

QUANTITATIVE LONGITUDINAL RESEARCH: A REVIEW OF IS LITERATURE, AND A SET OF METHODOLOGICAL GUIDELINES

Complete Research

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Abstract

Data captured at different points in time provides the basis for longitudinal research. It is unquestioned that several IS phenomena deal with change over time such as post-adoption behavior with respect to IT artifacts. However, cross-sectional research designs are predominantly applied in the IS field up till now. This paper is therefore written not only to motivate the IS community to apply longitudinal research to time-variant IS phenomena but also to discuss common pitfalls. For this purpose, we outline various longitudinal studies and provide four guidelines that should be considered during their planning. In particular, common methodological issues like space and amount of repeated observations or attrition are discussed. Finally, an overview of common longitudinal research questions and corresponding methods of longitudinal analyses is provided.

Keywords: Longitudinal Research, Literature Review, Data Analysis, Research Methods, Study Design

1 Introduction

A substantial part of information systems (IS) and IS-related research aspires to *describe*, *explain* and predict phenomena related to technology and its characteristics. Research on the adoption and diffusion of technology, for example, may strive to *describe* the spread of a certain technology in society (Bass, 1969; Mahajan et al., 1990; Rogers, 2003), *explain* differences in adoption and diffusion between technologies (Venkatesh et al., 2003; Venkatesh et al., 2012) or *predict* the success of future technologies by analysing promoting and inhibiting aspects of IS adoption and diffusion (Davis et al., 1989; Rogers, 2003; Venkatesh et al., 2003; Venkatesh et al., 2012).

However, an extensive and complete *description* of certain phenomena should consider *all* kind of related aspects, including temporal oscillation, or change over time. That is, one can assume many constructs in IS to be unstable and subject to variation as time elapses. Privacy concerns, for example, may exponentially increase with age, while perceived enjoyment may decrease with usage time and frequency. Also, a doubtless *explanation* and *prediction* of IS-related phenomena requires a chronological perspective, given that causes precede effects (Maxwell and Cole, 2007; Maxwell et al., 2011; Mitchell and James, 2001). Stated differently, knowledge on past causes is required to *explain* current outcomes, and knowledge on actual causes is necessary to *predict* future events.

For the investigation of change over time, scholars have repeatedly used the term longitudinal research. However, different definitions of longitudinal research exist: Rindfleisch et al. (2008), for example, use this term to describe repeated observations of the same units on different outcomes, referring to the potential to increase reliability by splitting measurement occasions. In a similar vein, some

authors refer to longitudinal research when retrospectively assessing outcomes through one observation only, i.e. when requesting subjects to remember and report past changes (e.g. Shen and Ginn, 2012). Although valuing these approaches, our work is organized around a conceptualization of Singer and Willett (2003a), defining longitudinal research as *repeated* observations of the *same units* on the *same outcomes* over a certain amount of *time*. That is, we refer to longitudinal research as the science of tracing change by repeatedly measuring the same phenomenon under the same circumstances (e.g., using the same assessment method). Furthermore, our focus lies (1) on a “variance theory” perspective (Van de Ven, 2007, Chapter 7), emphasizing the increasing role of quantitative as opposed to qualitative research designs, and (2) on the design and conduction of studies that aim to collect data from primary sources, especially individuals – thus highlighting the growing importance of user studies in IS research. Against this background, the results and implications of the current work may apply when scholars are interested in studying the change of attitudes (Dubno, 1985), the spread and diffusion of innovations in organizations (Van de Ven et al., 1999) and society (Bass, 1969; Rogers, 2003), or the adoption of information technology (Bodker et al., 2009).

In the following, we take a critical perspective on longitudinal quantitative studies in IS (Myers and Klein, 2011) and strive to answer the following research questions:

RQ1: How widespread are quantitative longitudinal studies in the IS community?

RQ2: What are common pitfalls to quantitative longitudinal studies and how can they be addressed?

In order to answer these research questions, we will (1) report the results of a systematic literature review on quantitative longitudinal studies in the IS community (RQ1), (2) evaluate prior examples of IS studies with regard to four methodological guidelines designed to address common pitfalls when analysing change (RQ2), and (3) provide a typology of research questions and research designs that future IS scholars may find useful when planning and conducting a longitudinal study (RQ2). The paper is structured as follows: We will first outline the importance of quantitative longitudinal studies for theory and delineate a quantitative from qualitative approaches to the study of change. Next, we will present related work that already applied longitudinal research in the field of IS. Then, four methodological guidelines are presented and discussed, using concrete examples from prior IS literature to underline their importance. Synthesizing our results, we then provide an overview of common longitudinal research questions that may guide researchers in the selection of appropriate methods for the design, execution, and analysis of longitudinal studies, and conclude by summarizing our contributions to literature.

2 Conceptual Approach

As outlined above, we aim to explore longitudinal research from a “variance theory” (Van de Ven, 2007, Chapter 7) rather than a “process theory” (Van de Ven, 2007, Chapter 7) perspective, focusing quantitative rather than qualitative research designs. A main reason for this conceptual approach is that qualitative and quantitative research approaches make different contributions with regard to theory building and testing. In particular, qualitative research is commonly applied if researchers aim to explore and generate hypotheses (Creswell, 2013, p. 22) or understand a problem in detail “to see specificity and context in some fine grain” (Yates, 2003, p. 224). In contrast, scholars apply methods of quantitative research when aiming to test hypotheses that have been deduced from theory, often generalizing and transferring results to different populations and contexts (Creswell, 2013, p. 22). Regarding the analysis of change, consequently, a quantitative approach is needed in order to obtain more generalizable insights on how, when and why change occurs for a significant part of the analysed population (Singer and Willett, 2003b). Investigating the diffusion of innovations, for example, trajectories of innovation adoption may highly differ between individuals or organizations due to manifold reasons (Weigel et al., 2014). While a qualitative longitudinal approach (usually including a smaller

sample) enables scholars to explore these reasons and build hypotheses on factors that affect adoption, a quantitative longitudinal approach is necessary to test and confirm when and why innovations are adopted on a more generalizable level (Mustonen-Ollila and Lyytinen, 2003, p. 294). As such, the current research primarily addresses scholars who aim to investigate the nature of change through quantitative rather than qualitative methods. Yet, it must be noted that quantitative and qualitative longitudinal research are not strictly distinct approaches— in fact, quantitative longitudinal research is often informed by qualitative work (Ployhart and Ward, 2011), and mixed method approaches are favourable in many cases (Creswell, 2013).

3 Literature Review

We first conducted a systematic literature review to examine the state-of-the-art of quantitative longitudinal IS research that adopted repeated measures over time. We restricted our literature search to the AIS Senior Scholars' Basket of Journals over the last decade, i.e. from 2004 (inclusive) to October 2014. The eight IS journals in alphabetical order include the European Journal of Information Systems (EJIS), Information Systems Journal (ISJ), Information Systems Research (ISR), Journal of AIS (JAIS), Journal of Information Technology (JIT), Journal of MIS (JMIS), Journal of Strategic Information Systems (JSIS) and MIS Quarterly (MISQ).

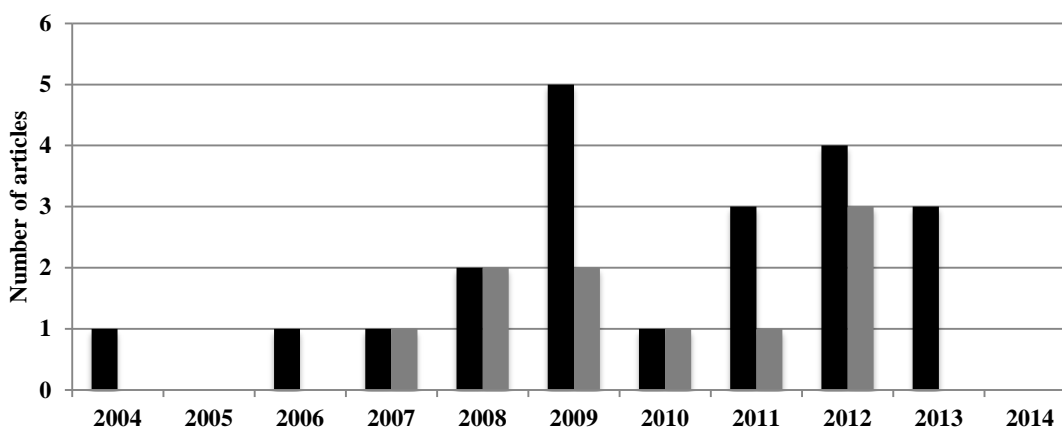


Figure 1. Number of IS Articles with repeated measures over time (black), including research investigating the same units on the same outcomes over time (grey).

In order to identify relevant terms for the database queries, we preliminary searched for articles that were published in the aforementioned journals with the following keywords to be included in the title or abstract or subject terms: “longitudinal”, “quantitative”, “process research”, “repeated measures”. As a result the term “longitudinal” was included in all relevant papers and thus, we used it as core search term and, wherever possible, excluded qualitative papers and case studies with appropriate terms. The common search query adopted in the Palgrave Journal Search Database (forEJIS and JIT), Wiley Online Library (for ISJ), EBSCOhost Research Database (for ISR, JMIS), ScienceDirect Expert Search (for JSIS) and AIS eLibrary Search (for JAIS and MISQ) was: title:longitudinal OR abstract:longitudinal OR subject:longitudinal AND publication_title:([JOURNAL TITLE]) NOT subject:(case stud*) NOT title:qualitative NOT subject:qualitative AND Range: 01/01/2004 - 11/01/2014 /. This step resulted in a list of 55 articles.

In a next step, two PhD students independently cross-validated the relevancy of the 55 articles based on title, abstract, keywords and the full text (in this order). Papers were included for further examination when they adopted repeated measures over time and at least one quantitative method of analysis (e.g. a paired-sample t-test). Furthermore, research notes were excluded from the results (e.g. Kim et al., 2005; Trier, 2008; Wang et al., 2013). For 47 of the 55 papers, the two coders agreed with each

other. That is, the first coder judged 14 of 55 papers as quantitative and longitudinal, while the second coder rated 22 of 55 papers as relevant with regard to the scope of this work. Consistent with prior work that reports inter-rater reliability measures (e.g. Moore and Benbasat, 1991), we calculated the raw agreement and Cohen's Kappa which revealed good results with .85 and of .83, respectively. In eight cases, in which an article was not classified consistently, both coders decided together on whether or not to drop them for further analysis.

#	Journal	Reference	Research objective	RM
1	EJIS	Veiga et al. (2013)	Effects of pre-adoption expectations on post-adoption proficiency	No
2	EJIS	Vitari and Ravarini (2009)	Investigation of the change trajectory of the software industry	No
3	ISJ	Shaft et al. (2008)	Understanding transitions from a structured to an object-oriented development environment.	Yes
4	ISR	Du et al. (2008)	Stability of characteristics of capacity provision networks for rich media content.	Yes
5	ISR	Goes et al. (2010)	Change in willingness to pay of repeat bidders in online auctions.	Yes
6	ISR	Kim et al. (2009)	Trust and satisfaction on long-term relationships with e-commerce websites.	No
7	ISR	Sasidharan et al. (2012)	Effects of social network structures of employees and their organizational units on post-implementation success of enterprise systems.	Yes
8	ISR	Setia et al. (2012)	Contribution of peripheral developers to product quality and diffusion of open source software	Yes
9	ISR	Venkatesh and Sykes (2013)	Technology use and economic outcomes of a digital divide initiative.	No
10	ISR	Venkatesh et al. (2011)	Understanding the predictors and effects of health IS usage over time.	No
11	JIT	Willcoxson and Chatham (2004)	Perceived difficulty and trends in the IT/business relationship	No
12	JMIS	Ayal and Seidman (2009)	Understanding the business value benefits after implementing and integrating an enterprise system in the healthcare context.	No
13	JMIS	Deng and Chi (2012)	Understanding use problems after adopting of a new business intelligence IS and how they evolve over time.	No
14	JMIS	He et al. (2007)	Evolution of communication and team diversity in software project teams.	Yes
15	JMIS	Lam and Lee (2006)	Understanding the role of Internet training, Internet self-efficacy and outcome expectations in the context of disadvantaged groups.	No
16	JSIS	Peng and Eunni (2011)	Whether and how employees' computer skills are rewarded in the workplace over time. (Theory of labor economics)	No
17	MISQ	Hahn et al. (2009)	Understanding the effects of push factors that drive firms to accept higher degrees of host country risk.	Yes
18	MISQ	Joseph et al. (2012)	Career histories, mobility patterns, and career success of 500 individuals in IT	Yes
19	MISQ	Kim (2009a)	Determinants of technology usage over three points in time	Yes
20	MISQ	Ransbotham and Kane (2011)	Effects of membership retention on collaboration success in online communities.	Yes
21	MISQ	Sun (2013)	Impact of herd behavior on technology adoption and post-adoptive IS use.	No

Table 1. Results of the literature review process. Note: RM = repeated measurement of the same units on the same outcomes.

The resulting list of 21 selected articles is shown in Table 1. For each of these articles, a summary of the research objective is provided. In addition, it is indicated whether the repeated measurement design was used for the *same units* of analysis on the *same outcomes* over a certain amount of time as per definition of longitudinal research in the current work. Considering this classification often referred to in social sciences (Singer and Willett 2003), the number of relevant articles reduced to ten, equaling “only” 0.125 papers per year and IS journal in average. Compared to an average of 31 articles published per year and journal (the average number of original research articles in EJIS, ISR, JMIS and MISQ in 2009), longitudinal research represents only a portion of *0.4 percent*. Figure 1 depicts the absolute frequency of articles identified from 2004 to 2013. Overall, these figures clearly outline not only state-of-the-art but also a lack of IS contributions in this regard.

Against this background and due to the fact that other research fields like economics and psychology have been adopting and researching change and its analysis for decades (Cronbach and Furby, 1970; Unsworth et al., 2013; Wu and Griffin, 2012), our goal is now to transfer specific knowledge from these research areas to the research questions and concepts typically addressed in the IS field. We therefore discuss theoretical, methodological and analytical aspects of longitudinal research designs and contribute a set of rules to set up a longitudinal study in the following sections.

4 Guidelines for Planning and Conducting a Longitudinal Study

Motivated by the limited theoretical and practical contributions to the analysis of change in the field of IS, we extensively reviewed literature from organizational research, consumer behavior, statistics and psychology. This review was done by using the Business Source Premier database of the EBSCOhost service without the restriction to IS-specific journals but with exactly the same search terms as listed above in Section 3. Qualitative articles have been dropped as well as articles that did not focus on methodological guidelines. From the final list of articles and the literature that was cited, we excerpted four (non-exhaustive) guidelines on longitudinal quantitative research that IS researchers may find useful as a **starting point** for further examination. In the following, we will discuss:

- (1) the importance of research designs that are able to capture reality, i.e. *follow natural oscillation*,
- (2) the role of valid measurement instruments and the hazards arising from repeated observations, i.e. issues concerning *measurement validity and the right amount of waves*,
- (3) threats to internal validity that affect longitudinal designs, i.e. *hazards to internal validity*, and
- (4) the interplay of the research question, collected data and analysis when investigating change, i.e. *methods of analysis that fit the data*.

4.1 Guideline 1: Follow Natural Oscillation

Scientists apply longitudinal research to describe, explain and predict changes occurring in reality based on limited data from a discrete number of measurement occasions (Oud and Folmer, 2011). Phenomena of interest, however, may differ in their form and velocity of change. While moods, for example, are supposed to change sinuously in rapid cycles (Weiss et al., 1999), technical innovations may only slowly diffuse in society, following a logistic curve (Bass, 1969; Bass, 2004). In longitudinal research, limited by resources and economic restraints, it may become unfeasible to correctly and extensively comprehend these natural curves without strong hypotheses on their characteristics. Thus, theoretical considerations on the expected fluctuation of the outcome variable must precede any decision on a particular study design, such as (1) the number and space of repeated measurements, or (2) the selection of an adequate time metric.

Referring to the operationalization of time, one must realize that any longitudinal study is based on time as a predictor of a continuous outcome that is expected to fluctuate. A reliable and valid determination of time is therefore essential for success. While most published studies use time itself as a measure by gathering data over days, weeks, or months (e.g. Daymont and Andrisani, 1983), a justifi-

able metric of time may include any measure that is non-reversible, e.g. age and grades, money spent, or hours of system use (Singer and Willett, 2003a). Buckler (2007), for example, used age to explain variance in weight and height velocity among adolescents. Yet, while this setup suits an adolescent sample, it may become unsuitable for adult populations, as height and weight become independent from age within grown-ups. Furthermore, using age as a metric of time to investigate the oscillation of moods would be inappropriate due to the heavy oscillation of moods, while age (if measured in the typical, coarsely granular way) only changes once a year. Researchers should therefore consider whether the selected time metric fits theoretical assumptions on characteristics of the target sample or the outcome (Ployhart and Vandenberg, 2010; Singer and Willett, 2003a).

With regard to the number and space of repeated observations, most longitudinal studies rely on equally paced measurement occasions (or waves) to gather data (e.g. Serva et al., 2011). Indeed, equidistant waves are highly feasible from a practical viewpoint due to low organisational overhead (Bijleveld et al., 1998, p. 2). From a theoretical perspective, however, equidistance is not obligatory (Mitchell and James, 2001; Singer and Willett, 2003a; Voelkle and Oud, 2013). Assuming a study that investigates satisfaction with a system after five, ten and 50 hours of use, for example, one should consider prior studies showing that individuals vary in their usage frequency – indicating that intervals between measurement occasions may also vary between subjects (Ployhart and Vandenberg, 2010). Similarly, phenomena known to heavily oscillate over short periods of time require a higher number of measurement occasions, while data from fewer waves has the ability to correctly mirror changes of outcomes that fluctuate slowly (ibid.). In this regard, the selection of three waves in the example above seems arbitrary without grounded hypotheses on the oscillation of user satisfaction, and may in addition lead to misleading conclusions on the form and velocity of change as depicted in Figure 2.

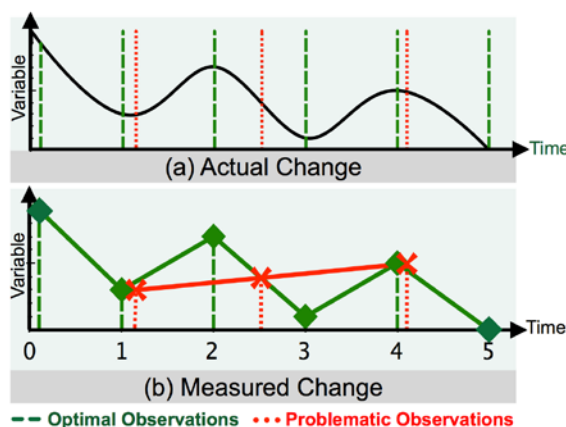


Figure 2. *Actual change (a) versus measured change (b) depending optimal (detects cyclic form and negative trend) and problematic (fails to detect form and trend) amount, space and time of observations.*

Against this background, we argue that decisions on research designs should follow theoretical assumptions on the nature of oscillation. More precisely, studies should rely on an extensive examination of previous theoretical work when operationalizing time or choosing the number and space of measurement occasions. If such groundwork is missing, scholars could still consider qualitative pre-studies to correctly anticipate oscillation (Ployhart and Ward, 2011), or align wave space and frequency to the fluctuation of the fastest changing variable (Lerner et al., 2009). Prior longitudinal research conducted in the field of IS, however, did only rudimentarily account for theory or pre-studies when justifying longitudinal study designs. More precisely, only two out of twenty-one studies presented in Table 1 provided a clear rationale for the selection and distance of measurement occasions: Kim (2009a) referred to prior empirical findings to justify the selection of time intervals, while Veiga et al. (2013) conducted preliminary user trials to learn on the evolvement of usage patterns over time. As argued above, however, omitting such justifications may lead to misleading conclusions: Ayal and

Seidman (2009), for example, analysed the revenue per diagnostic procedure before and after the implementation of a picture archiving and communication system in a hospital. Using asymmetrical time distances between the measurement occasions, the authors found weaker linear increase in the outcome before as compared to after system implementation, leading them to conclude that revenue increased steadily, “at a rate of \$3 per procedure per month” (p. 62). With regard to the arguments outlined above, however, this conclusion could be premature, given that a higher number or different allocation of waves could have output different results.

4.2 Guideline 2: Choose the right Amount of Waves

Some authors have argued for a general requirement of at least three waves as a defining attribute of longitudinal research (e.g. Ployhart and Vandenberg, 2010; Singer and Willett, 2003a). They state that the form of change may not be mirrored with two repeated observations and true change and measurement error are inseparable in two-wave designs, leading to erroneous results. In the following, we will discuss a more pragmatic view on these issues, emphasizing that some research questions may not address the form of change and that methodological issues can be bypassed using control techniques on reliability and validity of the outcome metric.

Longitudinal research is applied for research questions ordered around the how, whether and why of change (Podsakoff et al. 2003). With regard to the first question, researchers follow trajectories of individuals or groups to generate insights on the form and velocity of change. In diffusion of innovations research, for example, one could hypothesize on a logistic form of change for the diffusion of a certain technology and may test it longitudinally (Bass, 1969; Bass, 2004). This class of research questions indeed requires at least three measurement occasions to correctly and extensively describe linear growth, and even more waves are required to identify non-linear change over time (Ployhart and Vandenberg, 2010). Similarly, any research question that combines the rationale and form of change will require a minimum of three measurement occasions. Serva et al. (2011), for example, analysed differences in form and velocity of computer anxiety that declined during a MIS course based on inter-individual (i.e. individual form and velocity) and intergroup differences (i.e. form and velocity based on sex or instruction group) at four points in time.

However, there is a feasible class of research questions aiming to detect *whether* or *why* a change exists *at all*. With regard to the evaluation of a new customer relationship management system, for example, one may not be interested in how perceived ease of use of that system develops over time, yet only whether the introduction lead to a significant increase in new customers or not. Similarly, it may be of minor importance for scholars to learn on interindividual differences in learning advancements of a one-day MIS course whereas evaluating its effectiveness on a group level may be highly relevant. Typically, pretest-posttest designs with two measurement occasions are applied in such a context (e.g. Hurling et al., 2007; Lu et al., 2012). However, these designs have been subject to continuous criticism alluding to reliability and validity artifacts (Cronbach and Furby, 1970; Howard et al., 1979). As a silver bullet to these issues, scholars typically apply randomized control group trials, assuming that measurement errors will equally affect all groups, whereas true change will reflect in differences of change between samples with identical pre-conditions (Dimitrov and Rumrill, 2003). Most longitudinal research in the context of IS, however, did not integrate control groups: Out of the twenty-one studies reported in Table 1, only two studies were found to use control groups: Sun (2013) deployed a randomized controlled trial to compare pre- and post-adoption beliefs and behavior of participants who either received or did not receive certain information on the adoptive stage of the system under investigation, while Venkatesh and Sykes (2013) applied a quasi-experimental approach by comparing effects of computer skill courses in rural India between a village that received, and a village that did not receive instruction. The major part of reviewed literature, however, referred to one-group designs only, e.g. in the context of career path analysis (Joseph et al., 2012), computer literacy trainings for older adults (Lam and Lee, 2006), or team cognition and collaboration in software developer teams (He et al., 2007).

As an alternative approach to separately examine true change and measurement error, scholars in psychology have proposed variance decomposition techniques, such as Latent State Trait Theory (Schmitt and Steyer, 1993; Steyer and Riedl, 2004; Steyer et al., 1999). In this approach, variances of a measured variable are separated into a true score τ (denoted as η , here), an unchangeable factor ξ (denoted as “latent trait”) and a changeable factor ζ (“latent state”), implying a measured value Y consists of a latent trait, a latent state and an residual ε :

$$Y = \xi + \zeta + \varepsilon$$

While the latent trait similarly influences measured values at all measurement occasions, change is reflected in the latent state, enabling separate treatment of measurement error and true change. Following a similar logic, generalizability theory (GT) (Cranford et al., 2006; Cronbach et al., 1972) proposes variance decomposition into distinct and combined factors of individuals, items and measurement occasions. Within this framework, Cranford et al. (2006) also propose a manageable reliability index designed for use in longitudinal studies (e.g. Xu and Shrout, 2013). Variance decomposition techniques apply to research designs with at least two measurement occasions, yet one must note they set certain requirements to study design, such as the use of at least two parallel test at each measurement occasion when applying LST (Steyer and Riedl, 2004). Embracing the potential of such techniques, we propose longitudinal research to be also applicable in restricted research designs (1) that aim to explain whether or why a change occurred *at all*, (2) use only one-group designs, and (3) rely on data from two measurement occasions only.

4.3 Guideline 3: Watch Hazards to Internal Validity

Internal validity of a study refers to the unambiguousness of the findings and insights generated, implying found effects solely base on the hypothesized factors (Jarvenpaa et al., 1985). For longitudinal research, this means form, velocity and rationales of change in the data doubtlessly reflect correspondent change characteristics of a certain outcome in reality for a certain sample. Validity issues gain special interest for longitudinal researchers as time may not only add to desired changes, but also mask whether, how and why changes occur. Repeatedly observing performance in the same task of a usability test during product development, for example, may result in the observation users’ effectiveness increases as improvements in product design are implemented. One may interpret this as an advancement of product usability. However, higher effectiveness may also be confounded by a simple training effect – users accustomed to the existing usability issues and learned to bypass them, resulting in a shorter time needed to fulfill the task. Furthermore, erroneous planning on the amount and space of waves may result in data incapable to reflect changes occurring in nature, as addressed above. When applying longitudinal research, we therefore suggest scientists to consider hazards to internal validity arising from (1) confounded variables and (2) research design and planning.

With regard to the role of confounded variables, one must realize that human beings generally strive to present themselves in a self-consistent manner (Heider, 1958) as non-consistency may raise perceptions of unsteadiness and dishonesty and thus lead to social punishment (Heider, 1958; McGuire, 1966; Podsakoff et al., 2003). As such, hazards of this consistency motif may arise from memory effects: If subjects remember their answers from preceding measurement occasions, they will probably aspire to repeat their responses to keep consistency, despite real changes, resulting in false-negative findings (Laenen et al., 2010). Furthermore, repeated measurements increase the likelihood of subjects correctly guessing the study purpose, leading to experimenter demand effects (Zizzo, 2010). In a study by Venkatesh and Davis (2000), for example, technology acceptance was found to increase over time, depending on correspondent stages of product development. However, subjects might have built hypotheses on the investigators’ expectations during study progress, and might have answered in a way they thought the authors wanted them to behave, despite their real perceptions of acceptance change. In other words, product quality didn’t really increase, but the subjects intentionally produced change in order to please the investigators. The reverse effect is possible, too: Hypotheses on the study purpose

might be faulty, leading to unintentional adulteration contrary to researchers' expectations, or subjects may intentionally behave contrary to the hypotheses to harm the investigators (*ibid.*).

One might argue this class of validity threats only distorts results when studying rationales of change. However, subjects may differ in the degree they e.g. strive for consistency or build hypotheses on the study purpose, so validity threats may also influence interunit differences in intraunit change, resulting in misleading interpretations on whether and how change occurs. Thus, researchers deploying longitudinal studies should generally counteract validity hazards, e.g. by considering randomization of response sets, distractor items or reasonable wave spacing (Zizzo, 2010). When studying why a change occurs, we suggest introducing a control group of similar individuals as a silver bullet to these issues. Comparing groups with identical pre-conditions, real effects reflect in differences of change on the group level, while confounded variables should equally distribute between groups. As mentioned above, however, the use of control groups has not been widespread in prior longitudinal IS literature.

With regard to research design and planning, longitudinal research comprehends tracing subjects over a long period of time, sometimes years (e.g. Plotnikoff et al., 2012), with a possibly high amount and frequency of repeated observations. It seems feasible subjects lose motivation to participate, move to other regions, sicken or even die during that time, resulting in missing data for any following wave (Graham and Collins, 2012). One could even suppose likelihood of participant loss, or attrition, to be positively correlated with study length, as well as number and frequency of waves. In fact, attrition is an expectable and, in most cases, unavoidable issue when dealing with longitudinal data (Ployhart and Ward, 2011), and entails severe consequences: First, sample sizes decrease, diminishing statistical power and the amount of available analysing techniques (*ibid.*). Second, systematic differences between respondents and non-respondents may threaten internal and external validity (Anseel et al., 2010; Graham and Collins, 2012). Venkatesh and Davis (2000), for example, found technology acceptance to increase over time as a product advances. If, for any reason, all subjects with low perceived acceptance had left the study at some point of time, an artificial elevation in average acceptance would have resulted. Thus, one should anticipate and expect attrition by including more participants than needed (Ployhart and Vandenberg, 2010), by adopting response enhancement techniques like incentives (Anseel et al., 2010) or by reducing the amount and spaces of waves to a reasonable number. In prior IS literature investigating change over time, however, most studies did not explicitly account for attrition (20 out of 21), but simply excluded incomplete data sets (e.g. Goes et al., 2010; He et al., 2007) or used statistical methods to control for attrition retroactively (e.g. Sasidharan et al., 2012). Only one prior study, in contrast, explicitly mentioned attrition as a potential threat to validity and undertook steps to obviate it (Kim et al., 2009). Therefore, we recommend IS scholars to more intensively consider literature on missing values and procedures to avoid them when planning and conducting a longitudinal study (e.g. Goodman and Blum, 1996; Newman, 2003).

In this regard, careful weighting of required sample sizes and sample recruitment, estimated effect sizes and statistical power becomes important. In estimating the number of necessary study participants, for example, Muthén and Muthén (2002) recommend scholars to conduct Monte Carlo simulations a priori, stating that simulation studies allow for more accurate anticipation of sample sizes and statistical power than rules of thumb. Similarly, scholars should consider recruiting homogenous samples and increasing the number of waves to reduce bias resulting from small sample sizes (Hamilton et al., 2003). Planned missing values as discussed by Graham et al. (1996) may be helpful to achieve this goal. Applying this technique, researchers split samples into subgroups, and every subgroup participates only in a certain number of repeated observations. In a study with eight repeated observations, for example, sample may be split to two subgroups with subgroup 1 participating at time 1, 3, 5, 7, and subgroup 2 at measurement occasion 2, 4, 6 and 8. Techniques of planned missing values can be combined with methods of imputation, i.e. methods allowing for estimation of missing values based on available data (Graham, 2009). Therefore, they build a powerful approach to increase power in longitudinal studies with small sample sizes, while simultaneously decreasing the likelihood of attrition due to the lowered effort required from a single participant.

4.4 Guideline 4: Choose the right Method of Analysis

In contrast to cross-sectional data, longitudinal data is interdependent, i.e. data gathered from a successive wave can be, to a certain extent, predicted by data gathered at a preceding wave (Bijleveld et al., 1998, p. 4). With regard to many common methods in statistics (e.g. ANOVA), however, interdependent measurement values most likely violate the assumption of uncorrelated residuals (Ployhart and Vandenberg, 2010), resulting in a need for different approaches in studies that analyse change. Our review of prior longitudinal IS literature, however revealed a lack of standards in applied methods of analysis. That is, only 8 out of 21 studies in our literature review used established and appropriate statistical methods, such as repeated measures general linear modeling (GLM, Shaft et al., 2008), hierarchical linear modeling (HLM, Goes et al., 2010; He et al., 2007; Sasidharan et al., 2012; Setia et al., 2012), or time series and sequence analysis (Deng and Chi, 2012; Du et al., 2008; Joseph et al., 2012). Other scholars, in contrast, relied on descriptive statistics (Vitari and Ravarini, 2009), correlation analysis (Kim, 2009a), or structure equation modeling (e.g. Kim et al., 2009; Venkatesh and Sykes, 2013), potentially reporting inflated relationships between analysed variables due to autocorrelation. In the following, we will thus overview three frameworks for longitudinal design most commonly applied in social sciences: repeated measures general linear model (GLM), hierarchical linear modeling (HLM) and latent growth modeling (LGM).

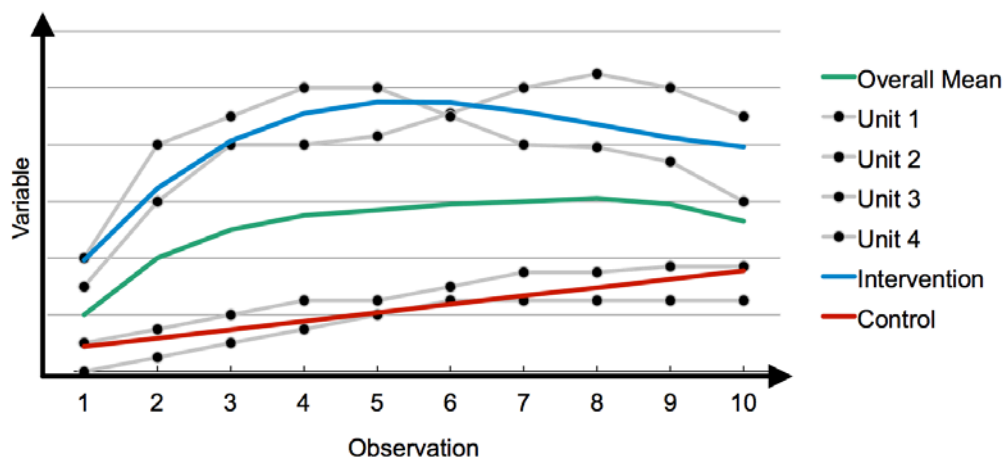


Figure 3. *Complex hierarchical data structures: Every unit changes differently on level 1, and groups of units change differently on level 2.*

Repeated measures GLM (e.g. repeated measures ANOVA, paired-samples t-test, trend analysis by regression) is applicable for any research question referring to the group level, i.e. any hypotheses excluding the analysis of interunit differences in intraunit change (Ployhart and Vandenberg 2010). When comparing groups of subjects to each other, for example, one may apply repeated measures ANOVA in a randomized control group trial design to investigate whether and why change differs between groups (Shadish et al., 2002). Moreover, one could use trend analysis to study natural oscillation on a group level by fitting measurements to a linear or logistic regression function (Bass 1969; Bass 2004). Yet, application of repeated measures GLM requires adherence to a set of assumptions and limitations, rendering GLM demanding to apply to more complex data structures. When using more than two measurement occasions, for example, repeated measures ANOVA assumes sphericity, i.e. equivalent variances for every pair of observations (Huynh and Feldt, 1970). Most likely violated, the sphericity assumption raises the need for correction formulas like Greenhouse-Geiser (Greenhouse and Geisser, 1959) to avoid biased F-Tests. Moreover, differential data analysis like multiple group comparisons or post-hoc analyses may become fuzzy in repeated measures GLM due to restricted or missing statistical values. Argumentation on the right effect size value for longitudinal data in the GLM framework, for example, has been going on since decades (Bakeman, 2005). Nonetheless, gen-

erally disadvising repeated measures GLM would ignore (1) its suitability for simple research questions and straightforward data sets, and (2) a large body of research and important findings relying on repeated measures GLM (e.g. Goes et al. 2010).

Hierarchical linear modeling (HLM), in contrast, enables researchers to model interunit differences in intraunit changes using a multiple level approach (Raudenbush and Bryk, 2002). In HLM, regression functions determine each level of analysis, and intercepts and slopes of lower levels are explained by regression functions of higher levels, resulting in the opportunity to explain differences of group averages and differences in intraunit change simultaneously (ibid.). Describing and explaining changes in user perceptions, for example, subjects may follow individual traces over time, while groups of subjects (e.g. gender groups, regional groups, experimental groups) may generally differ in their progress (see Figure 4). Its potential to investigate and reflect hierarchical structures frequently occurring in nature, such as pupils within classes or employees within organizations, has made HLM a comparatively wide-spread tool in education (e.g. Bryk and Raudenbush, 1988) and organizational science (e.g. Ozkaya et al., 2013). Moreover, its robustness and flexibility with regard to multiple predictors, differing measurement occasions, level of hierarchy and missing data render HLM a powerful tool for analysing change (Ployhart and Vandenberg, 2010). However, accounting for mediation and moderation may become complicated with HLM (ibid.), and accounting for common method variance may require some effort (Lai et al., 2013). Also, limited opportunities of graphical representation may hamper model illustration and reporting (e.g. Fu et al., 2010). Interested readers may consult Raudenbush and Bryk (2002) for a comprehensive introduction to HLM.

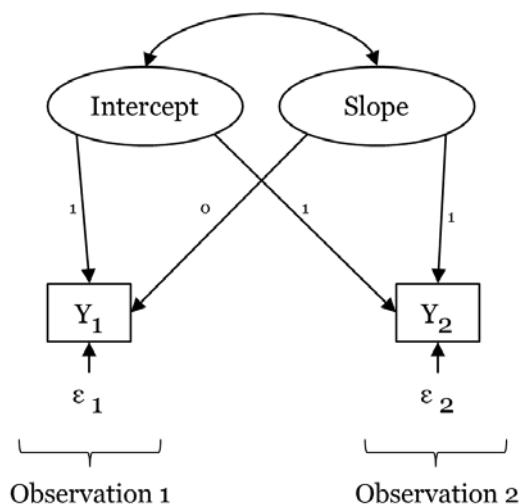


Figure 4. General linear modeling.

LGM estimate change using latent factors drawn from the data (McArdle and Epstein, 1987). Likewise structural equation modeling (SEM), proportions of variances are attributed to both indicators of latent variables and to relations between these variables (Serva et al., 2011). Consequently, LGM has widely spread from educational science (McArdle and Epstein, 1987) to psychology (Wu and Griffin, 2012) organizational science (Chen et al., 2011) and, recently, IS research (Serva et al., 2011). As with HLM, LGM allow for simultaneous modeling of interindividual differences in intraunit change and intergroup differences, resulting in the opportunity to trace both individuals and groups over time. Yet, advantages compared to HLM are twofold: First, the measurement error for every manifest indicator is modeled explicitly in LGM, resulting in a more advanced control for reliability. Second, LGM allows for more complex and dynamic models, including mediating and moderating variables, and results can be visualized powerfully by means of SEM standards (Ployhart and Vandenberg, 2010; Ployhart and Ward, 2011). However, LGM is less flexible with regard to missing data and variable space of observations and modeling non-linear shapes of change may become difficult using LGM (ibid.). Serva et

al. (2011) give an excellent introduction to the application of LGM in the context of IS research, and an example of a two-wave unconditional model is depicted in Figure 5.

5 Synopsis

This work attempted to (1) provide a state of the art overview of quantitative longitudinal studies in the field of IS, and (2) introduce and discuss four theoretical guidelines for scholars attempting to apply longitudinal research. With regard to the first goal, an extensive literature review comprising the AIS Senior Scholars' Basket of Journals and a 10-year period from 2004 to 2014 revealed only 21 studies claiming to use longitudinal data. When applying the well-established classification of Singer and Willett (2003), defining longitudinal research as *repeated* observations of the *same outcomes* over a period of time, the number of suitable studies even narrowed down to only ten. Given that describing, explaining, and predicting IS-related phenomena noticeably includes the analysis of change over time, the scarce number of trials engaging in outcome trajectory is alarming.

Research Question	Focus of change lies on...			Research Design & Hazards	Method of Analysis	Example
	Form	IDIC	Rationale			
Is there a change at all?	No	No	No	<ul style="list-style-type: none"> at least 2 RM consider variance decomposition techniques 	<ul style="list-style-type: none"> GLM 	Goes et al. (2010)
Is there a change at all?	No	Yes	No	<ul style="list-style-type: none"> at least 2 RM consider variance decomposition techniques 	<ul style="list-style-type: none"> LGM 	-
Why is there a change?	No	No	Yes	<ul style="list-style-type: none"> at least 2 RM at least 2 groups (e.g. intervention and control) confounded variables consider variance decomposition techniques 	<ul style="list-style-type: none"> GLM 	Hurling et al. (2007)
How does change of time evolve?	Yes	Yes	No	<ul style="list-style-type: none"> at least 3 RM for linearity (more recommended) attrition, confounded variables 	<ul style="list-style-type: none"> HLM LGM 	Setia et al. (2012) (HLM) Serva et al. (2011), H2 _{a/b} (LGM)
Why is there a change? And: How evolves change over time?	Yes	Yes	Yes	<ul style="list-style-type: none"> at least 3 RM for linearity (more recommended) control for influential factors (conditions) attrition, confounded variables 	<ul style="list-style-type: none"> HLM LGM 	LGM: Serva et al. (2011), H3 _{a/b} (LGM)

Table 2. Overview of research designs and methods of analysis in longitudinal research. Note: Interunit differences in intraunit change (IDIC), repeated measurements (RM), general linear modelling (GLM), latent growth modelling (LGM), hierarchical linear modelling (HLM).

In response, our study rigorously compiled knowledge from related fields, such as psychology, consumer behavior, or management science, and introduced four guidelines on longitudinal study design to the IS community: the proper use and operationalization of time, the choice of the right amount of waves and actions to counteract validity threats when using study designs with two measurement occasions only, dealing with validity hazards unique to the analysis of change, such as attrition, and the choice of an appropriate method of analysis. In parallel, we have exemplified that prior IS research has often failed to meet these standards, e.g. by omitting to report rationales of time measure operationali-

zation, relying on one-group designs rather than randomized controlled trials, rarely testing for measurement invariance between waves to ensure equivalent psychometric properties over measurement occasions, or operating doubtful statistical methods when analysing longitudinal data. Table 2 provides an overview of options for longitudinal analyses and summarizes the work at hand.

6 Conclusion and Contribution

As outlined in Section 2, the potential of quantitative longitudinal research lies in its capability to analyse how, when and why change occurs from a *generalizable* perspective that allows for transfer of knowledge to different populations and contexts. As reflected by the low number of quantitative longitudinal studies published in the IS community (cf. Section 3), however, one could conclude that IS scholars have largely neglected this opportunity. This is especially alarming given that many established IS theories implicitly or explicitly make assumptions on the nature of change, e.g. when referring to the diffusion of innovation (Bass, 1969; Bass, 2004), post-adoption behaviour (Kim, 2009b; Kim and Malhotra, 2009), or habits (Venkatesh et al., 2012).

Against this background, this work attempted to provide insights for novice and experienced researchers interested in describing, explaining and predicting change over time by comprising four guidelines of quantitative longitudinal research informed by IS-related disciplines. Limiting the comprehensiveness of our results, it must be however noted that the guidelines presented in this paper are not meant to be complete, yet represent a quick summary of the interplay between methodological and analytical aspects of quantitative longitudinal research. Thus, our study may be regarded as a preliminary attempt to provide a toolset for IS scholars interested to investigate the fluctuation of IS phenomena over time, and more studies are needed that enhance and improve the guidelines presented in the current work.

To the knowledge of the authors, still, the guidelines presented in this study are the first within the IS community to focus both on study design and analysis of quantitative longitudinal research, attempting to provide a comprehensive picture and detailed instruction on its application. As such, our work uniquely adds to existing literature by providing a first attempt to guide researchers in discovering the exciting, yet largely unexplored field of quantitative longitudinal research.

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