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RESEARCH PAPER

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Designing Social Nudges for Enterprise Recommendation Agents: An Investigation in the Business Intelligence Systems Context

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Abstract

According to behavioral economists, a "nudge" is an attempt to steer individuals toward making desirable choices without affecting their range of choices. We draw on this concept, and design and examine nudges that exploit social influence's effects to control individuals' choices. Although recommendation agent research provides numerous insights into extending information systems and assisting end consumers, it lacks insights into extending enterprise information systems to assist organizations' internal employees. We address this gap by demonstrating how enterprise recommendation agents (ERAs) and social nudges can be used to tackle a common challenge that enterprise information systems face. That is, we use an ERA to facilitate information (i.e., reports) retrieval in a business intelligence system. In addition, we use social nudges to steer users toward reusing specific recommended reports rather than choosing between recommended reports randomly. To test the effects of the ERA and the four social nudges, we conduct a within-subject lab experiment using 187 participants. We also conduct gaze analysis ("eye tracking") to examine the impact of participants' elaboration. The results of our logistic mixed-effects model show that the ERA and the proposed social nudges steer individuals toward certain choices. Specifically, the ERA steers users toward reusing certain reports. These theoretical findings also have high practical relevance and applicability: In an enterprise setting, the ERA allows employees to reuse existing resources (such as existing reports) more effectively across their organizations because employees can more easily find the reports they actually need. This, in turn, prevents the development of duplicate reports.

Keywords: Behavioral Economics, Nudge, Social Influence, Recommender System, Workaround Systems, Laboratory Experiment, Eye Tracking, Elaboration

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1 Introduction

Employees in many organizations supplement their information systems (IS) with additional workaround systems (WS) to adapt their IS to daily work routines (Alter, 2014; Jasperson, Carter, & Zmud, 2005). For instance, employees frequently supplement their organizations' core business intelligence systems (BIS) with spreadsheet applications when preparing business reports (Burton-Jones & Grange, 2013; Davenport, 2014; Li, Hsieh, & Rai, 2013). Generally, such WS are considered flexible and are very popular with end users (Bagayogo, Lapointe, & Bassellier, 2014; Sun, 2012; Gass, Ortbach, Kretzer, Maedche, Niehaves, 2015). Since many employees have the expertise required to develop and/or change WS, the latter are well suited to implementing emerging requirements rapidly (Alter, 2014). For instance, using spreadsheet applications, many users can quickly and easily extend a report with additional fields (Panko & Aurigemma, 2010; Powell, Baker, &

Lawson, 2008, 2009). However, from an organization's perspective, the development and use of supplementary WS creates problems, such as the limited reuse of reports,[1] inconsistent data, and poor decision-making if decisions are based on outdated and erroneous data (e.g., Brazel & Dang, 2008; Tyre & Orlikowski, 1994). In addition, the use of WS may also lead to flawed and nonstandard routines and procedures (Alter, 2014).

To address these challenges, the extant literature has focused on two IS governance-based approaches (Tiwana & Kim, 2015). For the first approach, researchers focus on reducing the generation and use of WS by defining IS governance policies and enforcing compliance (Liang, Xue, & Wu, 2013; Rivard & Lapointe, 2012). Empirical studies in this stream examine, for instance, individuals' compliance with organizational guidelines and policies (Abubakre, Ravishankar, & Coombs, 2015; Xue, Liang & Wu, 2011). However, recent articles indicate that attempts to prohibit the use of WS foster the use of "hidden" WS, known as *shadow systems* (e.g., Alter, 2014; Behrens, 2009).

A second research stream centers on empowering employees and managing WS. This stream acknowledges the value of WS, allowing and empowering employees to build and use WS (Tiwana & Konsynski, 2010; Weill & Ross, 2005). However, additional organizational units need to be established to manage and balance the use of organizations' core IS and supplementary WS. For instance, in the BIS context, these units are generally cross-functional and focus on tasks such as gathering and synthesizing requirements, integrating data, designing report templates, developing user authorization concepts, and defining data and application responsibilities (O'Neill, 2011; Unger, Kemper, & Russland, 2008).

Unfortunately, establishing and running these additional, cross-functional organizational units creates high costs for organizations and, by introducing an additional governance layer, reduces the WS' flexibility. Thus, both governance-based approaches have significant limitations.

As a consequence, we suggest that BIS should recommend existing reports to users in order to complement governance-based approaches and to support report reuse. This supports reuse of reports and prevents users from creating redundant reports in WS. Specifically, BIS should be extended with recommendation agents (RAs) that help users search for required reports. RAs typically elicit users' preferences and requirements, as well as recommend items that address these. RAs therefore facilitate users' information searches (Arazy, Kumar, & Shapira, 2010). For instance, many online stores adopt RAs to help them recommend products to their customers (Xiao & Benbasat, 2007). However, although RAs are very popular extensions to systems that target end consumers such as online stores (Li & Karahanna, 2015), they are rarely used as extensions to enterprise IS such as BIS. We make this distinction explicit by referring to RAs that extend enterprise IS as enterprise recommendation agents (ERAs). To date, ERAs have rarely been examined in the literature (Hess, Fuller, & Campbell, 2009), although information retrieval is very important in the enterprise IS context (Bernstein & Haas, 2008; Mukherjee & Mao, 2004). To address this gap and to support report reuse, the first objective of this paper is to *extend a BIS with an ERA that recommends reports to users*. By increasing the reuse of existing reports, such an ERA could prevent redundant reports, data inconsistencies and, eventually, poor decision-making.

However, simply identifying and recommending reports is not sufficient to influence an individual's decision to actually reuse a certain report. Instead, in line with Simon's (1954) multistage decision-making process, the ERA must also influence an individual's actual decision to click on a certain recommendation and, thus, to reuse a certain report. Hence, the second objective of this paper is to *influence users to choose a specific report recommendation*.

We address this second objective by drawing on the body of works that behavioral economists have produced. It is well known that individuals' behaviors are not entirely rational, because their cognitive biases influence individuals (Goes, 2013). For instance, changing how different options are presented to individuals affects their choices (Hanna, 2015). Hence, even if the range of available choices is not affected, individuals can be enticed to make certain choices. Social psychologists and behavioral economists Richard Thaler and Cass Sunstein (2003) refer to this form of influencing as a *nudge.* Thaler was recently awarded with the prestigious Nobel Prize in Economic Sciences (The Royal Swedish Academy of Science, 2017) for his work. Designing an ERA that influences users' report recommendation choices is just such a nudge.

To support report reuse, a nudge should be based on a cognitive bias that frequently occurs in organizational settings. In particular, the ERA in this study exploits the effects of previous users' social influence. The social influence of one individual on another is a well-known phenomenon in organizations. For instance, the hierarchical power of individuals often influences others in organizations (Clegg, 2013; Courpasson, Golsorkhi, & Salaz, 2012). Consequently, we refer to the ERA's effects as *social*

[1] In this paper, reuse refers to different individuals' usage of an IS resource. It does not refer to repeated usage of the same IS resource by the same individual.

nudges. Building on behavioral economists' concept of a nudge (Sunstein & Thaler, 2003; Sunstein, 2014), we define two criteria for a social nudge: (1) a social nudge steers an individual's choice toward a desired option by exploiting the effects of social influence between individuals, and (2) a social nudge does not change the range of choices available to the individual.

Three common forms of social influence in organizations are social cohesion (proximity), institutional isomorphism (similarity of positions), and hierarchical power (Borgatti & Foster, 2003; Fiske, 2010; Friedkin & Cook, 1990). Building on these three forms of social influence, we design four social nudges. The first social nudge aims to control an individuals' recommendation choices by exploiting their tendencies to be biased by proximity to other individuals. The second and third social nudges aim to determine individuals' recommendation choices by exploiting their tendencies to be biased by the similarity between their positions in the organization and other individuals' positions. Finally, the fourth social nudge aims to determine an individuals' recommendation choices by exploiting those individuals' tendencies to be biased by other individuals' hierarchical power.

As a third objective of this paper, we *examine recommendation elaboration as a moderator.* Although the described social nudges are based on social influence's well-known effects, RAs provide an important new context. Since RAs display "social" information about previous users, but are not themselves human, only the displayed reference information should exert social influence. Researchers therefore need to determine whether individuals actually cognitively process the displayed information about previous users. For instance, an ERA seeking to steer users' choices toward certain report recommendations can only succeed if users view and process the information it provides. If users fail to carefully evaluate—or engage in elaboration about—the provided information about previous users, this information will be ignored. We therefore follow Meservy et al.'s (2014) recommendations and use contemporary eye-tracking devices to reliably compute users' fixation and to control for the moderating effects of recommendation elaboration.

To summarize, this paper has three objectives: First, we propose an alternative approach to balancing BIS use and WS use. Extending a BIS with an ERA that supports report retrieval, and thus report reuse, reduces the need to develop supplementary WS. Second, we design and investigate the effects of four social nudges. Since employees in an organization work together and influence each other, the social influence of prior report users is a suitable bias in respect to designing nudges in organizational settings. Third, using eye-tracking technology, we highlight the importance of recommendation elaboration as a moderator of the effects of social nudges on individuals' recommendation choices.

The remainder of this article is structured as follows. Section 2 introduces the underlying theoretical foundations for designing social nudges, while Section 3 develops our hypotheses. The ERA that aims at steering users toward choosing certain report recommendations is introduced in Section 4, which also describes a lab experiment to evaluate the ERA's effects. Subsequently, Section 5 presents our manipulation checks, data analysis, and the experiment results. The implications of our work for theory and practice are discussed in Section 6, and Section 7 concludes this paper.

2 Theoretical Foundations

2.1 Nudge

The Nobel Prize Foundation introduced Richard Thaler's 2017 Prize in Economic Sciences with the words "Humans behave in complex ways. Although we try to make rational decisions, we have limited cognitive abilities and limited willpower. . . . Moreover, cognitive abilities, self-control, and motivation can vary significantly across different individuals." (The Royal Swedish Academy of Science, 2017, p. 1)

In actuality, peoples' decision-making is not entirely rational, because many environmental features can influence their decisions (Thaler, Sunstein, & Balz, 2010). For instance, decisions can be influenced by changing a person's environment. Literature refers to such intentional changes in one's environment as nudges (Thaler et al., 2010). A nudge aims to influence decision-making in certain ways without people necessarily noticing that they have been influenced. Sunstein (2014, p. 17), one of the advocates of the nudge concept, defines a nudge as an "initiative that maintains freedom of choice while also steering people's decisions in the right direction." This definition is consistent with the meaning of a nudge in everyday life, which refers to a gentle hint or suggestion, and is the reverse of an obligation, a strict requirement, and/or the use of force (Halpern, 2015, p. 22).

For example, a restaurant's menu is a nudge. Even if the selection on the menu does not change, changing its presentation on the menu may affect a guest's choice of food. For example, by clustering the items differently, using larger/smaller images of them, and showing/hiding their prices, restaurant managers can steer guests toward making certain choices (Thaler et al., 2010). A picture of a smoker's lungs on a pack of cigarettes is another example of a nudge (Sunstein, 2014). Although the picture does not force individuals to stop smoking, it presents the hazards of smoking, thereby steering individuals toward reducing the number of cigarettes they smoke. However, pictures and warnings are not the only form of nudges. Other popular forms of nudges include the disclosure of information, default rules that become individuals' choices if they do not opt out, the framing of choices, and "cooling-off" periods (Hanna, 2015; Leonard, 2008).

The nudge concept is based on a stream of behavioral economist research called *libertarian paternalism* (Thaler & Sunstein, 2003). Advocates of this stream observe that there are ways of influencing decision-making that do not limit liberty, but also do not quite fit the mold of ordinary persuasion. Because individuals are susceptible to various cognitive biases, the way that options are structured and presented affects their decision-making (Hanna, 2015). Libertarian paternalism aims to exploit these effects in order to encourage more prudent decision-making. In particular, libertarian paternalism promotes the use of nudges to create *choice architectures*. Like an architect who creates buildings, a *choice architect* creates a contextual background against which choices need to be made (Thaler et al., 2010). By doing this, the choice architect deliberately builds a choice architecture that presents choices in a certain way and, thus, nudges individuals toward making certain choices (Sunstein, 2014).

On the whole, we can highlight three essential nudge characteristics: first, a nudge does not restrict the choices available to an individual (Bovens, 2008; Cohen, 2013). Second, a nudge changes the environment in which choices are made (Sunstein, 2014). Third, a nudge "harnesses cognitive biases for good" ends (Thaler & Sunstein, 2008, p. 8; Trout, 2005, p. 432). Deception, or the deliberate withholding of information that one is obliged to disclose, is not considered a nudge (Hanna, 2015). Hausman and Welch (2010) describe a nudge as a preference-shaping intervention as opposed to a non-preference-shaping intervention.

The use of nudges may seem morally disputable to advocates of freedom of choice (Leonard, 2008). According to their criticism, any intentional influence of individuals' decision-making should generally be avoided, including individuals' rights to take risks and make errors. However, liberal paternalists counter that decisions are not made in a vacuum (Thaler et al., 2010). Influences on choices are inevitable, whether they are intentional, or the product of any kind of conscious design (Sunstein, 2014). Hence, Sunstein (2014) argues that nudges should support individuals' autonomy rather than reduce their freedom of choice. For instance, nudges may enable individuals to consider relevant alternatives that would otherwise be ignored due to information overload.

IS research studies on examining and designing nudges are still very rare. However, there are related studies on cognitive biases (Goes, 2013). For instance, IS researchers have examined default options in the past (Thaler et al., 2010). Allen and Parsons (2010) have shown that providing anchors affects individuals' decision-making and, specifically, that anchoring leads to an adjustment bias. If individuals who need to write program code are provided with an anchor (i.e., code pieces), they frequently fail to make sufficient changes to the anchor and are overconfident in their solution. Furthermore, Weinmann, Schneider, & vom Brocke, (2016) provide an overview of common forms of nudges and discuss them in the context of online product-rating platforms. These authors also suggest a process for designing and evaluating other forms of nudges (Weinmann, Schneider, & vom Brocke, 2015). Our work follows their suggestions.

In line with our second research objective, we design nudges to steer an individual toward choosing a certain report recommendation from a set of multiple recommendations. In particular, we focus on nudges that exploit social influence's effects in order to control an individual's recommendation choices. Social influence has been identified as an important determinant for explaining individuals' behaviors in organizations and institutions (Tichy, Tushman, & Fombrun, 1979; Tsai & Goshal, 1998). Consequently, the following sections introduce forms of social influence that arise from social networks within organizations and organizational hierarchies.

2.2 Social Influence

2.2.1 Social Influence Based on Social Networks

Social influence is a process through which individuals modify others' behaviors, thoughts, and feelings (Cartwright, 1959; Lewin, 1951). Social psychology has examined many different forms and perspectives of social influence (Fang et al., 2015; Kilduff & Tsai, 2003). For instance, Fiske (2010) and Hogg (2010) have reviewed different forms of social influence. These include, for example, social cognition of attitude change as a consequence of influence, propaganda and the mass transformation of attitudes, interpersonal persuasion, the development and change of behavioral norms, behavioral regularities on people's behavior, and of group socialization processes. Owing to the sheer number of effects based on social influence, the common approach to studying its effects is to focus on the specific effects in a particular context (Anderson & Kilduff, 2009). In this paper, we therefore focus on social influence processes that are particularly strong within organizations. Specifically, we focus on (1) social networks, because, from an employee's perspective, organizational structures represent a social network (Kilduff & Tsai, 2003; Sparrowe, Liden, Wayne, & Kraimer, 2001; Tichy et al., 1979), and on (2) hierarchical power, because most organizations are based on hierarchical structures.

There are two main approaches to researching social influence in social networks. Borgatti & Foster (2003) refer to them as a connectionist versus a structuralist approach (or a flow-based vs. a topology-based approach, or a relational vs. a structural approach). The connectionist approach highlights an interpersonal transmission process between those with preexisting social ties (Kilduff & Tsai, 2003). Connectionists argue that, at its core, the social cohesion between two individuals (typically defined as the proximity between them) causes them to influence each other (Borgatti & Foster, 2003). In contrast, the structuralist approach emphasizes the structural similarity of nodes in a network, although there is not necessarily a tie that connects them. According to this approach, the extent to which individuals share similar isomorphic positions in a network determines the social influence they exert on each other.

It is important to note that the effects that high proximity between individuals may have on social influence and the effects that the high isomorphic similarity between individuals' positions may have on social influence may overlap. Consequently, IS researchers focusing on social influence have developed and tested hypotheses based on both the approaches. For instance, Singh and Phelps (2013) find that individuals' decisions when choosing a license type for their open source projects are influenced by (1) the license type of the previous projects to which these individuals were closely connected, and by (2) the license choice of isomorphic similar projects (i.e., projects with similar social network structures).

2.2.2 Social Influence Based on Power in Organizational Hierarchies

Many organizations are based on hierarchical structures. Although recent studies indicate a shift to more heterarchical structures (Kellogg, Orlikowski, & Yates, 2006; Stark, 2009), organizations are still highly hierarchical (Courpasson, Golsorkhi, & Salaz, 2012) and organizational hierarchies represent people's most common daily experience of hierarchies outside the family (Fiske, 2010).

Status and power form the bases of hierarchical differentiation in organizations (Anicich, Fast, Halevy, & Galinsky 2016; Clegg, Courpasson, & Phillips, 2006). Social psychologists define status as social respect, recognition, importance, and prestige (e.g., Fiske, 1993). In contrast, power is defined as the control over valued resources (e.g., Fiske, 1993; Keltner, Gruenfeld, & Anderson , 2003; Magee & Galinsky, 2008). Power and status often depend on each other (Clegg, 2013). For instance, as explained by Fiske (2010), many managers in institutional hierarchies are respected (status) and control resources (power).

3 Hypothesis Development

We design and evaluate an ERA that supports the reuse of reports. Insufficient report reuse is a common phenomenon and a serious problem for organizations, because it results in operational inefficiencies and poor decision-making. To address these issues, our ERA uses social nudges that aim to steer individuals toward choosing certain report recommendations and, thus, toward reusing certain desirable reports. In particular, we describe the effects of these social nudges on individuals' recommendation choices. We model all nudges as external stimuli and individuals' recommendation choice as responses to those stimuli. In addition, we include elaboration in our model. This is important, because in our context, stimuli are messages displayed on screens rather than "real" physical influences. Consequently, the effect of these messages on certain individuals depends on the extent to which these individuals process them, which is commonly referred to as elaboration (Angst & Agarwal, 2009; Bhattacherjee & Sanford, 2006; Ho & Bodoff, 2014; Meservy, Jensen, & Fadel, 2014). Elaboration is defined as the amount of message-relevant thinking an individual engages in while evaluating a message (Petty & Cacioppo, 1986a, 1986b). In our model, we examine elaboration as a moderator, because it may strengthen the effects of messages displayed on computer monitors.

3.1 Social Nudges as External Stimuli

We design specific nudges by drawing on theoretical knowledge about social influence in networks, because organizations can be viewed as networks (Kilduff & Tsai, 2003). We suggest effects based on (1) social cohesion and (2) institutional isomorphism. We also consider (3) power in organizational hierarchies, because most organizations are based on hierarchical structures.

3.1.1 Social Cohesion: Social Influence Based on Proximity Between Individuals

The connectionist view of social influence is based on the proximity between two individuals in a network, which is commonly referred to as *social cohesion* (e.g., Gargiulo & Benassi, 2000). Social cohesion focuses on how two individuals are connected to each other and how they communicate; it is sometimes also referred to as the flow approach to social influence (Borgatti & Foster, 2003).

Social cohesion refers to the ties between individuals. Marsden and Friedkin (1993) coined the term cohesion in terms of the number, length, and strength of the paths that connect actors in a network. According to this approach, the degree of proximity (i.e., the degree of social cohesion) between two individuals is high if they are directly tied in a network via a short connection. Conversely, the degree of proximity between two individuals is low if they are not connected, or only connected via many intermediaries.

In line with the nudge concept, changing the presentation of recommendations may influence the recommendation a user chooses. Displaying information about the previous users of recommended items may specifically influence the choices of new users presented with a set of alternative recommended items. This study aims to exploit this potential bias using the effects of social influence.

We therefore first draw on theoretical knowledge about social cohesion's effects and suggest that new users are likely to choose a certain recommendation if the social cohesion between them and the previous user (about whom information is displayed) is high. As such, we suggest the following hypothesis:

Hypothesis 1 (H1): High social cohesion between two individuals increases the probability that each of them will choose a recommended item associated with the other.

Note that social cohesion focuses on the proximity between two individuals within a network. Multiple biasing factors could, however, change the effects of social cohesion; for instance, if two individuals had bad experiences when working together, this could reverse social cohesion's effect. While H1 assumes that, as such, the effect of social cohesion is positive, biasing factors, such as bad experiences, could cause it to have a negative effect. That is, individuals would then be less likely to choose a recommended item associated with the other. However, we do not consider these possibilities in our study, because we focus on social cohesion and not on potentially biasing external factors.

3.1.2 Institutional Isomorphism: Social Influence based on Similar Positions in Organizational Structures

The structuralist view of social influence is based on the extent to which individuals have equivalent positions in an organizational structure. The *institutional isomorphism* concept best captures the process of structural equivalence in organizations (DiMaggio & Powell, 1983). Unlike social cohesion, isomorphism does not depend on proximity (Borgatti & Everett, 1992). In an isomorphic network, "nodes may be adjacent, distant, or completely unreachable from each other" (Borgatti & Everett, 1992).

In this study, we use the concept of isomorphism rather than equivalence. Whereas structural equivalence only views two individuals as occupying the same position if they are connected to the same third individual, structural isomorphism views two individuals as occupying the same position if they are connected to corresponding others (Borgatti & Everett (1992). Isomorphism does not, therefore, depend on a direct connection and can be distinguished from social cohesion. Structural equivalence, however, is an inseparable part of social cohesion, as it requires links to the same individual (Borgatti & Everett, 1992). Furthermore, institutional isomorphism specifically addresses the structural determinants that individuals perceive (DiMaggio, 1986). It does not consider, for example, psychological determinants, which are difficult to separate from the effects resulting from social cohesion (DiMaggio & Powell, 1983).

In Hawley's (1968) description, isomorphism is a constraining process that forces one actor to resemble other actors who face the same set of environmental conditions. Early research on institutional isomorphism focused on isomorphic processes at the organizational level. For instance, DiMaggio and Powell (1983) examined isomorphic processes that cause organizations to change and adapt the structural models of other organizations if these organizations are competitors that are more successful. However, the theory of isomorphism also applies to the individual level. Individual actors within organizations may adopt their colleagues' successful practices. For instance, an internal blog may influence a software developer working in the US department of a global company, because another software developer in the same company wrote the blog. Even if the second software developer worked in Asia and was unconnected to the software developer in the US via a direct, personal tie, the similarity of their positions could cause the software developer in Asia to influence the American software developer. Note that the social influence exerted in this example arises from the individuals' isomorphic positions within their organization—both individuals are software developers in the same organization.

The effects of institutional isomorphism and social cohesion may, obviously, overlap and leverage each other (DiMaggio & Powell, 1983; Borgatti & Everett, 1992). For instance, if the software developer in the US also knows the software developer in Asia personally, or if they are connected via the same supervisor, the influence would be all the stronger. This shows that social cohesion and institutional isomorphism complement each other.

However, it is important to keep the key differentiator between the two in mind. While influence based on social cohesion depends on a tie between individuals, influence based on institutional isomorphism does not need a direct tie, but does require an understanding of the structure or context of the individuals' relationships. Consequently, we also theorize that an individual is more likely to choose a report recommendation that is based on a colleague who works in an isomorphic position.

We specifically examine business function and location (i.e., geographical regions, countries) as positions in organizations' networks, because organizations are usually structured according to business function and/or location (Miles, 2012). For instance, in an organization, common business functions include accounting, marketing, IT, sales, and human resources. Since individuals working in the same business function are considered likely to cooperate and exchange resources and knowledge frequently, many organizations are primarily built on such functions. Consequently, we theorize as follows:

Hypothesis 2 (H2): High institutional isomorphism between two individuals (in terms of their primary business functions) increases the probability that both of them will choose a recommended item associated with the other.

Organizations are also frequently structured according to locations. These may correspond directly to countries (e.g., Brazil, China, India, the US, and the UK), but also to more generic regions, such as time-zone-based and continent-based regions (e.g., America, Europe-Middle-East-Africa, Asia-Pacific-Australia). Again, since employees in the same time-zone and/or the same country would be expected to be able to work together closely, many organizations are structured according to locations. We therefore theorize that:

Hypothesis 3 (H3): High institutional isomorphism between two individuals (in terms of location) increases the probability that each of them will choose a recommended item associated with the other.

In our study, we focus on these two social nudges based on institutional isomorphism. However, organizations, or researchers, could also design and test alternative social nudges based on institutional isomorphism. These could, for instance, focus on employees' job roles, such as sales analysts, ad campaign analysts, software engineers, etc. In real organizations, institutional isomorphism in terms of job role seems to be an especially powerful basis for nudging employees toward reusing certain reports, because we assume that, for example, two sales analysts will use their BIS to achieve similar objectives. We did not investigate this nudge, because institutional isomorphism in terms of job roles and business functions (e.g., sales departments, marketing departments, IT departments) would be very similar. We therefore only focused on institutional isomorphism in terms of business function, because we assumed that job roles (e.g., ad campaign analysts) would be more difficult to understand in a lab setting than business functions (e.g., marketing departments).

3.1.3 Power in Organizational Hierarchies

Like social networks, power in social hierarchies often causes influence in terms of changing other people's beliefs and behavior (Hogg, 2010). In general, in a hierarchy the upper levels have more power than the lower levels (Fiske, 2010).

The items that a RA suggests are often at least partly based on their historical usage. For instance, a movie RA may suggest a movie to a new user, because another user, who seems to be similar to the (potential) new user, had watched it. In general, RAs based on structured information (e.g., movies categorized into movie genres) often provide more useful recommendations than those solely based on unstructured information, or substantially less structured information (e.g., uncategorized news articles) (Paterek, 2007). We therefore propose that using RAs for information retrieval within organizations is particularly useful, because they already have a structure that could be used to compute similarities between potential users. For instance, an ERA based on an organization's hierarchy may suggest a report to an employee, because this employee's supervisor used it in the past. Drawing on the effects of power within organizational hierarchies (Anicich et al., 2016; Clegg et al., 2006), we propose that an employee would prefer a recommendation from a relatively powerful user in the organization's hierarchy who controls financial budgets and employees. Thus, we offer the following hypothesis:

Hypothesis 4 (H4): The probability that people will choose a recommended item associated with an individual increases in relation to the level of that individual's power (in terms of his or her hierarchical position and control of financial budgets and employees).

The hierarchical effect of power further affects the influence of social cohesion, or whether individuals know each other. Employees in a high-power position, such as directors, may influence other employees even if they are not directly connected to them. Conversely, employees who have low-power positions in the hierarchy positions, such as interns, generally only successfully influence directly connected employees (e.g., colleagues whom they directly assist), but are unlikely to influence other employees. Thus, the influence of social cohesion (i.e., proximity) for employees in lower organizational positions will be more important than it is for employees in higher organizational positions.

Accordingly, we define an interaction effect between hierarchical power and social cohesion:

Hypothesis 5 (H5): An individual's degree of power (in terms of his or her hierarchical position and control over financial budgets and employees) moderates the effect of social cohesion between that individual and others. Specifically, higher levels of power weaken the influence of social cohesion.

3.2 Recommendation Elaboration as Moderator

Individuals' decision-making is based on the identification of candidate options that are then evaluated and reduced to the most appropriate choice or choices (Simon, 1957). This process depends greatly on the degree to which an individual scrutinizes the set of available choices (Petty and Cacioppo, 1986a, 1986b). In our study, individuals had to choose from a set of available recommendations, and, although they were not familiar with the recommended item (i.e., the report), they could process information about the recommendation. For instance, they could consider information about the colleagues associated with recommended items. This is important, because individuals' likelihood of engaging in effortful processing of such information determines their chosen recommendations.

Petty and Cacioppo (1986a, 1986b) describe this likelihood in terms of an elaboration continuum. At the high end of the elaboration continuum, people assess all of the available information to obtain a carefully considered, although not necessarily unbiased, evaluation (Gawronski & Creighton, 2013). This means that the greater the extent to which individuals carefully consider a certain recommendation, the greater the probability that any additional information about the recommendation will influence them. For instance, if a recommendation is displayed with a short message describing the data on which the recommendation is based, this message is more likely to affect users who elaborate very extensively. Accordingly, at the low end of the elaboration continuum, people engage in considerably less scrutiny of object-relevant information (Gawronski & Creighton, 2013). Any additional information provided about a certain recommended item is therefore less likely to affect these individuals. In other words, if individuals do not engage in "recommendation elaboration," they will ignore additional information about recommended items and choose recommendations randomly.

Thus, the extent to which an individual carefully considers all the information related to a set of recommended items—i.e., *recommendation elaboration*—determines the effect that any additional information will have on that individual's decision to choose a certain recommended item. Accordingly, we define the following hypotheses:

Hypothesis 6a (H6a): The effect of providing information about the social cohesion between one individual and another individual associated with a recommended item increases in relation to that individual's level of recommendation elaboration.

Hypothesis 6b (H6b): The effect of providing information about institutional isomorphism (in terms of business function) between one individual and another individual associated with a recommended item increases in relation to that individual's level of recommendation elaboration.

Hypothesis 6c (H6c): The effect of providing information about institutional isomorphism (in terms of location) between one individual and another individual associated with a recommended item) increases in relation to that individual's level of recommendation elaboration.

Hypothesis 6d (H6d): The effect of providing information about the power of an individual associated with a recommended item (in terms of hierarchical position and control over financial budgets and employees) increases in relation to that individual's level of recommendation elaboration.

As such, we believe that the effect of additional information about the social cohesion of previous users associated with the recommended items would depend on the new user's level of recommendation elaboration (H1). Similarly, concerning the effect of institutional isomorphism, we theorize that additional information about institutional isomorphism in terms of business function (H2) and location (H3) of previous users influence only those high-elaboration individuals accustomed to carefully considering all related information before making a decision. Finally, we argue that the impact of providing information about previous users' relative power (H4, H5) also depends on the level of elaboration of the new user, because users on the low end of the elaboration continuum would deem such information superfluous.

3.3 Recommendation Choice as Response to Social Nudges

In this section we examine individuals' recommendation choices as responses to the defined social nudges. Currently, many RAs provide multiple recommendations, rather than just one. Individuals can therefore choose between several recommendations. In line with our hypotheses, we suggest that social nudges could be used to steer individuals toward choosing certain recommendations. We operationalize our measure of recommendation choice in Section 4.4. We do not examine any individual responses other than recommendation choice; recommendation choice is our study's only dependent variable.

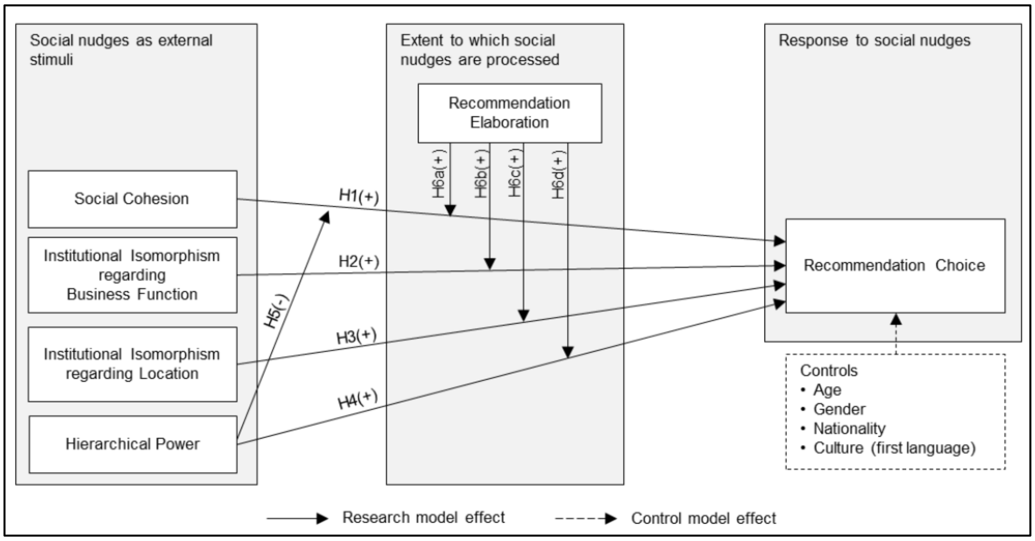


Figure 1. Research Model

Figure 1 summarizes our research model. In line with other IS studies focusing on various design features (e.g., Choi, Jiang, Xiao, & Kim, 2015; Day, Junglas, & Silva, 2009; Xu, Benbasat, & Cenfetelli, 2014; Zhang, Venkatesh, & Brown, 2011), we model our social nudges as independent variables. In addition to the hypotheses developed above, we examine the influence of four control variables: age, gender, nationality, and culture (measured as first language).

4 Research Method

To test our research model we conducted a laboratory experiment. Lab experiments are particularly suited to examine the temporal precedence of a cause and to eliminate alternative explanations of possible cause-effect connections in the IS discipline (Cook & Campbell, 1979; Colquitt, 2008; Dennis & Valacich, 2001; James, 1980).

4.1 Material: BIS with ERA and Report Recommendations

Our study uses a self-developed prototype of a web-based BIS. This BIS is extended with an ERA that provides users with report recommendations. Figure 2 shows a screenshot of the BIS and the ERA. The report recommendations (lower box on the left side of the screen) change every few seconds.

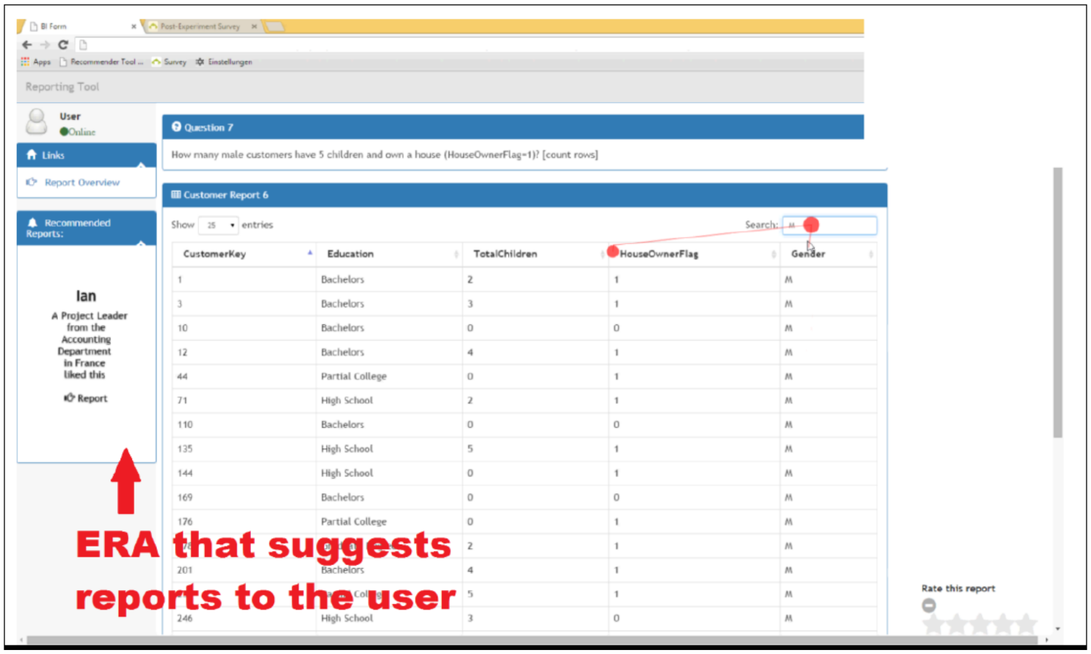


Figure 2. BIS Extended with an ERA That Suggests Reports to Users

All the participants in our experiment used the BIS with the ERA that recommends reports. The BIS provides users with business reports and the basic functionality for analyzing these reports, such as filtering reports, sorting results, adjusting the number of rows shown on a single webpage, etc. Specifically, we used Microsoft's publicly available "Contoso" (Microsoft, 2016) BIS training data as the dataset. This dataset contains data of an electronics retailer called "Contoso." The data includes all of Contoso's sales transactions over a period of three years, as well as detailed information about its stores, locations, customers, orders, marketing campaigns, and inventory stocks. Using this dataset, a simulation program created a set of 75 reports. These reports only provide information in tables and not in charts, dashboards, or other visualizations. The BIS provides access to these reports. Although each report is unique, parts of the reports may overlap, which means that some reports may contain the same columns. Consequently, in some cases, users may find the information they require in multiple reports.

The BIS provides a list of all reports and an ERA recommending reports to support users searching for certain information. The BIS entry page shows a list of all the reports on the left side of the screen. Users can scroll through the list and click on the names of reports to open them. All the report names start with the type of business facts they provide. Based on the Contoso dataset, five types of business facts are distinguished: sales transactions, orders, inventory stocks, product categories, and promotions. Examples of report names are "Sales Report 1" and "Orders Report 4."

In addition to this list of available reports, the BIS provides an ERA that recommends reports for users. It is important to note that, linked to a recommended report, each report recommendation provides additional information about a previous user. In particular, each recommendation provides information about previous users in terms of their business functions (e.g., sales department), the locations in which they work (e.g., the USA), and their positions (e.g., project manager). The recommendation also indicates whether the recommended report's previous user is directly connected to the current users (e.g., "*Your* director . . .") or not (e.g. "*A* director . . ."). For instance, an example recommendation would be "Michael, *a project manager* from the *Sales* Department in the *USA* liked this report" whereas "this report" is a link that opens the recommended report. Note that the recommendation does not show the name of the recommended report, nor does the gender of the previous report users change within a set of alternatively displayed report recommendations. The experiment participants cannot therefore select a certain report recommendation on the grounds of gender preferences. We only use common names derived from an online database of baby names (World-English, 2015).

Our experiment used additional information provided about previous users of recommended reports to nudge new users toward choosing certain report recommendations. The information allowed new users to infer the social influence of the previous report users. Extant studies have shown that users viewing information about others on their screen associate the information with those people (Guadagno, Swinth, & Blascovich, 2011; Teubner, Adam, & Riordan, 2015). This additional information provided in our experiment conveyed the social influence of those previous users. We used this effect to generate different social nudges in our experiment. Table 1 lists our experimental treatments of social nudges. In line with these treatments, Table 2 shows exemplary report recommendations as provided to users by the ERA.

Table 1. Experimental Treatments of Social Nudges

Social Nudge	Experimental Treatment	
Social cohesion	High	“Your [project manager . . .]”
	Low	“A [project manager . . .]”
Institutional isomorphism in terms of business function	High	Same department
	Medium	Similar, closely related department (e.g., sales and marketing)
	Low	Different, unrelated department (e.g., sales and risk mgmt.)
Institutional isomorphism in terms of location	High	Same country
	Medium	Different country from same continent
	Low	Different country from different continent
Hierarchical power	High	Director
	Medium	Project manager, project leader
	Low	Intern

Table 2. Example Report Recommendations

Social cohesion	Institutional isomorphism as		Hierarchical power	Example report recommendation
	(a) bus. funct.	(b) location		
High	High	High	High	“Your director from the Sales Department in Germany liked this report.”
Low	Medium	Medium	Medium	“A project leader from the Marketing Department in France liked this report.”
Low	Low	Low	Low	“An intern from the Risk Management Department in Canada liked this report.”

4.2 Experiment Design

Our experimental treatments distinguished between (a) low and high levels of social cohesion, (b) low, medium, and high levels of institutional isomorphism in terms of business function, (c) low, medium, and high levels of institutional isomorphism in terms of location, and (d) low, medium, and high levels of power in organizational hierarchies.

Since we argue that there is an interaction effect between social cohesion and power in organizational hierarchies (H5), we needed a 2x3 cross-factorial design between these treatments. Crossing this design with additional treatments was not reasonable, because (1) we did not theorize any interaction effects with institutional isomorphism, and (2) the unnecessary crossing of experimental treatments would have reduced the analysis's statistical power. We therefore crossed the two forms of institutional isomorphism using a 3x3 cross-factorial design, but did not cross the two factorial designs with each other. Consequently, we got 2x3 + 3x3 = 15 experimental treatments, with one experimental treatment included in both the factorial designs. This study therefore includes 14 experimental treatments. Appendix 9.1 provides the details of all the experimental treatments.

To collect data for each experimental treatment, we employed a counterbalanced within-subject experimental design for the following two reasons: first, each treatment represents one set of recommended items from which a participant could choose one recommended item. This relatively fast experimental task takes less than a minute to complete. Subjects could therefore participate in multiple treatments, which made a within-subject design feasible for our experiment. Second, the total of 14 experimental treatments is relatively high. A between-subject design would have required too many participants and was therefore not practically feasible.

We used common approaches to reduce bias from carryover effects. In particular, we randomized the order of experimental treatments by using a Latin square design. However, since experience with experimental treatments did not help participants complete their tasks (i.e., answer the questions), the risk of carryover effects was already low.

4.3 Sample, Scenario, and Task

The experiment was conducted with 187 students at a public university. The group consisted of 91 graduate students specializing in business intelligence systems and 96 undergraduate students specializing in development and management of information systems. Detailed information about the sample is provided in Section 5.1 "Demographic Data" and in Appendix 9.2. Although the experiment was conducted in an organizational setting, students are suitable subjects, and students may also tend to be less biased than experienced professionals due to their general relative youth and lack of work experience.

For our experiment, we provided participants with an organizational scenario. In this scenario, they assumed the role of Thomas, an employee at Contoso—i.e., an employee at the company introduced above for which the BIS provides data—who works in Contoso's Sales Department in Germany.

In the scenario, Thomas needs to complete nine tasks. Each task consists of one question that needs to be answered. All the questions focus on information in a specific report that the BIS has provided. To answer the questions correctly, Thomas needs to identify the relevant report and find the required information. For instance, one question could be: "To which income group does the customer with the customer key '19037' belong?" Appendix 9.3.1 provides detailed information on all nine tasks, and Appendix 9.3.2 provides similar information on Contoso's organizational structure.

We used the following five techniques to train and prepare participants for the experiment: First, one week before the experiment took place, we provided participants with a 15-minute introductory video about the experiment. This video introduced them to the experiment, the scenario, and the usage of the BIS (including the ERA). Second, before the start of the experiment, the experiment instructor personally introduced participants to the scenario and the BIS, and demonstrated how to solve the first task. Third, we provided two training tasks to familiarize the participants with the role of Thomas and the BIS. Hence, the first two of the nine tasks were not considered in the data analysis. They were only used to familiarize participants with the role of Thomas and the BIS. Only tasks 3–9 were relevant for data analysis. Fourth, each participant received a reference paper illustrating Contoso's organizational setting, thus precluding the need to remember Thomas's role at Contoso and/or Contoso's institutional or hierarchical structure. The reference paper is provided in Appendix 9.3.2. Fifth, during the experiment, the experiment instructor provided personal support in the use of the BIS if required by participants.

The participants received a course credit for each task they answered correctly—excluding the training tasks 1 and 2—to motivate them to perform well. This was communicated to them, and they were also informed that the time they took to complete the tasks would not be considered.

The participants could answer the tasks by either (1) browsing through the list of reports and then checking those they thought would provide relevant information, or by (2) using the ERA's report recommendations. Table 3 shows the process for completing an experimental task. The participants were always given a set of three report recommendations, presented in turn (carousel effect). That is, every few seconds the recommendation changed to the next one, and after the third recommendation the first one appeared again.

The recommendations were not dynamic, but predefined. All the report recommendations within the same set of three alternative recommendations always linked to the same report. However, the participants did not know this. Predefined recommendations were important, because the participants' usage history would have influenced the recommended reports if dynamic recommendations were used. In turn, this could have affected the recommended reports' usefulness, which could have affected how the users continued using the system.

Each experimental treatment had three recommendations. After a participant had chosen one recommendation out of the set of three recommendations, all three recommendations were updated with the next experimental treatment's recommendations.

Furthermore, all sets of report recommendations were predefined because they represented our experimental treatments and thus had to be controlled. At the latest, the *third* set of recommendations forwarded participants to a report that gave them the information they needed to complete one experimental task. Consequently, we were able to gather data for up to *three* experimental treatments per experimental task.

Finally, after completing the nine tasks, participants were asked to complete a postexperiment survey. All 187 experiment participants completed the postexperiment survey.

Table 3. Exemplary Experimental Task

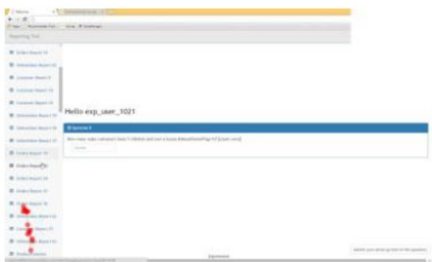
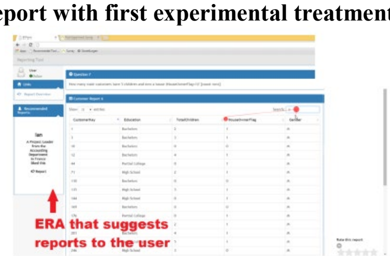
Step	**Description**
1. Entry page  *(each experimental task begins on the BIS entry page)*	In total, each participant receives nine tasks (two introductory tasks and seven that will be analyzed). Each task consists of a question that has to be answered (e.g., "How many female customers have a Bachelor's degree?"). Throughout the task, this question is shown in the upper part of the screen. The participants enter their answer on the entry page (figure left). Once the answer has been entered, the next question is shown. In addition, the overview screen displays a list of 75 reports.
2.1 First report with first experimental treatment  *(report with ERA)*  *(ERA uses the three recommendations in turn (carousel effect))*	By clicking on a certain report, the selected report is shown (Figure 2). In addition, the ERA with a report recommendation is shown on the left side of the screen (Figure 2). This report recommendation changes every few seconds (carousel effect) and after the third recommendation, the first is again shown (figure left). Note that the report recommendations only indicate a previous user and do not provide a relevant description, name, or ID. Each set of three recommendations represents one experimental treatment. In Experimental Treatment 1, Recommendations 1 and 3 always have the same degree of social influence (low). Recommendation 2 only differs in its degree of social influence. Our analysis thus focuses on the probability that Recommendation 2 will be chosen. We thus code our dependent variable as a binary variable: "click Recommendation 2" versus "click Recommendation 1 or 3". Note: The use of the ERA is voluntary. Participants are not forced to use the report recommendations. The answers to the questions can also be found by examining the 75 reports one by one. The sample size differs slightly between the experimental treatments.

Table 3. Exemplary Experimental Task

2.2 More reports with more experimental treatments  *(the second report provides the second treatment; the third report provides the third treatment)*	After the participants have clicked on one of the three report recommendations, the next report ("Report 2") is shown. It is important to note that all three report recommendations from the same experimental treatment always link to the same report. Therefore, it does not matter which report recommendation is chosen when answering the question. Note that the participants do not know this. The new report ("Report 2") shows a new set of three report recommendations. This set of recommendations represents a new experimental treatment ("Treatment 2"). One experimental task can therefore examine multiple experimental treatments.

4.4 Measurement of Recommendation Choice

The recommendation choice is the dependent variable in our study. We anticipated that the probability of new users choosing a certain recommendation would change depending on the information provided about the previous users of recommended reports. Throughout the experiment, participants were able to select one of three recommendations or examine a list of all the reports.

Since each set of three recommendations represents one experimental treatment, our analysis compares the probabilities of choosing a certain manipulated recommendation *from different sets of (three) recommendations*. Consequently, it was important to consistently present the manipulated recommendation in the same position throughout all the sets of recommendations in order to prevent the position of the manipulated recommendation from biasing results. For instance, some participants may have simply clicked on Recommendation 1, because it was the first recommendation they encountered.

The manipulated recommendation was always shown as the second of three recommendations to avoid bias. In other words, by keeping the position of the manipulated recommendation constant across all experimental treatments (i.e., in all the treatments, the manipulated recommendation was shown in Position 2), we can assume that the position of the manipulated recommendation does not exert a differential effect, thus ensuring that comparability of the experimental treatments.

In contrast, a randomized approach would have limited such a comparison, because the participants wouldn't have had to use the ERA. Consequently, randomizing the position of the manipulated recommendation is provided, would have likely led to some variation between the ratio of users who used the ERA and viewed the manipulated recommendation at Positions 1, 2, and 3, respectively. For a certain treatment, for example, randomization could have caused 36% of ERA users to receive the manipulated recommendation as Recommendation 1, while, for another treatment, randomization may have caused only 30% of ERA users to receive the manipulated recommendation as Recommendation 1. Such a difference would have biased our results. Thus, instead of randomizing its position, the manipulated recommendation was always displayed as the second of three recommendations throughout the experimental treatments.

Regarding the manipulated recommendation (i.e., Recommendation 2), the degree of social influence changed between the experimental treatments. Conversely, Recommendation 1 and Recommendation 3 always referred to a previous user with the same degree of social influence: A project manager not directly connected to Thomas who worked in a different department and a different continent than Thomas (see Appendix 9.1 for a detailed overview of all the experimental treatments).

To collect data on the chosen recommendations, we logged the participants' clicks on the recommendations. We determined the probability of the participants choosing a certain recommendation by computing the frequency of Recommendation 2 being selected in each experimental treatment, divided by the frequency of any recommendation being selected in that experimental treatment (i.e., the sum of the clicks on Recommendations 1, 2, and 3). This ratio represented the probability of participants selecting Recommendation 2 in a specific experimental treatment. In turn, this probability allowed us to compare the effects of social influence because this only differed from the others in terms of Recommendation 2. Table 3 shows an example of the procedure in an experimental task.

4.5 Measurement of Recommendation Elaboration

To assess recommendation elaboration, we measured the extent to which users carefully considered recommendations. Since all recommendations were messages displayed on the screen, we measured the extent to which users cognitively processed these messages.

While a vast literature has used questionnaires and surveys to measure elaboration, or has focused on the antecedents of elaboration (e.g., Angst & Agarwal, 2009; Bhattacherjee & Sanford, 2006; Ho & Bodoff, 2014), only Meservy, Jensen & Fadel (2014) demonstrate the benefits of eye tracking as a means of measuring elaboration. Contemporary eye-tracking devices provide multiple biometric metrics that can be aggregated to compute users' fixation (i.e., gaze) on certain screen elements (Just & Carpenter, 1976; Loftus, 1972).

In particular, state-of-the-art eye-tracking devices can measure users' pupil size and, simultaneously, measure coordinate points on a screen that users look at. This makes it possible to compute the amount of time a user gazes at a message on a screen and is an important part of developing a reliable elaboration metric. In addition to gaze, users' degree of cognitive processing can be computed by means of the collected pupil size metrics (Goldberg & Kotval, 1999; Weigle & Banks, 2014). Analysis of pupil sizes allowed us to determine whether users focused on and processed the displayed texts, or whether they merely moved their heads to skim the texts. Therefore, the product of coordination point metrics and pupil size metrics allowed us to compute a reliable fixation metric.

To compute fixation, we used the fixation filter provided by the application ProStudio, because it is the recommended filter for our eye-tracking device Tobii Pro X2 (Tobii, 2015). This filter ensembles multiple fixation algorithms (Komogortsev, Gobert, Jayarathna, Koh, & Gowda, 2010; Rayner, Li, Williams, Cave, & Well, 2007; Over, Hooge, Vlaskamp, & Erkelens, 2007). Figure 2 above shows an example screen with the projection of fixation points (red dots). The size of the points represents the fixation length in milliseconds.

4.6 Pretest

A pretest with 26 participants was conducted two months prior to the main experiment to ensure that the manipulation of social cohesion, institutional isomorphism in terms of business function, institutional isomorphism in terms of location, and hierarchical power was successful and that the scenario and the experimental tasks were easy to understand.

5 Data Analysis and Results

This section first reports the experiment participants' demographic data. This is followed by a description of the manipulation checks and the presentation of our hypothesis tests' results.

5.1 Demographic Data

Appendix 9.1 summarizes the participants' characteristics. More men (73%) participated than women (27%). The majority were between 21 and 29 years old. As a cultural indicator, we asked them about their nationality and the first language they learned as a child. Overall, 57% of participants were German and 48% reported German as their first language. This is not surprising, since the study was conducted at a university in Germany. The other participants were from Arabic countries, China, Egypt, India, Russia, Spain, Turkey, Greece, Vietnam, and the USA. Other than the concentration of German participants, the demographic profile was fairly distributed across countries and cultures.

5.2 Manipulation Checks

We conducted manipulation checks for each experimental treatment, which are summarized in Table 4. We also administered a postexperiment survey, asking all the participants whether they had noticed that the four experimental treatments (social cohesion, institutional isomorphism in terms of business function, institutional isomorphism in terms of location, hierarchical power) differed among specific recommendations. We also added two general items to control for whether participants noticed that the recommendations always changed. Importantly, the items were phrased such that a consistent answer required the participant to answer one item with "yes" and the other item with "no" (see Table 4).

167 of the 187 participants (89.3%) reported that they had noticed all the differences and answered the two additional items consistently (i.e., the first item with "yes" and second item with "no"). This is a large majority, which indicates a successful manipulation of the experimental treatments.

5.3 Measurement Model

Besides the manipulation checks, no variables in this study were measured by means of surveys. All the independent variables represented experimental treatments. Recommendation elaboration was measured by using gaze data (eye tracking) and the dependent variable was measured using log data of the BIS and the ERA.

Table 4. Manipulation Checks for Experimental Treatments

Experimental treatment	Postexperiment survey items	Ratio of positive ("yes") answers
Social cohesion	• I noticed that some recommendations were based on a direct colleague (e.g., my own intern or my supervising project manager), while other recommendations were based on less close colleagues. {yes, no}	97.8%
Institutional isomorphism in terms of business function	• I noticed that the colleagues, who were shown in the report recommendations, worked in different departments. {yes, no}	100.0%
Institutional isomorphism in terms of location	• I noticed that the countries of the colleagues shown in the report recommendations changed. {yes, no}	98.3%
Hierarchical power	• I noticed that the colleagues, who were shown in the report recommendations, were assigned to different hierarchical levels. {yes, no}	98.9%
Overall	• I noticed that recommendations changed. {yes, no}	98.9%
	• All recommendations were based on the same user. {yes, no}	5.3%

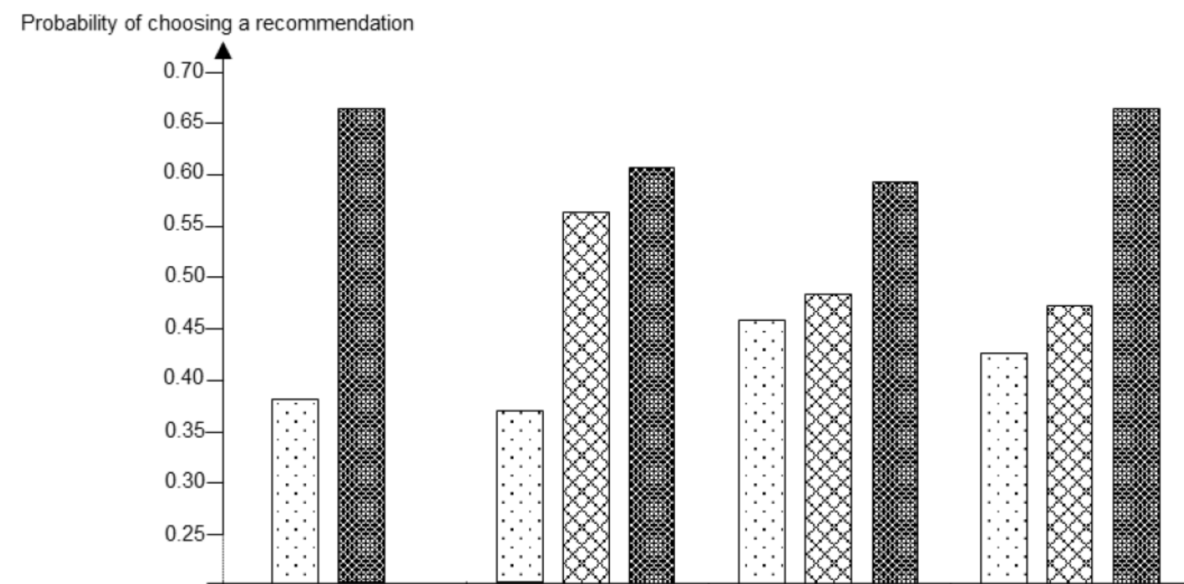
5.4 Results of Hypothesis Tests

As described above, our experiment participants were asked to complete several tasks by answering questions. Each task consisted of exactly one question. We assumed that the participants would answer these questions correctly, because the recommended reports provided the information required to answer correctly.

In the end, 93% of all questions were answered correctly. Regarding individual questions, this ratio ranged from 85% to 99%. The high ratio of correct answers indicates that the participants were motivated during the experiment and, as expected, were able to complete the tasks correctly. However, to avoid potential bias from unmotivated participants and/or guesses, our data analysis considered only the data of tasks completed correctly, i.e., tasks whose questions were answered correctly. We provide detailed information about all the tasks considered for the data analysis in Appendix 9.1; as well as a list of all the experimental treatments. Appendix 9.1 provides (a) the frequency with which a participant chose any recommendation out of a set of three and (b) the frequency with which a participant chose any recommendation out of a set of three and answered the question correctly.

Since the manipulated recommendation (and thus the recommendation of interest) was always Recommendation 2 out of a set of three recommendations, the list also provides (c) the frequency with which a participant chose Recommendation 2 and answered the question correctly. This information allowed us to compute (d) the probability of the participants choosing Recommendation 2 if they chose one of the three recommendations and answered the question correctly.

Overall, our results indicate that all the social nudges steered the users toward choosing a certain report recommendation. Changing the social influence of the recommended reports' previous users increased the probability that BIS users would choose a certain recommendation. Figure 3 shows the mean values of the probability of choosing a certain recommendation.



	social cohesion (H1)	inst. isomorphism reg. business funct. (H2)	inst. isomorphism regarding location (H3)	hierarchical power (H4)
low/different	0.380	0.369	0.458	0.429
medium/similar	n.a.	0.564	0.486	0.472
high/same	0.664	0.604	0.593	0.665

Figure 3. Mean Values of Probablility of Choosing a Certain Recommendation

We conducted logistic linear mixed effects analysis, using the *glmer()* function of the statistical software package *lme4* for R (version 1.1–12) (Bates, Mächler, Bolker, & Walker, 2015). A logistic linear model was suitable, because we invoked linear effects and used one binary dependent variable (values: choose the manipulated recommendation; do not choose the manipulated recommendation). Similarly, a mixed effects analysis was suitable, because we administered a within-subject experiment (i.e., each participant was presented with multiple treatments).

Table 5 and Table 6 present the results. As explained in Section 4.2, we used a 2x3 experiment design to test the effects of social cohesion, hierarchical power, and elaborated an additional 3x3 experiment design to test the effects of institutional isomorphism (in terms of business function), institutional isomorphism (in terms of location), and elaboration. Table 5 presents the results of social cohesion, hierarchical power, and elaboration (i.e., H1, H4, H5, H6a, H6d). Table 6 presents the results of institutional isomorphism (in terms of business function), institutional isomorphism (in terms of location), and elaboration (i.e., H2, H3, H6b, H6c). To compare competing models (i.e., main models versus moderator models), we focus on information criteria statistics because we have multiple variables and information criteria impose penalties for including variables that do not significantly improve fit (Williams, 2017). Particularly with large samples, as in our case, information criteria can lead to more parsimonious but adequate models. Consistent with recent statistics literature (Müller, Scealy, Welsh, 2013), we report Akaike's information criterion (AIC) and the Bayesian information criterion (BIC). AIC and BIC estimate the *difference* between the "true data" and a fitted model. Thus, the smaller their absolute values, the better the fit of the model. (Note: BIC penalizes model complexity more heavily. Müller et al. (2013). Our results show that the moderator models have greater fit than the respective main effect models because the AIC and BIC of the moderator models are smaller than the AIC and BIC of the main models.

In addition, to provide pseudo R^2 statistics, we report the R^2 for general linear mixed models (so-called R^2GLMM) following Nakagawa & Schielzeth (2013) and as implemented in the R package *MuMIn* version 1.4 (Barton, 2017). Note that the R^2GLMM aims to allow comparison of general linear mixed models and to represent an absolute value for the goodness-of-fit of a model (which is not yet given by the AIC or BIC). However, the R^2GLMM needs to be assessed with caution if compared to R^2 statistics from linear models or general linear models (Nakagawa & Schielzeth, 2013). In line with the AIC and BIC, the R^2GLMM values in study confirm that the moderator models significantly improve the fit of the model. Regarding the effects of social cohesion and hierarchical power, adding elaboration as a moderator increases the R^2GLMM from 17.2% to 42.3%.

Similarly, regarding the effect of institutional isomorphism, adding elaboration as moderator increases the R^2GLMM from 9.5% to 24.3%. (Note: We do not distinguish between R^2GLMM for the fixed-effects model and the entire model because differences only occurred after the fourth relevant digit.)

5.4.1 Table 5 and Table 6: Interpretation of Estimates (= Log Odds) and Odds Ratio

Estimates represent the log odds factor according to which the probability of choosing the manipulated recommendation changes in contrast to the baseline model (i.e., low social cohesion and low hierarchical power). Example: In the logistic linear mixed-effects model, high social cohesion (rather than low social cohesion) increases this probability by a factor of 1.280 log odds. We also show the odds ratio to facilitate interpretation further. Example: A factor of 1.280 log odds in a logistic linear model would reflect an $e^{1.280} = 3.596$ odds ratio change. In other words, the probability increases by a factor of 3.596 if the social cohesion is high in contrast to the baseline model, which has low social cohesion.

Table 5. Logistic Linear Mixed-Effects Model of The Effects of Social Cohesion, Hierarchical Power and Recommendation Elaboration on the Recommendation Choice

Main model (AIC=1248.6, BIC=1278.0, R²GLMM=17.2%):						
Fixed effects	***Estimate***	***Odds ratio***	***Std. error***	***z value***	***Pr(>|z|)***	***Hyp.***
Intercept	-1.042	0.353	0.157	-6.623	3.51E-11 ***	
Social cohesion [high]	1.280	3.596	0.141	9.085	2.00E-16 ***	**H1**
Hier. power [medium]	0.070	1.072	0.169	0.412	0.681	**H4**
Hier. power [high]	1.039	2.826	0.187	5.543	2.97E-08 ***	**H4**
Elaboration	0.091	1.095	0.056	1.626	0.104	
Random effects	***Var.***	***Std. dev.***	***Observations***	***Groups***		
Subject (Intercept)	0	0	999	175		
Residuals	***Min.***	***1Q***	***Median***	***3Q***	***Max***	.
Residuals	-2.083	0.685	-0.594	0.858	1.684	
Moderator model (AIC=1125.2, BIC=1189.0, R²GLMM=42.3%):						
Fixed effects	***Estimate***	***Odds ratio***	***Std. error***	***z value***	***Pr(>|z|)***	***Hyp.***
Intercept	-0.739	0.478	0.259	-2.857	0.004 **	
Social cohesion [high]	1.138	3.120	0.352	3.230	0.001 **	
Hier. power [medium]	0.389	1.476	0.310	1.255	0.209	
Hier. power [high]	0.727	2.068	0.363	2.000	0.046 *	
Elaboration	-0.311	0.733	0.120	-1.554	0.120	
Social Cohesion [high] * Hierarchy [med.]	-1.386	0.250	0.489	-2.832	0.005 **	**H5**
Social Cohesion [high] * Hierarchy [high]	-2.546	0.078	0.643	-3.958	7.55E-05 ***	**H5**
Social Cohesion [high] * Elaboration	0.293	1.341	0.288	1.019	0.308	**H6a**
Hierarchy [med.] * Elaboration	-0.485	0.616	0.260	-1.869	0.062	**H6d**
Hierarchy [high] * Elaboration	0.654	1.924	0.247	2.647	0.008 **	**H6d**
Social Cohesion [high] * Hierarchy [med.] * Elab.	1.743	5.714	0.422	4.128	3.65E-05 ***	

Table 5. Logistic Linear Mixed-Effects Model of The Effects of Social Cohesion, Hierarchical Power and Recommendation Elaboration on the Recommendation Choice

Social Cohesion [high] * Hierarchy [high] * Elab.	1.106	3.021	0.475	2.328	0.020 *	
Random effects	***Variance***	***Std. dev.***	***Observations***	***Groups***		
Subject (Intercept)	0	0	999	175		
Residuals	***Min.***	***1Q***	***Median***	***3Q***	**Max.**	
Residuals	-3.090	-0.716	-0.201	0.819	6.084	
Note: ***p<0.001, **p<0.01, *p<0.05.						

Table 6. Logistic Linear Mixed-Effects Model of the Effects of Institutional Isomorphism and Recommendation Elaboration on the Recommendation Choice

Main model (AIC=1990.6, BIC=2027.9, R²GLMM=9.5%):						
Fixed effects	***Estimate***	***Odds ratio***	***Std. error***	***z value***	***Pr(>|z|)***	***Hyp.***
Intercept	-0.973	0.3780	0.113	-8.640	2.00E-16 ***	
Inst. isomorphism in terms of business funct. [medium]	0.828	2.289	0.131	6.319	2.63E-10 ***	**H2**
Inst. isomorphism in terms of business funct. [high]	1.004	2.728	0.130	7.711	1.25E-14 ***	**H2**
Inst. isomorphism in terms of location [medium]	0.068	1.071	0.134	0.509	0.610451	**H3**
Inst. isomorphism in terms of location [high]	0.468	1.596	0.141	3.307	0.000943 ***	**H3**
Elaboration	0.119	1.126	0.041	2.871	0.004092 **	
Random effects	***Var.***	***Std. dev.***	***Observations***	***Groups***		
Subject (Intercept)	0	0	1513	179		
Residuals	***Min.***	***1Q***	***Median***	***3Q***	***Max.***	
Residuals	-1.618	-0.930	-0.615	0.910	1.627	
Moderator model (AIC=1888.6, BIC=1989.8, R²GLMM=24.3%):						
Fixed effects	***Estimate***	***Odds ratio***	***Std. error***	***z value***	***Pr(>|z|)***	***Hyp.***
Intercept	-0.349	0.705	0.172	-2.038	0.042 *	
Inst. isomorphism in terms of business funct. [medium]	-0.031	0.969	0.290	-0.107	0.915	
Inst. isomorphism in terms of business funct. [high]	-0.153	0.858	0.284	-0.539	0.590	
Inst. isomorphism w.r.t. location [medium]	-0.300	0.741	0.298	-1.006	0.315	
Inst. isomorphism in terms of location [high]	1.206	2.790	0.384	2.672	0.008 **	
Elaboration	-0.796	0.451	0.165	-4.807	1.53E-06 ***	
Inst. isomorph. (bf)[med.] * Inst. isomorph. (loc) [med.]	0.648	1.913	0.481	1.348	0.178	
Inst. isomorph. (bf) [high] * Inst. isomorph. (loc) [med.]	0.241	1.273	0.474	0.509	0.611	
Inst. isomorph. (bf) [med.] * Inst. isomorph.(loc)[high]	-1.801	0.165	0.697	-2.582	0.010 **	

Table 6. Logistic Linear Mixed-Effects Model of the Effects of Institutional Isomorphism and Recommendation Elaboration on the Recommendation Choice

Inst. isomorph. (bf) [high] * Inst. isomorph.(loc)[high]	-1.698	0.183	0.656	-2.589	0.010 **	
Inst. iso. (bf)[med.] * Elab.	1.490	4.438	0.261	5.719	1.07E-08 ***	**H6b**
Inst. iso. (bf) [high] * Elab.	1.609	4.999	0.256	6.292	3.13E-10 ***	**H6b**
Inst. iso.(loc)[med.] * Elab.	0.846	2.329	0.202	4.179	2.92E-05***	**H6c**
Inst. iso. (loc)[high] * Elab.	0.444	1.559	0.219	2.025	0.043 *	**H6c**
Inst. isom. (bf) [med.] * Inst. isom.(loc)[med] * Elab	-1.475	0.229	0.307	-4.809	1.52E-06 ***	
Inst. isom. (bf) [high] * Inst. isom.(loc)[med] * Elab	-1.222	0.295	0.308	-3.963	7.40E-05 ***	
Inst. isom. (bf) [med.] * Inst. isom.(loc)[high] * Elab	-0.530	0.589	0.356	-1.488	0.137	
Inst. isom. (bf) [high] * Inst. isom.(loc)[high] * Elab	-0.444	0.629	0.350	-1.327	0.185	
Random effects	***Variance***	***Std. dev.***	***Observations***	***Groups***		
Subject (Intercept)	0	0	1513	179		
Residuals	***Min.***	***1Q***	***Median***	***3Q***	***Max.***	
Residuals	-2.788	-0.840	-0.193	0.912	6.084	
Note: ***p<0.001, **p<0.01, *p<0.05.						

All the computed models' statistical results indicate that the residuals vary around a slightly negative median (between -0.2 and -0.6), that the first quantile varies between -0.9 and -0.7, and the third quantile between 0.7 and 0.9. However, the random effect (i.e., the variance explained by a certain participant or "subject") is approximately zero in all the computed models. This estimate by *glmer()* indicates that the residual term alone explains the extent of the subject variation (Barr et al., 2013). The variation between the participants is too small to add an additional random effect estimate.

While Figure 3 above shows the direct effects (H1–4), Figures 4a–d below show the moderation effects of recommendation elaboration (H6a–d), and Figure 5 visualizes the interaction effect between social cohesion and hierarchical power (H5). The following subsections explain the statistical and graphical results of all the hypotheses individually.

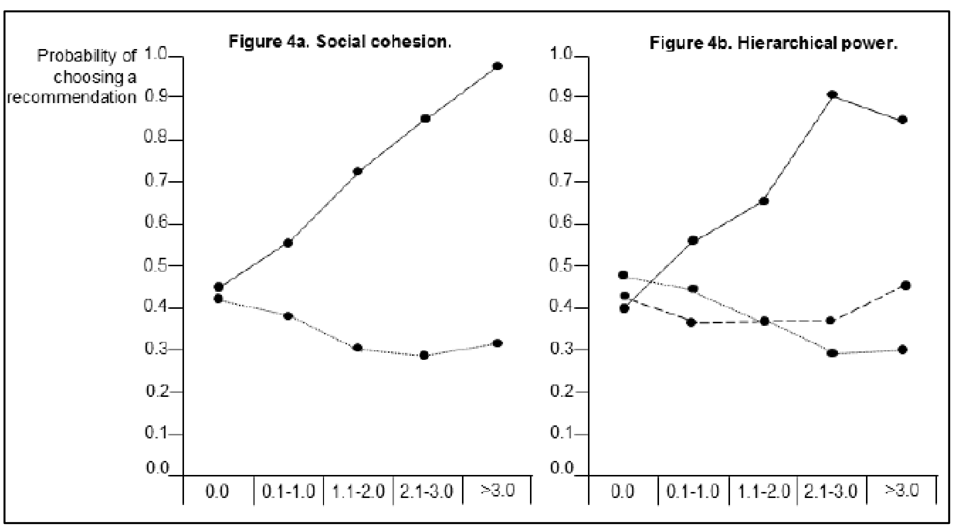


Figure 4a–b. Moderating Effects of Recommendation Elaboration

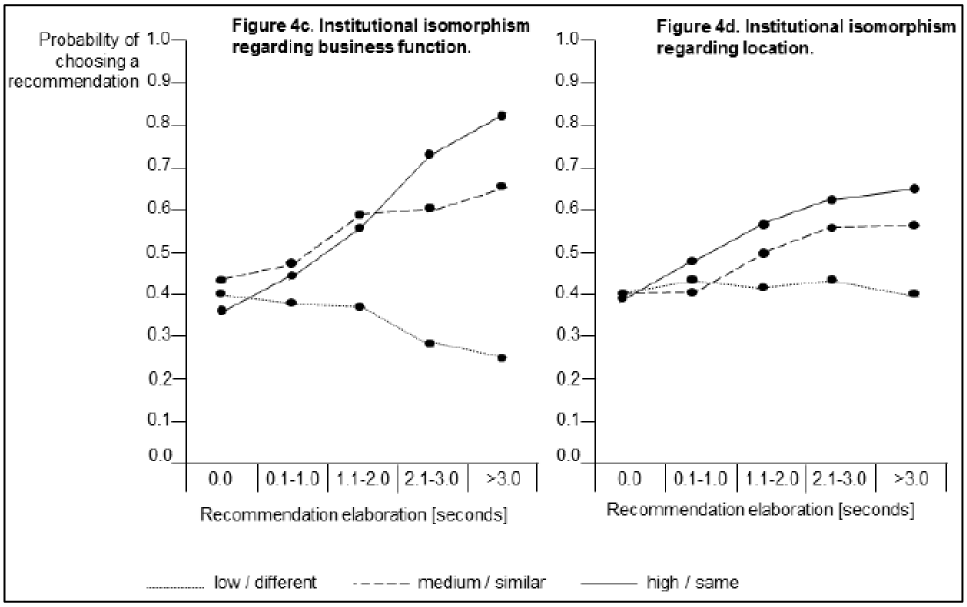


Figure 4c–d. Moderating Effects of Recommendation Elaboration

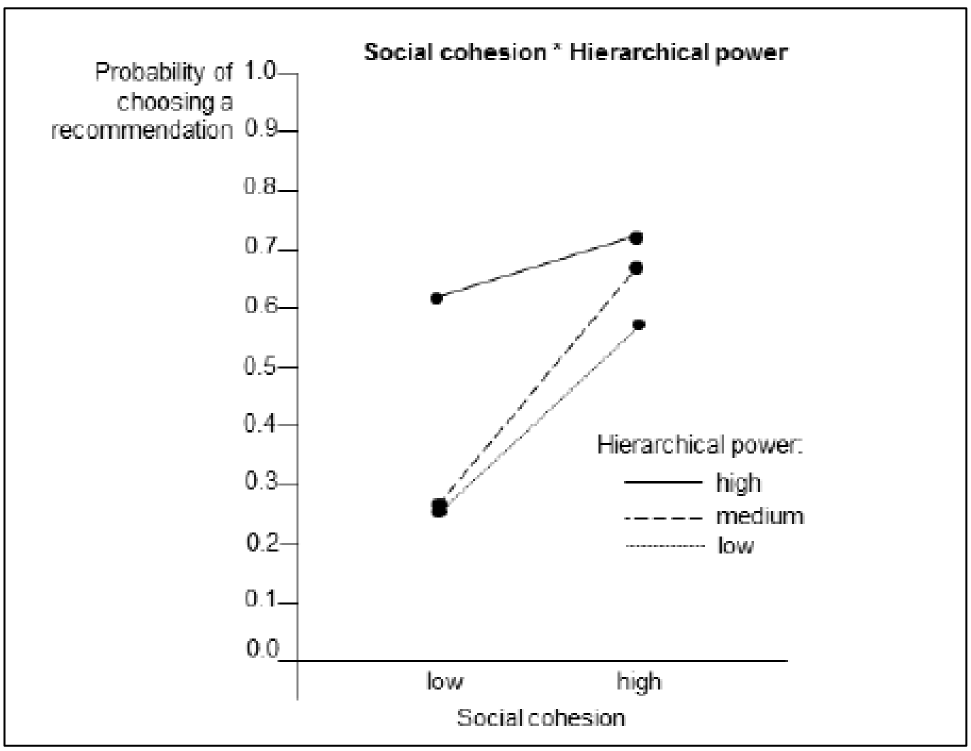


Figure 5. Interaction Effect Between Social Cohesion and Hierarchical Power

5.4.2 The Effects of Social Nudges Based on Social Cohesion and Hierarchical Power

As shown in Figure 3, each of the four social nudges increased the probability of the participants choosing a certain recommendation. The probability of a participant choosing a certain recommendation was significantly higher if the recommendation was based on the usage data of a direct colleague (i.e., high social cohesion), who was referred to, for example, as "your project manager" instead of "a project manager." Since this increase was also statistically significant at $p<0.001$, it provides evidence for H1. Specifically, the mixed-effects model in Table 5 (main-effects model) indicates that participants chose recommendations with high levels of social cohesion 3.6 times more often than they chose those with low levels of social cohesion.

In addition, we suggested that the probability of a participant choosing a certain recommendation would also be significantly higher if the previous user of the recommended report were assigned to a hierarchically more powerful position, such as a director or a project manager (H4). However, only a truly high hierarchical power level ("director") increased the probability significantly (at $p<0.001$). Compared to the low hierarchical power level ("intern"), the medium hierarchical power level ("project manager") only increased the probability by a factor of 1.1, while the high hierarchical power level ("director") increased the probability by a factor of 2.8. This indicates that a social nudge based on hierarchical power is generally suitable for influencing users' actions, but that the effect size varies strongly.

We found that employees in powerful positions, such as directors, can influence other employees even if they are not directly connected to them (H5). However, the opposite does not seem to hold true. Employees in less powerful hierarchical positions, such as interns, can usually only influence directly connected employees. In contrast to employees in highly powerful positions, such as directors, who can influence all employees, interns are unlikely to influence employees with whom they do not have any ties. Consequently, nudges based on low-power employees will benefit far more from social cohesion.

H5 defined this interaction effect between hierarchical power and social cohesion. Our results support H5. Figure 5 indicates that recommendations based on users with high hierarchical power will benefit very little from social cohesion (i.e., slight slope along the social cohesion dimension in Figure 5). However, recommendations based on users with only medium or even low hierarchical power will benefit strongly if the social cohesion between users is high (i.e., steep slope along the social cohesion dimension in Figure 5). The mixed-effects model also shows statistical significance at $p<0.001$ in terms of this interaction effect (Table 5, moderating-effects model).

5.4.3 The Effects of Social Nudges Based on Institutional Isomorphism

Furthermore, we designed two nudges based on institutional isomorphism. The results show that institutional isomorphism in terms of a user's business function (H2) increased the probability of that user choosing a specific recommendation. In contrast to low similarity between two business functions (e.g., a sales department and an IT department), medium similarity (e.g., a sales department and a marketing department) increased the probability by a factor of 2.3, while high similarity (e.g., two sales departments) increased the probability by a factor of 2.7 (Table 6, main-effects model). Both increases were statistically significant at $p<0.001$, which supports H2.

However, as can be seen in Figure 3, the effect size of the social nudge based on institutional isomorphism is smaller in terms of a user's location (H3). In contrast to users' locations on different continents (e.g., Germany and Canada), locations on the same continent (e.g., Germany and France) only increased the probability by a factor of 1.1, while locations within the same country (e.g., two locations in Germany) only increased the probability by a factor of 1.6 (Table 6, main-effects model). While this increase was still statistically significant at $p<0.001$, which supports H3, it is interesting to note that, in our study, institutional isomorphism in terms of user business function had a much larger impact than institutional isomorphism in terms of user location.

5.4.4 The Moderating Effect of Recommendation Elaboration

We suggested that the effect of any nudge depends on whether participants elaborate and choose a recommendation, or whether they merely click on one without processing it cognitively. As described above, we used an eye tracker to measure recommendation elaboration. We identified five relevant elaboration intervals to analyze recommendation elaboration: 0 seconds (i.e., no elaboration), 0.1 to 1 second, 1.1 to 2 seconds, 2.1 to 3 seconds, and 3.1 seconds or more. The plots of H6a–d in Figures 4a–d visualize the effects of these elaboration intervals on all the experimental treatments. Furthermore, Appendix 9.4 provides detailed information about all the combinations of elaboration intervals and experimental treatments.

The interaction plots support the directions of H6a–d. The probability of the participants choosing the manipulated recommendation increases with high levels of social influence (e.g., high social cohesion). However, the probability does not decrease with low levels of social influence (e.g., low social cohesion). Specifically, it can be noted that the probabilities of no elaboration (0 seconds) and low elaboration (0.1 to 1 second) are similar. As soon as elaboration increases, our nudges' effects become visible. This supports our assumption that people need to cognitively process a recommendation aimed at nudging them. Regarding the statistical significance of these results, our mixed-effects models (Table 5 and Table 6, moderating-effects model) show that H6b–d are significant. Only H6a is not significant.

5.4.5 Control Model

The hypotheses analyzed above represent the main research model. We analyzed the effect of potentially biasing factors. Our analysis controlled for the participants' age, gender, nationality, and their culture (measured as first language). However, none of these control variables had any significant influence on our main research model (Appendix 9.5, Table 12 and Table 13). We therefore conclude that the experiment participants' age, gender, nationality, and/or culture do not bias our results.

6 Discussion

Our findings provide important insights for improving the reuse of reports, as well as for designing social nudges in the context of BIS. The findings shed light on how individuals' recommendation elaboration determines the influence of RAs and, thus, the influence of recommendations that provide additional information to steer users toward specific choices.

6.1 Implications for Theory

6.1.1 A Novel Approach for Managing Core BIS and Supplementary WS

Our study describes a new approach for tackling the challenges of workaround systems (WS), such as the limited reuse of information, poor decision-making based on inconsistent data, and loss of synergies across employees. The idea behind our approach is that large BIS should proactively reduce individuals' need to develop and use WS. We therefore proposed and examined an enterprise recommendation agent (ERA) that extends existing BIS. This ERA reduces individuals' need to develop and use WS that store individuals' reports, because it facilitates the retrieval of relevant existing reports. Specifically, the ERA uses social nudges to motivate individuals to use report recommendations and, thus, increase report reuse.

While previous literature has focused on BIS governance in order to tackle the challenges of WS, the ERA focuses on facilitating information reuse. The ERA supports BIS users' search for potentially relevant reports. According to Simon's (1957) decision-making process, individuals first need to identify relevant choices and thereafter select the most suitable option. Meservy et al. (2014) show that this process also holds in the IS context. Thus, by suggesting that candidates should report to BIS users, the ERA supports their report reuse decisions. The ERA helps users identify potentially relevant reports, and thus facilitates the reuse of reports originally developed by their colleagues. Ultimately, this should reduce individuals' need to develop WS, because they will find existing reports with the required information more often. The ERA thus helps increase the reuse of BIS reports and reduce the use of WS.

The existing literature offers approaches focusing on IS governance to manage and balance the use of large enterprise IS and WS (Alter, 2014). The ERA proposed in this study complements these approaches, because the downsides of these IS governance-based approaches do not affect it. Most IS governance-based approaches emphasize either the need to prevent WS or the need to acknowledge the value of WS and the importance of helping individuals build WS. However, both approaches have their limitations. Attempts to control the use of large enterprise IS and prevent WS have been shown to lead to shadow systems (Alter, 2013, 2014; Behrens, 2009; Sun, 2012). Similarly, the value of empowering individuals is also limited. If organizations foster the development of WS, the complexity of the overall IS environment inevitably increases and must be managed, usually through additional IS governance units. However, establishing and running these organizational units is very costly and only the specific context can determine whether introducing additional IS governance units will increase the flexibility of IS (Brown & Magill, 1994, 1998; Gebauer & Schober, 2006; Tiwana & Kim, 2015). In contrast to these IS governance-based approaches, our ERA neither limits individuals' flexibility in terms of using existing information, nor does it require additional governance units to manage increasingly complex IS environments. The ERA is therefore a valuable complement to existing approaches for managing core BIS and supplementary WS.

6.1.2 Design and Evaluation of Social Nudges

Individuals' decision-making is not entirely rational. Numerous cognitive biases may influence their attempts to make rational decisions. Extant literature has showed that these biases also exist in the IS context (e.g., Adomavicius, Bockstedt, Curley, & Zhang, 2013; Allen & Parsons, 2010; Goes; 2013). However, empirical IS studies have not examined how additional information about previous users can be used to exert a social influence on new users and, thus, steer them toward making certain desirable choices. We address this gap by designing and evaluating four social nudges.

Social psychologists and behavioral economists use the notion of a *nudge* to refer to a change in the way different options are presented (without affecting the options themselves) in order to promote desirable choices (Thaler & Sunstein, 2003). A frequently mentioned example of a nudge is a picture of a smoker's lungs on a pack of cigarettes (Sunstein, 2014). Although the picture does not force smokers to stop smoking, it influences their choices. In other words, the picture of the smoker's lungs nudges (potential) smokers and influences their decisions in desirable ways (e.g., to quit smoking). Adapting the nudge concept to the IS concept, we introduced the notion of *social nudges*. In line with the nudge literature (Halpern, 2015; Sunstein, 2014), a *social nudge* is a nudge that uses the effects of social influence to promote desirable choices. Compared to pictures showing the adverse health effects of certain activities, social influence is far more relevant in the enterprise IS context and, thus, in the BIS context.

We present four social nudges based on three different forms of social influence in organizations: social influence based on proximity between individuals (i.e., social cohesion), social influence based on similar positions in organizational settings (i.e., institutional isomorphism) in terms of business function and location, and social influence based on the power in organizational hierarchies. Our results indicate that providing additional information about previous users may exert a social influence on new users, which would then increase the probability of these new users choosing a specific recommendation.

By demonstrating the concrete application of social nudges, this study motivates further IS research that would aim to explore ways of utilizing cognitive biases in order to promote desired user behaviors. While the vast body of works by behavioral economists theorizes deeply on the potential benefits of nudges (e.g., Hanna, 2015), IS research can contribute by refining and designing concrete nudges and by demonstrating and testing their effects.

6.1.3 Effect of Recommendation Elaboration

As a third theoretical implication, this study reveals how an individual's recommendation elaboration shapes the effect that a recommendation agent (RA) has on a user. We operationalized users' recommendation elaboration as their fixation on the recommendation agent and used eye-tracking devices to measure this fixation measure. The results demonstrate that, without recommendation elaboration, users' recommendation choice is random and not influenced by additionally provided information about a recommendation. Consequently, social nudges that provide additional information about previous users' influences do not affect the recommendation choice in the absence of elaboration.

The results of examining recommendation elaboration indicate that just 1 to 2 seconds of recommendation elaboration allowed the designed social nudges to influence individuals' recommendation choices. This finding indicates that even very little elaboration is influential, which addresses calls for research on recommendation timing (e.g., Ho, Bodoff, & Tam, 2011). Finally, the effect of recommendation elaboration could also be very interesting for other IS research and marketing domains that attempt to optimize the frequency with which display advertisements are updated (e.g., Balseiro, Feldman, Mirrokni, & Muthukrishnan, 2014).

6.2 Implications for Practice

Besides implications for theory, our findings offer interesting insights for managers, IS designers, IS developers, and RA designers. First, we present a novel approach for managing the trade-off between core BIS and supplementary WS. That is, we propose an ERA to increase the reuse of BIS reports. Higher report reuse generates synergies across employees. It reduces data inconsistencies, which in turn improves managers' decision-making. In contrast to other approaches, the proposed ERA targets report reuse without restricting user authorizations and without requiring expensive IS governance units. In addition, this study designed and tested four social nudges, using information about reports' previous users. This information included a proximity indicator ("a" vs. "your"), previous users' department and country, as well as their role in their organizations' hierarchies. These information chunks are concrete examples of social nudges in an enterprise IS context and provide useful guidelines for IS designers and developers.

Finally, our findings provide two interesting insights for RA designers. First, the proposed ERA indicates a new context for which RAs could be designed and developed. In addition, our findings indicate that RA designers need to take care when building RAs that update their recommendations after certain time intervals. Our experiment showed that most users required 1–3 seconds to process a small amount of additional information about the recommendations. However, since this finding may be highly context and RA-dependent, we recommend that RAs be tested within their specific contexts in order to determine suitable recommendation update frequencies.

6.3 Limitations and Suggestions for Future Research

Despite its contributions to theory and practice, our study has limitations and also creates opportunities for future research. To begin with, we focused on nudges in the context of BIS. Although BIS are a common context in the IS research domain, the generalizability of our results should also be examined in other contexts. We conducted a lab experiment for two main reasons. First, the lab experiment allowed us to control for external effects. In a field setting, controlling for social influence would have been almost impossible because of the numerous potentially confounding factors (e.g., experience working together, trust, looks, etc.). Second, the lab experiment allowed us to conduct fixation analysis and, thus, reliably measure recommendation elaboration. However, a future study could build on our findings and test our hypotheses in a field setting.

Next, choosing students as the experiment participants may have reduced our findings' generalizability to employees within organizations. However, although students do not have extensive experience working with BIS, we argue that they are a reasonably representative group, and also that external factors such as age and experience likely cause them to be less biased than some other groups (e.g., Choi, Jiang, Xiao, & Kim, 2015; Colquitt, 2008; Xu et al., 2014). To mitigate the risk associated with inexperienced participants, we used only tabular reports and very basic and intuitive functionalities and tasks (e.g., open a report from a list, open a recommended report, filter a report, and look for certain information within a report). We used several techniques to train the participants to use the BIS (i.e., introduction video, personal introduction, personal support, training tasks, and reference papers) and after the experiment, we did not find any indication that the participants had had difficulties using the BIS. The number of correctly completed experimental tasks (93%) also supports this assumption.

Finally, a third limitation relates to the measurement of elaboration, which we measured using state-of-the-art eye-tracking technology for each recommendation. However, since eye-tracking devices constantly improve, future studies could leverage, for instance, a more granular resolution. This would allow researchers to provide detailed elaboration measurements of the subparts of the recommendations.

Besides tackling these potential limitations, future research could extend our work and also design and investigate other nudges. We focused on social nudges due to the significance of social influence on individuals' behaviors in organizations (Tichy et al., 1979; Tsai & Goshal, 1998). However, IS user behaviors could perhaps be manipulated by means other than social effects and future studies could thus investigate similar nudges that leverage other cognitive biases (Goes, 2013). From a practitioner's perspective, future research could also extend our ERA by adding concrete information about the recommended reports. For instance, report recommendations could be extended with short descriptions indicating why other colleagues use the reports. These studies could specifically improve our ERA, because, in its current form, it focuses only on presenting information about previous users without considering information about the content of the recommended reports.

7 Conclusion

Recent IS articles have called on researchers to draw on and contribute to behavioral economists' research (Goes 2013). This study draws on their nudge concept. We offer a specific refinement described as a social nudge, which refers to the attempt to steer an individual toward desirable choices by exploiting the effect of social influence on the individual. However, in line with the nudge concept, a social nudge should not change the range of available options from which an individual can choose.

We designed four social nudges based on theoretical knowledge about social cohesion, institutional isomorphism, and hierarchical power, and mplemented them to examined their effects on BIS users. Our findings show that the four implementations of social nudges steered users toward making the targeted choices. These findings are interesting for IS researchers and behavioral economists because they offer insights into concrete applications and the effects of the nudge concept.

We examined the effects of the four social nudges in the context of RAs. Previous RA literature has focused on end consumers rather than employees as RA users. However, we argue that RAs should also be considered potential extensions of enterprise IS. We therefore proposed an enterprise recommendation agent (ERA) as an extension of BIS and showed that an ERA can complement existing approaches to managing core BIS and supplementary WS. Specifically, an ERA can facilitate information retrieval and thus increase reuse of existing information and reports. Since this reduces employees' needs to build redundant and duplicate reports using WS, the ERA represents a means for better balancing core BIS and supplementary WS. Finally, we also contribute to RA literature and elaboration research by empirically examining and reliably quantifying the effects of users' recommendation elaboration by using recent eye-tracking technology and conducting gaze analysis.

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Appendix

A1. Experimental Treatments and Probabilities

We used a within-subject experimental design. Experimental treatments 1–9 were used for the cross-factorial examination of institutional isomorphism in terms of business function and location. Experimental treatments 10–15 were used for the cross-factorial examination of social cohesion and hierarchical power. Note, in treatments 10 and 11, the hierarchical position of the user referred to in Recommendation 1 and Recommendation 3 is "intern," because, Recommendation 2 would otherwise have referred to users with a lower social influence than Recommendation 1 and Recommendation 3.

In total, 187 subjects participated in our experiment. However, since we did not want to force them to select a recommendation, some participants solved the experimental task without choosing any of the three provided report recommendations. The actual sample size N of each experimental treatment is therefore less than 187. Specifically, it ranges from 149 to 171.

Note that one experimental treatment is included in both of the cross-factorial designs. Experimental Treatment 1 and Experimental Treatment 12 are the same. Consequently, the sample size of these treatments is approximately twice the sample size of the other treatments.

Table 7 provides all experimental treatments. Table 8 shows (a) the frequency with which a participant followed any recommendation from a set of three, and (b) the frequency with which a user followed any recommendation from a set of three and answered the task correctly. Since the manipulated recommendation (and thus the recommendation of interest) is always the second from a set of three "rotating" recommendations, the list also provides (c) the frequency with which a user followed the second recommendation and completed the task correctly. Finally, this allowed us to compute (d) the probability of users selecting the second recommendation if they followed one of the three recommendations of the condition and answered the task correctly.

Note that the number of observations in Table 5 and Table 6 corresponds to the sum of Column (b) in Table 8. Specifically, the number of observations (1513) in the models estimating the effects of social cohesion, power, and elaboration equals the sum of Table 8, Column (b), Rows 1–9. In contrast, the number of observations (999) in the models estimating the effects of institutional isomorphism (in terms of business function and location) and elaboration equals the sum of Table 8, Column (b), Rows 10–15.

Table 7. Experimental Treatments: Overview.

Exp. treatment ID	Inst. isomorph. in terms of business function	Inst. isomorph. in terms of location	Social cohesion	Hierarchical power	(a) N
1	different	different	low	medium	(314)
2	different	similar	low	medium	160
3	different	same	low	medium	168
4	similar	different	low	medium	152
5	similar	similar	low	medium	163
6	similar	same	low	medium	153
7	same	different	low	medium	171
8	same	similar	low	medium	161
9	same	same	low	medium	166
10	different	different	low	low	150
11	different	different	high	low	149
12 (=1)	different	different	low	medium	(314)
13	different	different	high	medium	158
14	different	different	low	high	158
15	different	different	high	high	156

Table 8. Experimental Treatments: Analysis.

Exp. treatment ID	(a) N	(b) N with correctly answered question	(c) Recommendation 2 chosen	(d) Probability of choosing Recommendation 2
1	(314)	(297)	(78)	26,26%
2	160	150	54	36,00%
3	168	155	75	48,39%
4	152	147	82	55,78%
5	163	159	84	52,83%
6	153	140	85	60,71%
7	171	155	86	55,48%
8	161	146	83	56,85%
9	166	164	113	68,90%
10	150	141	37	26,24%
11	149	126	75	59,52%
12 (=1)	(314)	(297)	(78)	26,26%
13	158	141	96	68,09%
14	158	153	94	61,44%
15	156	141	101	71,63%

A2. Demographic Data

Table 9. Demographic Data

Category	Value	Absolute	Percentage
Participants	na	187	100.00%
Sex	Men	136	72.73%
	Women	51	27.27%
	Total	**187**	**100.00%**
Age	17 or younger	1	0.53%
	18–20	47	25.13%
	21-29	135	72.19%
	30–39	4	2.14%
	40–49	0	0.00%
	50–59	0	0.00%
	60 or older	0	0.00%
	Total	**187**	**100.00%**
Nationality	Albanian	4	2.14%
	Belarus	1	0.53%
	Bolivian	1	0.53%
	Bulgarian	3	1.60%
	Chinese	12	6.42%
	Colombian	2	1.07%
	Dutch	1	0.53%
	Egyptian	4	2.14%

Table 9. Demographic Data

	French	1	0.53%
	German	106	56.68%
	Greek	4	2.14%
	Hungarian	1	0.53%
	Indian	6	3.21%
	Iraqi	1	0.53%
	Italian	3	1.60%
	Jordanian	1	0.53%
	Korean (Republic)	2	1.07%
	Lithuanian	1	0.53%
	Mexican	2	1.07%
	Moroccan	1	0.53%
	Norwegian	1	0.53%
	Pakistan	1	0.53%
	Peruvian	1	0.53%
	Romanian	1	0.53%
	Russian	5	2.67%
	Spanish	4	2.14%
	Suisse	1	0.53%
	Swedish	2	1.07%
	Syrian	1	0.53%
	Turkish	6	3.21%
	US American	3	1.60%
	Vietnamese	4	2.14%
	Total	**187**	**100.00%**
First language as a child	Albanian	4	2.14%
	Arabic	8	4.28%
	Bulgarian	3	1.60%
	Cantonese	2	1.07%
	Chechen	1	0.53%
	Chinese	11	5.88%
	Dutch	1	0.53%
	English	2	1.07%
	German	90	48.13%
	Greek	3	1.60%
	Hindi	2	1.07%
	Hungarian	1	0.53%
	Italian	3	1.60%
	Korean	2	1.07%
	Lithuanian	2	1.07%
	Norwegian	1	0.53%
	Romanian	3	1.60%
	Russian	11	5.88%

Table 9. Demographic Data

	Serbian	1	0.53%
	Shanghainese	1	0.53%
	Slovak	1	0.53%
	Spanish	10	5.35%
	Swedish	2	1.07%
	Tamil	2	1.07%
	Telugu	2	1.07%
	Turkish	11	5.88%
	Urdu	1	0.53%
	Vietnamese	6	3.21%
	Total	**187**	**100.00%**

A3. Experiment Design

A3.1Experimental Tasks

The experiment participants were asked to complete nine tasks. Each task consists of one question, which they could answer by searching for specific information in the BIS and using the ERA and/or the list of all reports. The time needed to answer a question was not measured and participants were informed about this before the experiment. Table 10 provides the list of all tasks. Note that task 1 and task 2 were used as training tasks.

Table 10. List of experimental tasks.

Task	Type	Question	Answer
1	Training	Where does the customer come from who placed the order with the number 200701011CS567?	United Kingdom
2	Training	What is the product subcategory of order number 20070101311515?	Computers Accessories
3	Experiment	How many male customers have 5 children and own a house (HouseOwnerFlag=1)? [count rows]	2
4	Experiment	How many Contoso Carrying Case E312 Silver were ordered in the year 2007? [count the rows]	4
5	Experiment	What is the gender and customer key of the customer with the highest consumption?	M and 178
6	Experiment	What is the yearly income of customer 137?	40.000,00
7	Experiment	How many female customers have a Bachelor’s degree? [count rows]	6
8	Experiment	In which country does customer 343 place his orders?	France
9	Experiment	Where does customer 252 live and how old is he/she?	83 and Canada

A4. Organizational Structure of Contoso

The departments, org. hierarchy, and regions in which Contoso operates are displayed in Figure 6. Figure 6 was also printed and given to all the participants during the experiment.

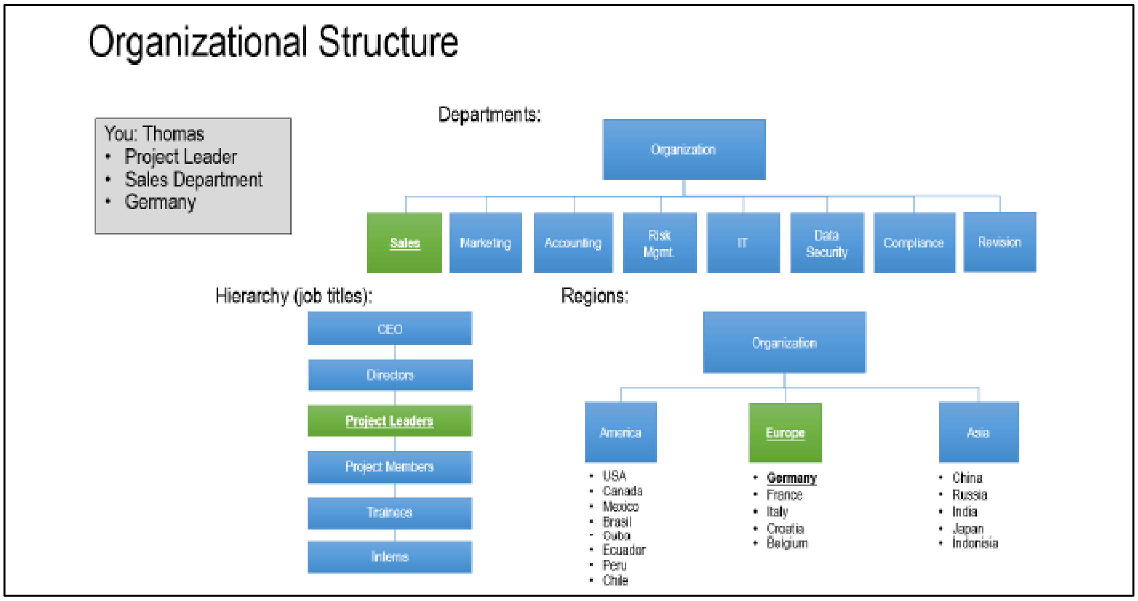

Figure 6. Contoso Reference Paper Provided to Participants During the Experiment.

A5. Recommendation Elaboration Analysis

Recommendation elaboration was measured using Tobii Pro X2 (Tobii, 2015) eye-tracking devices. A detailed description of this measure is provided in Section 4.5. To visualize the effects of recommendation elaboration, we defined five intervals and computed the probabilities that participants would choose the manipulated recommendation, i.e., Recommendation 2. The results are illustrated in Figures 4a–d in Section 5.4. Table 11 below provides detailed probabilities. Related statistical analyses and significance tests of H6a–d are presented in Table 5 and Table 6 in Section 5.4.

Table 11. Probabilities to Choose Manipulated Recommendation by Rec. Elaboration

Elaboration [sec] / Probability	0.0s	0.1–1.0s	1.1–2.0s	2.1–3.0s	3.1s–inf
Recommendation elaboration and social cohesion:					
Probability of choosing the manipulated rec. if social cohesion was high	0.47	0.56	0.72	0.86	0.97
Probability of choosing the manipulated rec. if social cohesion was low	0.42	0.37	0.30	0.29	0.31
Recommendation elaboration and institutional isomorphism in terms of business function:					
Probability of choosing the manipulated rec. if the business function was the same	0.37	0.44	0.55	0.72	0.82
Probability of choosing the manipulated rec. if the business function was similar	0.43	0.47	0.59	0.60	0.65
Probability of choosing the manipulated rec. if the business function differed	0.40	0.38	0.37	0.27	0.24
Recommendation elaboration and institutional isomorphism in terms of location:					
Probability of choosing the manipulated rec. if location was the same	0.39	0.48	0.57	0.61	0.64
Probability of choosing the manipulated rec. if the location was similar	0.40	0.40	0.49	0.55	0.56
Probability of choosing the manipulated rec. if the location differed	0.40	0.43	0.41	0.43	0.40
Recommendation elaboration and hierarchical power:					
Probability of choosing the manipulated rec. if the hierarchical power was high	0.40	0.57	0.67	0.90	0.84
Probability of choosing the manipulated rec. if the hierarchical power was medium	0.42	0.37	0.38	0.38	0.45
Probability of choosing the manipulated rec. if the hierarchical power was low	0.48	0.44	0.38	0.29	0.30

A6. Control Model Analysis

Table 12. Logistic Linear Mixed-Effects Model with Control Variables

Social cohesion, hierarchical power, recommendation elaboration, control variables:

Fixed effects	*Estimate*	*Odds ratio*	*Std. error*	*z value*	*Pr(>|z|)*
Intercept	-1.479	0.228	0.583	-2.538	0.011 *
Social Cohesion [high]	0.787	2.197	0.220	3.572	3.54E-04 ***
Hierarchical power [med.]	0.255	1.291	0.192	1.330	0.184
Hierarchical power [high]	0.469	1.599	0.227	2.066	0.039 *
Elaboration	-0.152	0.859	0.111	-1.369	0.171
Social Cohesion [high] * Hierarchy [med.]	-0.860	0.423	0.306	-2.810	0.005 **
Social Cohesion [high] * Hierarchy [high]	-1.576	0.207	0.397	-3.972	7.13E-05 ***
Social Cohesion [high] * Elaboration	0.120	1.128	0.174	0.695	0.487
Hierarchy [med.] * Elaboration	-0.286	0.751	0.141	-2.037	0.042 *
Hierarchy [high] * Elaboration	0.401	1.493	0.142	2.821	0.005 **
Social Cohesion [high] * Hierarchy [med.] * Elab.	1.067	2.907	0.248	4.300	1.71E-05 ***
Social Cohesion [high] * Hierarchy [high] * Elab.	0.670	2.014	0.283	2.471	0.013 *
Age	0.093	1.098	0.114	0.817	0.414
Gender [woman]	-0.031	0.969	0.132	-0.238	0.812
Nationality [Belarus]	0.129	1.138	0.933	0.138	0.890
Nationality [Bulgarian]	0.431	1.539	0.639	0.675	0.450
Nationality [Chinese]	-0.656	0.519	0.801	-0.819	0.413
Nationality [Colombian]	0.688	1.989	0.591	1.163	0.245
Nationality [Dutch]	0.496	1.642	0.621	0.799	0.424
Nationality [Egyptian]	0.489	1.631	0.527	0.928	0.354
Nationality [French]	0.185	1.203	1.043	0.177	0.860
Nationality [German]	0.052	1.053	0.690	0.075	0.940
Nationality [Greek]	5.573	26.313	162.452	0.034	0.973
Nationality [Hungarian]	1.780	5.927	0.748	2.380	0.017 *
Nationality [Indian]	0.729	2.072	0.992	0.735	0.463
Nationality [Iraqi]	0.548	1.730	0.783	0.700	0.484
Nationality [Italian]	1.157	3.181	0.574	2.017	0.044 *
Nationality [Jordanian]	0.454	1.574	0.702	0.646	0.518
Nationality [Korea (Rep.)]	1.409	4.090	0.638	2.208	0.027 *
Nationality [Lithuanian]	-5.182	0.006	132.642	-0.039	0.969
Nationality [Mexican]	0.714	2.041	0.578	1.234	0.217
Nationality [Moroccan]	0.759	2.137	0.715	1.062	0.288
Nationality [Norwegian]	0.510	1.665	0.692	0.737	0.461
Nationality [Pakistan]	0.154	1.167	0.967	0.160	0.873
Nationality [Peruvian]	0.488	1.629	0.638	0.764	0.445
Nationality [Romanian]	-0.542	0.581	1.100	-0.493	0.622
Nationality [Russian]	0.390	1.476	0.786	0.496	0.620
Nationality [Spanish]	0.998	2.712	0.541	1.842	0.065 .
Nationality [Suisse]	0.411	1.508	0.891	0.461	0.644
Nationality [Swedish]	0.922	2.515	0.764	1.207	0.228
Nationality [Syrian]	1.465	4.326	0.701	2.088	0.037 *
Nationality [Turkish]	0.312	1.367	0.800	0.390	0.696
Nationality [US American]	-4.829	0.008	132.641	-0.036	0.971
Nationality [Vietnamese]	0.600	1.822	0.566	1.059	0.289
Culture FL [Cantonese]	1.834	6.261	0.810	2.263	0.024 *
Culture FL [Chechen]	-0.168	0.845	0.861	-0.195	0.845
Culture FL [Chinese]	1.164	3.204	0.619	1.880	0.060 .
Culture FL [English]	0.656	1.926	1.084	0.604	0.546
Culture FL [German]	0.675	1.964	0.521	1.295	0.195
Culture FL [Greek]	-5.210	0.005	162.453	-0.032	0.974

Table 12. Logistic Linear Mixed-Effects Model with Control Variables

Culture FL [Hindi]	0.506	1.659	0.656	0.772	0.440
Culture FL [Lithuanian]	5.964	38.903	132.641	0.045	0.964
Culture FL [Romanian]	0.285	1.330	0.807	0.354	0.724
Culture FL [Russian]	0.342	1.407	0.591	0.578	0.563
Culture FL [Serbian]	1.056	2.875	0.735	1.437	0.151
Culture FL [Shanghainese]	1.284	3.612	0.884	1.453	0.146
Culture FL [Slovak]	5.071	15.938	132.642	0.038	0.970
Culture FL [Tamil]	0.097	1.102	0.952	0.102	0.919
Culture FL [Telugu]	-0.825	0.438	1.045	-0.790	0.430
Culture FL [Turkish]	0.615	1.850	0.579	1.062	0.288
Random effects	***Var.***	***Std. dev.***	***Observ.***	***Groups***	
Subject (intercept)	0	0	999	175	
Residuals	***Min.***	***1Q***	***Median***	***3Q***	***Max.***
Residuals	-3.245	-0.690	-0.142	0.766	7.481

Table 13. Logistic Linear Mixed-Effects Model with Control Variables

Institutional isomorphism in terms of business function, institutional isomorphism in terms of location, recommendation elaboration, control variables:					
Fixed effects	***Estimate***	***Odds ratio***	***Std. error***	***z value***	***Pr(>|z|)***
Intercept	-0.768	0.464	0.459	-1.671	0.095
Inst. isomorphism in terms of business funct. [medium]	-0.002	0.998	0.181	-0.012	0.990
Inst. isomorphism in terms of business funct. [high]	-0.083	0.920	0.177	-0.470	0.638
Inst. isomorphism in terms of location [medium]	-0.211	0.810	0.187	-1.127	0.260
Inst. isomorp. in terms of location [high]	0.681	1.976	0.242	2.816	0.005 **
Elaboration	-0.459	0.632	0.087	-5.300	1.16E-07 ***
Inst. isomorph. (bf)[med.] * Inst. isomorph. (loc) [med.]	0.454	1.574	0.305	1.489	0.136
Inst. isomorph. (bf) [high] * Inst. isomorph. (loc) [med.]	0.160	1.174	0.298	0.539	0.590
Inst. isomorph. (bf) [med.] * Inst. isomorph.(loc)[high]	-1.191	0.304	0.434	-2.747	0.006 **
Inst. isomorph. (bf) [high] * Inst. isomorph.(loc)[high]	-1.012	0.363	0.406	-2.496	0.013 *
Inst. isomorph. (bf)[med.] * Elab.	0.880	2.410	0.145	6.073	1.26E-09 ***
Inst. isomorph. (bf) [high] * Elab.	0.968	2.632	0.146	6.606	3.96E-11 ***
Inst. isomorph.(loc)[med.] * Elab.	0.500	1.650	0.114	4.389	1.14E-05 ***
Inst. isomorph. (loc)[high] * Elab.	0.218	1.243	0.126	1.734	0.083 .
Inst. isom. (bf) [med.] * Inst. isom.(loc)[med] * Elab	-0.895	0.409	0.178	-5.023	5.09E-07 ***
Inst. isom. (bf) [high] * Inst. isom.(loc)[med] * Elab	-0.732	0.481	0.181	-4.039	5.36E-05 ***
Inst. isom. (bf) [med.] * Inst. isom.(loc)[high] * Elab	-0.245	0.783	0.208	-1.175	0.240
Inst. isom. (bf) [high] * Inst. isom.(loc)[high] * Elab	-0.270	0.764	0.206	-1.311	0.190
Age	0.071	1.074	0.085	0.835	0.404
Gender [woman]	0.062	1.064	0.102	0.606	0.545
Nationality [Belarus]	-0.560	0.571	0.785	-0.713	0.476
Nationality [Bulgarian]	0.300	1.350	0.528	0.569	0.569
Nationality [Chinese]	0.216	1.241	0.663	0.326	0.745
Nationality [Colombian]	-0.180	0.835	0.481	-0.374	0.708
Nationality [Dutch]	0.582	1.789	0.576	1.009	0.313
Nationality [Egyptian]	0.109	1.115	0.421	0.258	0.797
Nationality [French]	-0.232	0.793	0.847	-0.274	0.784
Nationality [German]	0.204	1.226	0.591	0.345	0.730
Nationality [Greek]	-0.158	0.854	0.921	-0.172	0.864
Nationality [Hungarian]	0.557	1.745	0.538	1.035	0.301
Nationality [Indian]	0.979	2.663	0.832	1.177	0.239
Nationality [Iraqi]	0.322	1.380	0.533	0.603	0.546
Nationality [Italian]	0.442	1.555	0.477	0.926	0.354
Nationality [Jordanian]	-0.211	0.810	0.576	-0.366	0.715
Nationality [Korea (Rep.)]	0.664	1.942	0.524	1.268	0.205
Nationality [Lithuanian]	1.535	4.643	1.351	1.137	0.256
Nationality [Mexican]	0.434	1.544	0.466	0.932	0.351
Nationality [Moroccan]	-0.285	0.752	0.568	-0.502	0.616
Nationality [Norwegian]	0.429	1.535	0.582	0.737	0.461
Nationality [Pakistan]	0.818	2.265	0.623	1.312	0.190
Nationality [Peruvian]	0.351	1.421	0.571	0.615	0.539
Nationality [Romanian]	-0.313	0.731	0.923	-0.340	0.734
Nationality [Russian]	0.316	1.372	0.659	0.479	0.632
Nationality [Spanish]	0.390	1.476	0.422	0.923	0.356
Nationality [Suisse]	0.940	2.559	0.770	1.220	0.222

Table 13. Logistic Linear Mixed-Effects Model with Control Variables

Nationality [Swedish]	0.848	2.335	0.536	1.581	0.114
Nationality [Syrian]	-0.226	0.797	0.604	-0.375	0.708
Nationality [Turkish]	0.130	1.139	0.666	0.195	0.845
Nationality [US American]	0.896	2.450	1.172	0.765	0.445
Nationality [Vietnamese]	0.421	1.524	0.437	0.963	0.335
Culture FL [Cantonese]	-0.127	0.881	0.634	-0.200	0.842
Culture FL [Chechen]	0.331	1.392	0.703	0.470	0.638
Culture FL [Chinese]	-0.003	0.997	0.524	-0.006	0.995
Culture FL [English]	-0.920	0.399	0.877	-1.048	0.294
Culture FL [German]	0.192	1.211	0.466	0.412	0.680
Culture FL [Greek]	0.297	1.346	0.901	0.330	0.742
Culture FL [Hindi]	-0.396	0.673	0.560	-0.660	0.509
Culture FL [Lithuanian]	-1.520	0.219	1.223	-1.244	0.214
Culture FL [Romanian]	0.792	2.209	0.645	1.229	0.219
Culture FL [Russian]	0.030	1.031	0.504	0.060	0.952
Culture FL [Serbian]	0.265	1.303	0.613	0.432	0.666
Culture FL [Shanghainese]	-0.544	0.581	0.711	-0.765	0.444
Culture FL [Slovak]	-0.837	0.433	1.204	-0.695	0.487
Culture FL [Tamil]	-0.319	0.727	0.814	-0.392	0.695
Culture FL [Telugu]	-1.925	0.146	0.935	-2.059	0.040 *
Culture FL [Turkish]	0.170	1.185	0.513	0.331	0.740
Random effects	***Var.***	***Std. dev.***	***Observ.***	***Groups***	
Subject (Intercept)	0	0	1513	179	
Residuals	***Min.***	***1Q***	***Median***	***3Q***	***Max.***
Residuals	-3.487	-0.832	-0.163	0.870	7.524

About the Authors

Martin Kretzer works as a data engineer at PricewaterhouseCoopers (PwC) where he designs and implements large-scale data processing and machine learning pipelines for his clients. His research focuses on the use and optimization of large-scale information systems for analytics and machine learning in the enterprise. Before joining PwC, Martin worked in Germany, the U.S., and the U.K. as a data scientist and data warehouse expert for Daimler, as a statistician for the European Central Bank (ECB), and as a software developer for Lufthansa Technik and Bosch. Martin holds a PhD in business from the University of Mannheim. His current research focuses on the design of data pipelines for machine learning across on-premise and cloud systems. His research has been published in journals such as *Communications of the AIS* and has been presented at multiple leading international conferences such as the ACM Conference on Computer Supported Cooperative Work, the International Conference on Information Systems, the European Conference on Information Systems, the Americas Conference on Information Systems, and DESRIST.

Alexander Maedche is a full professor at Karlsruhe Institute of Technology. He heads the research group "Information Systems & Service Design" at the Institute of Information Systems and Marketing and serves as a director at the Karlsruhe Service Research Institute. Alexander Maedche received a *Diplom* degree in industrial engineering & management and a PhD in applied computer science from the University of Karlsruhe, and has worked in industry at Bosch and SAP in managerial positions in the fields of IT management and software product development. His research work focuses on designing interactive intelligent systems and has been published in leading international information systems and computer science journals such as the *Journal of the Association of Information Systems, Business & Information Systems Engineering, Information & Software Technology, Computers & Human Behavior, IEEE Intelligent Systems, VLDB Journal*, and *AI Magazine*. Alexander serves in various roles supporting international research conferences; recently, for example, he was a co-organizer of DESRIST 2017 in Karlsruhe, Germany.