

Expertise and Estimating What Other People Know: The Influence of Professional Experience and Type of Knowledge

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There is ample evidence that estimations of what other people know are often biased in the direction of one's own knowledge. Yet, it is still unclear if this bias is influenced by expertise. In Study 1, computer experts estimated the distribution of Internet concepts and general knowledge concepts among students. These estimations were compared with norm values and with estimations obtained from a sample of laypersons. Laypersons showed a stronger bias than experts. Study 2 revealed that knowledge estimations can be influenced by labeling knowledge items as specialist knowledge. The results are suggestive of ways in which communication between experts and laypersons could be enhanced. Especially in asynchronous communication situations, as for example in the use of e-mail based hot lines, if experts are to communicate effectively, they must make accurate assumptions about laypersons' knowledge of the topic.

The ability to estimate other people's knowledge is generally regarded as a central prerequisite for effective communication. Communication intentions can be expressed in different ways, and assumptions about the knowledge of the interlocutor can guide how a certain communication intention should be expressed. When someone is asked by a person in the street how to get to the train station, the answer is tailored according to one's assumptions about the interlocutor's knowledge of the town (Krauss & Fussell, 1991b).

Although assumptions about what one's communication partner knows are not the only variables influencing the formulation of a communication intention (Brown & Dell, 1987), they become increasingly important the more the topic-relevant knowledge of the communication partners differs. Such is the case when experts communicate with laypersons. Laypersons seek expert advice precisely because they experience a lack of knowledge in regard to a problem they want to solve.

This may further explain why expert communication often is a

favorite choice in psychological literature for illustrating the general relationship between assumptions about the interlocutor's knowledge and the communication. For example, Clark and Marshall (1981) clarified the meaning of their "community membership heuristic" through the example of a psychiatrist who can discuss Freud in a completely different way with a colleague than when she has to assume she is talking to a layperson (see also Isaacs & Clark, 1987; Schober, 1998). The article by Nickerson, Baddeley, and Freeman (1987), which presented the first systematic study of knowledge estimation, even begins with a prototypical expert-layperson constellation (physician-patient) to illustrate how important knowledge estimation is for successful communication.

Nonetheless, in most cases, the expert-layperson situation is used only to illustrate the general importance of knowledge estimation or to demonstrate general judgment errors. With very few exceptions (see below), there have been no systematic investigations of the impact of a person's education (expert vs. layperson) and the type of knowledge (general vs. specialist) on estimates of the distribution of knowledge among laypersons. Indeed, expert-layperson communication might well prove to be a special situation in which the heuristics found so far for knowledge estimations in everyday contexts either do not apply or are applied in other ways. Therefore, this article presents two studies that examine the influence of expertise on knowledge estimates in the computer and Internet knowledge domains.

What Is Meant by *Experts* and *Special Knowledge*?

The term *expertise* has to be understood in a twofold sense. This draws attention to two context variables in knowledge estimation: (a) the education and experience of the persons making the estimates and (b) the type of knowledge.

We define *expert* as a person with training in a particular field who is able to tackle complex problems because of this training and additional practical experience. In our context, the notion of *expert* is particularly important in contrast to *layperson* but not in

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Some of the data reported in Study 1 were collected by Dirk Pisula as partial fulfillment of the requirements for his master's degree at the University of Münster. The data reported in Study 2 were collected by Monika Piekarski for the same purpose. All data were completely reanalyzed in preparation for this article. Parts of this article were presented at the 1999 Fall symposium of the American Association of Artificial Intelligence on "Psychological Models of Communication in Collaborative Systems," North Falmouth, Massachusetts.

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contrast to *novice*. Much cognitive research on experts focuses on contrasts with novices, that is, with persons who are already on their way to becoming experts. Experts who have to estimate the knowledge of novices or intermediates can draw more or less successfully (see Hinds, 1999) on their personal experiences of becoming an expert. In contrast, experts, when estimating a layperson's knowledge of their domain of expertise, should not rely on their own experiences as beginners. Given that novices want to become experts, they will have developed a certain perspective and motivation and will have gained basic knowledge that sets them apart from an average layperson. For example, a first-year medical student is surely not an ordinary layperson with regard to medicine. Therefore, in these two studies, we speak of laypersons rather than novices.

A second conceptual clarification is necessary. With specialist knowledge, we do not only refer to a certain stock of knowledge that is held by a defined group of experts. Instead, specialist knowledge refers to a domain of knowledge that is recognized socially as an expertise domain as, for example, medicine or information technology (IT; Dingwall & Lewis, 1983; Bromme & Nückles, 1998). Of course, this knowledge is represented and processed mainly among experts, but it is possible that some pieces of it are also known by laypersons. In other words, the term *specialist knowledge* refers to a type of knowledge that is distinct from everyday knowledge because of its origin and systematicity, not only because of its ownership. This conceptual clarification is necessary because otherwise it would not make sense to ask for estimations about laypersons' possession of specialist knowledge. To emphasize this contrast to general knowledge, we use the term *specialist knowledge* instead of *expert knowledge*. Naturally, such conceptual definitions address ideal cases. Expert and specialist knowledge are prototypical concepts with a graded structure and fuzzy edges (as described in Barsalou, 1985). Medicine provides a good example of this because social regulations set precise standards regarding who can call herself or himself an approved medical doctor, and the body of knowledge assigned to the domain is relatively specific. Nevertheless, it is also easy to find examples of fuzzy borders regarding the demarcation to laypersons as well as what may be assigned to the body of specialist knowledge. Yet, hardly anybody would deny that there is a prototypical core of both medical experts and medical specialist knowledge that can be contrasted with laypersons and with their own everyday theories on medical topics. When these medicine experts communicate with laypersons, it is important that they have an idea which concepts might be familiar to a layperson. Of course, if specialist knowledge was not a fuzzy category, it would hardly make sense to investigate experts' estimations on the distribution of certain specialist concepts among laypersons. Concepts that are so specialized that they can only be discussed within the closed circles of the scientific community bear no relevance on expert-layperson communication.

Do Experts Overestimate the Distribution of What They Know?

Nickerson et al. (1987), and many other researchers since then, have provided empirical confirmation of a systematic bias in knowledge estimation (for an overview, see Nickerson, 1999). Findings can be summarized roughly by stating that, under most

circumstances, this bias can be traced back to the participants' orientation toward her or his own knowledge. Before considering whether this bias is influenced by expertise (in the twofold sense sketched above), we provide a sketch of Nickerson et al.'s (1987) three central hypotheses:

1. *The correspondence hypothesis.* It states that one is more likely to impute a bit of knowledge to others if oneself has it than if oneself does not have it. We call this the correspondence hypothesis because it says that the estimations will show some sort of correspondence with the estimator's own knowledge.

2. *The overestimation hypothesis.* This one says that persons tend to overestimate the commonality of their own knowledge.

3. *The expertise hypothesis.* The third hypothesis says that persons who possess an extraordinarily high level of knowledge in a certain domain will tend to overestimate what other persons know about this domain.

The first hypothesis is a direct transfer to the domain of knowledge estimation of the so-called *false consensus effect* found by Ross, Greene, and House (1977) in the realm of behavioral choices and attitudes. What has to be emphasized here is the relative nature of this phenomenon (Mullen et al., 1985). It postulates a difference between those who hold a certain opinion and those who do not. To make clear that this does not necessarily imply a general overestimation of the commonality of one's own perspective and to accentuate the distinction between the realms of attitudes and knowledge, we refer to it as the correspondence hypothesis.

To test this hypothesis, Nickerson et al. (1987) gave college students general knowledge questions taken from a standardized item pool. After answering each question, they had to estimate what percentage of all college students would also answer it correctly. This allowed a direct test of the correspondence hypothesis by comparing estimates for known and unknown questions. Results showed significantly higher estimates if an item was known than if it was not known, thus confirming that the effect found by others for attitudes extends to the realm of knowledge.

To test the overestimation hypothesis, in contrast, estimates have to be compared with norm values about the actual distribution of knowledge in the population. Nickerson et al. (1987) managed to confirm this hypothesis as well: Participants rated questions they could answer themselves as being significantly easier than they actually were. Nickerson et al. (1987) tried to test the expertise hypothesis on college students majoring in sports and those majoring in history. They failed to confirm the predicted effect that experts would tend to overestimate the distribution of knowledge from their own domain. Nonetheless, they also found that many of their experts actually knew hardly any more about their domains than the average college student. This methodological problem may well have been decisive in the failure to confirm predictions.

Both the correspondence hypothesis and the overestimation hypothesis were confirmed by Fussell and Krauss (1991, 1992) using modified tasks (correct naming of celebrities, buildings, and everyday objects) and slight variations in study methods. However, what can be expected when Nickerson et al.'s (1987) hypotheses are applied to experts and in a domain of expertise? Before continuing, note that with regard to the knowledge items included in this study, a true correspondence effect is rather improbable among real experts. Our expert subjects should know all of the items, more or less, that were used. It makes no sense to ask them about the distribution among laypersons of knowledge

that is so specialized that one is not even certain that all experts possess it. Therefore, estimates for known and unknown items cannot be compared in experts in this study. Nonetheless, one can test the overestimation hypothesis and the expertise hypothesis when specialist knowledge belongs to a domain that is at least partially accessible to and relevant for laypersons (e.g., medicine, IT). Although it does not make sense here to test the correspondence effect for specialist knowledge among domain experts, it can certainly be tested among laypersons. This is also necessary because it is still not known whether laypersons' estimates are also influenced by the type of knowledge (see below).

What Can Be Expected About Experts' Estimations?

We inspected the current theoretical explanations for the tendency to attribute one's own knowledge to other persons to see which could apply to experts' estimations of laypersons. Completely different experimental predictions emerged:

Overestimations

One explanation is that one's own knowledge is attributed to other persons because it functions, so to speak, as a default value so long as no indications of differences between one's own and the other's knowledge are available (Keysar, 1998; Nickerson, 1999). Other explanations place more emphasis on the bias aspect, that is, (a) the effort invested in one's own learning is forgotten (Hinds, 1999), (b) one's own knowledge is the easiest to access (Krauss & Fussell, 1991a, 1991b), and, (c) when considering their own perceptions of certain events, many people often find it hard to conceive that other people perceive the same events in a different way (Keysar, 1994, 1998). The *selective exposure hypothesis* (Ross et al., 1977) is also a bias explanation: Because persons tend to associate with others whose knowledge is similar to their own, they overestimate the commonality of their knowledge (Marks & Miller, 1987). These explanations lead to the expectation that experts will produce major overestimations of laypersons' knowledge because they often went through a particularly long training period, making the qualitative and quantitative aspects of earlier knowledge as a layperson and as a novice easy to forget. In addition, experts' own knowledge has to be particularly easy to access because it is often needed very quickly in their work. The selective exposure explanation also leads to the expectation of overestimations: The occupational environment of most experts is highly selective because, in most fields, communication and co-operation among experts is necessary.

Underestimations

On the other hand, it is also conceivable that experts will underestimate laypersons' knowledge. Knowledge associated with one's own abilities may be perceived as being particularly exclusive (Marks, 1984). A specialist status requires a process of social recognition (e.g., through examinations) that particularly emphasizes the exclusiveness of specialist knowledge compared with the understanding of laypersons (Stehr & Ericson, 1992). Accordingly, experts should be aware of not belonging to the same population as laypersons in terms of specialist knowledge. Possibly, the need to

distinguish oneself from laypersons leads to an underestimation of laypersons' knowledge (the false uniqueness assumption).

Experts' Experiences With Laypersons and the Labeling of Specialist Knowledge

However, the selective exposure hypothesis also suggests a differentiation: The tendency to estimate laypersons' knowledge incorrectly should depend on the frequency an expert has contact with laypersons or on the extent to which the expert works with other experts only. The following two prototypical kinds of experts can be distinguished: those who are involved in expertise-related interactions with laypersons, and those who do not have to communicate with laypersons regularly about issues of their knowledge domain.

Smaller deviations of estimates from the true values of the knowledge distribution would be expected in the first case than in the latter case. Furthermore, labeling the knowledge to be judged as specialist knowledge can also be assumed to have an impact on the ability to estimate laypersons' knowledge. Some domains of specialist knowledge are clearly marked as such because of expert terminology. Other domains of knowledge tend to be regarded as also being part of general knowledge; in these cases, it is not always clear whether a certain concept belongs to specialist knowledge. We assume that estimations will be influenced by the presence or absence of such labels. Uncertainty about the type of knowledge should influence the estimations, although no clear predictions can be made on the direction of that influence.

Laypersons' Judgments on the Distribution of Specialist Knowledge

Before performing any empirical study of whether "real" experts make the same errors when estimating the knowledge of laypersons as laypersons themselves make for general knowledge, it is first necessary to ascertain whether laypersons continue to make such errors when specialist knowledge is at stake. It is possible that laypersons will not tend to assign their own knowledge to other persons to such an extent in this situation. As with the experts above, some contradictory possibilities can be formulated regarding how laypersons judge specialist knowledge. Therefore, it is worthwhile to assess laypersons' estimates on the distribution of specialist knowledge (among laypersons). This will not only broaden the existing empirical evidence on biases in laypersons' knowledge estimations (which is already of interest in itself), but also provide a basis for comparing experts and laypersons on knowledge estimation.

Research Questions and Overview of Studies

1. Can Nickerson et al.'s (1987) three hypotheses be confirmed among laypersons who have to estimate the distribution of specialist knowledge in their population? In other words:

(a) Is there a correspondence effect for specialist knowledge among laypersons?

(b) Do laypersons who possess a lot of this type of knowledge (compared with those with less knowledge) consider that other persons have more specialist knowledge? Note that this is a weak

version of Nickerson et al.'s (1987) expertise hypothesis. It refers to knowledge differences within a certain sample and not between independent samples of different expertise status.

(c) Do laypersons tend to overestimate specialist knowledge and, if so, is this overestimation tendency just as large or does it differ quantitatively from the errors made about frequency of everyday knowledge?

2. We studied the expertise hypothesis directly by assessing the estimates of "real" experts. We asked the following:

(a) Do experts tend to overestimate laypersons' knowledge of concepts in their domain of expertise?

(b) Do experts and laypersons produce the same judgment errors in terms of degree and direction when estimating specialist knowledge in laypersons?

(c) Does experience with laypersons influence experts' judgments on the distribution of their specialist knowledge among laypersons?

To answer these questions empirically, we selected the domain of IT (i.e., concepts about computers and the Internet) because it is a fine example of a specialist topic that is highly relevant for many laypersons.

In Study 1, we surveyed the definitions of IT concepts and general concepts in a representative sample of college students. Participants also estimated the frequency of correct answers in their lay population. Two expert groups from the domain of computer science worked on the same questionnaires. After answering the items, they also estimated the distribution of correct answers in laypersons. Expert groups differed in how much professional contact they had with laypersons. There was a group of Internet advisers providing user support for laypersons and a group of "theory experts" recruited from advanced students of computer sciences. These two groups of experts did not differ in terms of descriptive content knowledge about the computer-related topics covered in our study but did differ in terms of specific communicative experiences. Our assumption was that the experts' tendency to overestimate laypersons' knowledge would be reduced by actual communication experiences with laypersons. We pointed out earlier that specialist knowledge is itself a concept with a graded structure. Therefore, in Study 1 we labeled the concepts from the IT domain clearly as specialist concepts and presented them within the context of expert communication. Because it is possible that ambiguity in the classification of an item to expert or everyday knowledge could lead to a change in the estimated knowledge distribution, we asked the following:

3. Does the labeling of specialist concepts influence experts' estimates on the distribution of this knowledge among laypersons? To answer this question, in Study 2 we developed a questionnaire that first tested the actual distribution of knowledge in a control sample of laypersons. In addition, questions on general knowledge were formulated. The questionnaire was then assembled in three different versions, each processed by one group of computer experts. Two groups had to estimate the knowledge distribution of expert concepts among laypersons within contexts in which the difference from general knowledge was marked clearly. A third group received the same concepts mixed with general knowledge concepts, and all concepts taken together were labeled as questions on items from "modern life."

Study 1

The design of Study 1 was an incomplete 3 (Type of Expertise: practical experts vs. theory experts vs. laypersons) \times 2 (Type of Knowledge: specialist vs. general) factorial design with knowledge estimations averaged across items as the dependent variable. A second dependent variable was obtained by calculating the deviation of the estimations from the corresponding empirical norm values.

Method

Participants

Two groups of IT experts volunteered to participate in the study. The first group consisted of 26 graduate students in computer sciences (24 men and 2 women). Their mean age was 23.6 years ($SD = 2.0$). To accentuate the relevant difference, these participants are referred to as *theory experts* hereinafter, even though this is an oversimplification. The other group, called *practical experts*, was a selection of 25 Internet advisers and consultants, some of whom were college students providing Internet support for university departments on a regular basis and others who were professionals from commercial Internet consultancies. This group (1 woman and 24 men) had a mean age of 27.7 years ($SD = 6.5$). All experts were screened to check that they knew at least 90% of the specialist concepts. Additional criteria for inclusion in one of the expert groups were years of practice, daily time spent professionally with the computer, type of experience, and similar variables.¹ The third group, called *laypersons*, consisted of a representative sample of 178 college students from all departments of the University of Münster (76 women and 97 men, 5 missing gender reports; mean age = 23.9 years). This group was a subgroup of the norm sample ($N = 188$ students) described below in the *Materials* section, formed by excluding those 10 participants who were too knowledgeable to be laypersons because they knew more than 80% of the specialist concepts. We had to decide what to do with those laypersons who were just as knowledgeable as our experts; we included them in the norm sample of college students because estimations had to be made with reference to "the layperson," that is, to a person who is considered representative for the whole sample.

When, on the other hand, the status as a layperson was the independent variable (i.e., when laypersons' estimations were to be compared with experts' estimations), we decided to drop these semi-experts from the sample.

Materials

A questionnaire was developed that contained 33 specialist concepts, all related to the IT domain. Items were selected in the following way: First, a pool of specialist concepts was compiled from the glossaries of introductory Internet literature (Gilster, 1995; Kehoe, 1994; Krol, 1994; Levine & Levine, 1996; Rosenbaum, 1996). In addition, 10 general knowledge concepts were selected from a popular German vocabulary game. The resulting item pool was pretested with 30 psychology students, and the Internet concepts were scored for domain relevance by four Internet experts. Main criteria for inclusion in the final sample were semantic clarity, domain relevance, and item difficulty. For the direct comparison

¹ Bear in mind that, in spite of all the necessary care invested in the selection of expert groups, it is hardly possible to avoid a relatively high heterogeneity of actual professional background in the sample. The expertise variable is too complex to find 25 highly qualified participants with exactly the same task profile and professional history who are willing to participate, especially in a domain as young and dynamic as Internet consulting.

between general knowledge and specialist knowledge, a subsample of 10 specialist items was selected, with item difficulties matched to those of the 10 general knowledge items (see Appendix, Table A1).

The real-knowledge distribution was ascertained through the students' answers. We made sure that the departmental affiliations of the participants were similar to the overall distribution in the student population of the University of Münster. Difficulty was computed as the percentage of participants in the norm sample ($N = 188$) who gave a correct answer.

Procedure

Questions were presented in the form of a booklet. After participants were given brief instructions, the specialist concepts were presented in randomized order. Each specialist concept was followed by several free lines for a short definition and by a blank space in which participants had to report their estimate regarding the percentage of all students who would be able to give the correct definition. Then, the general knowledge concepts were presented in the same format, introduced by a short passage emphasizing their status as general knowledge. The booklet ended with a page of questions gathering demographic information and several indicators of IT expertise.

The theory experts were approached individually in their rooms at the Department of Computer Science. They filled out the booklets in the presence of the experimenter. No time limit was given. The practical experts were contacted via telephone or electronic mail. Most of them agreed to fill out the questionnaire during a workplace visit by the experimenter, but some of them preferred to receive the booklet via mail, completed it without supervision, and returned it in a stamped and addressed envelope.

The laypersons were contacted through lecturers in their respective departments who had agreed to cooperate. The booklets were filled out as part of their lectures and courses following a short verbal introduction by the experimenter. As a reward, all participants received tickets for a lottery offering a 1:3 chance of winning two movie tickets. For all three groups, the task took between 15 and 30 min.

Scoring

The definitions given by the participants were rated by two independent judges with substantial IT knowledge. A short and general definition was deemed sufficient (e.g., Internet: "worldwide computer network"; Download: "local storage of data from the internet"; Baud: "measure of data transmission rate"; UNIX: "operating system"; TCP/IP: "protocol for data transmission" [all examples translated from original German wording]).

The definitions were scored as being either right or wrong. The interrater reliability was .95. Unclear cases were discussed with a third rater and scored on the basis of a majority decision. All in all, 8% of all definitions were scored as wrong. These were excluded from further analyses and the associated estimates were treated as missing values.

Results

Replication of the Correspondence and Overestimation Hypotheses

As noted earlier, the correspondence hypothesis can only be tested for laypersons. Two scores were computed for each of the 33 specialist concepts: the mean estimate of those laypersons who knew the item, and the mean estimate of those who did not know it. With an alpha level of .05 (used for all statistical tests), individual t tests for each item revealed significant differences for 14 of the 33 items. All of them had the hypothesized direction. Figure 1 illustrates this result, closely analogous to that of Nickerson et al. (1987, Figure 1). When the estimates of those who

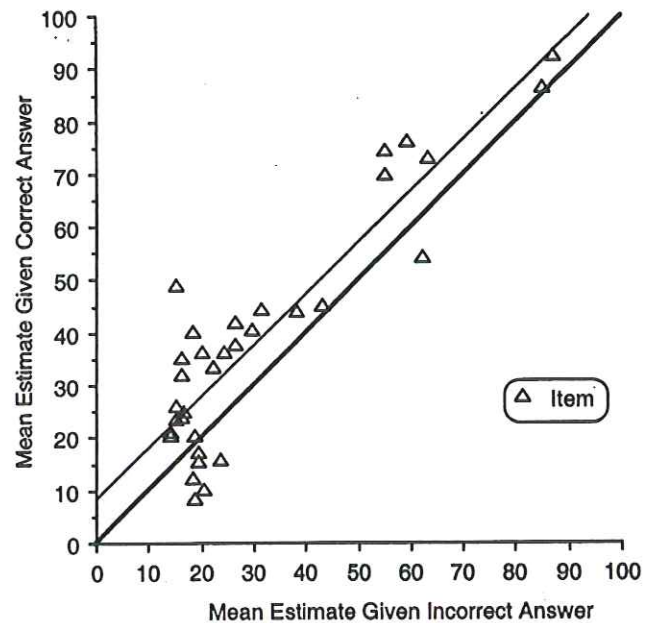


Figure 1. Mean estimates associated with correct answers plotted against mean estimates associated with incorrect answers to the same questions. Each point represents a question. The ordinate indicates the mean of the estimates of the percentage of participants who would know the answer to that question, produced by people who knew the answer themselves; the abscissa indicates the mean of the estimates, produced by people who did not know the answer themselves. The unit line (bold diagonal) is shown beside the regression line ($R^2 = .80$).

knew an item were higher than the estimates of those who did not know it, the triangle representing this specific item lies in the sector above the diagonal. The overall mean of the estimates was 38.6% for known and 31.3% for unknown items. The difference proved to be significant in a two-tailed paired t test, $t(32) = -4.3$, $p = .001$, which is in agreement with the correspondence hypothesis. Nickerson et al. (1987) performed an additional analysis to ensure that the pattern in Figure 1, and thus the confirmation of the correspondence hypothesis, was not just an artifact due to each data point being composed of estimates by a different number of participants. It is possible that very knowledgeable participants generally tend to impute more knowledge to laypersons than less knowledgeable participants. Thus, a weak variant of the expertise hypothesis could be responsible for the results. The more difficult an item is, the more likely it is for its ordinate value to be constituted by more knowledgeable participants. On the other hand, the easier it is, the more its abscissa value is influenced by participants with low IT knowledge. One possible way to test this explanation is to compute the correlation between the individual knowledge score and the individual estimation score. Nickerson et al. (1987) reported a coefficient of $-.025$; we found a correlation of $-.033$. Hence, this alternative explanation can be ruled out for our data as well.

In the next step, the overestimation hypothesis was tested by comparing the mean estimates of laypersons with the norm values. Once again, this was performed on an individual item basis and separately for known and unknown items. The results are depicted in Figure 2, which is constructed analogously to Figure 3 from

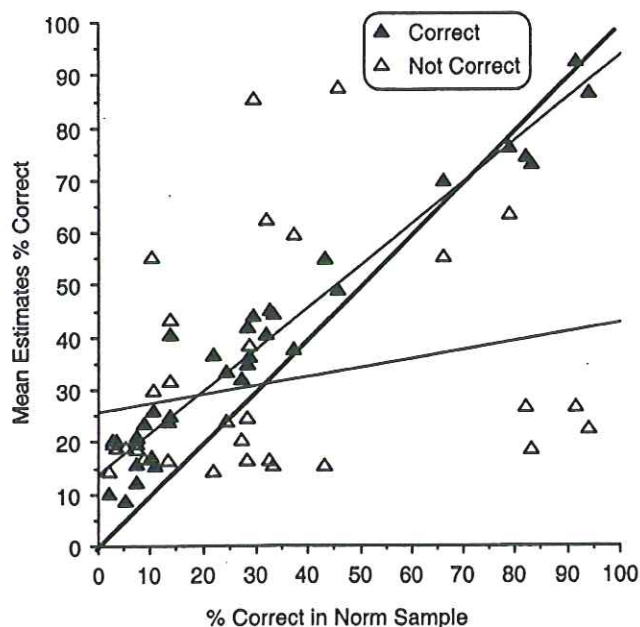


Figure 2. Mean estimates by laypersons plotted against empirical norm values. Each question is represented by two triangles: The ordinate of a filled triangle represents the mean of the estimates associated with known items; the ordinate of an open triangle represents the mean of the estimates associated with unknown items. The unit line (bold diagonal) and separated regression lines for both types of estimates are included. Estimates associated with correct answers: $R^2 = .94$; estimates associated with incorrect answers: $R^2 = .05$.

Nickerson et al. (1987). Each of the 33 items is represented by two points. The filled triangle represents the mean estimate of all laypersons in the sample who knew that specific item, and the unfilled triangle represents the mean estimate of those participants who did not know it. Remember that the number of participants forming the basis of each point varies considerably. Two aspects of the data are clearly visible: First, most filled points are in the sector above the diagonal, which means that people who knew an item indeed overestimated its commonality. This was the case in 29 of 33 cases, or 88%. Second, in the case of the estimates by participants who did not know an item, no clear tendency toward overestimation can be seen. Whereas 19 of the items (58%) were overestimated, 14 (42%) were underestimated. The range of over- and underestimation, as shown by the deviation from the diagonal, was much higher for estimates associated with unknown items than for estimates associated with known items. This difference in degree is much clearer in our data compared with Nickerson et al.'s (1987, p. 253) results, which is mainly due to the comparatively small variance in our data for known items ($SD = 7.8$ vs. $SD = 30.6$ for unknown items). The mean deviation between estimates and norms was 7.6, $t(32) = 5.6$, $p < .001$ (paired t test), for those who knew the item and was 0.07, $t(32) = 0.01$, $p = .98$ (paired t test), for those who did not know the item.

Types of Knowledge

To differentiate further, we examined whether the two types of knowledge (IT-related specialist knowledge vs. general knowl-

edge) were treated differently in the laypersons' estimates. Computations were based on the matched subsample of 10 items each (see *Materials* section). Because of many missing values for individual persons (the least knowledgeable persons produced hardly any "known" answers, whereas the opposite was the case for very knowledgeable persons), an item analysis was carried out and items were averaged (known/unknown) within each type of knowledge. For all 20 items, the mean difference between estimate and norm value (estimate–norm deviation) was computed separately for known and unknown items (see Figure 3).

These mean deviations were compared with two paired sample t tests. For known items, both types of knowledge were overestimated, but the amount of overestimation was considerably higher for general knowledge than for specialist knowledge ($M = 10.1$, $SD = 13.4$ vs. $M = 2.8$, $SD = 8.0$), $t(9) = 2.5$, $p < .05$. For unknown items, on the other hand, both types of knowledge were underestimated. However, once again, this effect was much stronger for general knowledge than for specialist knowledge ($M = -20.5$, $SD = 21.3$ vs. $M = 8.7$, $SD = 12.2$), $t(9) = 3.0$, $p < .05$.

In summary, both the correspondence hypothesis and the overestimation hypothesis were confirmed within our sample of German university students. Overestimation was, however, less pronounced for specialist knowledge than for general knowledge.

Do Experts Tend to Overestimate Laypersons' Knowledge?

To examine whether experts tended to overestimate laypersons' IT knowledge, we first analyzed both expert groups together.² For each of the 51 experts, an individual difference score (individual estimate–norm deviation) was computed by averaging the directed differences between estimates and norm values for all 33 items.³ The mean individual estimate–norm deviation (END) for all experts was 3.9 ($SD = 11.8$), indicating a weak, but significant tendency toward overestimation, $t(50) = 2.06$, $p < .05$. Because there were such large interindividual differences in terms of over- or underestimation, individual t tests were computed for each expert. Of 51 experts, 19 (37.2%) showed significant overestimation and 10 (19.6%) underestimated the laypersons' IT knowledge. However, 22 (43.1%) experts showed no bias in either direction ($p < .05$, $df = 32$, two-tailed tests).

The fragility of the overestimation tendency among experts was confirmed by an item-based analysis. The mean of all 33 item scores, computed as the directed difference between estimate and norm value averaged across all 51 experts, was 3.4 ($SD = 11.9$) and did not differ significantly from zero, $t(32) = 1.6$, $p = .11$.

² All analyses of experts in Study 1 were restricted to the sample of 33 specialist concepts because there was no reason to expect any differences in general knowledge between experts and laypersons or between the two expert groups.

³ The following analyses do not differentiate between known and unknown items because the number of unknown items was very small due to the expertise of the participants. In these cases, the corresponding estimates were treated as missing values.

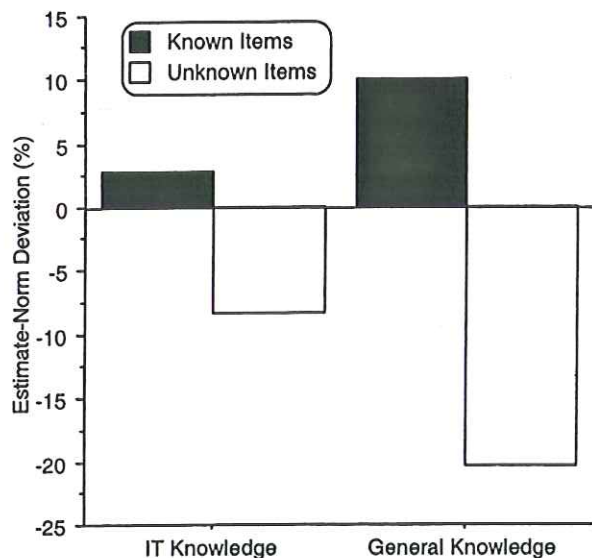


Figure 3. Directed estimate-norm deviations (mean deviations between laypersons' estimates and norm values) differentiated for type of knowledge (specialist IT concepts vs. general knowledge concepts) and knowledge of estimating person (estimates associated with known items vs. estimates associated with unknown items). Positive bars indicate overestimations; negative bars indicate underestimations.

Comparison Between Experts' and Laypersons' Estimations

Testing the expertise hypothesis requires a comparison of estimation bias in experts and laypersons. This comparison poses particular methodological difficulties: The size of the END usually exhibits a substantial negative correlation with item difficulty; that is, the commonality of knowledge is overestimated for difficult items and underestimated for easy items. Hence, item difficulty should be held constant for every comparison between groups or between types of knowledge. However, if experts and laypersons are compared regarding specialist concepts, then the number of laypersons in the sample differs for every item because only the estimates of those who knew an item are taken into account.

To cope with this difficulty, we based the comparison between experts' and laypersons' estimates on item means instead of individual person scores. This made it possible to average within different subsets of items. Hence, for each of the 33 Internet concepts, the average deviations between estimation and norm value were computed separately for both groups. Then, means for three different item samples were computed and compared for the following: (a) all 33 specialist concepts, (b) all items ($n = 19$) with norm values greater than .2 (i.e., concepts known by more than 20% of all laypersons in the norm sample), and (c) all items ($n = 8$) with norm values greater than .4. The results of all three analyses are shown in Figure 4.

When all concepts were considered (mean difficulty = 0.31, $SD = 0.27$), laypersons ($M = 7.6$, $SD = 7.8$) showed a significantly stronger bias than experts ($M = 3.5$, $SD = 11.9$), $t(32) = 2.97$, $p = .01$. When the very difficult items (concepts known by less than 20% of the norm sample) were excluded (mean difficulty = 0.48, $SD = 0.25$), the difference between the two

groups was even larger ($M = 5.6$, $SD = 7.8$ vs. $M = -0.2$, $SD = 13.3$), $t(20) = 3.3$, $p = .01$. Within this item subsample, laypersons overestimated the commonality of knowledge significantly, $t(20) = 3.3$, $p < .01$, whereas the experts' estimates showed no significant bias in either direction, $t(20) = -.08$, $p = .93$. When only the eight easiest concepts were taken into account (mean difficulty = 0.73, $SD = 0.19$), the gap between laypersons and experts broadened once again ($M = -1.1$, $SD = 7.4$ vs. $M = 10.2$, $SD = 10.6$), $t(7) = 4.7$, $p = .01$. Here, there was no significant tendency toward over- or underestimation in laypersons, $t(7) = 0.43$, $p = .67$, whereas experts significantly underestimated the commonality of knowledge, $t(8) = -2.7$, $p < .05$.

The following two patterns became apparent: (a) The relation of the END to zero depended greatly on the difficulty of the items for which commonality had to be estimated; however, (b) the difference between experts and laypersons was stable across subsets of items with different levels of difficulty. For all subsets, the estimates of the laypersons were significantly higher than those of the experts.

Estimate-Norm Correlations

In addition to difference scores providing information on the amount of deviation between estimates and norm values, estimate-norm correlations (ENC) were analyzed as a measure of relative accuracy. Individual Pearson product-moment correlations were computed and transformed into Fisher's Z values. This computation was based on a lay sample restricted to those 66 participants who knew at least 10 of the specialist concepts. The restriction was necessary because it did not seem reasonable to compute correlations based on fewer than 10 items. Keep in mind that this analysis

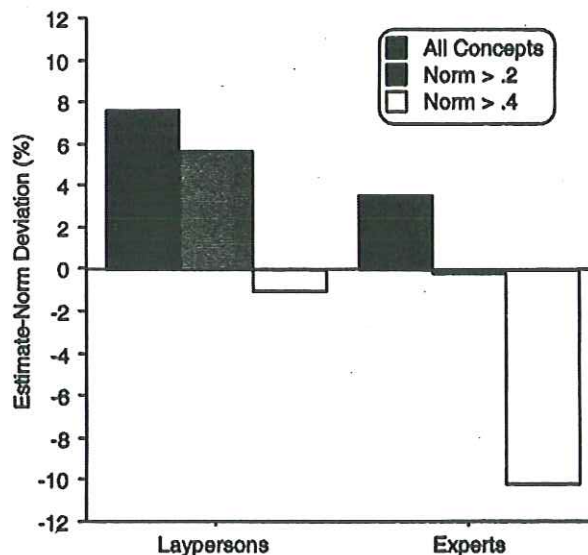


Figure 4. Comparison of estimation bias between experts ($n = 51$) and laypersons ($n = 178$). Estimate-norm deviation is the directed deviation between estimates and norm values averaged across all 33 IT concepts (black bars), across all concepts known by at least 20% of the laypersons (gray bars, $n = 19$), and across all concepts known by at least 40% of the laypersons (white bars, $n = 8$).

is based on data from the most knowledgeable third of the laypersons and cannot be generalized to the population as a whole; mean ENC: $Z(51) = 1.0$ for the experts, and $Z(66) = 1.06$ for the restricted lay sample. The difference in correlations between the groups was not significant, $t(115) = -1.3$, $p = .23$. The retransformed correlations were .76 for the experts and .79 for the laypersons.

Differences Between Expert Groups

Our hypothesis was that practical experts avoid bias better than theory experts. This was tested by calculating the two bias indices separately for both subgroups of experts.

Estimate–norm deviations. For each expert, we computed the mean difference between estimate and norm value across all 33 specialist concepts. Whereas the mean deviation was 1.8 ($SD = 11.6$) for practical experts, it was 4.8 ($SD = 12.2$) for theory experts. Although this difference took the expected direction, it failed to attain significance, $t(49) = -0.92$, $p = .18$. An additional analysis tested the mean deviation in the two groups against zero. Theory experts revealed a significant tendency to overestimate laypersons' knowledge, $t(25) = 2.14$, $p < .05$, whereas the estimates of the practical experts did not differ significantly from zero, $t(24) = 0.78$, $p = .45$.

Estimate–norm correlations. These results are also confirmed by a comparison of ENC scores. As hypothesized, practical experts had a higher ENC than theory experts, $Z(25) = 1.07$ ($SD = 0.24$) vs. $Z(26) = 0.94$ ($SD = 0.27$), $t(49) = 1.8$, $p < .05$. The retransformed correlations were .79 for practical experts and .73 for theory experts.

Discussion

This study had two main purposes: (a) to replicate the findings of Nickerson et al. (1987) in the domain of Internet computing, and (b) to determine the influence of domain expertise on knowledge estimation.

Summing up, the use of specialist concepts from IT does not lead to serious deviations from the pattern of results that Nickerson et al. (1987) reported for general knowledge questions. The correspondence hypothesis was confirmed within a sample of German university students.

The overestimation hypothesis was also confirmed. Laypersons in the present study reliably overestimated the commonality of IT concepts, whereas there was no systematic tendency toward underestimation for unknown concepts. However, the degree of over- and underestimation, as depicted by the deviation from the diagonal in Figure 2, was much higher for participants who did not know an item than for those who knew it. Compared with Nickerson et al.'s (1987, p. 253) data, this effect was stronger in our sample.

Does the amount of estimation error exhibited by laypersons depend on the domain from which the concepts to be assessed are taken? It is interesting that for known as well as unknown items, estimation error was substantially larger for general knowledge concepts than for specialist concepts. The laypersons in our study used more conservative estimates for IT concepts than for general concepts. When faced with specialist knowledge, they seemed to rely less on their own knowledge as a reference point for estimation.

In other words, they thought of their own knowledge as being rather untypical (Nickerson, 1999), leading them to a cautious estimation strategy.

The second part of Study 1 focused on experts' estimations. We found that expertise—understood as systematic superior knowledge in a certain domain—did not lead to a strong and uniform bias toward overestimation. Moreover, compared with laypersons, IT experts clearly tended to produce more cautious estimates concerning the commonality of specialist knowledge from their own domain. In line with Nickerson et al. (1987), we did not find convincing empirical support for the expertise hypothesis. We therefore conclude that the expertise hypothesis—at least in the version that people with high knowledgeability in a certain domain will tend particularly to overestimate the commonality of their own specialist knowledge—should be abandoned.

How far is the IT experts' inclination to estimation bias influenced by their professional experience with laypersons? Although both expert groups were quite good at assessing laypersons' IT knowledge, the practical experts performed slightly better. So far, our hypothesis was confirmed in that practical experts who spent a considerable part of their working time communicating with laypersons produced better estimates of laypersons' knowledge than experts who lacked such communication experience. However, note that the two expert samples did not only differ with respect to their working context but also with respect to their age (a mean difference of about 4 years). Therefore, one could argue that it is simply the age difference that led to more realistic judgments about laypersons' knowledge. This possibility cannot be ruled out completely, but it seems rather improbable. Expertise research in different domains has shown that experience is much more relevant than time spent on a job (Ericsson & Smith, 1991). Moreover, in other studies with experts from other domains, no correlation between age and several measures of quality of estimation was found (Rambow, 2000).

Study 2

Study 2 was designed to explore the notion of *types of knowledge* in greater depth. As stated above, both specialist knowledge and general knowledge are graded concepts. It makes sense to separate them and treat them differently because they refer to different entities. Nevertheless, when it comes to a single item of knowledge, it might be difficult to tell whether it belongs exclusively to one type of knowledge. With graded concepts, decisions about category membership tend to be based on the context within which a certain concept appears (Barsalou, 1985). In fact, all of the items we presented as general knowledge concepts could be interpreted just as well as specialist concepts if presented in a homogeneous context of other concepts from the same domain. For example, *Dow Jones* might be considered part of general knowledge when presented together with *Nasi Goreng* and *Jihad*, but it also belongs to the specialist knowledge of the financial world.

In Study 1, the context was clearly defined by means of an explicit classification, objectified by domain experts. In Study 2, we shifted attention from the objective to the subjective categorization of knowledge and intentionally manipulated the participants' perception of context in three conditions. Our research question was as follows: Do experts' estimations of laypersons'

knowledge differ when the same set of specialist concepts is embedded in different contexts?

Method

Participants

Norm sample (laypersons). A total of 199 students from the University of Münster were tested regarding their Internet-related knowledge. The distribution of faculties (fields of study) in the sample was very close to that of the population of students at the university. Of the total, 96 of the students were men and 102 were women (1 participant failed to report gender). Their mean age was 23.5 years (range: 20–31 years). At the time of the study, participants had been attending the university for an average of 3.2 years. None of them had been there for less than 1 year.

Experts. Participants in the expert sample were students at the University of Dortmund's Department of Computer Science. Questionnaires were filled out by 158 persons. Of these persons, 56 had to be excluded for failing to meet one or more of the following criteria: (a) Participants had to be working toward a master's or doctoral degree; (b) they had to be in at least their second year of study; (c) they had to give appropriate definitions for all 10 specialist Internet concepts. The final sample ($n = 102$) contained 3 women and 99 men. This gender distribution is quite representative for the population of students in computer science. Their mean age was 23.1 years ($SD = 2.3$, range: 20–30 years), and they had been studying for an average of 5.6 semesters ($SD = 3.5$).

Materials

We changed the criteria for item selection in two ways compared with Study 1: First, to reduce the risk of differential topic effects, we made the items more thematically homogeneous. All concepts were related closely to the structure and use of the Internet. Second, we varied item difficulty more systematically. Our aim was to achieve a mean difficulty of about .5 and an even distribution over the whole range from 0 to 1. The following procedure was applied: A large pool of Internet-related concepts of varying complexity and difficulty was sampled by means of a detailed analysis of the relevant literature, consultations with experts from professional practice, and recourse to the item pool of Study 1. From the combination of these three sources, 22 items were compiled for a pretest with the reference sample. Criteria for inclusion were clarity of definition, practical importance, and assumed level of difficulty. On the basis of these items, two versions of a booklet were prepared with different item orders.

On the basis of results from the norm sample, the item pool was further restricted to 10 items meeting the criterion of even distribution of difficulty. In addition, a set of 13 general knowledge items was constructed. These should enable a plausible blurring of the distinction between types of knowledge. Therefore, concepts with a "modern" flavor (from the perspective of a German native speaker) were chosen, which means that most of the items are of English origin and stem from fields such as business (e.g., *franchise*), mass media (e.g., *sitcom*), or consumer technology (e.g., *airbag*). Because we had no intention to compare specialist and general knowledge, no norm values were ascertained for the latter (see Appendix, Table A2).

Procedure

To obtain norms, questions were given to participants in the last part of a booklet containing several other scales used for a survey of Internet and computer usage among college students. Booklets were filled out either in group sessions at the end of courses or individually in different university rooms. Completing the whole booklet took between 15 and 20 min. The 22 Internet-related items were presented in two versions with different item orders. Participants were asked to write down a short and precise

definition of each concept. The norm sample was not asked to perform any estimations.

For participants in the expert sample, three different booklet versions were prepared. Booklets for Group 1 (specialist knowledge condition) highlighted the difference between the two categories of concepts. They were presented on different pages, and each set of items was introduced by a short text explaining the task. The first set of items was labeled *specialist concepts*, and participants were addressed as "experts in the domain of Internet computing." The other set was labeled *general knowledge from different areas of modern life*. Participants were asked to give a short definition of each concept and then to estimate what percentage of all students would be able to define that item correctly. The last page of the booklet contained demographic questions. Group 2 (functional context condition) first read a short scenario describing the task of preparing a short introductory Internet course for students from other departments. Then they defined the Internet concepts and estimated their commonality. No general knowledge concepts were presented in this version of the task. Group 3 (general knowledge condition) received a short introduction explaining that we were interested in the participants' assumptions about the distribution of an assortment of "concepts related to modern life." The two sets of concepts were then presented in a random order. As in the other conditions, participants had to give definitions first and then estimate commonality.

The correctness of definitions was rated independently by two judges. The judges had considerable domain knowledge and were unaware of assignments to conditions. The interrater reliability was .97. Ambiguous cases were discussed until consensus was reached. Estimates based on incorrect definitions were treated as missing values.

Results

Effect of Context Manipulation on Estimates of Specialist Concepts

A univariate analysis of variance (ANOVA), with context condition as the independent variable and END (averaged across the 10 Internet items) as the dependent variable, was computed. There was a significant effect of context, $F(2, 99) = 4.1, p < .05$. Post hoc tests (Fisher's protected least significant difference [PLSD], $p < .05$) revealed that participants in the specialist knowledge ($M = -0.6, SD = 10.1$) and the functional context ($M = -1.4, SD = 12.4$) conditions gave significantly lower estimates than participants in the general knowledge ($M = 6.2, SD = 13.5$) condition.

Participants in the general knowledge condition significantly overestimated the commonality of the Internet concepts, $t(35) = 2.8, p < .01$, whereas scores did not differ from zero in either the specialist knowledge ($M = -0.62, t(33) = -0.4, p = .72$), or the functional context condition ($M = -1.4, t(31) = -0.6, p = .54$). Therefore, whereas the blurring of the distinction between specialist and general knowledge concepts resulted in their commonality being overestimated by experts, both contexts in which the expert status of the participants was addressed openly did not lead to any systematic bias.

In addition to analyzing ENDS, we investigated the ENC as in Study 1. For each participant, an individual correlation coefficient was computed and transformed with Fisher's Z . These scores formed the dependent variable in a univariate ANOVA with context as the independent variable. Here, too, the effect of context was significant, $F(2, 99) = 5.2, p < .01$. Post hoc tests (Fisher's PLSD, $p < .05$) revealed that the participants in the general knowledge condition had significantly lower ENCs than the experts in both the specialist knowledge and functional context

conditions. The mean scores, retransformed into Pearson product-moment correlations, were .68 for the general knowledge condition, .78 for the expertise condition, and .8 for the functional context condition. Taken together, both measures of quality of estimation pointed in the same direction.

Effect of Context Manipulation on Estimates of General Knowledge Concepts

As mentioned earlier, the general knowledge concepts were not construed in a way that permitted a systematic comparison with the specialist concepts, and no norm values were gathered. Nonetheless, the estimates associated with the general knowledge items could be considered as a sort of control variable. The question was whether the influence of context manipulation was restricted to the specialist concepts or generalized to the general knowledge concepts as well. An unpaired *t* test showed that the former was the case: mean estimates were 70.0 (*SD* = 13.5) in the specialist knowledge condition and 72.6 (*SD* = 11.4) in the general knowledge condition, $t(68) = -0.85$, $p = .40$. The blurring of the distinction between specialist knowledge and general knowledge influenced the estimates associated with the former but not those associated with the latter.

Discussion

Study 1 provided evidence that laypersons' proneness to estimation error is clearly influenced by the type of knowledge to which the concepts being assessed belong. Study 2 was designed to further explore the role of context in the estimation of other people's knowledge. How does the context of item presentation influence the quality of Internet experts' estimates?

Study 2 provides a straightforward answer to these questions inasmuch as both measures of quality of estimation (i.e., END and ENC) showed the same pattern of results. When the distinction between specialist and general knowledge concepts was blurred, the experts significantly overestimated the commonality of their specialist knowledge, and the relative accuracy of their estimations was lower. On the other hand, when contexts were created in which the expert status of the participants was addressed openly, there was no systematic misjudgment of the commonality among laypersons; at the same time, the relative accuracy of the estimations was better. Neither embedding the estimation task in a concrete scenario nor the absence of general knowledge items led to any relevant differences in estimates.

The results further show that the influence of context manipulation was restricted to specialist concepts. Blurring the distinction between general knowledge and specialist knowledge had no significant impact on the estimation of the commonality of general concepts. Hence, emphasizing the affiliation of a concept to a domain of specialist knowledge may help to prevent estimation biases. This result is in line with our finding that laypersons generate more conservative estimates for the specialist concepts they know than they do for the general ones.

One could argue that these results were to be expected. If someone is told that certain concepts are part of general knowledge, he or she will assume that these concepts are known by a higher percentage of the population than if he or she is told that these concepts are specialist concepts. However, we emphasize

again that not only the mean estimation was higher in the general knowledge condition but also the estimate-norm correlation (i.e., the relative accuracy of the estimates) was substantially reduced. That shows that the context manipulation had differential effects on the estimations of single concepts, which cannot be explained by a simple strategy of judging more cautiously. Moreover, the specialist concepts were from the core of the experts' own domain of expertise; it is by no means self-evident that they should be susceptible to such a simple labeling manipulation. The empirical evidence that, in fact, they are has practical implications, which will be discussed below.

General Discussion

Do people also tend to attribute their own knowledge to other people when it is specialist knowledge? The answer to this question has to differentiate between laypersons and experts. Although laypersons take more care when having to estimate the distribution of specialist knowledge rather than general knowledge, they still show the well-known judgment tendencies, that is, correspondence and overestimation. When it comes to specialist concepts, the judgments are more cautious. We therefore conclude that the mere information about the knowledge type (general knowledge vs. specialist knowledge) may have influenced the amount of estimation bias, but it did not change the general pattern demonstrated in the Nickerson et al. (1987) study.

In contrast, these systematic errors are far less prominent in experts. They are so much more conservative in their estimates that they tend to underestimate the commonality of most knowledge items (if they are not too difficult) or even hit the norm precisely. In the following section, we start by discussing possible explanations for this finding. We then consider some remaining questions regarding the expertise hypothesis. Finally, we discuss some practical implications for the improvement of communication between experts and laypersons.

Three Assumptions About Experts' Successful Strategies

It is amazing how precise some of the experts' estimates of laypersons' knowledge were because, compared with laypersons, they were confronted with a far more difficult task. They had to estimate the distribution of knowledge in a population to which they do not belong themselves, and major errors were not unexpected. The fact that this was not the case suggests that they did not simply take their own knowledge as a default model. However, how did they achieve their estimates?

We discuss a few potential explanations, using a heuristic suggested by Brown and Dell (1987). One possible explanation is that experts recall their own (lack of) knowledge as laypersons (analogous to the "speaker experience account" of Brown & Dell, 1987; see also Hinds, 1999). This explanation is the least convincing. First, computer and Internet concepts are developing so dynamically that experts must have come across a great number of them for the first time when they were experts already. Second, when they were still laypersons, experts were probably subject to the same judgment errors as those one finds among laypersons now, so it is unlikely that the recall of their former knowledge as laypersons would contribute to better estimates.

An alternative explanation is that they have gathered experiences with the lay population in their expert roles (analogous to the "listener need account" of Brown & Dell, 1987; see also Nückles, 2001; Nückles & Bromme, 2001). Our findings support this explanation in that our practical experts' estimations were better than those of the theory experts. However, this difference was not very large and the theory experts' estimations were still relatively good.

One further explanation, which supplements the previous one, comes from the finding that merely indicating that a concept is specialist knowledge leads to more correct estimates. It might be that assumptions about knowledge distribution are part of the deeper levels of a concept's meaning. Specialist concepts have relatively complex meanings, and they are linked to other specialist concepts on different levels (Bromme, 1990). These links are part of their intensional meaning and may include links to more or less concept-specific assumptions about their availability for laypersons in a certain cultural context. Indicating that the concepts to be estimated are specialist knowledge—as stipulated in Study 1 and as part of the experimental variation in Study 2—may activate deeper levels of meaning, and this may have contributed to the better estimates.

This explanation, though rather speculative, is inspired by the "linguistic division of labor" hypothesis developed by Putnam (1975). In his analysis, Putnam pointed out that, as laypersons, our ideas about the meaning of a concept include the assumption that most concepts are more precisely defined than we ourselves know. His example was the concept of water. We know that there are some experts (e.g., chemists in the case of water) who know the full range of aspects or the exact definition of a concept that we use more vaguely. Nevertheless, we can use the concept without difficulty. If the linguistic division of labor really is part of our implicit linguistic knowledge, this would imply that specific concepts come along with specific assumptions about their social distribution (Bromme, 2000). For many general concepts, a simple default value of "every adult person knows its meaning" would work very well. However, for specialist concepts, more sophisticated assumptions are necessary; these seem to be triggered by the labeling of our concepts as specialist concepts. On the other hand, when concrete "exclusivity markers" are present as surface features of a concept (e.g., acronyms, complex compounds, Latin loan-words; see Rambow, 2000; Rambow & Bromme, 2000), such an explicit labeling is possibly not necessary.

Consequences for Further Research on Nickerson et al.'s (1987) Expertise Hypothesis

Do these results apply to this domain of expertise only? In the present studies the expertise hypothesis was tested in the domain of IT. There are certain special features of this domain of expertise. For example, the domain of IT is relatively young. There are other, much older knowledge domains (e.g., medicine, literature), and they may therefore be interwoven with general knowledge in a certain culture in different ways. In addition, it should be taken into account that, within our exemplary domain, a gender effect is necessarily implied: Up to now, the majority of IT experts have been male; when estimating laypersons' knowledge, these experts have implicitly estimated their own knowledge as well as that of the opposite sex. Therefore, one may conclude that the stability of our results across domains of expertise needs to be established.

We already conducted a similar study in the domain of architecture (Rambow, 2000; Rambow & Bromme, 2000) that corroborates our results but that also points toward the necessity of further comparison between knowledge domains. Part of this research was quite similar to the studies reported here. A questionnaire was constructed with items from five thematic fields of architectural knowledge and given to a norm sample of college students. An expert sample of 41 experienced architects was then asked to estimate the distribution of knowledge among college students for each item. Across all items, no significant bias was found in either direction. As in the studies reported here, a large part of this variance had to be attributed to the above-mentioned dependency between item difficulty and estimation bias. Nonetheless, thematic aspects contributed significantly to the explanation of variance. For example, although experts significantly underestimated the laypersons' knowledge of architectural history, they grossly overestimated their knowledge of contemporary architecture. An explanation for this might be that concepts from architectural history look more difficult on the surface because architectural history is a somewhat codified discipline, whereas concepts and names from contemporary architectural discourse lack peculiar exclusivity markers. Once again, this points to a question posed earlier that would be interesting for further research: How closely are knowledge distribution assumptions related to the specific concepts forming the domain of expertise?

Apart from the question of how experts' knowledge estimations depend on features of the domain, it might also be interesting to pursue the issue of different levels of specificity. For example, rather than making a global assessment about the concept of *modem*, experts could assess the likelihood that a layperson would know specific facts about modems.

Implications for the Improvement of Expert-Layperson Communication

In the introduction, we pointed out that the asymmetry of knowledge—and often of power as well—between experts and laypersons often reduces the effectiveness of the ongoing process of monitoring and repairs, which is necessary for mutual understanding (Keysar, 1998; Nickerson, 1999). Realistic assumptions about laypersons' knowledge are therefore necessary to improve these processes of adaptation. How can the studies presented here contribute to the education and training of experts in a way that leads to a higher level of listener adaptation? We propose four practical implications:

1. The research design of the Nickerson et al. (1987) study can be used as a didactic tool in training courses aimed at experts' communication skills. We have implemented such courses for experts in several fields. When the participants in such courses are asked to estimate the knowledge distribution of important items from their domain, they experience the confrontation between their guesses and the empirical values as very revealing. This serves as a useful and convincing starting point for discussion and explanation of the general principles of audience design. One point to be discussed would be the reported result, that the experts in our study tend to underestimate the laypersons' knowledge about items of low or medium difficulty. Starting communication with an underestimation of laypersons' knowledge in mind could be a good heuristic for the expert if one assumes that delivering more infor-

mation as necessary is less detrimental for the layperson than a shortage of information. In any case, such a heuristic would be helpful only if the expert is aware that his or her assumptions about laypersons' knowledge are provisional. Only if experts know that they start with nothing more than an assumption, they may be open enough to avoid talking down to laypersons (by explaining concepts the layperson already knows) as well as open enough to discern signals of laypersons' misunderstanding.

2. The close relation between item difficulty and direction of bias is important and should be discussed with practitioners who interact with laypersons. Only if they are aware to what extent laypersons know several subdomains of their expertise will they be able to successfully adjust to laypersons' communicational needs.

3. The fact that the experts' assumptions are influenced by the context in which the knowledge items are embedded seems to be important. It is a widespread belief among laypersons that their difficulties in understanding experts' explanations are caused mainly by the special terminology and the experts' unwillingness or incompetence to translate them. However, such a translation strategy not only fosters the illusion of mutual understanding on the layperson's side but it also leads the experts to rely on the biased estimation strategies that are typical for general knowledge. When it comes to concepts in which the distinction between general and specialist knowledge is blurred, it might be necessary to explicitly label these concepts as specialist concepts. Making the distinction between specialist and general knowledge more salient should help the experts to develop more realistic assumptions about their social distribution.

4. It cannot be assumed that such knowledge will be taken into account by experts when they are interacting face-to-face with laypersons (Brown & Dell 1987; Keysar, 1994). Nevertheless, there are communication contexts in which assumptions about the audience are very important, such as in computer-mediated, asynchronous communication (Clark & Brennan, 1991). When experts in World Wide Web-based hotline services communicate with laypersons, they usually have to rely to a great extent on their a priori assumptions about laypersons' knowledge. Often, laypersons' requests are short, and it is not usually possible in such a constrained context to get an overall impression about the recipient's background knowledge; this could be more easily ascertained in a face-to-face situation. Data about laypersons' knowledge distribution as well as the conditions that might improve the quality of experts' estimations (as presented here and to be gleaned from further research) could help to prepare experts who work in these hotline services.

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Appendix

Table A1
Items Used in Study 1 and Corresponding Norm Values

Item (specialist knowledge)	Norm value	Item (general knowledge)	Norm value
Festplatte [hard disk]	94.1		
Internet	91.4		
DOS	83.0	Nasi-Goreng	86.1
Modem	81.9	Apokalypse [apocalypse]	80.9
Betriebssystem [operating system]	78.7	Elixier [elixir]	63.6
ISDN	66.0	Placebo	62.6
Download	45.7	Raddicchio	52.4
CD	43.1		
ASCII	37.2	Despotie [despotism]	37.4
Unix	33.2	Dschihad [jihad]	33.0
Server	32.4		
DFÜ [dial-up networking]	31.7		
Editor	29.4		
Multitasking	28.7		
Baud	28.2		
Browser	28.2		
mk dir	27.1		
Account	24.5	Periodikum [periodical]	23.4
Prompt	22.0	Fatum [fate]	20.7
Telnet	13.9		
LAN	13.8		
Host	13.4		
Domain	10.8		
Finger	10.7		
ftp	10.2		
TCP/IP	9.0		
<body><body>	7.5		
Client	7.5		
HTML-Tags	7.5		
Router	5.4		
Gateway	3.7		
MIME	2.7		
Carrier	2.1	Palliativ [palliative]	2.7

Note. Norm values are the percentage of correct answers in the norm sample. Items are listed in their original version, with English translations in brackets where necessary.

(Appendix continues)

Table A2
*Specialist Items Used in Study 2 and Corresponding
 Norm Values*

Item	Norm value
www	96.1
e-mail	91.8
Chat-room	83.2
Provider	66.9
Intranet	44.5
HTML-Editor	34.6
Cache	31.2
FAQ	26.3
Hypertext	19.4
WYSIWYG	10.1

Note. Norm values are the percentage of correct answers in the norm sample. General knowledge items: Event Marketing, Globalisierung [globalization], Joint Venture, Handy [mobile phone], Airbag, Sitcom, PR-Agentur [public relations agency], Design, Merchandising, Global budget, Dow Jones, OSZE [OSCE], Franchise.

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