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Dealing with self-report bias in mobile Internet acceptance and usage studies

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ABSTRACT

Self-report bias is a known validity threat to IS usage studies. Respondents may find it even more difficult to assess their actual usage of mobile services as these can be used in highly variable contexts. This paper examines the extent of self-report bias in mobile acceptance and usage studies and suggests counter-measures. We demonstrate that several Type-1 and Type-2 errors are made when relying on self-reports rather than log data. Weighing can partly mitigate self-report bias as older people are more accurate than younger people. Log data replace self-reports in order to reduce self-report bias in mobile acceptance studies.

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1. Introduction

A vast body of knowledge is accumulating on why consumers accept and use mobile Internet services (also labeled as mobile applications) [1–3]. These studies largely rely on self-reports to assess usage levels [e.g., 1,2,4,5,6] with only few exceptions [e.g., 7]. Earlier studies on information systems (IS) usage show that using self-reports can introduce bias as respondents find it difficult to recall past behavior [8–10]. Other studies suggest that self-report is only a marginal problem [11]. For mobile voice services, self-report bias has well been demonstrated by epidemiologists [12,13] as well as communication scholars [14–16]. For mobile data traffic, Gerpott [17] shows that self-reports on megabyte consumption are biased, which threatens the validity of explanatory models. However, self-report bias regarding specific categories of mobile Internet services has not yet been assessed.

Studies on self-report bias of IS usage have been mainly done in organizational settings, and cannot simply be generalized to mobile Internet services for the general public. First, compared to stationary computing, mobile services can be used anywhere and anytime [18]. The resulting variety of temporal and spatial contexts of use increases the cognitive difficulty of recalling usage behavior. Second, mobile services are being used for work and private purposes. This implies that mobile services can be used to support a wide variety of tasks, which again increases the cognitive difficulty of recalling past behavior. Third, smartphones offer such a wide variety of services that respondents may find it difficult to distinguish and classify services that they use on a daily basis. Fourth, as smartphones are typically carried around all day, mobile services are far more ingrained in the everyday life of people than stationary applications. As a result, respondents may find it difficult to reflect on which types of services they use where and when.

In this paper, we assess if and how self-report bias threatens validity of studies on mobile Internet service acceptance and usage. We do so by comparing log data collected directly on smartphones with self-reported usage levels from survey questions. We compare nine categories of mobile Internet services with varying usage levels. Besides examining the magnitude and source of self-report bias, we examine whether using self-reported usage levels leads to Type-1 or Type-2 errors in an explanatory model. Based upon the analyses, we suggest counter-measures to mitigate self-report bias.

The paper contributes to the field of mobile Internet service acceptance and usage by illustrating how self-report bias may threaten the validity of such studies. More generally, the paper contributes to discussions in IS on self-report bias and method bias in system usage studies [9,19,20]. Practically, the paper has implications

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for the telecommunications and media industry, which rely heavily on surveys to measure acceptance and usage levels.

Section 2 provides an overview of related work. Section 3 provides the method including the field study setting, sample and metrics. Section 4 examines the extent of self-report bias in the dataset as well as the potential threats to the validity of explanatory models. Section 5 discusses results including tactics how to mitigate self-report bias and Section 6 provides conclusions.

2. Background

Self-report bias is a well-known methodological issue, and has been discussed in domains like medical research [21], organizational behavior [22,23] and consumer marketing [24]. Self-report bias may result from recall inaccuracy as well as the tendency to respond to questions in socially desirable ways [25,26]. Self-report bias depends on the nature of the construct, the cognitive capabilities of the respondent, the disposition of the respondent towards socially desirability and situational and task-related conditions [22,27,28].

In the field of Information Systems (IS), self-report bias is typically discussed in relation to the concept of system usage, which is prominent in IS success models [29] as well as IS acceptance models [30]. In a literature review, Jeyaraj et al. [19] find that almost all IT acceptance studies rely on perception scales to measure systems use. Self-report bias is demonstrated in several IS usage studies. Collopy [31] finds that computer use is not well estimated by users as infrequent users overestimate and frequent users underestimate usage levels. However, other IS scholars argue that self-report bias is not a major issue. Deane et al. [11] show that log data and self-reports on computer usage are moderately to strongly correlated. Venkatesh et al. [32] found a significant relation between intention to use and actual usage figures.

Besides showing that computer-recorded usage data and self-report scales are weakly correlated, Straub et al. [9] also show that self-report bias threatens the validity of explanatory models: effect sizes for the TAM model are higher when using self-report scales than when using computer-recorded usage data. Recently, debate on how to conceptualize self-report bias has been (re)started. For instance, Burton-Jones [20] argues to distinguish knowledge bias (i.e. not providing accurate assessments because of the respondents' lack of knowledge of the trait score) and rating bias (i.e. not providing accurate assessments because the respondents' unwillingness to do so).

Self-report bias regarding mobile phone use has especially received attention from epidemiologists, in order to validate studies on health risks associated with mobile phones. Several epidemiologists show that users overestimate both the frequency and duration of calls [13,33]. Others find that users underestimate call frequency but overestimate call duration [12,34]. One study shows that consumers are better at recalling frequency than total duration [35]. Recently, scholars from communication science have similarly shown self-report bias for mobile voice calling [14–16]. Demographics like gender and age are related to self-report bias according to some studies [16,36] but not to others [14,37]. Frequency of use is related to self-report bias according to some studies [12,16] but not according to others [37].

As far as we are aware, only one published study examines self-report bias for mobile data services. Gerpott [17] examines self-report bias by comparing several perception scales with the actual number of megabytes transmitted over the mobile network. He finds that self-report bias may be a large threat to explanatory models as correlations are higher when using self-report scales than with log data. He finds such inflated correlations for not only other subjective constructs but even for objective ones such as tariffs and costs levels. While Gerpott's study provides insights in self-report bias for mobile data usage, he does not examine the different categories of mobile Internet services, which can be used by consumers.

3. Method

3.1. Sample

A user panel comprising 20,000 households was used to sample respondents. The user panel is representative for the Dutch population in terms of demographics. The panel is regularly renewed through active recruitment (i.e. no self-selection bias is involved) and panelists are typically not compensated for taking part in surveys.

From the panel, a random sample was drawn. Next, an initial questionnaire was sent to the persons in the sample inviting them to participate in the study. As the software to collect log data only works with iPhone and Android smartphones, Blackberry and Windows phone users are excluded from the study. The initial questionnaire extensively explained how log data would be collected, stored and analyzed in the study. As the first round of recruiting did not lead to sufficient response, the procedure was repeated but only including the subset of panelists that were known to possess a smartphone. Finally, in a third recruiting round, panelists were approached who had already participated in an earlier study in which log data on smartphone use was collected.

After data cleaning for partial non-response, the three rounds of recruitment resulted in data from 1653 persons that filled in the initial questionnaire, out of which 519 were willing to participate in the study. Of the reasons for non-participation provided, the core reason was privacy (by 16% of the respondents). For 15% of the respondents the reasons were related to typical non-response reasons, such as holidays, sickness and travelling abroad. Technical reasons were mentioned by 2% of the respondents, and 3% indicated their employer would not allow them to download apps on their phone. Other reasons provided included low usage of the smartphone and no experience or know-how to install applications on the smartphone.

Although 519 respondents initially indicated that they were willing to participate in the study, only 369 downloaded and

Table 1
Demographics of final sample ($N = 233$).

Gender	Male	52%
	Female	48%
Education	Higher education	61%
	Middle education	34%
	Lower education	4%
Income	Below modus	13%
	Modus	25%
	Above modus	59%
	Do not know, no answer	3%
Household size	1	20%
	2	28%
	3	17%
	4	28%
	>4	8%
Position in household	Primary wage earner	28%
	Caretaker	27%
	Both	32%
	Child	12%
	Other	1%
Operating system	iOS (Apple)	26%
	Android	74%

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