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Digital transformation decoupling: The impact of willful ignorance on public sector digital transformation

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ABSTRACT

The public sector is actively pursuing digital transformation to ensure continuous operations and relevance. While existing research has outlined essential prerequisites for successful digital transformation, there is recognition of willful ignorance concerning these prerequisites. Public servants may in other words deliberately avoid understanding the necessary conditions for digital transformation, often driven by strategic motives such as evading responsibility and/or accountability. The phenomenon of willful ignorance constitutes an important yet under-researched area within the study of digital government. To close this gap, we investigate the latent factors of willful ignorance in public sector digital transformation, utilizing three sets of national panel data focused on digital transformation prerequisites. Employing exploratory factor analysis on an initial sample, we construct a factor model, subsequently assessing its validity through confirmatory factor analysis on two additional samples. Our research identifies and validates latent factors associated with willful ignorance in the digital transformation of the public sector. Building on these findings, we propose a mid-range variance theory termed "digital transformation decoupling". By integrating this theory with existing knowledge, we present a set of propositions to guide future research in the realm of public sector digital transformation.

1. Introduction

In a push for what Janowski (2015) refers to as digital government, public sector organizations are actively pursuing digital transformation. In this respect, digital transformation refers to a continuum of organizational change processes ranging from digitization (i.e., turning analog data into digital data) to a "…full stack review of policies, current processes and user needs…" (Mergel, Edelmann, & Haug, 2019, p. 12). Previous studies have identified an emerging set of necessary prerequisites for successful public sector digital transformation, ranging from the importance of internal champions (Wilson & Mergel, 2022), to changes in governance practices (Janssen & van der Voort, 2016a; Magnusson, Koutsikouri, & Päivärinta, 2020) and structural changes (Andersson, Hallin, & Ivory, 2022; Clarke, 2020). These prerequisites are mirrored in the general digital transformation literature (Vial, 2019), yet nuanced for the institutional settings of the public sector through a set of different capability- and maturity models (Andersen & Henriksen, 2006; Andersen, Medaglia, Vatrapu, Henriksen, & Gauld, 2011; Das, Singh, & Joseph, 2017; Kim & Grant, 2010; Layne & Lee, 2001; Singh, Das, & Joseph, 2007).

While the necessary prerequisites are acknowledged in the literature, less is still known about the level of competence and insight into said prerequisites among public servants, i.e., what may be referred to as digital transformation competence (Edelmann, Mergel, & Lampoltshammer, 2023). Without insight into the necessary prerequisites, the likelihood of public servants acting to enhance and support said prerequisites will be negatively influenced (see Steele-Vivas, 1996), resulting in decreased success in digital transformation. Previous research differentiates between a lack of insight and ignorance, i.e., "negative knowledge" (Gross, 2007; Ungar, 2008). Within the study of digital government, ignorance has previously mainly been addressed as a detrimental characteristic of citizens (Holzer, 2022; Weigl, Barbereau, & Fridgen, 2023) resulting in tendencies for opt-out and resistance to government initiatives (van Twist, Ruijer, & Meijer, 2023) as well as resulting in decreased propensity for data sharing (Alshahrani, Dennehy, & Mäntymäki, 2022). There is to date, however, a dearth of research on the role of ignorance among public servants. This is where we aim to make our contribution.

As noted by Alvesson, Einola, and Schaefer (2022), ignorance may be willful in respect to serving a strategic purpose (McGoey, 2012). If the

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individual can remain ignorant, i.e., avoid insight into certain issues, the person may be devoid of accountability and responsibility for assuring, e.g., the creation of the right prerequisites. Essén, Knudsen, and Alvesson (2022) further expands on the function of what they refer to as "self-inflicted" ignorance in upholding the established order and apparent incongruencies of organizational life. In other words, ignorance serves a particular function in organizations and for employees, and more research is called for (Plesner & Justensen, 2023). We argue that considering how digital transformation challenges the established order in public sector organizations, we expect to see instances of willful ignorance (Crusoe, Magnusson, & Torell, 2023).

Based on this brief rationale, our study explores how willful ignorance impacts public sector digital transformation using panel data and factor analysis. The focus is on the Swedish public sector, for two reasons: (1) its long history of digital transformation and e-government and (2) the Swedish government has the goal of Sweden being the best in the world in using the possibilities of digital transformation. We expect Swedish public servants to have a good understanding of the prerequisites related to digital transformation, but also display some areas of willful ignorance. Factor analysis is a multivariate statistical technique used to analyze underlying structures (latent factors) among observed variables (Hair, Black, Babin, Anderson, & Tatham, 2009). In this study, the technique was used to reveal how willful ignorance regarding digital transformation prerequisites rise and fall together as factors. The study answers the following research questions:

- What patterns can be identified regarding underlying common factors of willful ignorance concerning digital transformation prerequisites among Swedish public sector employees?
  - o Following patterns in these factors, what are some theoretical propositions for future research?

We answer the first research question through exploratory and confirmatory factor analysis, utilizing quantitative analysis of panel data (+9600 survey responses) from a national study of digital transformation prerequisites in the public sector. Our study contributes to previous research through answering the calls for additional research on the role of public sector digital transformation competence from Edelmann et al. (2023) as well as the role of ignorance in digital transformation practice from both Plesner and Justensen (2023) and Essén et al. (2022). From our findings, we propose a mid-range variance theory of digital transformation decoupling that is used to identify propositions for future studies of public sector digital transformation and digital government. Through the theory of digital transformation decoupling and the propositions for future studies, we hope to make a substantial contribution to the continued study of digital government and public sector digital transformation.

The remainder of the paper is organized accordingly: First, we introduce the extant research on competence and ignorance in public sector digital transformation. This is followed by the method of the study, where we expand on the empirical selection, data collection, and method of analysis. We then present the results in the form of the exploratory and confirmatory factor analyses. The paper ends with a discussion where the findings are contrasted to previous research on decoupling and ignorance, to deliver propositions for future research.

2. Previous findings

The previous findings that we base our study on are presented in two parts. First, we present the previous findings related to competence in public sector digital transformation, and second, the findings on ignorance in public sector digital transformation.

2.1. Competence in public sector digital transformation

Public sector digital transformation involves the dual aspiration of increased efficiency and relevance through the diffusion and utilization of digital technologies. As noted by Mergel et al. (2019) as well as Janowski (2015), digital transformation in the public sector ranges from the miniscule initiatives of e.g., digitizing previously physical forms, to fundamental changes in policy and means of citizen engagement. While research on public sector digital transformation is experiencing an increase in interest, there is still a lack of insight into both its prerequisites and implications. The extant research on digital transformation is dominated by private sector studies of single organizations (Hanelt, Bohnsack, Marz, & Marante, 2021; Vial, 2019; Zapadka, Hanelt, & Firk, 2022), with significant caveats for transferability of findings to the public sector (Bannister, 2007).

Previous research from the public sector highlights the critical role of individual co-workers and managers in the process of digital transformation. In a study of what drives success in public sector digital transformation, Wilson and Mergel (2022) find that individual champions play a critical role. With digital transformation often involving the challenging of the very organizational identity (Wessel, Baiyere, Ologeanu-Taddei, Cha, & Jensen, 2021) and the institution per se (Hinings, Gegenhuber, & Greenwood, 2018), this places strain on both the political savviness and competence of the individual (Edelmann et al., 2023). While there are multiple conceptualizations of competence, e.g., cognitive competence (Cheetham & Chivers, 1996), functional competence (Deist & Winterton, 2005), and emotional competence (Zeidner, Matthews, & Roberts, 2004), the concept generally refers to an individual's apparent characteristics (e.g., knowledge and skills) and underlying attributes (e.g., attitudes and values), leading to effective interactions with the environment to achieve goals and perform well (Benner & Tushman, 2003; Salman, Ganie, & Saleem, 2020). We differentiate between two types of competence necessary for assuring digital transformation.

First, several studies have highlighted the necessity of high levels of digital competence, i.e., the ability to use digital solutions and technologies (Pettersson, 2018). Without this type of competence distributed throughout the organization, new solutions will not be utilized or scaled. As noted by Mankevich, Magnusson, and Svahn (2023), a lack of digital competence also straddles the pace of digital transformation as a continuous process, given that technology continuously evolves. In a study of mobile device use in the public sector, Lemmer, Jahn, Chen, and Niehaves (2023) further identify the lack of digital competence as a deterrent to innovation, which is also supported by Mikalef et al. (2023) in relation to the adoption of artificial intelligence. This makes the appropriate level of digital competence a moving target, steadily increasing and changing in line with technological development.

Second, studies like Edelmann et al. (2023) and Ostmeier and Strobel (2022) show an additional type of competence necessary for driving and assuring digital transformation. We refer to this type of competence as "digital transformation competence", i.e., the ability to lead and be an active part in the digital transformation. This involves general change management related competence as well as specific competence surrounding how digital transformation differs from other types of organizational change. Singling out the type of managerial competence that is necessary for the organization to succeed in digital transformation fulfills two main purposes. First, it sensitizes the organization to the necessity for assessing and working with the sourcing and development of not only digital competence but also digital transformation competence. Second, it places a more general emphasis on *bildung* related to understanding the innate differences of digital materiality, something that has been highlighted in the literature (Baiyere, Grover, Lyytinen, Woerner, & Gupta, 2023). As noted by Simondon (1980), humans display a general tendency to misunderstand technological artefacts on account of not understanding their specific material constraints and affordances.

2.2. Ignorance in public sector digital transformation

So given the importance of competence for digital transformation, we turn our attention to its perceived absence. During the past two decades, the notion of ignorance has received an increased level of attention in research (Gross, 2007; Heimer, 2012; Jalonen, 2023; Liu, Tan, & Mookerjee, 2018; McGoey, 2012; Schaefer, 2019). In essence, ignorance refers to a lack of knowledge and recent studies have invested in establishing a new perspective on ignorance and its role in organizational behavior. Here, ignorance is imbued with new forms of agency and motivation, clearly differentiating it from the traditional perspective as merely a lack of knowledge (Alvesson et al., 2022). The reason for our utilization of the construct of ignorance in relation to digital transformation is two-fold. First, by using ignorance rather than the mere lack of knowledge, we may approach situations where there is a value to the individual in staying ignorant. McGoey's (2012) notion of strategic ignorance as well as Alshahrani et al.'s (2022) of willful ignorance highlights this potential value for the individual. Through being ignorant, individuals can remain unaccountable, offering political leeway. Jalonen (2023) contrasts that ignorance in organizations can have consequences, such as lack of innovation, inattention, emotional stress, and decay. Second, we see a potential value in ignorance since it simultaneously affords the individual a possibility of simply stating that this is not something they have any insight into. In this respect, ignorance shields the individual from (what they perceive as) unwarranted effort (Gross, 2007; Liu et al., 2018). A consequence of these reasons is that ignorance can be understood as a form of double-edged competence for individuals.

In a study of how individuals engage in the act of ignoring, Essén et al. (2022) identify four facilitating factors for willful ignorance. The first factor is related to fragmented accountability brought on through division of labor. We interpret the municipal organization nested in the functional perspective as directly facilitating ignorance related to digital transformation. Given the intricate dependencies between, e.g., a social service administration and the digital infrastructure in the potential use of Robotic Process Automation and Artificial Intelligence, the sequestering of responsibility over the infrastructure by the IT function affords the social service co-worker an opportunity for ignorance, thereby decreasing the scope of digital transformation.

The second factor is related to laissez-faire professionalism calling for non-interference with other professions in the organization. We perceive this to be a two-way street where technology- as well as business-side professionals are adamant to learn and acquire knowledge about issues where there is a risk of inter-professional jurisdictional conflicts (Abbott, 2010). This results in further hesitance for cross-functional communication and engagement and decreases the potential scope of digital transformation. The third factor is related to technological development and uncertainty. With technological opportunities constantly evolving, this inspires a "let's wait" attitude within the organization where they become reactive instead of proactive in learning. The resulting passivity is deeply rooted in ignorance of the opportunities, increasing the opportunity cost of non-adoption of new technical solutions, and decreasing the pace of digital transformation.

The fourth and final factor is related to external admiration. External admiration refers to the possibility of acquiring legitimacy through external recognition from e.g., rankings, competitions, and awards. As noted by Bruijn III and Tushman (2013), the aspiration for external legitimacy may be detrimental to the development of public sector organizations and decrease their ability for change over time. With digital transformation being a lucrative market for e.g., consultants and vendors, we see external admiration being integrated into marketing campaigns where these actors highlight certain clients as worthy of admiration. With the possibility of acquiring legitimacy through external sources, this decreases the pace of digital transformation. As noted in the four factors presented above, both the pace and scope of digital transformation is directly affected through the occurrence of willful ignorance (See Fig. 1).

Based on this brief review on the literature, we posit that willful ignorance directly impacts digital transformation in the public sector as argued by Crusoe et al. (2023), and that it is associated with a set of facilitating factors (Essén et al., 2022).

3. Method

Following a quantitative approach, we explore the latent factors behind willful ignorance among respondents from Swedish public organizations over the years of 2020, 2021, and 2022. The exploration focused on willful ignorance regarding digital transformation prerequisites, using an established framework for DT prerequisites (Magnusson & Nilsson, 2020), which is currently used as the de-facto model in the Swedish public sector. This framework guided the data collection and the analysis (Eisenhardt, 1989; Walsham, 1995). Sweden and its public sector have a long history with e-government and digitalization with IT-educational investments dating back to the 1980s. It is estimated that 67% of citizens have at least basic digital skills, while 36% have above the basic level and 8% ICT specialists (OECD, 2022a). The Swedish focus on digital transformation together with its IT-sector have been an important driver for the country's economic growth. The main goal of the Swedish digitalization politics is that the country should be the best in the world of using the possibilities of digitalization. However, recent measurements from OECD, such as the Digital Economy and Society Index, Digital Government Index, and OurData Index (OECD, 2019, 2020, 2022a, 2022b), highlight that Sweden is falling behind or is already far behind other EU countries when it comes to digitalization. Together, these contextual factors make Sweden an excellent candidate for the study of willful ignorance regarding digital transformation prerequisites.

Between 2020 and 2022, our survey received 20,351 responses. The survey used an ordered-categorical measurement (e.g., dichotomously-scored test items and Likert items (Millsap & Yun-Tein, 2004)) where we focused on respondents' selection of "Don't know" (DK). DK answers to the questions of prerequisites mirror areas where respondents lack an understanding. However, respondents may select DK for various reasons beyond ignorance, such as indecision and uncertainty about meanings (Sanchez & Morchio, 1992). Researchers can understand DK as a valid indicator of ignorance, a reflection of a missing attitude or opinion, or random missing data (Durand & Lambert, 1988). We designed the survey to reduce the chance that respondents select DK for any other reason than ignorance, such as task difficulty, low motivation, and lack of experience (Krosnick, 1991). We understand the selection of DK as a mix of ignorance and missing attitude or opinion.

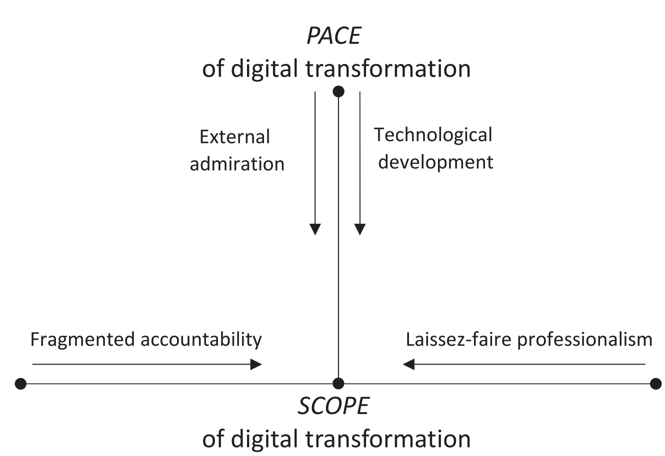

Fig. 1. Overview of impact of factors on the pace and scope of digital transformation.

3.1. Survey

We administered our survey as part of a digital service, which has been the de-facto standard since 2019 for measuring digital maturity in the Swedish public sector. It was developed through a research project where the public organizations pay for the digital service and in extension the survey. The intention of the digital service is to be used by all Swedish public organizations. The survey received responses from 42 public organizations in 2020, 77 in 2021, and 118 in 2022 (See Table 1 for details). The participating public organizations received an evaluation of the survey's results, providing them with insights into their digital maturity. This created a feedback loop where the respondents could be impacted by the survey, which should reduce DK answers because of low motivation over time (Krosnick, 1991). The survey questions are presented in Appendix A.

We designed the survey to ensure that respondents who lacked knowledge about a prerequisite would select DK, mirroring a lack of consideration, formulated position, interest, or awareness (Feick, 1989). A respondent may select DK if they misunderstand a question, lack attention, experience distractions, or find it difficult to select an answer (Feick, 1989; Krosnick, 1991). Therefore, we gave the survey a clean GUI where batches of related questions were presented at a time, helping to reduce this problem. The batching followed the categories of Magnusson and Nilsson (2020). Each batch started with an explanation of the used Likert items and with an open question at the end, which contributes toward a feeling of accountability (See Krosnick, 1991).

The questions were presented as strong statements of full achievement regarding the prerequisites, but also came with an on-demand explanation to ensure clarity. The respondents had to select to which extent they agree with these statements (Likert, 1–6; 1 = completely disagree, 2 = disagree, 3 = slightly disagree, 4 = slightly agree, 5 = agree, and 6 = completely agree). We did not include a middle option, as uncertain respondents can favour it (Feick, 1989; Krosnick, 1991). Instead, they could select DK. Respondents can also be encouraged to select DK, if the questions ask for information difficult to remember, require a difficult judgement, or are double-barrelled (Krosnick, 1991). As such, we created simple questions about present facts regarding the public organizations and the respondents' knowledge about them (Bryman, 2018). We decided not to probe respondents about their DK answers since it can encourage uninformed respondents to give guessed answers (Kuha, Butt, Katsikatsou, & Skinner, 2018; Sanchez & Morchio, 1992).

Once a public organization has paid for the digital service, the **survey administration process** starts with a public organization appointing an administrator who creates an organizational tree and selects respondents. It was recommended to select respondents that are involved in decisions regarding or are directly affected by digital transformation, which should ensure that the respondents can answer questions about the digital transformation prerequisites (Krosnick, 1991). This survey administration follows a two-step sampling technique: (1) random sampling and (2) snowball sampling. Random sampling means the researcher has limited ability to influence the sample since respondents have an equal chance of participating (Denscombe, 2010). For our survey, all Swedish public organizations can pay for the digital service and participate in the survey, expecting an evaluation of their digital maturity. It contributes to the randomness of our sample, but also a limitation (see Section 6.1). On the other hand, once an organization has paid for the digital service, the administrator uses snowball sampling to select respondents (Denscombe, 2010), following the previously stated recommendation. While the selected respondents came from all hierarchical levels, the sample contains a predominance of executives and managers. They were often from different organizational units within the public organization. The survey included a question about respondent expertise, helping to differentiate them between experts involved in decisions about digitalization and non-experts only impacted by digitalization (see Q1 in Appendix A). Table 2 presents the number of respondents over their selected role and expertise. In 2021, a question about respondent role was added (see Q2 in Appendix A), which came into serious use in 2022. A consequence is that there is a prominent selection of the"Other" option for roles. We do not know the role of these respondents, which is a limitation of this research. However, following the purpose and intended survey respondents, experts who select "Other" option for role are likely strategists, project-leaders, and organizational developers, while non-experts in the "Other" role are mostly users of digital solutions.

Table 1
Organization type with number of organizations and respondents for the years 2020, 2021, and 2022.

	2020		2021		2022	
Organization	#	Response	#	Response	#	Response
Public Agency	2	358	6	593	6	440
Municipality	29	2748	63	4923	98	7636
Region	1	7	5	438	12	1546
Other	10	188	3	73	2	54
Total	42	3301	77	6027	118	9676

3.2. Exploratory factor analysis

Exploratory factor analysis (EFA) is a multivariate statistical method used to model covariation among variables in terms of a smaller set of latent factors. In this study, EFA has been used to explore patterns of factors underlying the answers pertaining to digital transformation prerequisites. More specifically, it has focused on the subset of answers being "Don't know". Since this response option corresponds to a dichotomous (binary) variable, the factor model has been generated using an analysis of tetrachoric correlation. This correlation analysis assumes that the distribution of latent, continuous variables underlying a given pair of variables is bivariate normal (Brown & Benedetti, 1977).

In order to investigate whether or not the factor model is robust over time, we used a combination of exploratory and confirmatory factor analysis. More specifically, we have sampled the variables in two time periods $t_1 = [2020]$ and $t_2 = [2021{,}2022]$ followed by producing a factor model from the data sampled for t_1. The resulting factor model was subsequently evaluated using confirmatory factor analysis on the data sampled for t_2. To this end, we have used the R packages *lavaan* and *semTools* for structural equation modeling (SEM) with the estimator of diagonally weighted least squares (Barthes, 1987; Jorgensen et al., 2022). The confirmatory factor analysis as part of an evaluation of the factor model is further explained in Section 4.3, avoiding repetition. The EFA was conducted as follows.

3.2.1. Factor analysis suitability

Two tests were applied to investigate the suitability of EFA on the variables involved in this study. The Kaiser-Meyer-Olkin (KMO) test,

Table 2
The number of respondents is divided over their role and expertise.

	2020		2021		2022	
Role*	*Expert*	*Non-expert*	*Expert*	*Non-expert*	*Expert*	*Non-expert*
CEO/Director	–	–	1	1	555	5
Political leadership	–	–	–	–	65	17
Middle manager	–	–	12	2	2054	325
First-line manager	–	–	6	–	1633	466
Administrative officer	–	–	14	6	1050	446
Other	2542	759	4696	1289	1982	1078
Total	2542	759	4729	1298	7339	2337

* Question about role was added in 2021.

which analyses partial (pairwise) correlations between the variables, yielded a score in the interval [0.90, 0.98] with a mean of 0.96. This indicates strongly that EFA is meaningful for this sample. Moreover, Bartlett's test of sphericity was calculated over the entire set of variables, resulting in a p-value $< .05$, which indicates that the variables are mutually correlated and suitable for EFA. The variables have subsequently been grouped according to the identified factor structure and the internal consistency of survey was calculated by means of Cronbach's α. As can be observed in Table 8, the internal consistency of the survey over the years 2020–2022 is moderately high to very high (in the interval [0.773, 0.966]).

3.2.2. Factor extraction method

For the extraction of factors, the Ordinary Least Squares (OLS) method was used. The objective of this method is to minimize the sum of the squared errors (Cudeck, 2000). Revelle (2018) explains that it is one of the better extraction methods to find the minimum residual solution since it gives results similar to maximum likelihood even for badly behaved matrices. OLS has been shown to give loading matrices with better agreement to population and exhibit less bias and error (Coughlin, 2013). Therefore, we believe it to be appropriate.

3.2.3. Factor estimation

Several methods for estimating the optimal number of factors were tested. Using the criterion that the eigenvalues for the factors should be $\geq$1, the optimal number of factors was determined to be 3. Using a scree plot together with the "elbow" criterion, the optimal number of factors was determined to be 2. A third method used was parallel analysis (Horn, 1965) which determines the eigenvalue threshold for the optimal number of factors by means of comparison to the analysis of random matrices. According to this method, the optimal number of factors is 6. However, it should be noted that this method tends to yield a higher number of factors for larger samples (Revelle, 2018). Finally, we considered the factor loading of each variable according to the criteria that each factor should be associated with at least three or more variables and that each variable should have a high factor loading ($\geq$ 0.3) on one factor. Therefore, we chose to extract a factor model with four factors, fitting with our criteria and previous research (Magnusson & Nilsson, 2020).

3.2.4. Rotational method

The purpose of the rotational methods is to provide an easier interpretation of the results, while making them frugal. We used an oblique rotational method, as it is perceived to better fit with human behaviors (Williams, Onsman, & Brown, 2010), while assuming the existence of higher-order factors (Gorsuch, 1983; Navruz, Capraro, Bicer, & Capraro, 2015). Additionally, it is common procedure to generate an oblique factor model when there is a high mutual correlation between the factors (See e.g., (Grieder & Steiner, 2022)). We tested the eight rotational methods as offered by the R package *psych* (Revelle, 2018), which we iterated to select the one giving us the best fit and factorial suitability (Williams et al., 2010). In the end, we chose Promax as our rotational method.

3.2.5. Analysis of the correlation between factors

The extracted factors were analyzed for pairwise correlation, which ranged between 0.61 and 0.77, indicating an underlying factor (Navruz et al., 2015). Following Navruz et al. (2015), we estimated 2nd-order factors using a scree plot and parallel analysis. Both give the estimate of one 2nd-order factor. The 2nd-order EFA used the same parameters as described above. The usage of 1 factor fitted with the factor loading criteria of Johnson and Morgan (2016).

3.2.6. Examination of factors

We examined which variables are attributable to a factor, giving the factors a name and description. This labelling process is a subjective, theoretical, and inductive process (Williams et al., 2010). The interpretation of the 2nd-order factor was supported by using Gorsuch's product matrix: multiplying the 1st-order factor loadings with the 2nd-order factor loadings. It reveals how much observed variables loads to the 2nd-order factor, enabling interpretations rooted in measurements rather than interpretations of abstractions (Gorsuch, 1983; Navruz et al., 2015).

4. Results and analysis

This section first presents the exploratory factor analysis with factor loadings and then the resulting factor model, ending with an evaluation of the factor model. Fig. 2 presents the proportions of willful ignorance for the three samples. The prerequisites have been ordered following the mean of all years from highest to lowest. Shadow IT is as such the area with highest mean proportion of willful ignorance.

4.1. Exploratory factor analysis

We applied EFA on a sample of 3301 responses from 2020, collected through a survey with 26 Likert items (observed variables). OLS extracted factors with the oblique rotational method of Promax. Table 3 presents the factor loadings of the 26 items onto four factors with communalities in the interval [0.50, 0.86]. The reason for selecting four factors is further detailed in Section 3.2. In the table, we have highlighted any cell with a factor loading above 0.3. Together, the four factors account for 71% of the total variance, which is satisfactory (Hair et al., 2009). Factor 1 (Balancing ignorance) explains 16% of the variance, covering 6 items with a loading range in the interval [0.32, 0.84]. Factor 2 (Exploitation ignorance) accounts for 18% of variance, including 7 items with loadings in the interval [0.38, 0.91]. Factor 3 (Digital legacy ignorance) explains 20% of variance encompassing 8 items with a loading range in the interval [0.62, 0.92]. Factor 4 (Exploration ignorance) accounts for 17% of variance. This factor consists of seven items with factor loadings in the interval [0.40, 0.85]. The internal consistency of each factor is presented in Section 4.3. The Cronbach's α was in the interval [0.778, 0.861], meaning the reliability is at a statistically appropriate level (Hair et al., 2009). The EFA extracted a factor model as presented in Fig. 3.

We calculated the correlation between the 1st-order of factors as seen in Table 4. The high correlations indicate an underlying factor (Navruz et al., 2015).

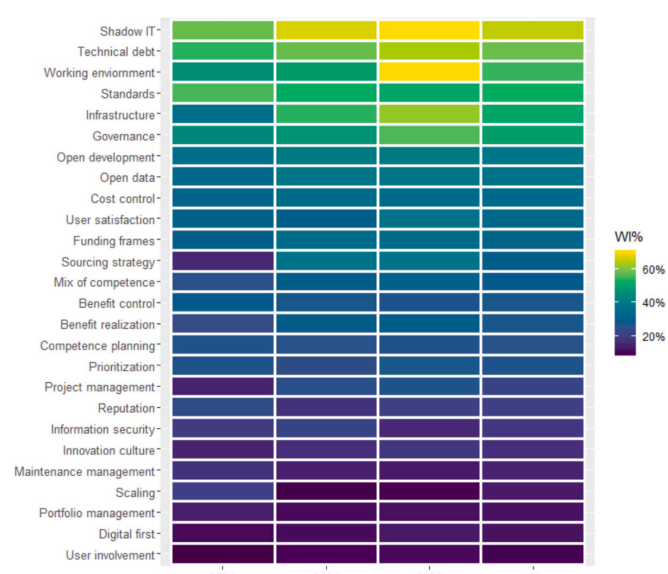

Fig. 2. Proportion of willful ignorance (WI%) per prerequisite over the years 2020, 2021, and 2022. All is the mean of the three years.

Table 3
Factor loadings from the exploratory factor analysis of 3301 responses from 2020. Factor columns have been rearranged for a pedagogical presentation.

Factor Loadings	Exploitation ignorance	Exploration ignorance	Balancing ignorance	Digital legacy ignorance	Communality
Portfolio Management	0.86	0.08	-0.01	-0.06	0.79
Maintenance Management	0.91	0.01	-0.07	0.06	0.82
Project Management	0.87	0.09	-0.01	-0.06	0.81
Sourcing Strategy	0.69	0.08	0.19	0.01	0.81
Funding Frames	0.65	-0.03	0.22	0.05	0.71
Information Security ...	0.44	0.17	0.05	0.15	0.54
Standards	0.38	0.27	0.07	0.15	0.59
User Involvement	0.06	0.85	-0.01	-0.05	0.74
Open Data	0.25	0.5	-0.03	0.03	0.50
Open Development	0.03	0.57	0.14	0.12	0.62
Innovation Culture	0.10	0.66	0.06	0.01	0.62
Digital First	0.05	0.65	0.2	-0.05	0.68
Scaling	0.01	0.71	0.23	-0.06	0.74
Prioritization	0.22	0.07	0.64	-0.03	0.74
Cost Control	0.05	0.03	0.77	0.06	0.77
Benefit Realization	-0.01	0.27	0.72	-0.05	0.82
Benefit Control	0.02	0.12	0.84	-0.04	0.86
Competence Planning	0.01	0.23	0.65	0.04	0.74
Mix of Competence	0.17	0.12	-0.14	0.68	0.63
IT-Working Environment	0.11	-0.17	-0.15	0.92	0.66
User Satisfaction	-0.17	0.24	-0.12	0.8	0.62
Reputation	-0.18	0.4	-0.08	0.62	0.56
Infrastructure	0.03	0.09	0.02	0.77	0.75
Shadow IT	0.05	-0.21	0.26	0.78	0.74
Technical Debt	-0.03	-0.21	0.32	0.84	0.82
Governance	0.11	-0.06	0.19	0.74	0.82

As a result, we calculated the factor loadings for a 2nd-order factor (See Table 5). This 2nd-order factor accounts for 69% of the total variance among the four 1st order factors, which is satisfactory (Hair et al., 2009).

Follow Gorsuch's product matrix, Table 6 presents the loadings of observed variables onto the 2nd-order factor (Digital Transformation Decoupling). We have highlighted all loadings above 0.30 similar to Table 3. This matrix reveals the factor loadings from variables onto the 2nd-order factor, enabling interpretations rooted in measurements rather than interpretations of abstractions (Gorsuch, 1983; Navruz et al., 2015).

4.2. *Hierarchical factor model of digital transformation decoupling*

The EFA extracted a factor model as presented in Fig. 3. When constructing this factor model, we included the highest factor loadings for each item, meaning the items of *Reputation* and *Technical Debt* only load onto Factor 3. The model shows five factors explaining changes in digital transformation ignorance among the 26 observed variables (Likert-items). It is divided over three levels: one 2nd-order factor, four 1st-order factors, and 26 observed variables. *Digital Transformation Decoupling* is the 2nd-order latent factor, meaning as it increases for a respondent so does ignorance related to balancing, exploitation, technology, and exploration and their associated variables. Consequently, it represents the extent to which a respondent is decoupled from digital transformation, which is further detailed below.

4.2.1. *1st-order factor 1: balancing ignorance*

Balancing refers to the core ambidextrous capability of dynamically and purposively allocating resources into exploitation or exploration activities. March (1991) notes that this capability is predictive for sustainable organizational performance, and as found by Luger, Raisch, and Schimmer (2018) this capability is less about finding the right balance but rather having the ability to swiftly and continuously re-balance in response to new contingencies. Previous research attributes balancing to either strategic management control and organizational design (Birkinshaw, Zimmermann, & Raisch, 2016; Stoiber, Matzler, & Hautz, 2022), enactment in the front-line of the organization (Zimmermann, Raisch, & Cardinal, 2018) or to a mix of these two (Cannaerts, Segers, & Warsen, 2019). As found in Magnusson, Khisro, and Melin (2020) in a study of balancing practices within two government agencies, balancing in relation to digital transformation is often biased toward exploitation, detrimentally impacting organizational ambidexterity.

4.2.2. *1st-order factor 2: exploitation ignorance*

Exploitation refers to the types of activities that are geared toward exploiting existing opportunities, i.e., low-risk activities where the expected outcomes are known and have little direct impact in terms of changes for the organization's strategy (March, 1991). As argued by Benner and Tushman (2003), exploitation is equatable with efficiency, i. e., minimal inputs for maximal outputs. Several previous studies have identified a general tendency in public sector organizations to overemphasize exploitation over exploration (Cannaerts et al., 2019; Magnusson et al., 2020, c; Palmi, Corallo, Prete, & Harris, 2021; Rose, Persson, Heeager, & Irani, 2015), increasing the risks of what is referred to as the competency or success trap within organizational ambidexterity (Levinthal & March, 1993).

4.2.3. *1st-order factor 3: digital legacy ignorance*

Digital legacy refers to the underlying digital infrastructure (e.g., legacy systems and other technological artefacts and their governance) that either facilitates or constrains digital transformation (Irani, Abril, Weerakkody, Omar, & Sivarajah, 2022; Khisro, Lindroth, & Magnusson, 2021; Rolland, Mathiassen, & Rai, 2018). As noted in previous research, the core technological aspects of digital transformation are perceived as relevant primarily for practitioners involved as experts in IS departments or similar (Edelmann et al., 2023). This is also found in the general digital transformation literature highlighting that digital transformation "is not about technology" (Escobar, Almeida, & Varajão, 2022; Frennert, 2019; Warner & Wäger, 2019), as well as in the literature surrounding governance where "IT championship" is argued for, i. e., avoiding the relinquishing of control over technology-related issues by the IS department (Gregory, Keil, Muntermann, & Mähring, 2015; Park, Son, & Angst, 2023).

4.2.4. *1st-order factor 4: exploration ignorance*

Exploration refers to the types of activities that are geared toward exploiting new opportunities, i.e., high-risk activities where the

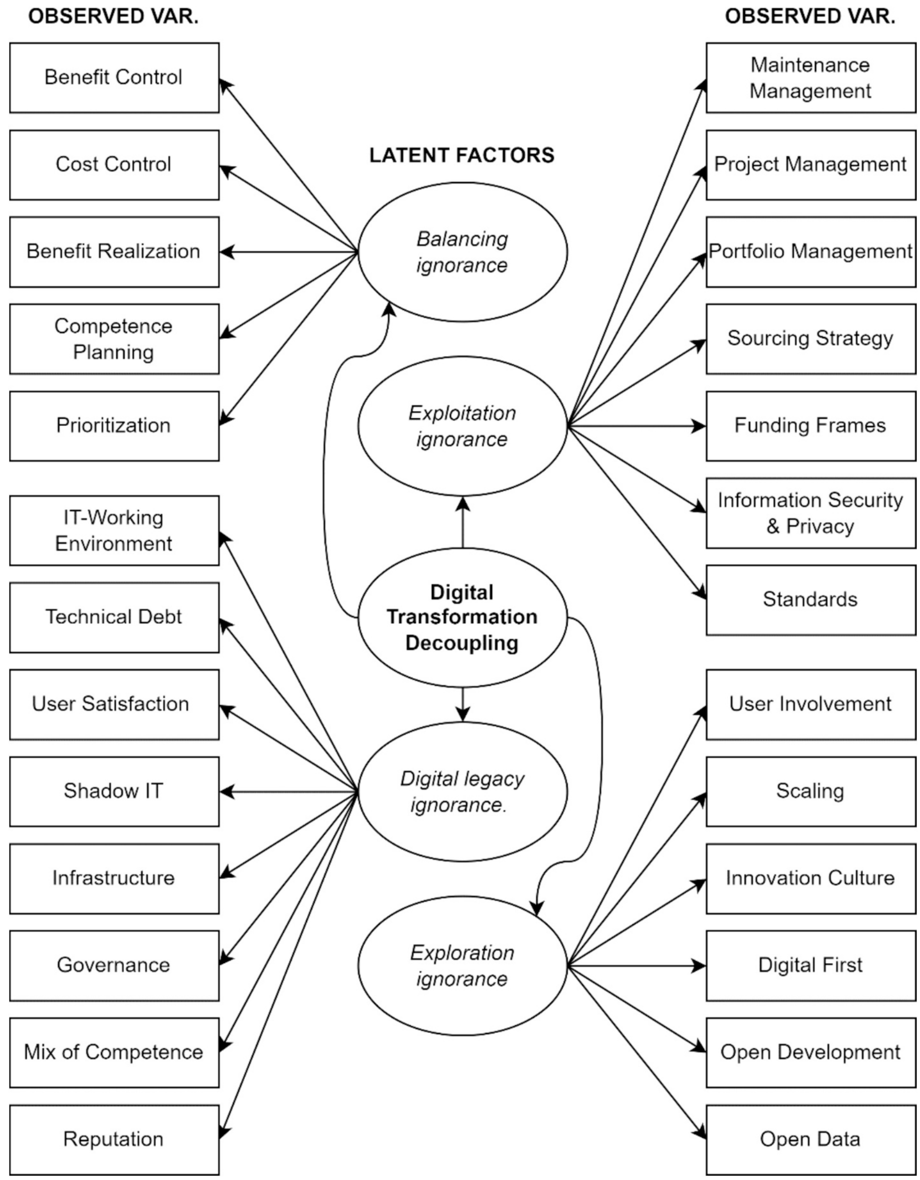

Fig. 3. Factor model for digital transformation decoupling in the public sector.

Table 4
1st-order factor correlations.

1st-*order* Factor Correlations	Digital legacy ignorance	Exploitation ignorance	Exploration ignorance	Balancing ignorance
Digital legacy ignorance	1	0.65	0.63	0.61
Exploitation ignorance		1	0.74	0.77
Exploration ignorance			1	0.72
Balancing ignorance				1

Table 5
2nd-order factor loadings.

2nd-order Factor Loadings	Digital legacy ignorance	Exploitation ignorance	Exploration ignorance	Balancing ignorance
Digital Transformation Decoupling	0.73	0.89	0.84	0.86
Communality	0.53	0.89	0.84	0.86

expected outcomes are not known (March, 1991). In line with Benner and Tushman (2003), exploration is equatable with innovation. Previous research highlights challenges associated with innovation in the public sector (Cinar, Trott, & Simms, 2019; Hong, Kim, & Kwon, 2022), yet at the same time it is perceived to be an absolute necessity for sustained relevance and operations.

4.2.5. 2nd-order factor: digital transformation decoupling

As noted by Meyer and Rowan (1977), organizations display a tendency for decoupling their formal and informal structures. This decoupling affords the organization to say one thing and do another, in the quest for assuring legitimacy in the eyes of its external stakeholders and avoid fundamental changes (Baptista, Wilson, & Galliers, 2021; Martinez & Dacin, 1999). In other words, decoupling implies a misalignment between the formal and informal that is used to create leeway and flexibility for the organization in its operations. In a population study of the digital transformation strategies of Swedish municipalities, Norling,

Table 6
The Gorsuch's product matrix of the observed variables loading to the 2nd-order factor. Factor columns have been rearranged for a pedagogical presentation.

Factor loadings from variables to 2nd order factor	Digital Transformation Decoupling
Sourcing Strategy	0.84
Benefit Realization	0.81
Benefit Control	0.81
Maintenance Management	0.80
Project Management	0.80
Portfolio Management	0.79
Funding Frames	0.78
Prioritization	0.78
Cost Control	0.78
Competence Planning	0.78
Scaling	0.76
Governance	0.75
Digital First	0.74
Standards	0.73
User Involvement	0.73
Open Development	0.71
Innovation Culture	0.70
Information Security ...	0.69
Infrastructure	0.68
Technical Debt	0.68
Shadow IT	0.66
Open Data	0.64
Mix of Competence	0.63
Reputation	0.56
User Satisfaction	0.53
IT-Working Environment	0.50

Lindroth, Magnusson, and Torell (2022) identify the existence of what they refer to as "digital decoupling" to explain the discrepancy between the actual allocation of resources (heavily geared toward internal efficiency) and the overarching jargon of digital transformation (balanced between internal efficiency and external innovation). We define digital transformation decoupling as a mechanism that affords organizational members the assurance of legitimacy despite not amply acting to assure digital transformation. In this vein, the process of digital transformation is decoupled from the attainment of the necessary prerequisites for digital transformation.

4.3. Evaluation

The above factor model was evaluated on a sample of 6027 responses and another sample of 11, 023 responses, collected in the time interval $t_2 = [2021, 2022]$. We tested the model's dimensionality, reliability, and validity (Boateng, Neilands, Frongillo, Melgar-Quiñonez, & Young, 2018).

The test of dimensionality assesses a hypothesized factor structure by determining if the structure is the same across two independent samples or within the same sample at different time points (Boateng et al., 2018). For this purpose, we applied Confirmatory Factor Analysis (CFA) that tests how well a prespecified measurement model fits collected data (Hair et al., 2009). We used the model fit indices of: Tucker-Lewis Index (Bentler & Bonett, 1980), Comparative Fit Index (Bentler & Bonett, 1980), the Root Mean Square Error of Approximation (Steiger, 1990), and the Standardized Root Mean Residual (Hu & Bentler, 1999). These model fit indices have previously been used within digital government research to test dimensionality (Lee, Lee-Geiller, & Lee, 2021). Following the accepted values provided by Boateng et al. (2018), the model fit indices indicate a good model fit for the two years as seen in Table 7.

The **test of reliability** assesses the degree of consistency exhibited when a measurement is repeated (Boateng et al., 2018). We tested the reliability of the 1st-order factors and the 2nd-order factor, using Cronbach's α (Cronbach, 1951). Table 8 presents the measured α coefficients, each above the acceptable threshold of 0.70 (Boateng et al., 2018).

Table 7
Factor model goodness-of-fit tests for data from 2021 and 2022. Accepted values from Boateng et al. (2018).

Fitness CFA Test	2021	2022	Accepted values
Root Mean Square Error of Approximation	0.039	0.037	≤ 0.06
Tucker-Lewis Index	0.993	0.993	≥ 0.95
Comparative Fit Index	0.993	0.994	≥ 0.95
Standardized Root Mean Square Residual	0.048	0.050	≤ 0.08

Table 8
Internal consistency of the survey over the years 2020–2022.

Cronbach's alpha	2020	2021	2022
Digital transformation decoupling	0.966	0.959	0.962
Digital legacy ignorance	0.861	0.840	0.850
Exploitation ignorance	0.841	0.816	0.805
Exploration ignorance	0.778	0.773	0.786
Balancing ignorance	0.861	0.857	0.851

The **test of validity** assesses the extent to which the survey measures the latent factors of the factor model (Boateng et al., 2018). We applied five tests of validity as presented below. First, the model fit indices of the CFA passed the acceptable values (See Table 7). Second, convergent validity was tested by comparing factor loadings with standard error for all factors. A factor loading twice its standard error is appropriate (Anderson & Gerbing, 1988). All 1st-order and 2nd-order factors have factor loadings twice their standard error (See Table 9).

Third, we also tested convergent validity by calculating the average variance extracted (AVE) for each 1st-order factor for the two years

Table 9
The factor loadings for the data of 2020, 2021, and 2022 against the factor model. Standard error is included for the CFAs. EFA = Exploratory Factor Analysis. CFA = Confirmatory Factor Analysis.

Factor Loadings (CFA standard error)	2020 (EFA)	2021 (CFA)	2022 (CFA)
Exploitation ignorance			
Portfolio Management	0.86	0.86 (0.011)	0.81 (0.012)
Maintenance Management	0.91	0.86 (0.011)	0.85 (0.012)
Project Management	0.87	0.83 (0.011)	0.78 (0.011)
Sourcing Strategy	0.69	0.79 (0.010)	0.78 (0.011)
Funding Frames	0.65	0.82 (0.011)	0.81 (0.012)
Information Security & Privacy	0.44	0.75 (0.010)	0.73 (0.010)
Standards	0.38	0.78 (0.010)	0.79 (0.011)
Exploration ignorance			
User Involvement	0.85	0.82 (0.010)	0.81 (0.008)
Open Data	0.50	0.70 (0.009)	0.71 (0.008)
Open Development	0.57	0.83 (0.011)	0.83 (0.009)
Innovation Culture	0.66	0.82 (0.010)	0.83 (0.009)
Digital First	0.65	0.85 (0.011)	0.84 (0.009)
Scaling	0.71	0.85 (0.011)	0.88 (0.009)
Balancing ignorance			
Prioritization	0.64	0.89 (0.009)	0.87 (0.008)
Cost Control	0.77	0.87 (0.009)	0.85 (0.007)
Benefit Realization	0.72	0.90 (0.009)	0.90 (0.008)
Benefit Control	0.84	0.90 (0.009)	0.88 (0.008)
Competence Planning	0.65	0.88 (0.009)	0.88 (0.008)
Digital legacy ignorance			
Mix of Competence	0.68	0.79 (0.005)	0.76 (0.004)
IT-Working Environment	0.92	0.66 (0.004)	0.80 (0.004)
User Satisfaction	0.80	0.70 (0.005)	0.70 (0.004)
Reputation	0.62	0.70 (0.005)	0.70 (0.004)
Infrastructure	0.77	0.90 (0.005)	0.91 (0.004)
Shadow IT	0.78	0.88 (0.005)	0.88 (0.004)
Technical Debt	0.84	0.88 (0.005)	0.89 (0.004)
Governance	0.74	0.92 (0.005)	0.92 (0.004)
Digital transformation decoupling			
Exploitation ignorance	0.89	0.95 (0.142)	0.97 (0.249)
Exploration ignorance	0.84	0.93 (0.086)	0.94 (0.084)
Balancing ignorance	0.86	0.93 (0.074)	0.94 (0.071)
Digital legacy ignorance	0.73	0.78 (0.013)	0.76 (0.004)

where the acceptable level is above 0.50 (Fornell & Larcker, 1981). Table 10 presents these AVE, which are all on an acceptable level.

Fourth, for testing convergent validity against divergent validity, we calculated the correlation among and between the factors, expecting them to correlate as it indicates the existence of an underlying 2nd-order factor (Barthes, 1987). Table 11 presents the correlations among and between the 1st-order and 2nd-order factors for survey data of 2021 and 2022. We have highlighted correlations related to the 2nd-order factor, clarifying the separation between the different orders.

Fifth, to assess discriminant validity, we examined the distribution of the factory model over one known binary item (Boateng et al., 2018): experts and non-experts (see Table 2). Experts are expected to have overall lower scores than non-experts since they are involved in decisions regarding digitalization (Crusoe et al., 2023). We assessed the mean score differences between these two groups using Welch's *t*-test and Cohen's d (Cohen, 2013; Welch, 1947). Table 12 presents the results, indicating the factor model as able to differentiate well between the two groups as all effect sizes are above a magnitude of medium (0.50) and all *p*-values below 0.05.

Together, the above tests of dimensionality, reliability, and validity indicate an appropriate factor model. The test of dimensionality indicates that the factor model has a good fit with the two survey samples from 2021 and 2022. The reliability test shows a high degree of consistency for the measurements, while the tests of validity indicate that the surveys measure the latent factors of the model, but also its ability to differentiate between respondents with expertise and not. As a result, following the factor model, the observed variables were aggregated as scores for the latent factors. Fig. 4 presents the mean proportions of respondents for the latent factors grouped by experts and non-experts, highlighting the difference between the two groups. This figure provides a better oversight over measured differences than Fig. 2 with limited loss of information.

5. Discussion

The latent factors identified in Section 4 confirm the existence of an underlying structure in the frequencies of willful ignorance in the three samples. Utilizing this finding, we identify latent factors that capture the existence of willful ignorance in public sector digital transformation. Based on the factor model (See Fig. 3), we propose a mid-range variance theory of digital transformation decoupling that provides organizations and researchers with a basis for capturing and understanding the relationship between different forms of ignorance related to digital transformation, i.e., the negative knowledge of prerequisites for digital transformation. Based on this theory, we contribute to existing and future research into the role of ignorance in public sector digital transformation as well as improved practice.

5.1. Digital transformation decoupling propositions

As argued by previous research, individual level competence is a dimensioning factor in digital transformation success (Edelmann et al., 2023; Mankevich et al., 2023). At the same time, research has also identified the purposiveness of ignorance, i.e., a function of willful ignorance (Alvesson et al., 2022). Related to digital transformation, we argue that the value of an empirical entry-point into civil servant willful ignorance offers both research and practice a novel and valuable

Table 10
Average variance extracted for the 1st-order factors given the data from 2021 and 2022.

AVE	Digital legacy ignorance	Exploitation ignorance	Exploration ignorance	Balancing ignorance
2021	0.655	0.659	0.657	0.785
2022	0.678	0.632	0.669	0.765

approach to digital transformation. Given the identification and evaluation of the latent factors, we can expect to see certain patterns emerging in organizations related to their distribution of willful ignorance. We use these patterns to identify propositions for future research.

In line with Wessel et al. (2021), we see that the digital transformation decoupling can be linked to issues pertaining to identity work. If the organization is set on true transformation, this would imply a change not only to the operations but simultaneously to the very identity of the organization. Here, digital transformation decoupling functions as a mechanism for the avoidance of identity work and the existence of willful ignorance can hence be seen as an indicator of said avoidance. Based on this, we propose a first proposition.

Proposition 1. *Digital transformation decoupling is negatively associated with digital transformation identity work.*

In lieu of the study of digital government, Selten and Klievink (2024) find that the adoption of AI challenges the identity of public sector organizations. Here, the first proposition highlights the role of willful ignorance and digital transformation decoupling as detrimental factors for the necessary identity work involved in adopting AI. According to Selten and Klievink, structural separation and contextual integration should be regarded as complementary mechanisms for mitigating the difficulties in identity work, whereas our findings offer a different approach to the underlying problem. This challenge of AI adoption is also tightly related to cultural identities, as found in Guenduez and Mettler (2022) in their study of government policies. As we expect to see an increased adoption and use of AI in public sector digital transformation, we also expect to see the difficulties associated with identity work increase.

Essén et al.'s (2022) work on facilitating factors for willful ignorance opens for an additional set of propositions. With both the facilitating factors and digital transformation decoupling empirically linked to the frequency of ignorance, we propose a second proposition.

Proposition 2. *Digital transformation decoupling is positively associated with the presence of facilitators of willful ignorance.*

This second proposition highlights the recursive role of digital transformation decoupling, indicating that it will act as a generative mechanism for willful ignorance. In other words, willful ignorance is self-enforcing, leading to additional consequences for public sector organizations over time. One of these consequences can be found in the long-term development of digital sovereignty. Here, Jansen et al. (2023) find that a decoupling of national security policies and IT provisioning decreases digital sovereignty, calling for a necessary integration of national security policies and policy work into IT provisioning, refraining from structural separation.

The third and fourth propositions link digital transformation decoupling to digital transformation practice. With Essén et al.'s (2022) four identified facilitating factors (fragmented accountability, laissez-faire professionalism, technological development, and external admiration) impacting either the scope or pace of digital transformation, we propose a third and fourth proposition.

Proposition 3. *Digital transformation decoupling is positively associated with lower scope of digital transformation.*

Proposition 4. *Digital transformation decoupling is positively associated with lower pace of digital transformation.*

As found by Distel and Lindgren (2023), e-government adoption pushes for divergent rather than convergent roles of citizens, calling for a necessity to cater to an increasing pluralism and diversity in citizen user types. This would in turn call for increased scope of digital transformation, whereby digital transformation decoupling will be detrimental for public sector organizations. In addition to this, decreased scope as well as decreased pace directly hinders the necessary modernization of digital infrastructure as called for by Irani et al.

Table 11
The correlations between 1st-order and 2nd-order factors for the CFA. The top half is for the year of 2021, while the bottom half is for 2022.

	Digital transformation decoupling	Digital legacy ignorance	Exploitation ignorance	Exploration ignorance	Balancing ignorance
Digital Transformation Decoupling	1	0.78	0.95	0.93	0.93
Digital legacy ignorance	0.76	1	0.75	0.73	0.73
Exploitation ignorance	0.97	0.73	1	0.88	0.89
Exploration ignorance	0.94	0.71	0.91	1	0.86
Balancing ignorance	0.94	0.71	0.91	0.88	1

Table 12
The results of the Welch's t-test and Cohen's d for the means of the factors over the years 2020, 2021, and 2022. DL = digital legacy ignorance. ET = exploitation ignorance. ER = exploration ignorance. BL = balancing ignorance. DTD = digital transformation decoupling.

	Mean		SD		Welch's t-test			Cohen's d	
Factor	*Expert*	*Non-expert*	*Expert*	*Non-expert*	*T*	*DF*	*P-value*	*Effect size*	*Magnitude*
2020									
DL	2.81	4.61	2.62	2.56	-16.93	1270	<2e-16	0.696	Moderate
ET	1.25	3.07	1.60	2.45	-19.31	985.5	<2e-16	0.881	Large
ER	0.95	2.27	1.34	1.93	-17.61	986.4	<2e-16	0.794	Moderate
BL	0.96	2.78	1.50	1.95	-23.65	1039	<2e-16	1.04	Large
DTD	5.98	12.74	5.74	7.40	-23.17	1044	<2e-16	1.02	Large
2021									
DL	3.22	4.74	2.55	2.44	-19.69	2140	<2e-16	0.609	Moderate
ET	1.57	3.43	1.75	2.38	-26.27	1720	<2e-16	0.890	Large
ER	0.98	2.30	1.29	1.89	-23.57	1641	<2e-16	0.812	Large
BL	1.05	2.79	1.55	1.95	-29.67	1771	<2e-16	0.988	Large
DTD	6.82	13.26	5.87	7.32	-29.19	1780	<2e-16	0.970	Large
2022									
DL	3.83	5.17	2.59	2.44	-22.69	4136	<2e-16	0.531	Moderate
ET	1.52	3.16	1.71	2.27	-31.99	3218	<2e-16	0.813	Large
ER	1.00	2.35	1.30	1.97	-31.16	3008	<2e-16	0.812	Large
BL	1.05	2.72	1.53	1.94	-37.87	3303	<2e-16	0.953	Large
DTD	7.40	13.40	5.82	7.32	-36.1	3327	<2e-16	0.906	Large

Fig. 4. The mean proportions are divided over year and expertise, following the factor model.

(2022). Here, digital transformation decoupling directly counteracts organizational capabilities for digital infrastructure modernization that in essence is both cross- and inter-organizational. Concerning the inter-organizational and other collaborative aspects of digital transformation, multiple studies have identified this as holding immense promise for digital government per se (e.g., Scupola & Mergel, 2022). Furthermore Gasco-Hernandez, Gil-Garcia, and Luna-Reyes (2022) find that collaboration requires sound technical insight, indicating that digital transformation decoupling will be detrimental to collaborative arrangements. In terms of the identified decrease of the pace in digital transformation, Moser-Moser-Plautz and Schmidthuber (2023) notes that pre-covid 19 characteristics and exposure to a necessity for digital transformation has increased the performance spread of digital transformation in public sector organizations. Digital transformation decoupling will in this regard function along the same lines, i.e., increasing the performance spread.

The fifth proposition links digital transformation decoupling to the type of decoupling seen as a core principle within strategies for organizational ambidexterity. According to previous studies, organizations striving for ambidexterity can pursue a decoupling between exploration and exploitation either sequentially (e.g., innovation sprints), structurally (e.g., innovation hubs) or contextually (e.g., individual decision to focus on innovation). While most studies perceive the positive notions of applying a combination of these strategies (Cannaerts et al., 2019; Peng, 2019; Smith & Umans, 2013; Stoiber et al., 2022), our study highlights a relationship between digital transformation decoupling and the modes of separation implied by the strategies for ambidexterity. In instances where exploration is functionally separated into a separate organizational entity, the co-workers may see exploration as "handled elsewhere", i.e., not see it as a necessary element of their everyday work. Hence, we will see levels of ignorance related to exploration or exploitation distribute across the organization, leading to increased levels of digital transformation decoupling. Since digital transformation is acknowledged as a type of activity involving both exploration and exploitation (Hanelt et al., 2021; Mergel et al., 2019), this leads to potential caveats for performance and our fifth proposition.

Proposition 5. *Digital transformation decoupling is positively associated with ambidextrous decoupling.*

The perils of ambidextrous decoupling are shown in numerous studies of digital government. Zhang and Mora (2023) show how symbolic compliance with state level policies decouple the transformative aspects of digital transformation, i.e., decoupling exploration from exploitation as a means for avoiding changes to core operations. A similar line of argument is found in Van Noordt and van Noordt and Tangi (2023), where AI capability dynamics require bridging exploration and exploitation capabilities to avoid fragility over time. With digital transformation decoupling positively associated with ambidextrous decoupling, it is directly detrimental for sustainable performance. This is also supported in studies of agile approaches in digital government, where e.g., Baxter, Dacre, Dong, and Ceylan (2023) show how said approach changes the institutional environment in government IT projects, pushing for a "one team culture" and teams becoming "mission collaborator". This in turn places significant importance on the avoidance of ambidextrous decoupling as agile approaches grow increasingly commonplace.

Finally, we expect to see a tendency for decoupling the digital (i.e., digital infrastructure and other technical aspects of digital transformation) from digital transformation. This leads to the sixth and final proposition.

Proposition 6. *Digital transformation decoupling is positively associated with digital decoupling.*

This has previously been addressed indirectly in the literature through a call for strong IT-championship (Gregory et al., 2015; Gregory, Kaganer, Henfridsson, & Ruch, 2018), yet we argue that this approach to solving the biased distribution of technological competence in the organization is detrimental to long term success (See Magnusson, Elliot, & Hagberg, 2021). Instead of accepting the existing division of labor where technical issues are handled through expert functions such as IT, the existence of this aspect of decoupling should be directly alleviated. If digital transformation is less of what Wessel et al. (2021) would refer to as "IT-enabled organizational transformation" and more of digital transformation as e.g., defined by Mergel et al. (2019), then continued decoupling of technical competence is directly counterproductive for the aspired change (Ongena, 2023). This is also supported in the work of Hein et al. (2023) on open government data ecosystems where there is a need to integrate contextual relevance and technical issues directly to avoid detrimental, long-term effects on the value of the ecosystem. The factor model and subsequent six propositions for future research are summarized in Fig. 5.

We urge future research to explore these six propositions further. While this study is quantitative, we call for additional research utilizing both qualitative and computationally intensive methods in addressing the propositions. As for the qualitative, we hope to see research that through either ethnographic observation or interview studies strive for a richer basis for understanding both the micro-foundations and consequences of willful ignorance. Here, we see the work conducted by Essén et al. (2022) as a potential source for inspiration through their combination of qualitative methods to address the act of ignoring in organizations. As for the computationally intensive methods, we hope to see research that utilizes non-traditional sources of data such as external and internal communications, minutes and other forms of manifestations of organizational "talk". Here, we see the work conducted by Miranda, Wang, and Tian (2022) on discursive fields as a potential source for inspiration for future studies.

6. Contributions and implications

Our study offers three main contributions to research. First, we identify the existence of willful ignorance on public sector digital transformation. Second, we present a validated factor model for how willful ignorance impacts public sector digital transformation. Third, we present a set of propositions to guide future research into public sector digital transformation and its links to ignorance. These propositions offer both explanations for why the current state of public sector digital transformation unfolds, and a basis for predicting future patterns in digital transformation. As such, we identify willful ignorance as a core factor impacting public sector digital transformation, complementing alternative perspectives to ignorance in previous digital government studies (Alshahrani et al., 2022; Holzer, 2022; Trüdinger & Steckermeier, 2017; van Twist et al., 2023; Weigl et al., 2023).

In addition to these contributions to research, our study also has two main contributions to practice. First and foremost, given the explanatory value of ignorance in relation to the organization's capability for digital transformation, we suggest that public sector organizations initiate conscious and direct measurements of potential willful ignorance in their organizations. As found in our study, the existence of willful ignorance is empirically probable, and given its detrimental impact on digital transformation performance it should be managed explicitly. We suggest that public sector organizations utilize our study of digital transformation prerequisites and our method for calculating ignorance as a source of inspiration for creating bespoke methods for management for decreasing the level of ignorance. In doing so, however, we urge organizations to consider the limitations of quantitative measures of willful ignorance and to refrain from over-simplified perceptions of the meaning of these measures. Second, given the identified digital transformation decoupling mechanism found in the study, we propose that public sector organizations use these to reflect on their own governance setups. In line with previous literature (Essén et al., 2022; Janssen & van der Voort, 2016b; Magnusson, Päivärinta, & Koutsikouri, 2020), current configurations of governance are likely to enforce detrimental forms of decoupling. This would call for revisions of existing governance to counteract digital transformation decoupling.

Our study also has one core contribution to policy. If policymakers seek to ameliorate digital transformation decoupling, they should present unified policies following the factor model. If policies are divided by content or topic, there is a risk that public organizations divide any bestowed responsibility among different members in various roles, introducing further digital transformation decoupling through division of labor. A policy should emphasize the need for experts to acquire knowledge covering the latent factors of the factor model, but also emphasize the need to inform non-experts about the organization's digital transformation prerequisites (see Keating, 1975). Ignorant non-experts may fail to leverage present digital transformation prerequisites to drive digital innovation for their benefit. It is also possible

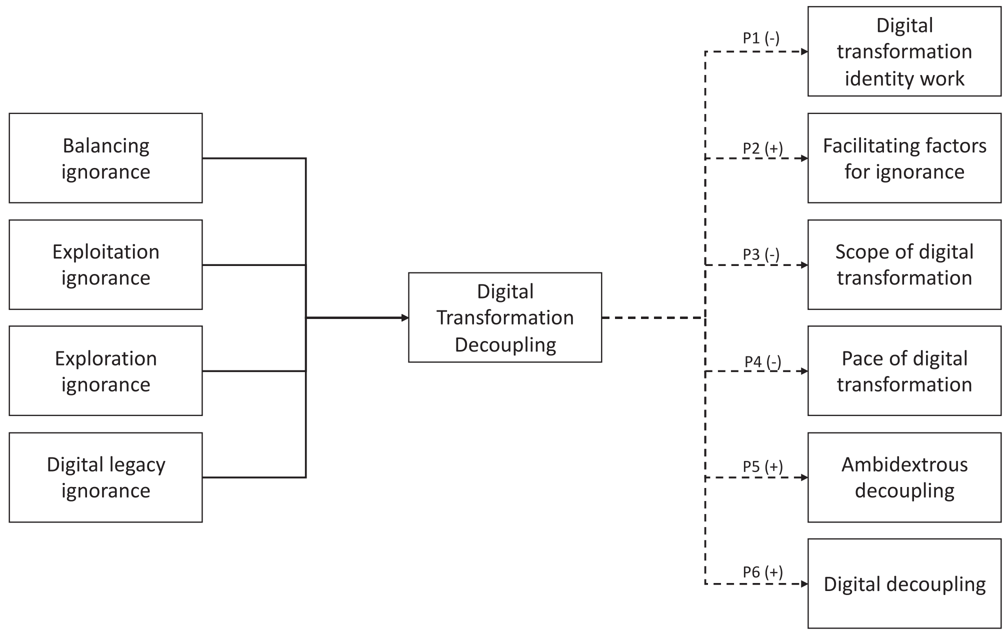

Fig. 5. Overview of digital transformation decoupling with 1st -order factors with propositions.

that experts and non-experts base digital transformation on assumptions about the quality of present digital transformation prerequisites, putting digital transformation projects and programs at risk of being impeded by, for example, shadow IT or lack of competencies.

6.1. Limitations

There are five main limitations of our research. First and as acknowledged by Bannister (2007), studies in public sector settings are associated with difficulties related to transferability and generalizability. Given the innate differences in terms of institutional settings in e.g., different countries, we acknowledge that the empirical patterns identified in our study may and most likely will differ in another setting. Second, the surveys focused on the self-assessed achievement of digital transformation prerequisites and not explicitly willful ignorance. Rather, this is captured through “don't know” answers, meaning the survey focuses on apparent characteristics (e.g., knowledge, skills, and behaviors) rather than underlying attributes (e.g., traits, motives, attitudes, and values) (Salman et al., 2020). These approaches together with the binary character of “don't know” answers implies that an observed variable is a rough estimate of a respondent's underlying competency. However, by combining several observed variables, following the factor model, we partly reduce this limitation and regain some graduality. Third, regarding the construct validity of the study, it should be observed that factor analysis involves non-deterministic decisions and interpretations that affect the conclusions of the study. These parameters include the number of selected factors, the rotation method used, and the qualitative interpretation of the factors. However, these decisions were strictly based on criteria and practices proposed in established theory on factor analysis but also on qualitative considerations based on the field of study (e.g., Magnusson & Nilsson, 2020). Fourth, there is a limitation to the organizational distribution of participants. The majority of respondents were from municipalities, meaning the factor model can be skewed toward a Swedish municipal representation. If the model is used with respondents from non-municipal organizations or other countries, it should be tested for goodness-of-fit (see Table 7). Fifth, the used sampling technique of pay-for-survey influences the sample. Public organizations who are invested in digital maturity are more likely to pay for the survey, while organizations who are disinterested or perceive themselves to be in a good maturity are less likely to participate. A consequence is that the sample probably lacks responses from two extremes: (1) organizations with high willful ignorance and (2) organizations with no or little ignorance. In addition, internally to the organization, an administrator selects respondents following a recommendation. We have limited control over who is included for or excluded from the survey, introducing some uncertainty regarding representativeness. The feedback loop together with the payment should ensure that the administrator selects relevant participants for their organization and, in the end, our research. Moreover, the factor model has stable good fit over two years of samples (see Table 7) even when the number of organizations and respondents differ. It aligns with previous research and can differentiate between experts and non-experts. It was constructed using samples from a Swedish context, but we are confident that our analytical approach can be applied in the context of other countries with further validation.

CRediT authorship contribution statement

Jonathan Crusoe: Conceptualization, Data curation, Formal analysis, Methodology, Project administration, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. **Johan Magnusson:** Conceptualization, Formal analysis, Funding acquisition, Validation, Writing – original draft, Writing – review & editing. **Johan Eklund:** Formal analysis, Methodology, Software, Validation, Writing – review & editing.

Declaration of competing interest

None.

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Appendix A. Survey questions

Information within [*] is not part of the survey but provides information relevant for this article. For Q3 to Q28, respondents can either select an answer on a Likert item with six alternatives or don't know

(DK). The alternatives ranged from strongly disagree to strongly agree with no middle option (neutral). However, in this article, we understand this choice as binary either respondents provide an answer or select DK. In addition, the questions have been translated from Swedish to English.

A.1. Demographic questions

- **Q1:** Are you involved in the decisions related to your organization's digitalization?
  o Yes [Respondent is considered as expert]
  o No [Respondent is considered as non-expert]
- **Q2:** What role do you have?
  o CEO/Director
  o Political leadership
  o Middle manager
  o First-line manager
  o Administrative officer
  o Other
- **Q3 [Portfolio Management]:** As an organization, we have a very good overview of all the organization's digital initiatives, as well as insight into how these initiatives support the business' objectives.
- **Q4 [Maintenance Management]:** As an organization, we have a very well-functioning system administration.
- **Q5 [Project Management]:** As an organization, we have a very well-functioning project management methodology.
- **Q6 [Sourcing Strategy]:** As an organization, we have a very well-functioning strategy for how we support ourselves with IT from e.g. cloud providers.
- **Q7 [Funding Frames]:** As an organization, we have sufficient financial resources to ensure long-term efficient management of our systems.
- **Q8 [Information Security]:** As an organization, we have a very high level of information security and guaranteed personal privacy for our users.
- **Q9 [Standards]:** As an organization, we have full compliance with open standards for both system development and system management.
- **Q10 [User Involvement]:** As an organization, we are very good at involving users in the development of digital services and solutions.
- **Q11 [Open Data]:** As an organization, we are very good at using and providing open data.
- **Q12 [Open Development]:** As an organization, we are very open to involving external development partners in the development of digital solutions.
- **Q13 [Innovation Culture]:** As an organization, we have a culture that strongly promotes innovation.
- **Q14 [Digital First]:** As an organization, we are very good at always thinking digitally first when we develop the organization.
- **Q15 [Scaling]:** As an organization, we are very good at spreading new digital solutions so that they are adopted by the entire organization.
- **Q16 [Prioritization]:** As an organization, we have a very well-functioning prioritization process for digital investments that enables both innovation and efficiency.
- **Q17 [Cost Control]:** As an organization, we have full control over costs related to the digital.
- **Q18 [Benefit Realization]:** As an organization, we are very good at bringing home/realizing the benefits of our digital investments.
- **Q19 [Benefit Control]:** As an organization, we are very good at consistently measuring and following up the impact of our digital investments.
- **Q20 [Competence Planning]:** As an organization, we are very good at ensuring long-term access to relevant digital competencies.
- **Q21 [Mix of Competence]:** Our IT-department (or similar organization responsible for delivering IT) has a very good mix of competencies among employees that allows us to use technology's full potential.
- **Q22 [IT-Working Environment]:** Our IT-department (or similar organization responsible for delivering IT) has a very good working environment.
- **Q23 [User Satisfaction]:** Our IT-department (or similar organization responsible for delivering IT) has very satisfied users.
- **Q24 [Reputation]:** Our IT-department (or similar organization responsible for delivering IT) has a very strong and positive reputation within the organization.
- **Q25 [Infrastructure]:** Our IT-department (or similar organization responsible for delivering IT) has a cost-effective infrastructure that enables innovation and rapid development.
- **Q26 [Shadow IT]:** Our organization's IT department is aware of all our use of different IT solutions (that is, there are no solutions that are not known and/or approved by the IT department).
- **Q27 [Technical Debt]:** Our IT-department (or similar organization responsible for delivering IT) has a very low level of technical debt (e.g., deficient system documentation and deferred development).
- **Q28 [Governance]:** Our IT-department (or similar organization responsible for delivering IT) has a very good governance that provides both control and conditions for innovation.

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