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RESEARCH ARTICLE

How do management factors influence digital adoption in the case of a large-scale digital transformation project – A process perspective

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Abstract
Although practitioners and scientists agree that user adoption of new technologies is a key success factor in digital transformations, little is known about how specific management factors are related to user behavior. In particular, the temporal nature of digital transformation projects is largely neglected. Therefore, we propose a systematic, theory-based framework for the management of digital adoption (MDA) and derive specific process-oriented hypotheses for content-, process-, and context-related management factors, their relationships to user adoption, and underlying psychological processes (e.g., performance expectancy or social influence). We applied the MDA framework in the context of a large digital transformation project in a logistics company in a two-wave research design. We tested the process-oriented hypotheses based on latent change score analysis among 1,095 users. The results support the assumption that changes in management factors, largely mediated by changes in the psychological processes, lead to changes in user behavior.

Keywords: organizational behavior; organizational change; managing IT-related organizational change; structural equation modeling

Introduction

With the ever-increasing availability of innovations in information technology (IT) and new digital technologies, digital transformation presents great opportunities for organizations (Ayoko, 2021; Westerman, Bonnet, & McAfee, 2014; World Economic Forum, 2020). Digital transformation describes 'organizational change triggered and shaped by the widespread diffusion of digital technology' (Hanelt, Bohnsack, Marz, & Antunes Marante, 2021, p. 2) and can take place at two key levels. At a fundamental level, existing digital technologies are transformed to enable higher-level value creation through new digital business models and products (Chanias, Myers, & Hess, 2019). For example, the implementation of company-wide standard software such as enterprise resource planning (ERP) systems – which have the goal to align and improve business processes – represents a major digital transformation at a fundamental level. At higher levels, this transformation then allows organizations to develop new digital products or services building on the newly available functionality, data, infrastructure, and insights. The strategic imperative of digital transformation, however, is already challenging at a fundamental level: endeavors to digitalize organizations rarely exploit the full potential of digital technologies and often fail (Zobell, 2018). In many cases, the human side of change is considered to be the main hurdle for successful digital transformations (e.g., Bughin, Holley, & Mellbye, 2015; Fitzgerald, Kruschwitz, Bonnet, & Welch, 2014). Indeed, user adoption is a key success factor in digital transformations, as usage behavior is often driven by attitudes and intentions toward working with new digital technologies (Andriole, Cox, & Khin, 2018; Cavalcanti, Oliveira, & de Oliveira Santini, 2022; Kohnke, 2017). Therefore, organizations are well-advised to monitor the digital adoption process closely and support their employees with appropriate management interventions to cope with the digital transformation. Management interventions are aspects subject to managerial decision allowing to either influence the content and scope of the transformation such as characteristics of the digital technology, the change process, or the context in which the transformation takes place (Straatmann, Kohnke, Hattrup, & Mueller, 2016).

With the accelerated pace of digital transformations in organizations and an increasing demand for evidence-based management interventions to support digital adoption processes in practice, a good understanding of how these management interventions impact digital adoption is required. Even though scholars called for action in this regard long ago (Venkatesh, 2006; Venkatesh & Bala, 2008), there still is little systematic evidence regarding the impact of specific management interventions on employee digital adoption. Instead, many studies focus either on individual, psychological factors related to the digital adoption of employees and consumers (e.g., Blut, Chong, Tsigna, & Venkatesh, 2022; Cavalcanti, Oliveira, & de Oliveira Santini, 2022; Venkatesh, Thong, & Xu, 2016) or on change management factors or more broadly speaking on key factors from an 'organizational perspective' related to the use of new technology in organizations (Ain, Vaia, DeLone, & Waheed, 2019, p. 7; Saghafian, Laumann, & Skogstad, 2021). The integration and interconnection of these two perspectives are important to increase our understanding of the management of digital transformation processes and their successful practical implementation.

Moreover, taking temporal relations and dynamics into account is of special importance in organizational life and especially during organizational change processes (Langley, Smallman, Tsoukas, & Van de Ven, 2013; Sonnentag, 2012). In particular, digital transformations at a fundamental level are often characterized by a change from a pre-change state with a legacy system and processes in use to a post-change state in which a new system and processes are implemented. However, research on digital transformation and user adoption typically applies a rather static perspective (Zheng, Pavlou, & Gu, 2014). Therefore, explicitly incorporating a temporal and process perspective by specifying how changes in perceptions of the old and the new system and associated management factors are related to changes in psychological variables and user adoption (e.g., Venkatesh, Sykes, Aljafari, & Poole, 2021; Zheng, Pavlou, & Gu, 2014) represents a valuable contribution to research on the management of digital transformations. More specifically, the longitudinal investigation of management interventions and employees' perceptions of digital technology holds the potential to both strengthen the empirical evidence for often assumed cause-and-effect relationships in change research (e.g., Bouckenooghe, Schwarz, Kanar, & Sanders, 2021; Oreg, Vakola, & Armenakis, 2011) and to provide a stronger foundation for deriving recommendations for managing digital transformation projects in practice (Cavalcanti, Oliveira, & de Oliveira Santini, 2022).

In summary, this study aims to enrich the theoretical and practical understanding of managing digital transformation projects in two ways. First, the study integrates and interconnects models of change management with psychological factors of technology acceptance to investigate the effects of management factors on user adoption in the context of a large-scale digital transformation project. Based on this integrative perspective, hypotheses on the effects of management and psychological factors are derived. Second, in light of change dynamics, these hypotheses are tested considering two points in time during the digital transformation project, thereby offering essential contributions to our understanding of organizational behavior and the impact of management factors from a process-oriented perspective (Langley et al., 2013; Venkatesh, 2006; Venkatesh et al., 2021; Zheng, Pavlou, & Gu, 2014). Thereby, this study contributes to a better understanding of how management interventions impact employee digital adoption and provides guidance for successfully managing digital transformation.

Literature review and development of hypotheses

Developing a framework for the management of digital adoption

As the pace and intensity of innovation and organizational change steadily increase due to the digital transformation itself (Brynjolfsson & McAfee, 2011; Kane, Phillips, Copulsky, & Andrus, 2019; Kotter, 2012), the successful implementation of digital technologies requires continuous adoption from employees (Andriole, Cox, & Khin, 2018; Cavalcanti, Oliveira, & de Oliveira Santini, 2022). However, in many cases, the importance of employees' reactions during digital transformations is underestimated (Kane et al., 2019; Kohnke, 2017). Therefore, organizations must recognize the relevance of the psychological processes and better understand how these are triggered by specific management interventions in digital transformation projects. Despite their high practical relevance, few attempts have been undertaken to systematically connect management interventions with technology adoption and its underlying psychological processes (Abbasi, Tarhini, Hassouna, & Shah, 2015; Kohnke, Wolf, & Mueller, 2011). However, the broader change management literature as a parallel research stream describes a plethora of management factors for organizational change processes, which also include changes relating to digital transformations (Oreg, Vakola, & Armenakis, 2011; Rafferty, Jimmieson, & Armenakis, 2013). In an effort to systematically integrate research in the general domain of organizational change, Armenakis and colleagues developed a taxonomy of change management factors that distinguished four major categories assumed to impact reactions to change processes (Armenakis & Bedeian, 1999; Holt, Armenakis, Feild, & Harris, 2007; Walker, Armenakis, & Bernerth, 2007). These four categories are described as content, process, context, and individual factors. The *individual factors* category (e.g., affect, status, age, gender, or organizational commitment), however, constitute pre-change conditions (Oreg, Vakola, & Armenakis, 2011) that are, by definition, often constant and therefore of limited use for managing specific digital transformation projects. The other three categories from the taxonomy provide a great foundation for the categorization and identification of relevant management factors in the specific context of digital transformation processes.

Content factors refer to what is being changed and comprise perceptions of the utility, necessity, and consequences of the change process. In the context of digital transformations, these factors are mainly related to specific characteristics of the digital technology at hand. Key aspects of IT systems frequently found in the literature are the quality of data, functionality provided by the system, and system performance (e.g., DeLone & McLean, 1992; Liu & Ma, 2006; Wixom & Todd, 2005). Management may influence these characteristics indirectly by choosing between technologies that differ in these regards and initiating improvements in case quality expectations are not met. *Process factors* refer to how things are being changed and encompass classical change management factors such as user information and communication (e.g., Amoako-Gyampah & Salam, 2004; Kohnke, Wolf, & Mueller, 2011), user training (e.g., Amoako-Gyampah & Salam, 2004; Kohnke, Wolf, & Mueller, 2011), user participation (e.g., Hartwick & Barki, 1994; Rouibah, Hamdy, & Al-Enezi, 2009), and user support (e.g., Igbaria, Zinatelli, Cragg, & Cavaye, 1997; Karahanna & Limayem, 2000). Since process factors can vary widely, in this study, we focus on user information about the transformation as basic process factor needed in any change process (Armenakis & Harris, 2002). *Context factors* refer to the organizational environment in which the change occurs. These factors include organizational conditions that facilitate the implementation process, such as top management support (e.g., Kohnke, Wolf, & Mueller, 2011; Rouibah, Hamdy, & Al-Enezi, 2009), supervisor support (e.g., Schepers, Wetzels, & de Ruyter, 2005; Schillewaert, Ahearne, Frambach, & Moenaert, 2005), or organizational antecedents like the change history (e.g., Hanelt et al., 2021). While those antecedents are not malleable in the management of a given change, leaders' behavior generally is and effectively shapes the change context (Oreg & Berson, 2019). Therefore, top management and supervisor support are considered as context factors in this study.

Content, process, and context factors are furthermore assumed to influence employee behavior through the psychological processes that they elicit (Oreg & Berson, 2019; Oreg, Vakola, &

Armenakis, 2011). Hence, a comprehensive approach to the management of digital transformation should reflect central variables from all three categories and relate them to changes in the psychological processes of digital adoption and actual behavioral change. Indeed, research combining management factors with specific psychological reactions of change recipients has demonstrated its value for understanding how change reactions can be influenced by change management (Jimmieson, Peach, & White, 2008; Straatmann et al., 2016).

One of the most cited models to define psychological variables that explain and predict user behavior and adoption of technologies by individuals is the unified theory of acceptance and use of technology (UTAUT) by Venkatesh, Morris, Davis, and Davis (2003). The UTAUT is integrating established mechanisms of previous theories of technology acceptance and behavior in general (e.g., the Theory of Planned Behavior; Ajzen, 1991; or the Technology Acceptance Model; Davis, 1989; Davis, Bagozzi, & Warshaw, 1989) and has been extensively used by many researchers (Blut et al., 2022; Dwivedi, Rana, Jeyaraj, Clement, & Williams, 2019; Venkatesh, Thong, & Xu, 2016). As such, the core elements identified in the UTAUT provide a useful theoretical foundation to describe the psychological processes that can help to explain how management interventions relate to actual behavior. In essence, the UTAUT specifies that the intention to use a system and facilitating conditions are core determinants of actual user behavior. Behavioral intention, in turn, is determined by performance expectancy, effort expectancy, and social influence. Performance expectancy is defined by Venkatesh et al. as 'the degree to which an individual believes that using the system will help him or her to attain gains in job performance' (2003, p. 447). Effort expectancy refers to 'the degree of ease associated with the use of the system' (2003, p. 450). Social influence describes 'the degree to which an individual perceives that important others believe he or she should use the new system' (2003, p. 451). Facilitating conditions refer to 'the degree to which an individual believes that an organizational and technical infrastructure exists to support the use of the system' (Venkatesh et al., 2003, p. 453) and from a psychological perspective reflect the belief of having the necessary resources and knowledge to use the system (Ajzen, 1991; Taylor & Todd, 1995). In addition to its direct influence on actual user behavior, facilitating conditions were considered as a fourth determinant of behavioral intentions later (Blut et al., 2022; Dwivedi et al., 2019). Similar to other scholars (e.g., Dwivedi et al., 2019), we focus on these core concepts of the UTAUT as this study aims to understand how psychological processes mediate the influence of management factors on user adoption.

Based on previous research in the context of technology adoption, we further include three modifications in terms of relationships among the core concepts of the UTAUT. First, it is assumed that social influence may also have an effect on user's perception of a system to be useful, i.e., performance expectancy (Schepers & Wetzels, 2007; Venkatesh & Davis, 2000). Second, previous research indicated that the latter also is higher, when users perceive the system as being easy to use (i.e., effort expectancy), as ease of use reinforces the expectation of high performance (e.g., Davis, Bagozzi, & Warshaw, 1989; Oliveira, Thomas, Baptista, & Campos, 2016; Venkatesh & Bala, 2008). Third, studies demonstrated that an individual's perception of having the resources to use a system (i.e., facilitating conditions) is positively related to the perception of a system as being easy to use (i.e., effort expectancy; e.g., Venkatesh, 2000; Venkatesh & Bala, 2008; Yi, Jackson, Park, & Probst, 2006).

In summary, we build on an established taxonomy of change management factors with a common and slightly modified model of technology adoption to derive an integrative model, which can provide insights into the psychological processes through which management factors exert their impact on employees' behavior in the case of a large-scale digital transformation project. More specific knowledge about the effect of management factors (i.e., content, process, and context factors) on psychological factors (i.e., performance expectancy, effort expectancy, social influence, and facilitating conditions) provides guidance for the management to identify how favorable user reactions and behavior can be promoted most effectively in digital transformations. Based on the theoretical framework, we adopt a process perspective on the digital transformation project and derive and test specific hypotheses in the following.

A process-oriented perspective on the management of digital adoption

At a fundamental level of digital transformation, often an existing IT system or infrastructure is replaced by a new system, implying a change process from the legacy to a new system. Also from a theoretical perspective, many Information Systems-related theories are rooted in the assumption that variables and their longitudinal relationships change over time, which makes the analysis of the change dynamics a crucial research question (Zheng, Pavlou, & Gu, 2014). Even so, research in the Information Systems context that follows a process-oriented research perspective is rare. Noteworthy exceptions are the studies provided by Bala and colleagues (Bala & Venkatesh, 2013; Bala, Venkatesh, Ganster, & Rai, 2021) who explicitly integrated temporal components into their longitudinal research and examined how perceptions of employees' job characteristics (Bala & Venkatesh, 2013) and interpersonal relationships (Bala et al., 2021) change over time during an enterprise system implementation. Investigating the longitudinal trajectory of employees' perceptions of IT presents an important path for identifying relevant changes in these perceptions and their causes. Thus, the explicit formulation of process-oriented hypotheses for variables and their relationships over time offers deeper insights into specific change dynamics during digital transformations and can strengthen the empirical evidence for often assumed cause-and-effect relationships (e.g., Langley et al., 2013; Venkatesh et al., 2021; Zheng, Pavlou, & Gu, 2014). Therefore, we take on a process perspective and hypothesize relationships between perceived changes in management factors, changes in psychological factors, and changes in employee behavior. To be precise, we will examine the (interindividual) relationships of intraindividual changes in employees' perception of management and psychological factors as well as in their behavior.

In particular and building on our theoretical framework, perceived technology improvements (content factors) should lead to intraindividual increases in the psychological factors effort expectancy, performance expectancy, facilitating conditions, and social influence – as others are also affected by the changes. Similarly, intraindividual increases in the perception of process factors (e.g., the amount of helpful user information) and in the perception of a supportive context during digital transformations should lead to an intraindividual increase in effort expectancy, performance expectancy, social influence, and facilitating conditions as psychological reactions. As we selected typical management factors that previous research had shown to facilitate user adoption of information systems, all relationships are assumed to be positive (e.g., Ain et al., 2019; Kohnke, Wolf, & Mueller, 2011). Hence, we hypothesize the following:

Hypothesis 1a: Changes over time in content factors are positively related to changes in effort expectancy, performance expectancy, social influence, and facilitating conditions.

Hypothesis 1b: Changes over time in process factors are positively related to changes in effort expectancy, performance expectancy, social influence, and facilitating conditions.

Hypothesis 1c: Changes over time in context factors are positively related to changes in effort expectancy, performance expectancy, social influence, and facilitating conditions.

In line with the theoretical framework described above, we expect the psychological factors to be related to employee behavior (e.g., Davis, 1989; Lee & Wan, 2010; Sun, Bhattacherjee, & Ma, 2009). From a process perspective, we assume usage behavior to change dependent on changing psychological factors. For example, employees might be reluctant to use the current system because it is not seen as particularly useful but rather complicated to use. If the new system is perceived as being more useful and easy to use, the employee may accept and use it even more. Specifically, intraindividual increases in one or more of the psychological model variables are assumed to lead to intraindividual increases in an individual's intention to use a digital technology and also to an increase in actual user behavior.

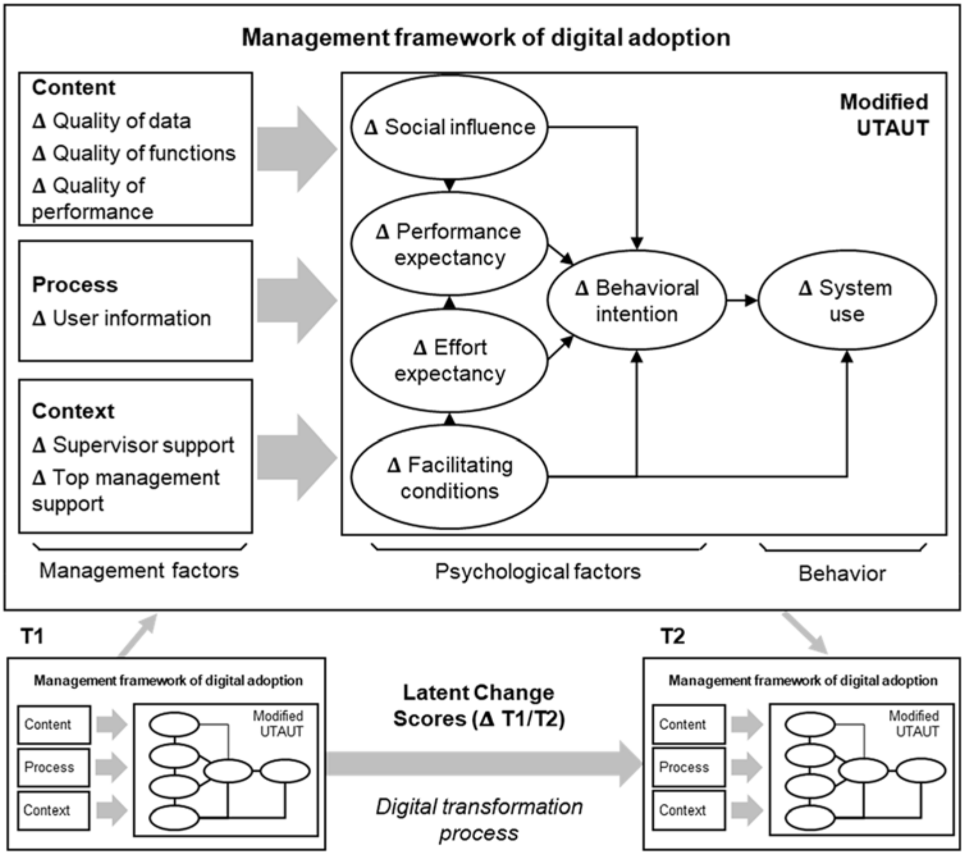

Figure 1. Proposed management framework of digital adoption.

Hypothesis 2: Changes over time in effort expectancy, performance expectancy, social influence, and facilitating conditions are positively related to changes in behavioral intention.

Hypothesis 3: Changes over time in behavioral intention and facilitating conditions are positively related to changes in system use.

Finally, we test the aforementioned assumption that management factors impact employee behavior through the psychological processes elicited (Oreg & Berson, 2019; Oreg, Vakola, & Armenakis, 2011). Translated into a process hypothesis, we examine whether intraindividual increases in perceptions of management factors lead to behavioral changes through intraindividual increases in psychological variables.

Hypothesis 4: Changes over time in management factors related to content, process, and context factors lead to changes in system use that will be fully mediated via changes in effort expectancy, performance expectancy, social influence, facilitating conditions, and behavioral intention.

The four hypotheses are summarized in the framework for the management of digital adoption (MDA) outlined in Figure 1. It postulates that intraindividual changes in one of the management factors should result in intraindividual changes in psychological variables and user behavior over time.

Thus, we argue that positive significant relationships between intraindividual changes of our study variables would provide evidence for a user adoption gain effect during a digital transformation process.

Method

Organizational setting

The setting for this field study is a multi-year digital transformation project that took place in a large international logistics company. To improve its competitive strength, the company investigated possibilities for optimization and simplification of the current company-wide standard software solution (an ERP system). Part of this investigation was an evaluation of various management factors such as the quality of the IT system (i.e., data, functionality, and performance), the quality of user information, and the level of support by supervisors and management from a user perspective. This evaluation indicated a clear need for change, and a baseline (t1) was set before a digital transformation project was initiated.

The digital transformation initiative was intended to overcome quality gaps by delivering globally standardized and harmonized business processes enabled by a new, user-friendly IT system. The project concentrated on a wide range of business processes covering financial (e.g., cash management, general ledger, or travel expense management), procurement (e.g., invoice management or terminal expenses), and reporting processes. These changes particularly impacted central and globally distributed departments for finance, operations, and services. Changes reflected in the new IT system included the elimination of manual tasks through automation (e.g., electronic invoicing and monitoring risks) and the simplification of tasks to reduce errors and delays in the process flow (e.g., removal of unnecessary data entry fields or approval steps, avoidance of data double-entry, and manual data extraction). Moreover, a new user interface and system functionality (e.g., for reporting and analysis tasks), as well as new roles and accountabilities for employees (e.g., centralizing approval processes and re-defining access rights to the system), were provided. The digital transformation project was facilitated by an organizational change management team. Key objectives of this team were an increase in the current level of management support (i.e., supervisors and senior management) for the IT system and an improvement of the existing communication content delivered through various channels. One previously used channel was the corporate portal, which gave access to a variety of communication assets such as quick reference guides, standard operation procedures, and learning material.

Three and a half years later, after the digital transformation project was completed, a second evaluation was conducted (t2) to assess the impact of changes in management and psychological factors as perceived by the users. At t2, all process, system, and organizational changes were fully implemented.

Survey administration

The surveys were provided to users in English as web-based questionnaires using an online tool. Invited users could access the questionnaire via a single-sign-on procedure to ensure the participation of only eligible users. Organizational data, such as region, country, and location, as well as objective usage data, had been provided by the company and was matched to the survey data by a unique identifier. Both surveys were hosted and conducted by an external research institute. One week before the survey, an e-mail message describing the purpose and content of the survey was sent by the management sponsor to all system users. The invitation e-mail indicated that participation in the survey was voluntary and anonymous. In countries where surveys require co-determination (e.g., works council), the relevant bodies had been involved. During the survey, if the participant left an item blank, the missing value was accepted by the survey tool without any further queries. If completion was interrupted (e.g., the connection was terminated prior to submission for any reason), the survey could be resumed by logging in again via the single-sign-on procedure. The data-gathering period was 3 weeks for each survey, with reminders sent to all invited users after the first and second week.

Sample

At both measurement points, all employees with a user role within the IT system were selected for the study. At t1, 4,638 of the invited 9,886 employees took part in the survey, resulting in a response rate of 46.9%. At t2, 18,094 users were invited and 4,956 participated in the survey, resulting in a response rate of 27.4%. The larger number of system users at the second measurement time resulted from a broader roll-out of the extended functionality. In total, $N = 1{,}095$ of the users reported their experience with the IT system at both measurement points. Sample characteristics such as business function or management level indicated that all employee groups affected by the digital transformation project were represented in the sample.

Measures

All measures used for the study were part of the surveys at both measurement points. While the survey included more variables than simply the ones necessary to the study, only those relating to the MDA framework were eventually analyzed. Measures that covered other content (e.g., open comments), that were only relevant for a specific subsample (e.g., filter questions), or that were changed from t1 to t2 were not included in the analysis. Generally, we adapted the items used to capture the theoretical constructs from prior research, with changes in wording to fit the target context and an additional summary item for each construct (see Table 1; the complete questionnaire is available upon request from the authors). We have not collected sociodemographic data in accordance with the policies of the organization's works council. Participants used a five-point Likert-type scale (1 = *strongly disagree* and 5 = *strongly agree*) to respond to the items. All constructs showed high reliability, with Cronbach's alpha ranging from .85 to .97.

Self-reported system usage served as a proxy to capture actual system use. We adapted two items from Davis (1993) to assess the frequency and intensity of use. Frequency of use was measured on a 5-point scale ranging from 1 = "Use less than once a week" to 5 = "Use several times a day". Intensity of use was assessed with an open question regarding the number of hours per week spent working with the system. Since the open format led to a large amount of missing and unrealistic values, this item was eliminated from further analysis. To obtain an additional, objective measure of actual user behavior, the number of dialogue steps in the IT system at t2 was collected. The measured count of dialogue steps refers to the user interaction with the system, such as navigating through a menu or searching in a database. This objective measure indicated the intensity of system use by a single user. As it had a positively skewed distribution, we used its logarithm for further analysis. Specifically, the mean logarithmized number of dialogue steps per day of the four months preceding t2 was used to validate the self-report measure obtained in the survey.

Data preparation and preliminary analyses

Across the model variables, 6.6% of the values were missing. Item-level missingness ranged from 0.1% to 17.1% with a tendency of higher values for items positioned toward the end of the survey. As Littles MCAR tests were significant, data were not missing completely at random, $\chi^2(27{,}836, N = 1{,}095) = 29{,}631.23$, $p < .001$. Following the assumption that most missing data can be considered random to some extent (Graham, 2009) and thus predictable by other variables in the dataset, we imputed missing data using the widely used EM algorithm (Lin & Tsai, 2020) implemented in SPSS.

Table 1. Items used for the scales with corresponding reliabilities across times of measurement

Scale	Cronbach's α	Example items	References
System use	–	How often do you work with the ERP system? Response format: Use less than once a week/about once/several times each week/about once each day/several times a day	Davis (1993)
Behavioral intention	.93–.94	I intend to use as much information/data from the ERP system as possible for my work	Davis (1989); Davis, Bagozzi, and Warshaw (1989)
Effort expectancy	.94	The ERP system makes it easy for me to access required functionality	Davis (1989); Davis, Bagozzi, and Warshaw (1989)
Performance expectancy	.96–.97	Using the ERP system increases my job performance	Davis (1989); Davis, Bagozzi, and Warshaw (1989)
Facilitating conditions	.85	Overall, I have the appropriate knowledge, skills, and resources to use the ERP system for my job	Taylor and Todd (1995); Sun, Bhattacherjee and Ma (2009)
Social influence	.90–.93	Colleagues I regard as competent recommend me to use the ERP system for my work	Taylor and Todd (1995); Yi et al. (2006)
Quality of data	.92–.94	The information/data provided by the ERP system is always up to date	Wixom and Todd (2005)
Quality of functions	.91–.93	The ERP system provides the key functionality I need for my work	Wixom and Todd (2005)
Quality of performance	.92–.94	The ERP system operates reliably (e.g., no server/system downtime)	Liu and Ma (2006)
User information	.95–.97	I am satisfied with the frequency of information about the ERP system changes and improvements	Amoako-Gyampah and Salam (2004); Bueno & Salmeron (2008)
Supervisor support	.94–.96	My direct manager supports me when I have problems using the ERP system (e.g., navigation, explanation of content, new requirements)	Igbaria et al. (1997)
Top management support	.96–.97	I believe the senior management is committed to the success of the ERP system	Igbaria et al. (1997)

Measurement models

As a prerequisite for examining latent change, strong measurement invariance across time is necessary (Geiser et al., 2015). We assessed longitudinal measurement invariance by comparing four sequentially restricted measurement models (Widaman, Ferrer, & Conger, 2010). The fit of the four models was compared assessing differences in the comparative fit index (CFI) and the root mean square error of approximation (RMSEA), interpreting a difference of $\Delta \leq .01$ as acceptable (Isiordia & Ferrer, 2018). Following this procedure, strict longitudinal measurement invariance could be established, with $\Delta\text{CFI} = .006$ and $\Delta\text{RMSEA} = .001$ when comparing the least restricted with the most restricted model. The measurement model – assuming equal loadings, item intercepts, and item variances across time – shows an acceptable fit with $\chi^2(5{,}525, N = 1{,}095) = 13{,}602.45$ and $p < .001$, $\chi^2/\text{df} = 2.46$, CFI = .923, Tucker–Lewis Index (TLI) = .920, standardized root mean square residual (SRMR) = .070 and RMSEA = .042.

To further test the hypothesized measurement model and discriminant validity, we compared competing models to the original model in which highly correlated latent factors ($r \geq .65$) were modeled as one. To compare the models, the Akaike information criterion was examined additionally, with lower values representing better model fit (Schermelleh-Engel, Moosbrugger, & Müller, 2003). In favor of the original model, no other model showed a better fit, with $\Delta\text{CFI} \geq .009$, $\Delta\text{RMSEA} \geq .004$, and the lowest Akaike information criterion for the hypothesized model. Because all constructs were assessed in one survey at both measurement times, we furthermore tested for a potential bias due to the common method of assessment (Lance, Dawson, Birkelbach, & Hoffman, 2010; Podsakoff, MacKenzie, & Podsakoff, 2012). In particular, we tested a single-factor model (Harman's one factor test; Podsakoff & Organ, 1986) and a model with two additional, orthogonal latent factors representing the measurement method at t1 and t2 (unmeasured latent factor technique, e.g., Jordan & Troth, 2020; Podsakoff, MacKenzie, & Podsakoff, 2012). For the latter, all items were associated with their theoretical construct and equally loading on one of the respective method factors (Jordan & Troth, 2020). The single-factor model showed inacceptable, worse model fit (ΔCFI $=$ .392 and ΔRMSEA $=$ .061), and the model including method factors showed acceptable, but not substantially improved model fit (ΔCFI $=$ .005 and ΔRMSEA $=$ .001). Thus, common method bias is not expected to have a serious impact in our study. In addition, we examined the correlation of the self-reported and objective measure of system use at t2 to test convergent validity. With $r(1{,}059) = .67$, $p < .00$, both measures were strongly related to each other. Descriptive statistics and intercorrelations of all model variables are included in Table 2.

Statistical analyses

The data were analyzed using R, version 3.6.0 (R Core Team, 2019), and the packages *lavaan*, version 0.6 (Rosseel, 2012), and *semTools*, version 0.5. (Jorgensen, Pornprasertmanit, Schoemann, & Rosseel, 2021). Regarding the impact of management factors on digital adoption and its underlying psychological process, we employed a latent change score (LCS) approach (e.g., McArdle, 2009) to model true intraindividual changes explicitly and to study both interindividual (between persons) and intraindividual (within a person) variability. First, all constructs of the MDA framework were modeled as latent variables indicated by four to six items at each measurement point. Only system use was included as a manifest variable in the model since it was assessed by a single item. Following Henk and Castro-Schilo (2016), superordinate latent variables (Δ variables) representing the true change from t1 to t2 in each variable were modeled (detailed model specification is available upon request from the authors). A baseline model, including only correlating latent change variables, served to examine mean intraindividual changes that 'inform the direction in which most of the sample is changing' (Henk & Castro-Schilo, 2016, p. 4) and guide the interpretation of the effects of latent change variables (see Table 3). For example, we refer to an increase in system use when the latent change variable has a significant positive mean, to a decrease when it has a significant negative mean, or simply to higher or lower change scores in system use when it does not have a significant mean.

The structural latent change model further included the hypothesized regression paths between the latent change variables, as well as the direct effects of the changes in management factors on changes in behavioral intention and system use to test Hypothesis 4. To examine the hypothesized mediating effects, we estimated the indirect effects of changes in all management factors on system use using Monte Carlo Bootstrapping. The indirect effects were added up to a total indirect effect of changes in each management factor on changes in system use.

All structural equation models, including the measurement models, were estimated using a robust maximum likelihood estimator with robust standard errors. We assessed model fit with common indices, such as the χ^2 to df ratio, SRMR, RMSEA, CFI, and TLI (Schermelleh-Engel, Moosbrugger, & Müller, 2003). An acceptable fit is indicated by a χ^2 to df ratio of $\chi^2/\text{df} \leq 3$, SRMR $\leq$ 0.10, and RMSEA $\leq$ .08 (Schermelleh-Engel, Moosbrugger, & Müller, 2003). For CFI and TLI, a value of .90 can be considered a lower bound (Jackson, Gillaspy, & Purc-Stephenson, 2009). The robust version of model fit indices is reported when applicable.

Results

Overall, the structural latent change model resulted in an acceptable fit with $\chi^2(5{,}553, N = 1{,}095) = 13{,}782.49$ and $p < .001$, $\chi^2/\text{df} = 2.48$, CFI $=$ .922, TLI $=$ .919, SRMR $=$ .070, and RMSEA $=$ .042, 90%

Table 2. Manifest means, standard deviations, and correlations of the variables ($N = 1{,}095$)

Variable	*M* (SD) t1	*M* (SD) t2	1	2	3	4	5	6	7	8	9	10	11	12
1. System use	4.2 (1.3)	4.1 (1.4)	.67***	.56***	.44***	.46***	.42***	.37***	.36***	.33***	.02	.28***	.35***	.25***
2. Behavioral intention	4.0 (0.8)	4.0 (0.8)	.53***	.57***	.60***	.63***	.59***	.52***	.52***	.49***	.16***	.40***	.47***	.37***
3. Social influence	3.8 (0.7)	3.9 (0.7)	.42***	.60***	.47***	.66***	.61***	.61***	.61***	.57***	.26***	.54***	.64***	.58***
4. Performance expectancy	3.7 (0.8)	3.8 (0.7)	.44***	.61***	.65***	.61***	.72***	.63***	.76***	.74***	.45***	.61***	.58***	.56***
5. Effort expectancy	3.6 (0.9)	3.6 (0.8)	.40***	.56***	.57***	.76***	.63***	.66***	.72***	.68***	.41***	.60***	.52***	.52***
6. Facilitating conditions	3.8 (0.6)	3.9 (0.6)	.32***	.47***	.57***	.59***	.62***	.46***	.64***	.63***	.39***	.56***	.52***	.52***
7. Quality of functions	3.7 (0.7)	3.8 (0.7)	.37***	.54***	.62***	.80***	.74***	.59***	.54***	.80***	.45***	.64***	.54***	.61***
8. Quality of data	3.7 (0.7)	3.8 (0.7)	.33***	.48***	.56***	.77***	.73***	.59***	.80***	.50***	.51***	.60***	.53***	.56***
9. Quality of performance	3.4 (0.8)	3.4 (0.8)	.06	.18***	.25***	.37***	.37***	.30***	.42***	.44***	.38***	.49***	.31***	.40***
10. User information	3.5 (0.7)	3.5 (0.8)	.26***	.40***	.44***	.55***	.55***	.51***	.57***	.56***	.38***	.44***	.55***	.60***
11. Supervisor support	3.7 (0.7)	3.7 (0.7)	.27***	.41***	.60***	.53***	.47***	.41***	.52***	.47***	.28***	.47***	.38***	.75***
12. Top management support	3.7 (0.7)	3.7 (0.7)	.21***	.34***	.53***	.52***	.50***	.41***	.54***	.52***	.35***	.49***	.71***	.40***

Note. t1 is the first and t2 the second measurement point. In the lower triangle, correlations at t1 are displayed, and in the upper triangle, correlations at t2. Correlations across measurement points are shown in the diagonal.
$^{***}p < .001$

Table 3. Intercepts, standardized intercepts, and variance of latent change variables within the baseline model

Estimate	ΔSystem use	ΔBehavioral intention	ΔSocial influence	ΔPerformance expectancy	ΔEffort expectancy	ΔFacilitating conditions	ΔQuality of functions	ΔQuality of data	ΔQuality of performance	ΔUser information	ΔSupervisor support	ΔTop management support
Intercept	−0.12***	0.05	0.03	0.13***	0.09***	0.11**	0.07*	0.08*	0.02	0.02	0.06	−0.03
Standardized intercept	−0.11***	0.05	0.03	0.15***	0.12***	0.11**	0.08*	0.08*	0.01	0.02	0.05	−0.02
Variance	1.33***	0.82***	1.07***	0.72***	0.67***	0.88***	0.87***	1.01***	1.28***	1.27***	1.23***	1.23***

Note. The standardized intercept can be interpreted as effect size.
$^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$

CI [.041; .043]. As displayed in Table 3, the mean intraindividual changes in the content factors quality of functions and quality of data, as well as the changes in performance expectancy, effort expectancy, and facilitating conditions, were significant and positive; hence, these evaluations increased over time on average. The mean change in system use was significant and interestingly negative, indicating a decrease from t1 to t2. Intraindividual changes in the other management and psychological factors did not have a significant mean and showed high variance. Hence, directly relating intraindividual changes in management factors to those in psychological factors with the LCS approach seems even more appropriate.

Concerning Hypothesis 1a, higher latent change scores in content factors indeed predicted higher latent change scores in psychological factors (see Table 4). Intraindividual changes in all content factors were related to increases in performance expectancy as a psychological variable, βs ≥ 0.10 and *p*s $\leq .009$. In particular, the increase in quality of functions was most strongly related to higher latent change scores in all psychological factors, βs ≥ 0.27 and *p*s $< .001$, with the strongest relationship to increases in facilitating conditions, $\beta = 0.36$, $p < .001$. With regard to Hypothesis 1b, higher latent change scores in the process factor user information also had significant effects on change scores in all psychological factors, βs ≥ 0.07 and *p*s $\leq .040$. In particular, higher latent change scores in the process factor most strongly predicted increases in facilitating conditions, $\beta = 0.17$, $p < .001$. Concerning Hypothesis 1c, intraindividual changes in context factors had mixed effects on psychological factors; that is, higher latent change scores in supervisor support predicted higher latent change scores in social influence, $\beta = 0.26$, $p < .001$ but were not related to increases in other psychological factors, βs ≤ 0.08 and *p*s $\geq .089$. Changes in top management support did not predict changes in psychological factors, βs ≤ 0.06 and *p*s $\geq .204$. All in all, however, intraindividual changes in management factors were significantly related to intraindividual changes in psychological factors in line with Hypothesis 1a-c.

Hypothesis 2 also received support, as higher latent change scores in all psychological factors predicted higher latent change scores in the intention to use the system. More specifically, the intraindividual change in social influence was the strongest predictor of changes in behavioral intention, $\beta = 0.21$, $p < .001$, followed by increases in performance expectancy and effort expectancy, both βs $= 0.17$ and *p*s $\leq .001$, as well as increases in facilitating conditions, $\beta = 0.10$, $p = .023$.

In support of Hypothesis 3, intraindividual changes in behavioral intention ($\beta = 0.14$, $p = .001$) and facilitating conditions ($\beta = 0.12$, $p = .010$) predicted intraindividual changes in system use. A closer investigation of the direction of effects shows that higher latent change scores in behavioral intention and increases in facilitating conditions are related to a decrease in system use.

Hypothesis 4 posited that the effect of management factors on system use is mediated by the psychological factors. Indeed, higher latent change scores in content, process, and context factors had significant total indirect effects on decreases in system use (βs ≥ 0.02, see Table 4), with increases in the content factor quality of data producing the largest effect, $\beta = 0.44$, CI [0.15; 0.80]. Only changes in the quality of performance (content) and top management support (context) did not show total indirect effects. In line with the mediation assumption – with two exceptions – changes in management factors had almost no direct effects on changes in behavioral intention and system use, βs $\leq |0.10|$ and *p*s $\geq .059$. Only increases in quality of functions ($\beta = -0.18$, $p = .022$) and higher latent change values in top management support ($\beta = 0.09$, $p = .046$) showed direct effects on decreases in system use. Therefore, Hypothesis 4 is largely supported.

Discussion

The adoption of new digital technologies by affected users is an important success factor for realizing the desired business benefits of digital transformations (Andriole, Cox, & Khin, 2018; Kohnke, 2017). The current study addresses important questions regarding the management of digital transformation projects in organizations by proposing and testing a framework that integrates management interventions and psychological factors underlying user adoption. Going beyond previous research,

Table 4. Standardized regression coefficients and standard errors in the MDA framework

	Dependent variables												
	ΔSystem use			ΔBehavioral intention		ΔSocial influence		ΔPerformance expectancy		ΔEffort expectancy		ΔFacilitating conditions	
Independent variables	β (SE)	z	Indirect effect	β (SE)	z	β (SE)	z	β (SE)	z	β (SE)	z	β (SE)	z
ΔBehavioral intention	0.14 (0.05)	3.31**		–		–		–		–		–	
ΔSocial influence	0.07 (0.05)	1.57		0.21 (0.04)	5.14***	–		0.10 (0.03)	3.11**	–		–	
ΔPerformance expectancy	0.08 (0.06)	1.63		0.17 (0.05)	3.47**	–		–		–		–	
ΔEffort Expectancy	0.01 (0.06)	0.18		0.17 (0.05)	3.94***	–		0.07 (0.03)	2.31*	–		–	
ΔFacilitating conditions	0.12 (0.05)	2.57*		0.10 (0.04)	2.27*	–		–		0.23 (0.03)	6.47***	–	
ΔQuality of functions	−0.18 [a] (0.09)	−2.30*	0.08[b] [0.04;0.13]	−0.02 [a] (0.07)	−0.26	0.33 (0.07)	5.25***	0.29 (0.06)	4.88***	0.27 (0.06)	4.42***	0.36 (0.07)	5.59***
ΔQuality of data	0.00[a] (0.07)	0.03	0.44[b] [0.15;0.80]	−0.02[a] (0.06)	−0.33	0.06 (0.07)	0.89	0.25 (0.05)	3.99***	0.13 (0.05)	2.08*	0.12 (0.06)	1.78
ΔQuality of perfor-mance	−0.05[a] (0.03)	−1.34	0[b] [−0.01;0.02]	−0.04[a] (0.04)	−0.90	−0.01 (0.03)	−0.41	0.10 (0.03)	2.62**	0.06 (0.03)	1.78	0.01 (0.03)	0.26
ΔUser informa-tion	−0.01[a] (0.03)	−0.26	0.03[b] [0.01;0.05]	0.00[a] (0.03)	0.01	0.10 (0.03)	2.86**	0.07 (0.02)	2.23*	0.08 (0.03)	2.06*	0.17 (0.03)	4.15***
ΔSupervisor support	−0.03[a] (0.04)	−0.60	0.02[b] [0.01;0.04]	0.10[a] (0.04)	1.89	0.26 (0.05)	5.16***	0.07 (0.03)	1.70	0.07 (0.03)	1.57	0.08 (0.04)	1.52
ΔTop manage-ment support	0.09[a] (0.04)	2.00*	0[b] [−0.01;0.02]	−0.08[a] (0.04)	−1.53	0.06 (0.04)	1.27	−0.01 (0.03)	−0.25	0.03 (0.04)	0.60	0.01 (0.04)	0.13

[a]Direct paths were included to examine mediation effects, not hypothesized in the MDA framework.
[b]Bootstrapped point estimates of total indirect effects with 95% confidence interval.
*$p < .05$ **$p < .01$ ***$p < .001$

we employed a process-oriented perspective to understand how perceived intraindividual changes in management interventions are related to intraindividual changes in user behavior.

Overall, the results of the study largely supported the proposed MDA framework by showing adequate model fit and significant amounts of explained variance in user behavior. In line with our hypotheses, intraindividual changes in the perception of management factors affected changes in user behavior and were to a large extent mediated by changes in the proposed psychological factors. Moreover, our results point to content and process factors as important levers in digital transformations, as changes in these were related to changes in all the psychological factors, which in turn predicted the intention to use the new system as well as actual user behavior.

Theoretical contributions and implications

Looking specifically at the management interventions, changes in content factors (quality of functions, quality of data, and quality of performance) had multifold effects on changes in psychological factors. In particular, the findings highlight the importance of system quality for the successful adoption of digital transformations. In fact, increasing system quality – for example by implementing extended functionalities relevant to the job, improving data correctness and completeness, and fastening the response time of the system – showed the strongest effects on changes in psychological factors and user behavior. Moreover, the additional direct effect on system use suggests that quality improvements in system functions (e.g., simplification of functions and automating system steps) may have directly increased the efficiency of system usage beyond psychological factors by leading to fewer interactions and less time spent working with the system.

Furthermore, the results indicate that changes in process factors exerted a substantial and additional effect on changes in users' behavioral, normative, and control beliefs. Specifically, changes in user information were related to all psychological factors – most strongly to facilitating conditions – and led to changes in user behavior. These results are in line with previous research on the importance of information and communication for supporting organizational changes (e.g., Straatmann et al., 2016) and digital transformations (e.g., Amoako-Gyampah & Salam, 2004; Kohnke, Wolf, & Mueller, 2011). Thus, our findings underscore the fundamental and multifaceted potential offered by change-related communication activities (Armenakis & Harris, 2002; e.g., Armenakis, Harris, & Mossholder, 1993).

Concerning context factors, changes in the behavior of the direct supervisor were most strongly associated with changes in the perception of normative beliefs of the users and changes in system use. Consistent with previous research, this result highlights the important role of direct supervisors in supporting digital transformations (Schepers, Wetzels, & de Ruyter, 2005; Schillewaert et al., 2005). In contrast, changes in top management support only had a direct effect on changes in system use and were not significantly related to psychological acceptance factors. Due to a higher psychological distance (Berson, Halevy, Shamir, & Erez, 2015) and potentially lower visibility during a digital transformation, top management support is likely to exert only minimal effects on users' psychological factors. Yet, certain strategic choices – such as top management's decision to replace a legacy system – may still have a direct effect on employees' behavior (Oreg & Berson, 2019). The results emphasize the importance of distinguishing direct supervisor support and top management support (Rafferty, Jimmieson, & Restubog, 2013).

Overall, the present study demonstrates that user behavior is mainly determined by preceding psychological processes in line with the theoretical arguments made by Kim et al. (2011) and Rafferty, Jimmieson, and Armenakis (2013). As part of many digital transformation projects, existing systems are often replaced. Hence, a process-oriented perspective (Langley et al., 2013; Sonnentag, 2012; Venkatesh et al., 2021) to determine changes in relation to the previous state is of particular interest. Based on the applied LCS approach, our results indicate a high potential of proactive management, as management interventions can effectively promote favorable changes in psychological reactions that lead to changes in user behavior. As such, our findings on the mediated relationships contribute to the understanding of the effects of managerial decisions and interventions assisting organizational changes during digital transformations (see Straatmann et al., 2016).

Additionally, our study reveals two effects of management interventions on user behavior that need to be considered in a differentiated manner. First, it is important to note that objective changes in management factors need to be perceived as changes by the users to be effective. In other words, only a delta in the users' minds (i.e., intraindividual change in cognitions and intentions) can lead to a delta in behavior and user adoption. Second, our study showed that changes in management factors can also directly lead to behavioral changes bypassing the underlying psychological processes. Future research should further investigate how different management factors influence user behavior.

Implications for management

Based on the proposed MDA framework and the empirical investigation in the context of a real organizational setting, the present research offers a rich source for deriving specific practical recommendations for managing and monitoring large-scale, multinational digital transformation projects. The MDA framework, composed of relevant factors for promoting digital adoption, enables practitioners to systematically evaluate the effectiveness of management interventions. Multiple evaluations during a digital transformation allow the observation of trends and the derivation of important information in order to refine the management strategy and development of appropriate interventions, depending on the identified effects on user adoption.

The present study also gives guidance in allocating scarce project resources and budgets to the most promising management factors to foster user behavior. In particular, changes in content factors reflecting relevant system characteristics, such as quality of functions and quality of data, demonstrated stronger effects on changes in psychological factors than process and context factors. Therefore, high priority should be placed on improving system characteristics (e.g., data quality, response times, and adequate functionalities) when implementing a new system because of the substantial positive effects on users' beliefs toward the new digital system. In addition, as improvements in system characteristics need to be perceived as such by the users to increase user adoption, it is highly recommended to highlight the changes through specific change management interventions such as user information, training, participation, or support.

Improving the quality of data had the highest total indirect effect on changing user behavior during the digital transformation. This result is especially important in the context of company-wide standard software (such as ERP or cloud solutions) because system adaptations during the implementation process are usually limited or focused on local requirements (e.g., for tax reasons or other specific regulations). However, organizations have full control of managing the data quality of the system during the digital transformation project. Thus, ensuring a high quality of data is an important lever of successful digital transformations. It should be noted that establishing high data quality during data migration is not merely a technological topic but also comprises psychological aspects, as employees must be motivated to support data integration and cleansing before go-live. Hence, high data quality should be ensured as a project in itself with organizational change management in the form of explicit and ongoing user information, as well as the support of direct managers.

The current research shows that changes in user information can affect all psychological reactions of the user. The multifaceted potential in designing user information to accompany system changes helps to foster user adoption (e.g., Armenakis & Harris, 2002; Elving, 2005). In particular, user information should be designed to address all psychological mechanisms of digital adoption. For example, information should explain how to use the system (targeting effort expectancy), present the benefits of using the system (targeting performance expectancy), communicate the new system's desirability within the organization (targeting social influence), and instill confidence in using the new system (targeting facilitating conditions).

Moreover, the support of direct managers was found to be a relevant context factor and should be considered when designing specific change interventions. Specifically, it is important to mobilize the direct managers to give adequate and visible support for their employees, e.g., providing sufficient time to try out the new system and attend training sessions, offering help in case of questions, and motivating them to work with the system.

Limitations and future research

The current findings should be interpreted in light of a few limitations. First, data were collected from one organization implementing a company-wide standard software solution (an ERP system) that was mandatory in use for the employees. Although these software packages are very common in many organizations and industries, it limits the generalizability of our findings. For example, other types of digital technologies and other implementation contexts – such as voluntary system use or varying degrees of organizational and software adaptations – might produce different employee perceptions and usage behaviors during digital transformation projects. Hence, future research should test the proposed MDA framework in different organizational and IT settings.

Second, this study relied on self-reports to capture the psychological processes and perceptions of the users, running the risk of social desirability responding and common method variance (Podsakoff & Organ, 1986). To prevent and detect possible bias, careful measures were taken in the design of the study and the analysis of the data. For example, participants were informed about the anonymity guaranteed throughout the process of data collection and analysis. In addition, common method variance was examined by analytical procedures and can be considered negligible in this study. Consistently, the objective and subjective indicators of system use showed a high convergence, further indicating the validity of the self-reported data.

Although not unusual in organizational research (e.g., Bala & Venkatesh, 2013; Straatmann et al., 2016), a third limitation lies in the relatively low response rate at the second survey of around 30% and the high level of drop-out from t1 to t2. Given the long-time interval between the measurements and the nature of field studies, a relatively high drop-out seems to be inevitable (Ployhart & Vandenberg, 2010). Comparisons of the longitudinal sample with the overall samples at both times of measurement revealed no substantial differences.

Third, we selected specific management factors that we assumed were representative of the content, process, and context categories of our MDA framework. However, there is no doubt that other management factors related to content (e.g., business process and job characteristics), process (e.g., training and participation), or context variables (e.g., incentive systems and organizational culture) could also be relevant. Future research should therefore expand the range of variables considered by the taxonomy of management factors with the potential to influence user adoption during digital transformations and integrate them into the MDA framework. In addition, the organizational context of this large-scale study was an international company. Hence, cross-cultural aspects may also have influenced the studied relationships. While cultural effects relating to psychological acceptance factors are already addressed (e.g., Blut et al., 2022; Marangunić & Granić, 2015), more research is needed to investigate the effects of management factors under different cultural conditions to better guide management in global digital transformation programs.

Finally, while the longitudinal design with two measurement times is more extensive than much management research practice (Aguinis, Edwards, & Bradley, 2017), more measurement times would have more accurately reflected the temporal precedence of assumed causes on their effects. However, in this field study, only two measurements were feasible, and the assumed sequence of effects was in line with theory and empirical findings (e.g., Rafferty, Jimmieson, & Armenakis, 2013). While our two-wave research design enabled us to investigate how changes in management factors are related to changes in user adoption, more measurement times would have increased our ability to analyze time effects more precisely in the course of the digital transformation. Future research should consider examining the relationships between management factors, psychological processes, and user adoption with a more fine-grained longitudinal design to gain insights into the specific change dynamics and trajectories during different phases of digital transformation projects (Venkatesh et al., 2021). For example, it would be promising to investigate how specific learning processes relate to digital adoption during sequential roll-out projects, as some user groups are more experienced than others with regard to the technology in question when they start working with it at an earlier stage. Also, a more short-cycled approach will be valuable given the high pace of innovations and deployments of new system functionalities at the workplace, requiring continuous adoption from employees (Andriole, Cox, & Khin, 2018).

Conclusion

The current study provides several contributions to the management of digital transformation projects in organizations. First, it demonstrates the usefulness of the proposed MDA framework for systematically integrating previously suggested management factors of organizational change with psychological processes of user adoption and actual user behavior at the workplace. Second, the longitudinal investigation of the MDA framework supports the assumption that changes in management factors impact changes in user adoption during digital transformations and reveals the salience of specific management factors in digital transformation projects. Taken together, the results of the study advance our knowledge about the management of digital adoption in digital transformation projects.

Competing interests. Oliver Kohnke also works for the company whose product was introduced as part of the transformation process described in the paper. The other authors declare none.

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