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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. In this paper, we draw on the nudge concept. We 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 are using an ERA to facilitate information (i.e., reports) retrieval in a business intelligence system. In addition, we are using 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-subjects lab experiment with 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 easier 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.*

# 1 Introduction

Employees in many organizations supplement their Information Systems (IS) with additional Workaround Systems (WS) to adapt their IS to their daily work routines (Alter, 2014; Jasperson et al., 2005). For instance, employees frequently supplement their organizations' core Business Intelligence Systems (BIS) with spreadsheet applications when preparing business reports (Burton-Jones and Grange, 2013; Davenport, 2014; Li et al., 2013). Generally, such WS are considered flexible and are very popular with end users (Bagayogo et al., 2014; Sun, 2012; Gass et al., 2015). Since many employees have the expertise required to develop and/or change WS, the latter are well suited for implementing emerging requirements rapidly (Alter, 2014). For instance, using spreadsheet applications, many users can quickly and easily extend a report with additional fields (Panko and Aurigemma, 2010; Powell et al., 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 and Dang, 2008; Tyre and Orlikowski, 1994). In addition, the use of WS may also lead to flawed and nonstandard routines and procedures (Alter, 2014).

To address these challenges, extant literature has focused on two IS governance-based approaches (Tiwana and Kim, 2015). First, certain researchers focus on reducing the generation and use of WS by defining IS governance policies and enforcing compliance (Liang et al., 2013; Rivard and Lapointe, 2012). Empirical studies in this stream examine, for instance, individuals' compliance with organizational guidelines and policies (Abubakre et al., 2015; Xue et al., 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 and Konsynski, 2010; Weill and 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 et al., 2008). Unfortunately, establishing and running these additional, cross-functional organizational units create high costs for organizations and, by introducing an additional governance layer, reduce 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 usually elicit users' preferences and requirements, as well as recommend items that address these. RAs therefore facilitate users' search for information (Arazy et al., 2010). For instance, many online stores adopt RAs to help them recommend products to their customers (Xiao and Benbasat, 2007). However, although RAs are very popular extensions

[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.

to systems that target end consumers such as online stores (Li and 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 et al., 2009), although information retrieval is very important in the enterprise IS context (Bernstein and Haas, 2008; Mukherjee and 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, only identifying and recommending reports are not sufficient to influence an individual's decision to actually reuse a certain report. Instead, in line with Simon's (1954) multi-stage decision-making process, the ERA also needs to 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 the way in which 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 refer to this form of influencing as a *nudge* (Thaler and Sunstein, 2003) and recently were awarded with the prestigious Nobel Prize and Laureate in Economic Sciences (The Royal Swedish Academy of Science, 2017). Designing an ERA that influences users' report recommendation choices is such a nudge.

To support report reuse, such 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 et al., 2012). Consequently, we refer to the ERA's effects as *social nudges*. Building on behavioral economists' concept of a nudge (Sunstein and 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 and Foster, 2003; Fiske, 2010; Friedkin and Cook, 1990). Building on these three forms of social influence, we design four social nudges. The first social nudge aims to control an individual's recommendation choice by exploiting that individual's tendency to be biased by his/her proximity to other individuals. The second and third social nudges aim to determine individuals' recommendation choice by exploiting their tendency to be biased by the similarity between their position in the organization and other individuals' positions. Finally, the fourth social nudge aims to determine an individual's recommendation choice by exploiting that individual's tendency to be biased by other individuals' hierarchical power.

In addition, as a **third objective**, 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 only display "social" information about previous users, but are not humans, only the displayed reference information exerts social influence. Researchers therefore need to determine that individuals actually cognitively process the displayed information about previous users. For instance, an ERA that wants to steer users' choices toward certain report recommendations can only succeed if users view and process the information it provides. If users were to not elaborate on the provided information about previous users, this information would 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 recommendation elaboration's moderating effect.

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 of designing nudges in organizational settings. Third, using eye-tracking technology, we highlight the importance of recommendation elaboration as a moderator of social nudges' effects 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. Section 7 concludes this paper.

# 2 Theoretical Foundations

## *2.1 Nudge*

The Nobel Prize Foundation introduces the 2017 Prize in Economic Sciences for Richard Thaler 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 fact, peoples' decision making is not entirely rational, because many environmental features can influence their decisions (Thaler et al., 2010). For instance, through changing a person's environment, the person's decisions can be influenced. Literature refers to such intentional changes in a person's environment as nudges (Thaler et al., 2010). A nudge aims to influence peoples' decision making in certain ways without them 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. Although the selection on the menu does not change depending on how it is presented on the menu, its presentation 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 a second 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 disclosure of information, default rules that become individuals' choices if they do not change these, the framing of choices, and "cooling-off" periods (Hanna, 2015; Leonard, 2008).

The nudge concept is based on behavioral economists' research stream, called *libertarian paternalism* (Thaler and 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 in which 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 and 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 showed 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 of their solution. Furthermore, Weinmann et al. (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 et al., 2015). This 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 et al., 1979; Tsai and 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 and 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 its specific effects in a particular context (Anderson and 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 and Tsai, 2003; Sparrowe et al., 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 and 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 pre-existing social ties (Kilduff and 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 and Foster, 2003). In contrast, the structuralist approach emphasizes the structural similarity of nodes in a network, although no tie may connect 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 et al., 2006; Stark, 2009), organizations are still highly hierarchical (Courpasson et al., 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 et al., 2016; Clegg et al., 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 et al., 2003; Magee and 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. Limited 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, these messages' effect on certain individuals depends on the extent to which these individuals process them, which is commonly referred to as elaboration (Angst and Agarwal, 2009; Bhattacherjee and Sanford, 2006; Ho and Bodoff, 2014; Meservy et al., 2014). Elaboration is defined as the amount of message-relevant thinking in which an individual engages while evaluating a message (Petty and Cacioppo, 1986a, 1986b). In our model, we examine elaboration as a moderator, because it might 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 and 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 and 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 and 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 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 by means of social influence's effects.

This study therefore first draws on theoretical knowledge about social cohesion's effects and suggests 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. We therefore 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 effect 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, may cause it to have a negative effect. That is, individuals will 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 degree to which individuals have equivalent positions in an organizational structure. The **institutional isomorphism** concept best captures the process of structural equivalence in organizations (DiMaggio and Powell, 1983). Unlike social cohesion, isomorphism does not depend on proximity (Borgatti and Everett, 1992). In an isomorphic network, "nodes may be adjacent, distant, or completely unreachable from each other" (Borgatti and 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 and 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 and 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 and 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 were working in Asia and was not connected 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 and Powell, 1983; Borgatti and 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 functions and locations (i.e., geographical regions, countries) as positions in organizations' networks, because organizations are usually structured according to their business functions and/or locations (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 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 (regarding 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 are expected to work together closely, many organizations are structured according to locations. We therefore theorize that:

Hypothesis 3 (H3). *High institutional isomorphism between two individuals (regarding the location in which they primarily work) 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 with regards to job roles seems to be an especially powerful basis for nudging employees toward reusing certain reports, because we assume that, for example, two sales analysts use their BIS to achieve similar objectives. We did not investigate this nudge, because institutional isomorphism regarding job roles and business functions (e.g., sales departments, marketing departments, IT departments) would be very similar. We therefore only focused on institutional isomorphism regarding business functions, 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 suggest the following hypothesis:

Hypothesis 4 (H4): *The extent of an individual's power (regarding this individual's hierarchical position and control of financial budgets and employees) increases the probability that others will choose a recommended item associated with this powerful individual.*

Whether individuals know each other affects the hierarchical effect of power further. Employees in a high position, such as directors, may influence other employees even if they are not directly connected to them. Conversely, employees who are in low hierarchical positions, such as interns, may generally only influence directly connected employees (e.g., colleagues whom they directly assist), but are unlikely to influence other employees. Thus, the influence of employees in lower organizational positions will be impacted more by providing additional information about their social cohesion (i.e., proximity) than about that of employees in higher organizational positions. Accordingly, we define an interaction effect between power and social cohesion:

Hypothesis 5 (H5): *The extent of an individual's power (regarding this person's hierarchical position and control over financial budgets and employees) moderates the effect of social cohesion between this individual and others. Specifically, the degree to which the individual is powerful weakens the effect 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 this study, individuals have to choose from a set of available recommendations, and, although they do not know the recommended item (i.e., the report), they could process information about the recommendation. For instance, they could consider information about 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) described 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 and Creighton, 2013). This means that the greater the extent to which individuals elaborate on 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 and 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 elaborates additional information about a set of recommended items determines the effect this information has on this individual's decision to choose a certain recommendation. For instance, the effect of additional information about previous users associated with the recommended items depends on new users' elaboration of this information. Accordingly, we define the following hypotheses:

Hypothesis 6a (H6a). *The degree to which an individual elaborates on information about a recommended item strengthens the effect of providing information about social cohesion between that individual and another associated with the recommended item.*

Hypothesis 6b (H6b). *The degree to which an individual elaborates on information about a recommended item strengthens the effect of providing information about institutional isomorphism (regarding business functions) between that individual and another associated with the recommended item.*

Hypothesis 6c (H6c). *The degree to which an individual elaborates on information about a recommended item strengthens the effect of providing information about institutional isomorphism (regarding locations) between that individual and another associated with the recommended item.*

Hypothesis 6d (H6d). *The degree to which an individual elaborates on information about a recommended item strengthens the effect of providing information about the power of another individual associated with the recommended item (regarding hierarchical position and control over financial budgets and employees).*

For instance, the effect of providing information about the social cohesion between the potential new user and a previous user (H1) depends on the new user's elaboration of such information. Similarly, concerning the effect of institutional isomorphism, we theorize that an individual needs to elaborate on a recommended item in order for additional information about institutional isomorphism regarding business functions (H2) and locations (H3) of previous users to influence this individual. Finally, the impact of providing information about previous users' power (H4, H5) also depends on new users' elaboration of that information because, without elaboration, the new user would ignore the information.

### *3.3 Recommendation Choice as Response to Social Nudges*

As responses to the defined social nudges, we examine individuals' recommendation choices. 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 other individual responses besides recommendation choice. Recommendation choice is our study's only dependent variable.

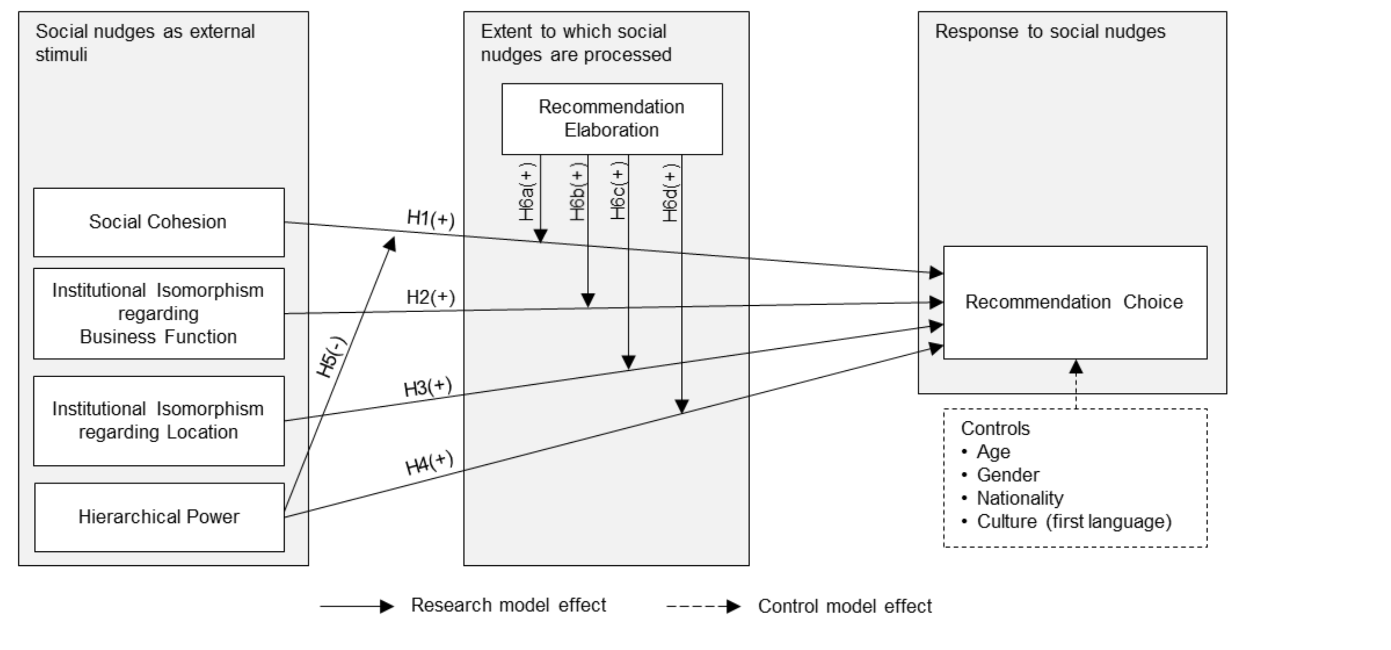



**Figure 1. Research model.**

Figure 1 summarizes our research model. In line with other IS studies focusing on various design features (e.g., Choi et al., 2015; Day et al., 2009; Xu et al., 2014; Zhang et al., 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 (with regard to one's first language as a child).

# 4 Research Method

To test our research model, we conducted a laboratory experiment. Lab experiments are particularly suited to examine the cause's temporal precedence and to eliminate alternative explanations of possible cause-effect connections in the IS discipline (Cook and Campbell, 1979; Colquitt, 2008; Dennis and 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 which provides users with report recommendations. Figure 2 shows a screen-shot of the BIS and the ERA. The report recommendations (lower box on the left side of the screen) change every few seconds.

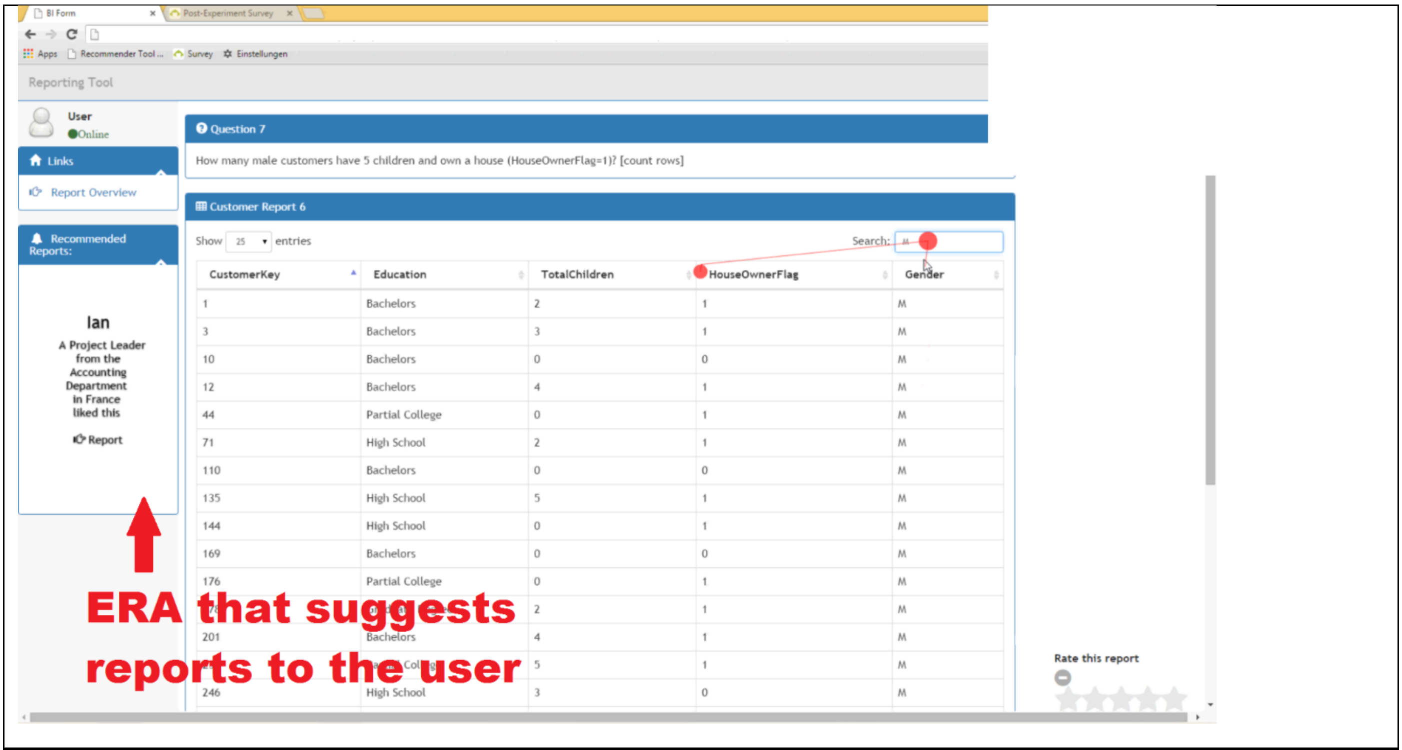



**Figure 2. BIS extended with an ERA that suggests reports to users.**

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 reports' names 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 with regard to 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).

With the additional information provided about previous users of recommended reports, we intend to nudge new users toward choosing certain report recommendations. The information allows new users to infer the social influence of the previous report users. Existing studies have shown that users viewing information about others on their screen, associate this information with those people (Guadagno et al., 2011; Teubner et al., 2015). This additional information conveys the social influence of these previous users. We use 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 with regard to 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 with regard to 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 w.r.t. business funct. | Institutional isomorphism w.r.t. location | Hierarchical power | Example report recommendation |
|---|---|---|---|---|
| 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 Mgmt. department in Canada liked this report." |

## *4.2 Experiment Design*

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

Since we suggest an interaction effect between social cohesion and power in organizational hierarchies (H5), we need a 2*3 cross-factorial design between these treatments. Crossing this design with additional treatments is not reasonable, because (1) we did not theorize any interaction effects with institutional isomorphism and (2) the unnecessary crossing of experimental treatments would reduce the analysis's statistical power. We therefore crossed the two forms of institutional isomorphism using a 3*3 cross-factorial design, but did not cross the two factorial designs with each other. Consequently, we get 2*3 + 3*3 = 15 experimental treatments, with one experimental treatment included in both the factorial designs. In this study, there are therefore 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-subjects experiment design for the following two reasons: first, each treatment represents one set of recommended items from which a participant can choose one recommended item. This relatively fast experimental task does not take longer than a minute. Subjects can therefore participate in multiple treatments, which makes a within-subjects design feasible for our experiment. Second, the total of 14 experimental treatments is relatively high. A between subjects design would require too many participants and is 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 does not help participants complete their tasks (i.e., answer the questions), the risk of carryover effects is 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, because they are much less likely to be biased due to personal experiences than experienced professionals. If the latter have had bad experiences when working with people from certain countries, these experiences might influence whether they would, in the experiment, choose a recommendation from someone working in that country.

In the experiment, the participants are provided with an organizational scenario. In this scenario, they take the role of Thomas, who is an employee at Contoso; i.e., an employee at the company introduced above and for which the BIS provides data. Thomas works for 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 similar information on Contoso’s organizational structure.

We used the following five techniques to train and prepare participants for the experiment: First, we made a 15-minute introductory video about the experiment available to participants one week before the experiment took place. This video introduced them to the experiment, the scenario, and the usage of the BIS (incl. 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 are not considered in the data analysis. They are 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, which avoided 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 with the use of the BIS if participants required this.

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, as well as that the time they required 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 expected to 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 the first recommendation appeared again.

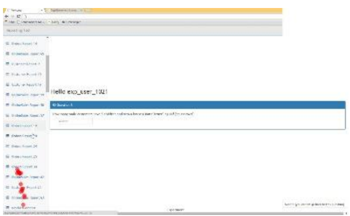
The recommendations were not dynamic, but predefined. All the report recommendations within the same set of three alternative recommendations would always link to the same report. However, the participants did not know this. Predefined recommendations were important, because the participants' usage history 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.

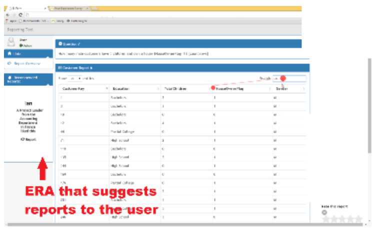
Each experimental treatment had three recommendations. After a participant had chosen one recommendation out of the set of three recommendations, all three recommendations were updated with the next experimental treatment's recommendations.

Furthermore, all sets of report recommendations were predefined because they represent our experimental treatments and thus had to be controlled. At the latest the *third* set of recommendations would forward participants to a report that would provide them with the information they needed to answer one experimental task. Consequently, we could gather data for up to *three* experimental treatments per experimental task.

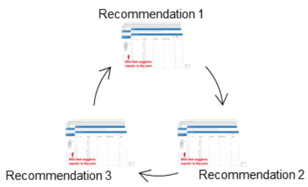
Finally, after completing the nine tasks, participants were asked to answer a post-experiment survey. All 187 experiment participants also participated in the post-experiment survey.

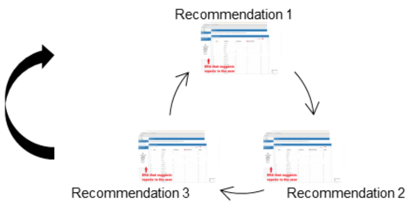
**Table 3. Exemplary experimental task.**

| **Step** | **Description** |
|---|---|
| **1. Entry page**<br><br>*(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.<br><br>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. |

<table>
<tr>
<td>2.1 First report with first experimental treatment<br>


(report with ERA)<br>


(ERA uses the three recommendations in turn (carousel effect))</td>
<td>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.<br><br>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”.<br><br>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.</td>
</tr>
<tr>
<td>2.2 More reports with more experimental treatments<br>


(the second report provides the second treatment; the third report provides the third treatment)</td>
<td>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.<br><br>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.</td>
</tr>
<tr>
<td>3. Final report that provides the answer to the exp. task<br>


(recommendations in the final report link to the final report)</td>
<td>The “final report,” which is shown after completion of all the experimental treatments of a specific experimental task, provides the answer to the question.<br><br>We varied the number of experimental treatments per experimental task. The “final report” is shown after one, two, or three experimental treatments. This variation is useful, to prevent the participants recognizing that the “final report” is always shown once the same number of recommendations have been clicked.<br><br>The “final report” also shows a set of three report recommendations. However, these do not represent an experimental treatment. When clicking on one of them, the “final report” is reloaded.</td>
</tr>
</table>

## 4.4 Measurement of Recommendation Choice

The recommendation choice is the dependent variable in our study. We suggest that the probability of new users choosing a certain recommendation changes depending on the information about the previous users of recommended reports. Throughout the experiment, participants can 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 will compare the probabilities of choosing a certain manipulated recommendation *between different sets of (three) recommendations*. Consequently, it is important that the manipulated recommendation is always shown in the same position throughout all the sets of recommendations to prevent the position from biasing our results. For instance, some participants could simply click on recommendation 1, because it is the first they encounter.

The manipulated recommendation is always shown as the second of three recommendations to avoid bias. In other words, by keeping the position constant in which the manipulated recommendation is shown across the experimental treatments (i.e., in all the treatments, the manipulated recommendation is show in position 2), we can assume that the position of the manipulated recommendation does not affect these treatments differently. In turn, this ensures that the experimental treatments are comparable.

In contrast, a randomized approach would limit such a comparison, because the participants do not have to use the ERA. Consequently, randomization of the position in which the manipulated recommendation is provided, would probably lead to some variation between the ratio of users who used the ERA and received the manipulated recommendation at position 1, 2, and 3. For a certain treatment, randomization could, e.g., lead to 36% of ERA users receiving the manipulated recommendation as recommendation 1, while, for another treatment, randomization could lead to 30% of ERA users receiving the manipulated recommendation as recommendation 1. Such a difference would bias our results. Thus, instead of randomizing its position, the manipulated recommendation was always displayed as the second of three recommendations throughout the experimental treatments.

In respect of the manipulated recommendation (i.e., recommendation 2), the degree of social influence changes between the experimental treatments. Conversely, recommendation 1 and recommendation 3 always refer to a previous user with the same degree of social influence: A project manager not directly connected to Thomas and who, compared to Thomas, works in a different department and on a different continent (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 at which recommendation 2 was selected in respect of each experimental treatment, divided by the frequency at which any recommendation was selected within that experimental treatment (i.e., the sum of the clicks on recommendations 1, 2, and 3). This ratio represents the probability that participants would select recommendation 2 within a certain experimental treatment. In turn, this probability allows us to compare the effects of social influence because this only differed from the others in recommendation 2. Table 3 shows an example of the procedure in an experimental task.

### *4.5 Measurement of Recommendation Elaboration*

We measure the extent to which users elaborate on recommendations. Since all recommendations are messages displayed on the screen, we need to measure the extent to which users process these messages cognitively.

While a vast literature has used questionnaires and surveys to measure elaboration, or focused on the antecedents of elaboration (e.g., Angst and Agarwal, 2009; Bhattacherjee and Sanford, 2006; Ho and Bodoff, 2014), only Meservy et al. (2014) demonstrate the benefits of eye tracking as a means to measure 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 and 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 at which users look. This allows computing the amount of time a user has gazed at a message on the screen and is an important part for 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 and Kotval, 1999; Weigle and Banks, 2014). Analysis of pupil sizes allows us to determine whether users either focus and process the displayed texts, or whether they only move their heads and merely skim the texts. Therefore, the product of coordination point metrics and pupil size metrics allows us to compute a reliable fixation metric.

To compute fixation, we use the fixation filter that the application ProStudio provides, because it is the recommended filter for our eye-tracking device Tobii Pro X2 (Tobii, 2015). This filter ensembles multiple fixation algorithms (Komogortsev et al., 2010; Rayner et al., 2007; Over et al., 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 with regard to business function, institutional isomorphism with regard to 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 cultural indicator, we asked them about their nationality and the first language they learned as a child. Overall, 57% of participants were Germans and 48% learned German was the first language they learned as a child. This is not surprising, since the study was conducted at a university in Germany. The participants from Arabic countries, China, Egypt, India, Russia, Spain, Turkey, Greece, Vietnam, and the USA were minorities. Thus, besides the focus on German participants, the demographic profile is fairly distributed across countries and cultures.

### *5.2 Manipulation Checks*

We conducted manipulation checks in respect of the experimental treatments. These are summarized in Table 4. We administered a post-experiment survey, asking all the participants whether they had noticed that the four experimental treatments (social cohesion, institutional isomorphism regarding business function, institutional isomorphism regarding location, hierarchical power) differed between specific recommendations. We also added two general items to control whether they had 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).

Eventually, 167 of the 187 participants (89.3%) stated 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 allows us to consider the manipulation of the experimental treatments successful.

### 5.3 Measurement Model

Besides the manipulation checks, no variables in this study were measured by means of surveys. All the independent variables represent 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 | Post-experiment 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 regarding business function | • I noticed that the colleagues, who were shown in the report recommendations, worked in different departments. {yes, no} | 100.0% |
| Institutional isomorphism regarding location | • I noticed that the countries of the colleagues shown in the report recommendations were changing. {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 were changing. {yes, no} | 98.9% |
| | • All recommendations were based on the same user. {yes, no} | 5.3% |

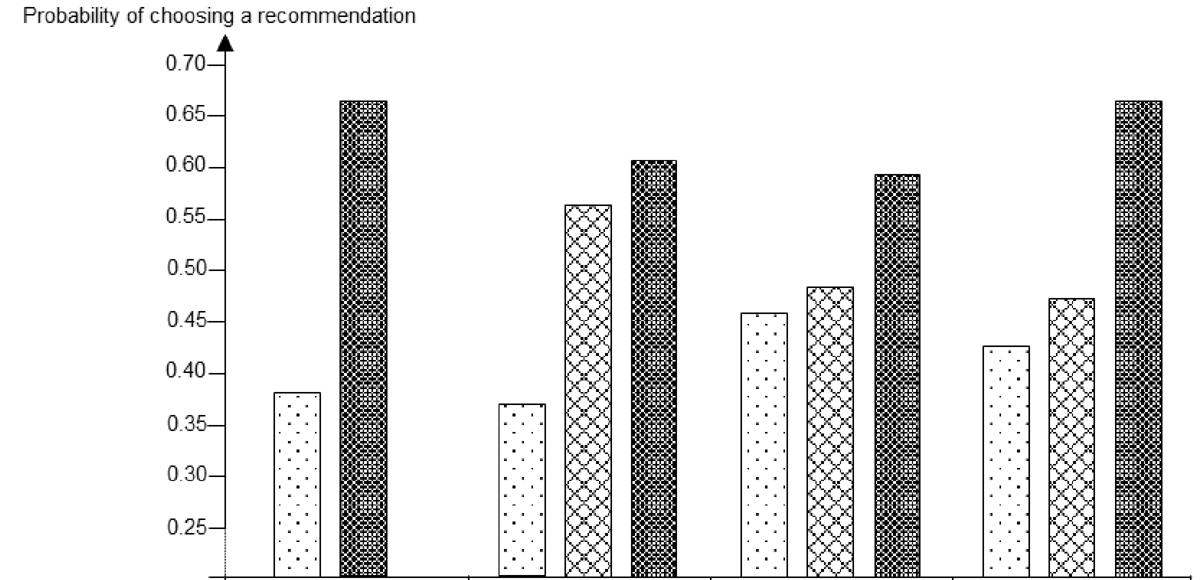
### 5.4 Results of Hypothesis Tests

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.

Eventually, 93% of all questions were answered correctly. In respect of 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, could complete the tasks correctly. However, to avoid potential bias from unmotivated participants and/or guesses, our data analysis only considered 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) is always recommendation 2 out of a set of three, the list also provides (c) the frequency with which a participant chose recommendation 2 and answered the question correctly. Finally, this allows 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. By changing the social influence of the recommended reports' previous users, the probability that BIS users would choose a certain recommendation was increased. 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 probability 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 et al., 2015). A logistic linear model is suitable, because we suggested linear effects and have one binary dependent variable (values: choose the manipulated recommendation; do not choose the manipulated recommendation). Similarly, a mixed effects analysis is 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 2*3 experiment design to test the effects of social cohesion, hierarchical power, and elaborated an additional 3*3 experiment design to test the effects of institutional isomorphism (with regard to business functions), institutional isomorphism (with regard to 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 (regarding business functions), institutional isomorphism (regarding 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 have 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 et al., 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 a pseudo $R^2$ statistics, we report the $R^2$ for general linear mixed models (so-called $R^2_{GLMM}$) after Nakagawa and Schielzeth (2013) and as implemented in the R package *MuMIn* version 1.4 (Barton, 2017). Note that the $R^2_{GLMM}$ 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 $R^2_{GLMM}$ needs to be assessed with caution if compared to $R^2$ statistics from linear models or general linear models (Nakagawa and Schielzeth, 2013). In line with the AIC and BIC, the $R^2_{GLMM}$ 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 moderator increases the $R^2_{GLMM}$ from 17.2% to 42.3%. Similarly, regarding the effect of institutional isomorphism, adding elaboration as moderator increases the $R^2_{GLMM}$ from 9.5% to 24.3%. (Note: We do not distinguish between $R^2_{GLMM}$ for the fixed effects model and the entire model because differences only occurred after the fourth relevant digit.)

**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, $R^2_{GLMM}$=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, $R^2_{GLMM}$=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 | *** | |
| 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 | | |

**Significance levels:** ***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, $R^2_{GLMM}$=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 regarding business funct. [medium] | 0.828 | 2.289 | 0.131 | 6.319 | 2.63E-10 | *** | **H2** |
| Inst. isomorphism regarding business funct. [high] | 1.004 | 2.728 | 0.130 | 7.711 | 1.25E-14 | *** | **H2** |
| Inst. isomorphism regarding location [medium] | 0.068 | 1.071 | 0.134 | 0.509 | 0.610451 | | **H3** |
| Inst. isomorphism regarding 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 | | | |

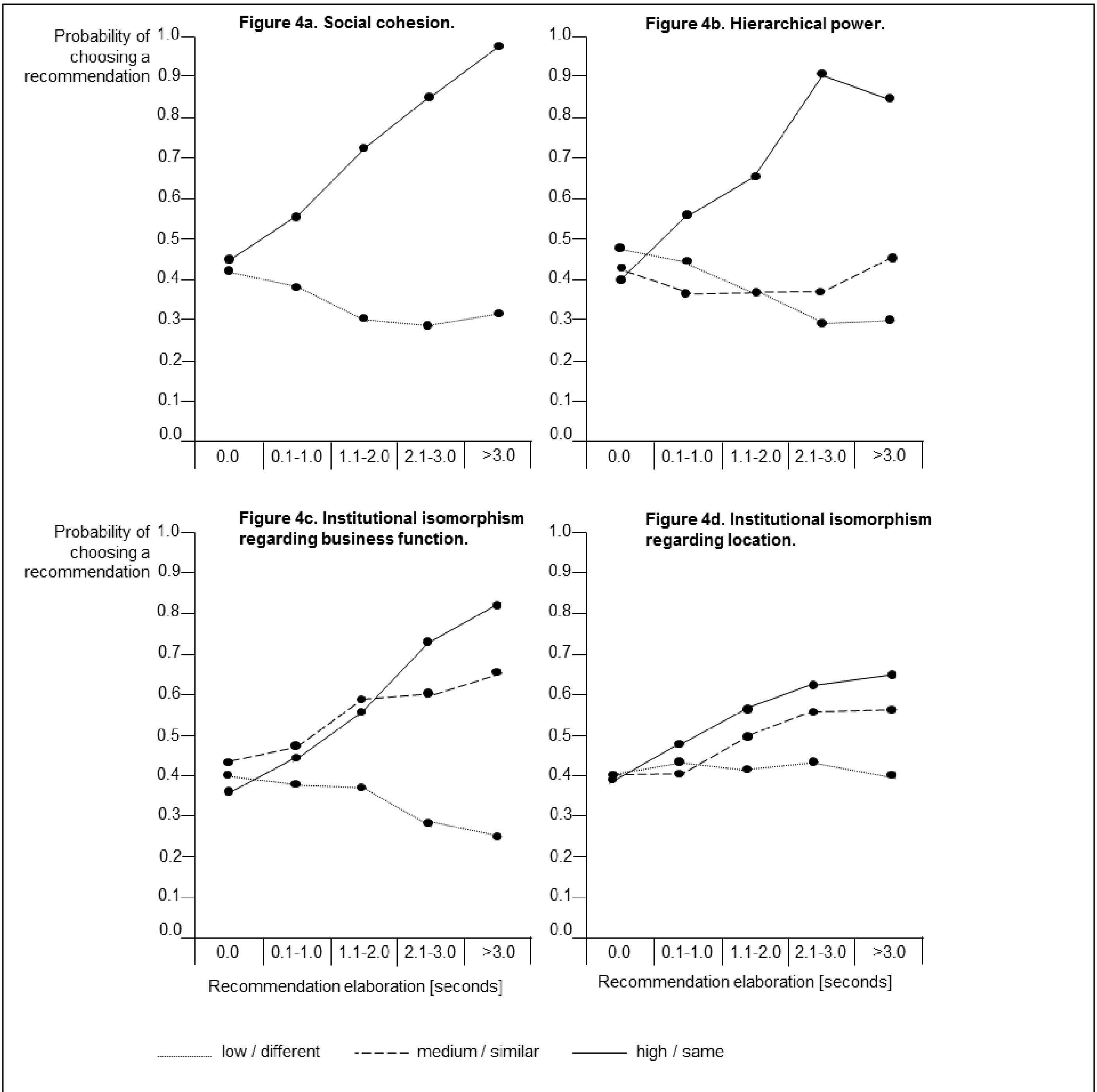
| | | | | | | |
|---|---|---|---|---|---|---|
| *Residuals* | *Min.* | *1Q* | *Median* | *3Q* | *Max.* | |
| Residuals | -1.618 | -0.930 | -0.615 | 0.910 | 1.627 | |
| ***Moderator model (AIC=1888.6, BIC=1989.8, $R^2_{GLMM}$=24.3%):*** | | | | | | |
| *Fixed effects* | *Estimate* | *Odds ratio* | *Std. error* | *z value* | *Pr(>\|z\|)* | *Hyp.* |
| Intercept | -0.349 | 0.705 | 0.172 | -2.038 | 0.042 * | |
| Inst. isomorphism regarding business funct. [medium] | -0.031 | 0.969 | 0.290 | -0.107 | 0.915 | |
| Inst. isomorphism regarding 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 regarding 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 ** | |
| 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 | |

**Significance levels:** ***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.




**Figures 4a-d. Moderating effects of recommendation elaboration.**

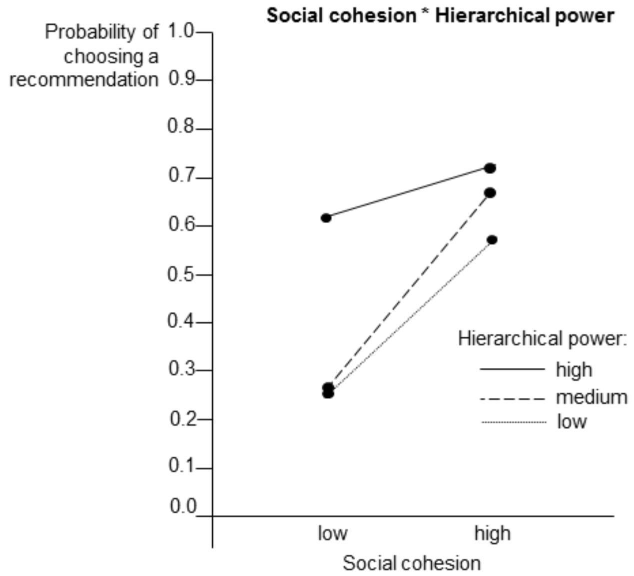



**Figure 5. Interaction effect between social cohesion and hierarchical power.**

### 5.4.1 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 is significantly higher if the recommendation is based on the usage data of a direct colleague (i.e., high social cohesion), who is referred to, for example, as “your project manager” instead of “a project manager.” Since this increase is 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 choose recommendations with a high social cohesion 3.6 times more often than those with a low social cohesion.

In addition, we suggested that the probability of a participant choosing a certain recommendation is also significantly higher if the recommended report’s previous user is assigned to a hierarchical powerful position, such as a director or a project manager (H4). However, only a high hierarchical power level (“director”) increases the probability significantly (at $p<0.001$). Compared to a low hierarchical power level (“intern”), the medium hierarchical power level (“project manager”) only increases the probability by a factor of 1.1, but a high hierarchical power level (“director”) increases the probability by a factor of 2.8. This indicates that a social nudge based on hierarchical power is generally suitable to influence users’ actions, but the effect size varies strongly.

We found that employees in a powerful position, 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. Employees in less powerful hierarchical positions, such as interns, can usually only influence directly connected employees. Contrary 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 them 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 already 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 social cohesion between these 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 respect of this interaction effect (Table 5, moderating effects model).

### 5.4.2 The Effects of Social Nudges based on Institutional Isomorphism

Furthermore, we designed two nudges based on institutional isomorphism. The results show that institutional isomorphism with regards to a user's business function (H2) increases the probability of that user choosing a specific recommendation. Contrary 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) increases the probability by a factor of 2.3, while high similarity (e.g., two sales departments) increases the probability by a factor of 2.7 (Table 6, main effects model). Both increases are 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 regarding a user's location (H3). Contrary to users' locations on different continents (e.g., Germany and Canada), locations on the same continent (e.g., Germany and France) only increase the probability by a factor of 1.1, while locations within the same country (e.g., two locations in Germany) only increase the probability by a factor of 1.6 (Table 6, main effects model). While this increase is still statistically significant at $p<0.001$, which supports H3, it is interesting to note that, in our study, institutional isomorphism with regard to users' business functions has a much larger impact than institutional isomorphism with regard to users' locations.

### 5.4.3 The Moderating Effect of Recommendation Elaboration

We suggested that the effect of any nudge depends on whether the 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.

#### 5.4.4 Control Model

The hypotheses analyzed above represent the main research model. We analyzed potentially biasing factors' effects. Our analysis controlled for the participants' age, gender, nationality, and their culture (with regard to their 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 focused on BIS governance 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 suited 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, the reuse of reports that their colleagues originally developed. Ultimately, this should reduce individuals' need to develop WS, because they will find existing reports that provide them 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 suggests 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 either emphasize the need to prevent WS, or the need to acknowledge the value of WS and help individuals build WS. However, both approaches have their limitations. Attempts to control the use of large enterprise IS and to prevent WS have shown to cause 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, which in turn needs to be managed, usually by means of additional IS governance units. However, establishing and running these organizational units are very costly and only the specific context can determine whether introducing additional IS governance units will increase the IS' flexibility (Brown and Magill, 1994, 1998; Gebauer and Schober, 2006; Tiwana and Kim, 2015). In contrast to these IS governance-based approaches, our ERA neither limits individuals' flexibility regarding using existing information, nor requires 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 a rational decision. Extant literature has showed that these biases also exist in the IS context (e.g., Adomavicius et al., 2013; Allen and 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 addressed 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 and 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 choice. In other words, the picture of the smoker's lungs nudges (potential) smokers and influences their decisions in desirable ways (i.e., 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 presented 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) regarding business functions and locations, and social influence based on the power in organizational hierarchies. Our results indicate that providing additional information about previous users may have a social influence on new users and, thus, increases 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 aims to explore ways to utilize cognitive biases in order to promote desired user behaviors. While the vast body of works by behavioral economists' theorizes deeply on nudges' potential benefits (e.g., Hanna, 2015), IS research can contribute by refining and designing concrete nudges, as well as 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.

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 et al., 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 et al., 2014).

### *6.2 Implications for Practice*

Besides implications for theory, our findings provide 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", "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. They are therefore 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 should be tested within their specific context 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 opens 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 with 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 with working with BIS, we argue that they are a reasonably representative group, because external factors, such as historical experiences, bias them less (e.g., Choi et al., 2015; Colquitt, 2008; Xu et al., 2014). In addition, to mitigate the risk associated with inexperienced participants, we only used tabular reports, as well as 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 with 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 with regard to each recommendation with state-of-the-art eye-tracking technology. 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 sub-parts of the recommendations.
Besides tackling these potential limitations, future research could extend our work, as well as 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 and Goshal, 1998). However, IS users' behaviors could perhaps not only be manipulated by means of social effects and future studies could therefore 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 that indicate why other colleagues use the reports. These studies could specifically improve our ERA, because, in its current form, it only focuses on presenting information about previous users without considering information about the content of the recommended reports.

# 7 Conclusion

Recent IS articles have called researchers to draw on and contribute to behavioral economists' research (Goes 2013). This study draws on their nudge concept. We suggested a specific refinement described as a social nudge, which refers to an attempt to steer an individual toward desirable choices by exploiting social influence's effects on this individual. However, in line with the nudge concept, a social nudge should not change the range of available options from which the individual can choose.
Moreover, we designed four social nudges based on theoretical knowledge about social cohesion, institutional isomorphism, and hierarchical power. We implemented these social nudges and examined their effects on BIS users. Our findings showed 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 provide insights into concrete applications and the effects of the nudge concept.
We studied the effects of the four social nudges in the context of RAs. Previous RA literature focused on end-consumers rather than employees as RA users. However, we suggest 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 using recent eye tracking technology and conducting gaze analysis.

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# 9 Appendix

## *9.1 Experimental Treatments and Probabilities*

We used a within-subjects experiment design. Experimental treatments 1-9 are used for the cross-factorial examination of institutional isomorphism with regard to business function and location. In addition, experimental treatments 10-15 are 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 recommendation. 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 <u>and</u> answered the <u>task correctly</u>. 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 <u>second recommendation</u> <u>and</u> answered the <u>task correctly</u>. Finally, this allows us to compute (d) the <u>probability</u> of users selecting the <u>second recommendation</u> if they followed one of the three recommendations of the condition <u>and</u> answered the <u>task correctly</u>.

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 (regarding business functions and regarding location), and elaboration equals the sum of Table 8, column b, rows 10-15.

**Table 7. Experimental treatments: Overview.**

| Exp. treatment id | Inst. isomorph. regarding business functions | Inst. isomorph. regarding locations | 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% |

### 9.2 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% |
| | 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% |
| | 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% |

## *9.3 Experiment Design*

### 9.3.1 Experimental 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 and not considered in our data analysis.

**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 sub-category 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 usually place his orders? | France |
| 9 | Experiment | Where does customer 252 live and how old is he/she? | 83 and Canada |

### 9.3.2 Organizational structure of Contoso

Contoso is the scenario company in the experiment. The departments, organizational 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.

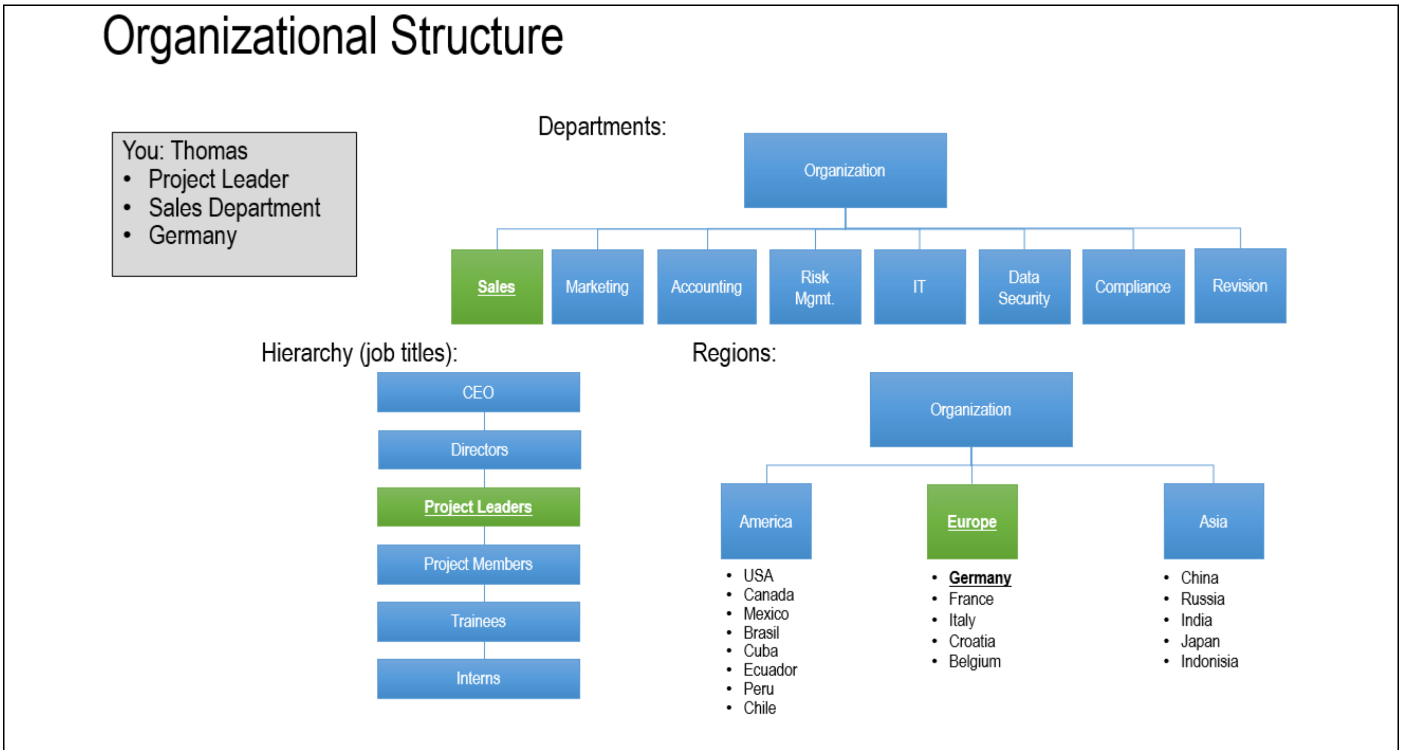


**Figure 6. Contoso reference paper provided to participants during the experiment.**

## *9.4 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 regarding 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 regarding 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 |

## 9.5 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 | |
| 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 regarding business function, institutional isomorphism regarding 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 regarding business funct. [medium] | -0.002 | 0.998 | 0.181 | -0.012 | 0.990 |
| Inst. isomorphism regarding business funct. [high] | -0.083 | 0.920 | 0.177 | -0.470 | 0.638 |
| Inst. isomorphism regarding location [medium] | -0.211 | 0.810 | 0.187 | -1.127 | 0.260 |
| Inst. Isomorp. regarding 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 |
| 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 | |