tend to oversimplify the memories of certain scenarios. There is a general tendency to underestimate in these situations, as reported by seven interviewees.
- (4) **Overconfidence:** Expert tends to be overconfident in general while encoding the memories of certain situations and imagine the best case scenario or the most skilled person caring out this task. There is a general tendency to underestimate in these situations, as reported by five interviewees.
- (5) **Using incorrect rules of thumb:** Experts often estimate using rules of thumb based on past experience, some of these rules of thumb might never been validated while the expert continuous to rely on an incorrect rule of thumb. There is a general tendency to underestimate in these situations, but there were also cases where experts overestimate in these situations, as reported by three interviewees.

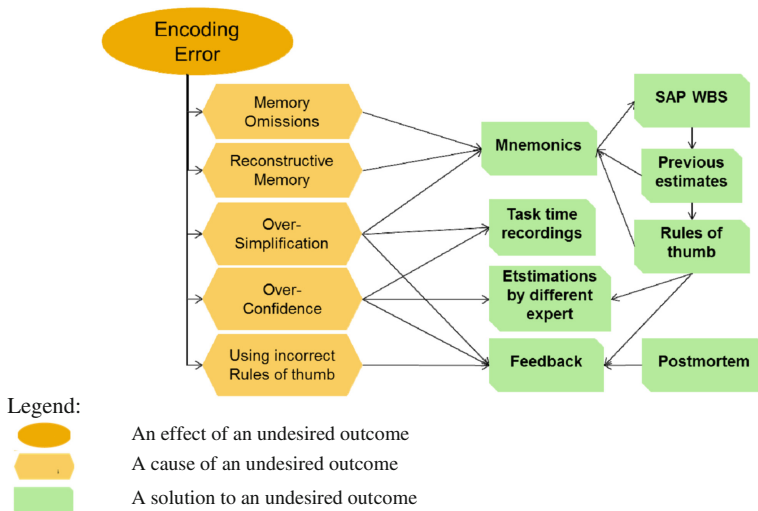


Fig. 2. Memory correction during encoding.

RQ3. What memory correction techniques do ERP experts use in ERP project estimation?

Our case study found that in the experiences of our participants, memory correction techniques could be used to reduce memory bias during both memory retrieval (Fig. 3) and memory encoding (Fig. 2).

In particular, we found five memory correction techniques:

- (1) Producing mnemonics could aid our memory, which acts as memorable anchor points. Mnemonics could be delivered in retrieval schematics, which helps to fill gaps in our memory. In the case of SAP projects, the following material were used to produce mnemonics: SAP Work Breakdown Structures which is delivered by the ERP vendor for each of its solutions, SAP Notes (which is created for most issues identified) and general rules of thumb provided by experts.
- (2) Actual time recordings per task would benefit and correct most cases where memory bias occur, but shown to be in short supply and infrequently available.
- (3) A task estimated and provided by an expert and validated by a second expert shown to reduce some of the memory bias.
- (4) Experts who get general feedback (via postmortem reports) about estimated project durations and overall completed status seems to deliver more accurate estimates with a lower degree of memory bias.

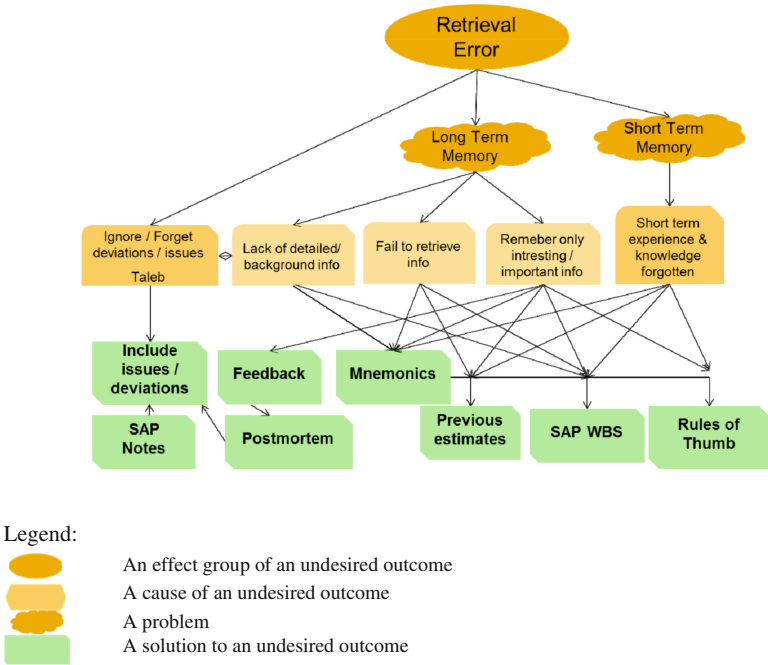


Fig. 3. Memory correction during memory retrieval

- (5) Estimates which include possible issues found during previous project (via searching for SAP Notes associated with a certain solution) enable a lower degree of memory bias and helps reminding an expert of the expected deviations which reduce memory bias.

As indicated earlier, the resulting models are compatible with any estimation technique that employs expert judgments. The models are not prescriptive in the sense that we do not suggest any process or propose a new method, but instead just describes what we found in the case study. This means that an ERP professional could use our conceptual models as a framework for reasoning about his/her own estimation process independently of his/her concrete context. Clearly, not all of the possible biases or error types that are described in Figs. 1, 2 and 3 are necessarily present in each estimation process that an ERP professional can get engaged into. In other words, some biases might be traceable to the project context. For example, one can use the concepts of the models to depict the estimation situation of a specific professionals, be it an architect, a project manager, a consultant, in a specific project, in a specific client organization and, thus, take into account the bases and errors important in his/her own case. The model's completeness still should be validated empirically, e.g. by new case studies in our case study organization or in other ERP vendors' organizations.

An interesting observation we made while creating the models, was that the consultants and the solution architects talked about memory errors when thinking of project scope, while technical architects thought of experiencing more errors when thinking of particular tasks. Also, the consultants and the solution architects were more certain in their estimates regarding tasks, while technical architects felt more certain when estimating scope.

5 Discussion

This section discusses our finding in the light of prior publications that were included in Sect. 2. First, our results (Fig. 1) are consistent with the findings in [3, 24] regarding the inaccurate estimates coming out of experts due to bias. Our findings agree with the findings of Jørgensen regarding the planning fallacy phenomenon – which happens regardless of a software engineering professional's knowledge that past tasks of a similar nature have taken longer to finish than generally planned [24]. According to Jørgensen, this is an indication of optimist's bias. Our findings support this claim. However, we contributed to what is already published on expert bias but in a different domain, the result are similar to studies from other domains such as medical studies focus on experts such as doctors or surgeons retrieving how long an operation took or in criminology, remember the events and appearances of a crime scene. This all add to our understanding of memory bias documented in psychology literature studies [22, 27, 30, 40] by including descriptions of biased situations that occur due to memory retrieval error and memory encoding error. We clearly observed that experts had coping strategies in those situations (Figs. 2 and 3). However the strategies were implicit and specific to experts, and were not organization-wide established practices. The coping strategies (Figs. 2 and 3) were common sense and experts were willing to discuss them with each

other, however each expert seemed to have preference for some techniques over others. Investigating why these preferences exist and if the preferences indicate that some strategies are better choices in some contexts than in others would be an interesting line for future research.

Second, we observed that our practitioners did use the feedback-giving solution similarly to [24, 34]. However, they did not think of other solutions that we found mentioned in literature (such as e.g. controlling the consciousness of experts [10] and leveraging the use of consistent information [12]).

Third, our results agree with the findings in the planning fallacy studies of Roy et al. [40]. Their memory bias explanation for why experts are incorrect in estimating future tasks holds that this is due to experts having incorrect memories of how long previous tasks have taken, and that these biased memories cause biased predictions. The coping strategies in Figs. 2 and 3 converge with the ideas proposed by these authors, particularly the ways of using feedback by colleagues to correct an expert's memory in order to increase predictive accuracy in estimation. Another related or similar memory correction technique used in criminology and psychology that detectives and psychologist often used is to ask victims or patient to go back to certain moment in time, to focus on the surroundings and different senses of what they experienced before and after the event they trying to recall. This assists the memory to recall finer details that might help cycle through the actual event.

However, we found two strategies which were not previously discussed: the use of rules of thumbs embedded in Work Breakdown Structures and SAP Notes (a special tool within the SAP's implementation toolbox).

6 Limitations

We note that in this paper we propose conceptual models only. Such models, as suggested by Charmaz [38], are not supposed to be validated against the data that has been used for the development of the model. We used the checklist in [38] to evaluate the possible threats to validity of the observations and conclusions in this research. Because our research is exploratory interview-based case study, the key question to address when evaluating the validity of its results, is [9]: to what extent can the practitioners' experiences in memory bias and bias correction could be considered representative for a broader range of projects and project organizations. We cannot deem our interviewees' settings representative for all the possible ways in which experts could inject errors and counter memory bias in ERP project estimation. However, following [39], we think that it could be possible to observe similar experiences in projects and companies which have contexts similar to those in our study, e.g. where (i) technical and non-technical experts collaborate, (ii) the projects are global and large scale, and (iii) experts are pressured to finish the estimation tasks quickly and have no time to review, re-think, and possibly revise their estimates.

We also acknowledge the inherent weaknesses of interview techniques [9, 37]. A threat is the extent to which the practitioners answered our question truthfully. We took two steps to minimize this threat by (i) recruiting colleagues of the first author who were

willing to have a conversation on our topic of research and to whom the first author had good work relationship; (ii) that we ensured no project or expert identity-revealing data will be used in the study. Next, a well-known threat in interview studies is that an interviewee has not understood a question. However, we think that in our study, this threat was nearly non-existent because: (i) the first author is a contributor to some of the interviewee's projects and shared the work context of the interviewees, the domain knowledge and the vocabulary used to talk about project concepts. Next, we accounted for the possibility that the first researcher might instil his bias in the data collection process. We implemented Yin's recommendations [6] in this respect, by establishing a chain of findings: (i) we included participants with diverse backgrounds (i.e. type of ERP projects being delivered), and this allowed the same phenomenon to be evaluated from diverse perspectives (data triangulation [37]).

7 Conclusions and Future Work

This exploratory study contributes to increasing our understanding of expert-judgment based processes in estimation of ERP projects. Using a qualitative research method, we explored memory bias situations that ERP practitioners experienced during their processes of estimating their ERP projects. We also explored the correction/de-biasing strategies those experts were using in their estimation. The results of our effort are, respectively, three conceptual models which describe on a generic level the concepts that ERP project implementation experts use when reasoning about situations in which they witness memory bias to occur. These models came out of applying a GT approach. As such, the models present the state of practice described by concepts which we discerned from our interviews with 11 practitioners. Of course, these models should be subjected to further empirical studies in order to improve their generality. More work in the future is necessary to include at least these steps: (1) an empirical study to evaluate the three models with ERP practitioners in other roles, and (2) an evaluation study of the utilization of the coping strategies in other non-ERP software projects. This research included four roles of experts: consultants, technology architects, solution architects and project management. Another type of expert which plays an important role in effort estimation is key account managers. They understand the specific customer organizational structure, skill and resources available, and are able to adjust effort estimations accordingly, removing or improving assumptions made about a specific customer.

7.1 Implications for Research, Practice and Teaching

Our results have some implications. First, being aware of the limitation of our work, we think the results of this first exploratory study could be of value in at least two ways: (a) it could possibly serve as a roadmap for further empirical studies on bias due to memory errors and on de-biasing techniques that can possibly help in ERP context, and (b) it could be used as a conceptual framework [39] to provide explicit guidance to practitioners and allow for better-checked discourse-based process.

Second, the study has some implications for practice. Perhaps, the most important implication is that memory correction techniques could and should be deployed as part of project estimation processes in the ERP industry, because of the impact they may have on the resulting estimates. While expert judgment had shown to be the predominant method for deriving estimates by practitioners in the ERP domain, this study signals that memory bias seems to be problematic during the estimation and scoping process. Furthermore, we also found that the different types of experts seem to have an impact on the accuracy of the estimates depending on where and how a project lead assigns them to provide estimates: technology architects have shown to be more accurate than solution consultants to determine the initial scope. Solution architects and consultants have shown to be more accurate than technology architect to derive the estimates for certain tasks. Based on these observations, we could recommend ERP project managers to invite technology architects to derive the estimation scope and rely on the solution architects and consultants to provide the estimates for the individual tasks.

Third, our exploration into memory bias in ERP project estimation has some implications for teaching. Most project management courses in Computer Science schools are designed with the software measurement discipline in mind, and in turn place a heavy accent on the use of functional size estimation and of algorithmic models for project estimation. While these textbooks are indispensable, students might benefit also by developing awareness of the bias-injecting circumstances in their project estimates and the possible range of de-biasing strategies at their disposal in a particular context. Students who would consider a career in the consulting sector (e.g. in ERP in particular) would certainly be better off if could have acquired deeper knowledge on expert judgment based techniques, and the role of de-biasing therein.

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